

T.C.
BAHCESEHIR UNIVERSITY
GRADUATE SCHOOL
THE DEPARTMENT OF INDUSTRIAL ENGINEERING

**INTEGRATED SMART OLIVE CULTIVATION SYSTEM DESIGN BY ARTIFICIAL
INTELLIGENCE TECHNOLOGY**

DİLAN SARPKAYA

PHD THESIS
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ISTANBUL 2025

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PHD THESIS

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ABSTRACT

INTEGRATED SMART OLIVE CULTIVATION SYSTEM DESIGN BY ARTIFICIAL INTELLIGENCE TECHNOLOGY

Sarpkaya, Dilan

Industrial Engineering PhD Program

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The climate change and increasing population result in critical impacts especially in food sector worldwide. This situation addresses planning and prediction implications in agriculture field. Even though olive fruit is a kind of climate resistant, it is inevitable to avoid from global changes. In terms of artificial intelligence based studies in smart farming, long short term model (LSTM) model's dataset developed by meteorological and production data of 13 cities which consist of Türkiye's 90% of olive production between 2010-2023. 4 different LSTM models developed based on annual, monthly and integrated basis. The model that predicts only output as a production achieved 0.94 R^2 value. In addition to LSTM, Hesitant Fuzzy AHP methodology was also integrated considering the importance of sectoral knowledge and experience in agriculture. 9 criteria and 6 alternatives are determined by literature review and expert opinions in order to conduct multi criteria decision making (MCDM) method. Collection of data from experts indicated that climate change has the highest weight. Giving direction of various action plans were aimed by this methodology. Strategic directions were provided with achieved findings for decision makers in the context of smart farming.

Keywords: Olive Cultivation, Smart Farming, Prediction, LSTM, Hesitant Fuzzy MCDM

ÖZ

YAPAY ZEKA TABANLI ENTEGRE AKILLI ZEYTİN TARIMI SİSTEMİ

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Dünya çapında artan popülasyon ve iklim krizinin, özellikle gıda alanında, kritik etkilere sebep olması beklenmektedir. Bu durum ise tarım alanında planlama ve tahminleme alanlarında çeşitli yeni yöntemlerin uygulanmasına ve gelişmesine yön vermektedir. Zeytin meyvesi iklim değişimlerine karşı en dirençli ürünlerden olsa da küresel çapta yaşanan değişimlerden etkilenmesi kaçınılmazdır. Yapay zeka tabanlı akıllı tarım uygulamaları kapsamında, uzun kısa vadeli bellek (LSTM) modeli veri seti, 2010-2023 yılları arasındaki Türkiye’de zeytin üretiminin %90’ını oluşturan 13 ilin meteorolojik ve üretimsel verileri kullanılarak geliştirilmiştir. Geliştirilen 4 farklı LSTM modeli, yıllık bazda, aylık bazda ve bütünlük yaklaşımlarla oluşturulmuştur. Sadece üretim tahmini yapılan modelde 0.94 R^2 değeri elde edilmiştir. Sektörel anlamda bilgi ve deneyimin tarım uygulamalarında öne çıkması da göz önünde bulundurularak LSTM’in yanı sıra uzman görüşleri alınarak Tereddütlü Bulanık AHP yöntemi uygulanmıştır. Tereddütlü Bulanık AHP ile karar vericilerin farklı kriterlerde hangi alternatiflerin daha önemli olduğu vurgulanmıştır. Literatür taraması ve uzman görüşleri sonucunda belirlenen 9 kriter ve 6 alternatifin kullanıldığı çok kriterli karar verme (ÇKKV) yönteminde en yüksek ağırlığa sahip kriter iklim uygunluğu olmuştur. Bu sayede çeşitli aksiyon planlarına yön verilmesi hedeflenmiştir. Elde edilen bulgular akıllı tarım uygulamaları kapsamında karar vericilere stratejik yönlendirme sağlamaktadır.

Anahtar kelimeler: Zeytin Tarımı, Akıllı Tarım, Tahminleme, LSTM, Tereddütlü Bulanık AHP



Together with my Vera for my mother and Yiğit

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LIST OF ABBREVIATIONS

AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
DL	Deep Learning
DSS	Decision Support System
EWS	Early Warning System
FAO	Food and Agriculture Organization
GIS	Geographic Information System
HF	Hesitant Fuzzy
IoT	Internet of Things
LSTM	Long Short Term Memory
MADM	Multi Attribute Decision Making
MCDM	Multi Criteria Decision Making
ML	Machine Learning
MLP	Multi Layer Perceptron
MSE	Mean Squared Error
NLP	Natural Language Processing
RBF	Radial Basis Function
RMSE	Root Mean Squared Error
RS	Remote Sensing
UN	United Nations
UAV	Unmanned Aerial Vehicle

Chapter 1

Introduction

Throughout human history, agriculture and animal husbandry have played pivotal roles, it is a serving milestone where events emerge, and directions are drawn. This thesis aims to search for the foundational aspects of agricultural processes. The advancements and studies in this domain bear significant importance for multifaceted reasons. Primarily, increasing global population rates, food research yields critical outcomes for sustainability. Although sometimes excluded, the problems related to food security and scarcity are significant, particularly due to the worsening water constraints. While various alternatives exist to address scarcity concerns, paramount attention is necessitated towards mitigating wastage.

Olea europaea L., from past to present times olive trees have been the most important source of employment and income, as mentioned in the field of agriculture especially in the poorer parts of the Mediterranean (de Graaff and Eppink, 1999). The production of olives carries significant cultural importance, as it is very rooted in the traditions of many communities throughout the Mediterranean region. Moreover, it assumes a crucial function in the economic viability of many areas, offering means of subsistence for farmers and making a substantial contribution to worldwide agricultural commerce (Iofrida et al., 2020). It is stated that olive cultivation and olive oil production in the Mediterranean region meet 98% of the consumption in the world (Ghanbari et al., 2012). In addition to economic factors, the fact that olives and olive oil are very beneficial for health, they have been used almost as a medicine in history and similar reasons can be considered as the reason for its continued popularity. In Spain, UNESCO gave world heritage to Serra de Tramuntana considering olive groves in that landscape as one of the criteria. This indicates the importance of olive trees not only for being the oldest tree in the world but also continual various cases such as it can decrease the climate change level with proper applications. Moreover, considering United Nation's sustainable development goals' point significant directions toward planting. No poverty-zero hunger, decent work and economic growth, climate action (for plant health) and life on land goals can be considered.

According to the Food and Agriculture Organization (FAO) data in 2017, Türkiye ranks 4th as an important contributor to olive production on a global scale, with an olive production of 1,768,000 tons. In addition to the fact that olives are more profitable than other products, the rapid spread of olive cultivation in most regions of Türkiye can be explained by the government's support of agriculture (Dervis et al., 2010). According to the study carried out by Efe et al. (2009), olive cultivation in Türkiye can be examined in five main groups. Olives grown in each of these groups may differ in terms of production process, yield and taste. It is divided into Aegean, Marmara, Mediterranean, South-eastern Anatolia and Black Sea regions' groups.

Climate change can be defined as the change in global or regional climate patterns seen from the middle to the end of the 20th century. This change is particularly and largely attributed to increased atmospheric carbon dioxide levels brought about by the use of fossil fuels. In this context, climate change affects the land area which is suitable for olive cultivation and changes production levels, causing serious damage to this economically important and highly productive olive (Arenas-Castro et al., 2020). Global warming, which is one of the causes of climate change, affects the quality of the olive product as well as the yield of the product output in olive cultivation. The size and water content of the fruit vary based on the output of olives, as well as the area, climate, geographical location, and agricultural purposes (Ozturk et al., 2021). Due to the labour-intensive nature of the fruit sector and the time-sensitive nature of production quality, careful planning of management interventions (such as spraying and harvesting) is essential to develop climate-smart agricultural solutions (Oses et al., 2020). There are various studies in this field in academia. In the case of Türkiye, there are many studies from the past to the present in the literature, as will be explained in detail later. However, these studies generally consist of topics such as water scarcity/irrigation system improvements, crop damage, disease and food security, especially those associated with global warming and climate change.

The global population is expected to be around 9-10 billion between 2045 and 2050 (Abdollahi et al., 2021). The challenges arising from population growth led to modifications in conventional agricultural methods. In order to increase the productivity in production in the soil, the number of crops obtained from the existing systems can be increased, as well as minimizing the losses experienced in the current capacity. While smart agriculture focuses on the most efficient use of resources in the

process of obtaining products from a certain soil, it can be defined as managing the soil and product in an environmentally sensitive manner for sustainability. Based on information technologies, studies on smart agriculture applications are carried out in both academic and sectoral fields (Jegadeesan et al., 2023). According to the study of Bhatia et al., (2023), smart agriculture consists of location, connectivity, sensors, software and data analytics.

In terms of olive growing, there are different growing systems. The characteristics of these systems generally differ according to planting density such as practicable olive growing, traditional olive growing with irregular planting, intensive olive growing, high density olive growing (Vieri and Sarri, 2010) and so on. In addition to growing systems, also olive farming types are clustered as a traditional and organic farming. The difference mostly occurred as a result of green awareness in the world, trends in sustainability and clean farming operational standards. Main dissimilarities can be considered as during the farming operations, decreasing level of chemical fertilizers, exposing fewer toxic pesticides, less or no carbon footprint level and considering or much more efficient use of natural resources such as water and electricity. In the literature, it is seen that studies are carried out by applying various techniques in order to achieve various goals such as identifying and numbering olive trees. Image segmentation, template matching, blob detection, and supervised learning techniques can be considered as examples (Khan et al., 2018). When examined in practice, olive trees are resistant to drought and bad situations which can be noticed by experts. Considering global trends between 2012 and 2021, Spain's olive oil production nearly doubled, primarily due to technological advancements, improved agricultural practices, and enhanced irrigation systems. Similarly, Tunisia's olive yield improved significantly, reflecting strategic investments in modern cultivation techniques, efficient resource management, and policy-driven agricultural support. The advancements demonstrate why organizations need to adapt technology and develop strategic plans to boost olive production efficiency and sustainability.

The current research indicates that Spain and Tunisia dominate olive cultivation studies which serve as fundamental references for worldwide olive research. The countries have received benefits from technological advancement while simultaneously promoting scientific research and precision agriculture and policy-based incentives for olive farmers.

During this period, Türkiye saw a minor decrease in olive production because of weather conditions and unstable climate patterns and possibly other agricultural and economic factors. The majority of Turkish olive production comes from 13 key cities as indicated in Figure 1 which include Antalya, Aydın, Balıkesir, Bursa, Çanakkale, Denizli, Gaziantep, Hatay, İzmir, Kilis, Manisa, Mersin and Muğla. This is why, it is essential to study how changes in climate patterns affect agricultural output. The long-term sustainability and market competitiveness of Turkish olive production will depend heavily on data-based agricultural management approaches and predictive modelling solutions to overcome current challenges.



Figure 1. Distribution of cities' that produce 95% of olive production in Türkiye

ML algorithms exist in three distinct categories which include supervised learning, unsupervised learning and reinforcement learning. Supervised learning requires guidance from a supervisor or observer to function. The algorithms work with data that includes input-output pairs which are labelled by a supervisor. The method creates a link between inputs and outputs by using the labelled dataset before it extends or forecasts outputs for new inputs. The classification algorithms determine category values, yet regression methods determine numerical values. Unsupervised learning algorithms operate on unlabelled data and identify unfamiliar entities by clustering related entities. The objective of an unsupervised learning algorithm is to uncover

hidden information from the training dataset, making it more challenging to perform compared to supervised learning algorithms. Reinforcement learning is an alternative methodology that acquires knowledge from the surrounding environment by means of rewards and penalties. AlphaGo, a chess-playing game developed by DeepMind, employed reinforcement learning to win over the world's most advanced chess-playing computer program. In this study, climatic parameters and production data will be utilized instead of sensor-based monitoring. The model will evaluate historical climate data together with olive production parameters to predict yield fluctuations and provide early warnings by analysing temperature, humidity, precipitation and other meteorological factors. The model will evaluate current and future olive cultivation conditions before generating recommendations for farmers and stakeholders. The model will undergo a training phase with historical climate and production data to learn patterns and relationships before addressing olive yield prediction across different growing seasons and their negative climate variability effects. The collected data will serve as input for the Long Short Term Memory (LSTM) based predictive modelling to achieve accurate olive yield and production level predictions. Machine learning (ML) algorithms have become fundamental tools for both industrial and academic fields because web resources supply large datasets along with innovative techniques to address various problems. The specific branch of machine learning algorithms known as deep learning (DL) uses artificial neural networks (ANNs) to make intelligent decisions after being trained with large datasets.

In addition, for the purpose of the study, a comprehensive data-driven approach will enable early detection of yield fluctuations, allowing for proactive decision making in agricultural management. Taking necessary management actions in line with this decision support system (DSS) is also within the scope of this study. Through climate driven analysis and LSTM-based modelling, potential risks will be identified in advance, and predictive strategies will be developed to maintain sustainable and efficient olive production. In order to reach this solution, various decisions need to be taken. At this point, considering that the incoming data consists of various parameters, it is foreseen that these data will be solved with the multi-criteria decision making (MCDM) technique. Decision-makers are able to identify the problems' major contributing variables and use MCDM methods to narrow down their choices among possible solutions. This study will make use of the MCDM technique known as the

Hesitant-Fuzzy MCDM, which helps to reduce any consistency issues that may arise in the surveys with experts.

1.1. Definitions

1.1.1. Smart Agriculture

Smart agriculture describes a modern agricultural production system which combines internet technology with IoT and big data and cloud computing and artificial intelligence (AI) systems to enhance agricultural information perception and quantitative decision making and intelligent control and precise investment and personalized service (Yang et al., 2021). Table 1 indicates the processes through smart agriculture period. IoT combines a variety of sensors, devices, and nodes that can interact with one another without human involvement which makes the environment smarter which is deeply explained in the study of Sehrawat and Gill (2019). Proximity sensors, temperature sensors, humidity sensors, chemical sensors, position sensors, motion sensors, pressure sensors, and many others are examples of IoT sensors. In order to create a smart world, smart agriculture activities are inevitable. For that reason, numerous functions, including soil moisture detection, climate monitoring, and crop irrigation and pesticide application on autopilot are the part of smart agriculture. Monitoring environmental conditions is not a complete and sufficient method to increase agricultural productivity and numerous additional elements can have a significant impact on productivity (Gondchawar & Kawitkar, 2016). As the study also highlighted, the yield has increased in regions where automation has been used, and human labour has been substituted by mechanical machinery. Patil and Kale (2016) defined smart agriculture as using the IoT, smart agriculture is an automated and guided information technology. A three-tier structure is used on the internet of things. It consists of the application, network, and perception layers. The sensor motes in the perception layer. Sensor motes and devices with information and communications technology capabilities are the fundamental units of sensor technology. It consists of cameras, RFID tags, sensors, and sensor networks that are used to identify things and gather real-time data. The network layer is a component of the IoT's architecture that enables universal service. It emphasized the integration of the application layer and the perception layer. The application layer is a layer where IoT and industry-specific

technologies are combined.

Table 1

Evolution of Agriculture (*Adapted from Zhai et al., 2020*)

Agriculture 1.0	Agriculture 2.0	Agriculture 3.0	Agriculture 4.0
1784	1950	1992	2017
Traditional agricultural area by human and animal power	Mechanized agriculture era	Automatic agriculture era	Smart agriculture era
Inefficient process	Low level of utilization	Process intelligence is missing	Security concerns

Song et al. (2012) provided an explanation of a wireless sensor network-based monitoring system that makes use of modules for detecting the ambient temperature, humidity, CO₂ level, and enough light. Precision agriculture can now track and control greenhouse parameters because of advancements in wireless sensor networks technology (Devi & Kumari, 2013). It is significant because by more effectively operating the equipment through appropriate tracking of the environment, overall savings on costs may be increased which explained by Wang et al. (2006). Environmental monitoring, precision agriculture, machine and process control, building and facility automation, and traceability systems are five distinct categories into the applications that could be grouped for sensor networks for agriculture and food industry. It is also possible to indicate that developments of these industries are not at the mature level.

The accuracy of monitoring the production system is significantly impacted by a number of factors, including cause-effect modelling, optimization benchmark, optimization technique, performance evaluation, and strategy execution, all of which have a substantial impact on the placement of optimal sensors (Pellicer et al., 2023). Specifically, use of soil sensors in smart agriculture research are very popular. In one of the studies, soil sensors make it simple to transfer data wirelessly, allowing for quick periodic monitoring of the substrate moisture content across a greenhouse or field. It also makes it possible to bury sensors deep under the substrate or soil for repeated

long-term observations (Rusu et al., 2019). Besides the sensors, map-based approaches are also available in the literature. Basically, in order to use this method, you must first grid sample a field, then analyse samples of soil in the lab, create a location-specific map, and then use that map to operate a variable rate applicator (Zhang et al., 2002). Vieira et al., (2003) gave a thorough comparison of the platforms for sensor nodes, energy management strategies, commercial microcontrollers, battery kinds, and radio devices.

1.1.2. Sensing Technologies

Real time data from sensing technologies remains essential for smart agriculture because it enables farmers to make informed decisions. Sensors that track temperature and humidity and rainfall and wind speed and direction enable exact climatic assessments which help maximize crop management operations (Bendre et al., 2015; Utama et al., 2019). Soil monitoring systems that assess moisture content and pH levels and nutrient concentration and salinity enable farmers to deliver precise irrigation and fertilization while monitoring soil health (Lukas et al., 2009; Yu et al., 2021). Crop health monitoring systems enable farmers to detect diseases and pests together with nutrient deficiencies and abnormal growth patterns at an early stage. The system enabled prompt action which results in better agricultural harvests. (Sishodia et al., 2020). The implementation of wearable sensors in livestock monitoring enables farmers to track animal health alongside animal behaviour and productivity. The system enables efficient management of the herd (Eckelkamp et al., 2019). Water management systems that use sensors optimize water usage through precise irrigation plans and conservation strategies (Kassim et al., 2014; Thakur et al., 2019; Boursianis et al., 2022). The sensing technologies that indicated in Table 2 deliver vital information to farmers which enhances their ability to manage resources and boost agricultural productivity and sustainability.

Table 2

Sensing Technologies in Agriculture

Aim	Explanation	Reference
Soil Monitoring	Devices that measure soil moisture, pH levels, nutrient content, salinity, and soil health.	<i>Hareesh et al. (2024)</i> <i>Yu et al. (2021)</i> <i>Barbosa et al. (2019)</i> <i>Lukas et al. (2009)</i>
Crop Health Monitoring	Tools for earlier recognition of pests, illnesses, nutrient deficits, and abnormalities in plant growth.	<i>Sishodia et al. (2020)</i> <i>Zhang et al. (2019)</i>
Weather Monitoring	Weather sensors measure characteristics such as temperature, humidity, rainfall, wind speed, and wind direction.	<i>Utama et al. (2019)</i> <i>Chandana et al. (2018)</i> <i>Bendre et al. (2015)</i>
Livestock Monitoring	Wearable devices or sensors that track and analyse the health, behaviour, location, and production of animals.	<i>Zhang et al. (2021)</i> <i>Eckelkamp et al. (2019)</i> <i>Mayer et al. (2004)</i>
Water Management	Monitoring systems for assessing water quality, quantifying water consumption, and optimizing irrigation effectiveness in agricultural practices.	<i>Boursianis et al. (2022)</i> <i>Kamienski et al. (2019)</i> <i>Thakur et al. (2019)</i> <i>Kassim et al. (2014)</i>

1.1.3. Early Warning Systems (EWS)

Agricultural pest and disease spread prediction through EWS enables farmers to take preventive measures at the right time (Che'Ya et al., 2022; Gent et al., 2013). These systems use pest and disease dynamics analysis through the combination of satellite data and field sensor readings and weather forecasting information. The implementation of digital farming tools enables farmers to reduce environmental impacts through better pesticide usage management (Dayıoğlu & Turker, 2021). The performance of these systems depends on how accurately data is acquired and processed. Through EWS farmers achieve two major benefits by minimizing their crop losses and maximizing their agricultural production. The wide adoption of these

systems faces barriers from both data unification challenges and user accessibility limitations (Fang et al., 2015).

1.1.4.AI

The application of AI in agriculture enables precision practices by optimizing source management through data analytics and forecasting models (Mohammed and Munir, 2025). AI algorithms serve to determine irrigation needs and forecast pest spread patterns. Through these techniques farmers gain the ability to select their actions with greater awareness (Linaza et al., 2021).

Through AI practices agricultural producers can boost their production efficiency as well as protect the environment. AI systems enable both improved environmental outcomes and enhanced crop wellness through optimized pesticide application (Titirmare et al., 2024).

1.1.5.LSTM

The LSTM models analyse agricultural yield time series data to forecast future values and make predictions (Mateo-Sanchis et al., 2023). These models enable farmers to make better decisions because they incorporate both climate variables and crop growth patterns (Gupta et al., 2022).

The main strength of LSTM involves its ability to discover long-range relationships in datasets even when some information is missing. These models act as essential tools for improving efficiency while optimizing resource use in agricultural production (Sharma et al., 2024).

1.1.6.MCDM

The agricultural decision making process identifies optimal choices by evaluating multi criteria in MCDM methods. The agricultural field benefits from MCDM to manage water resources and make product and crop selection decisions (Hester et al., 2013). Group decision making processes benefit from these methods when implemented efficiently. Farmers using MCDM methods for pesticide selection or pest management decisions benefit from the approach according to Chowdhury and

Bharadwaj (2021).

1.1.7. Hesitant Fuzzy Analytical Hierarchy Process (Hesitant Fuzzy AHP)

Hesitant Fuzzy AHP functions as a type of MCDM approach which enables the representation of decision makers' uncertainties and hesitations (Mousavi et al., 2014). This method creates flexibility especially for group decision making periods and contributes to management of uncertainties of agricultural implementations. The most important advantage of this method is modelling hesitation and uncertainty of decision makers (Mi et al., 2019). From the agricultural perspective, a farmer group can evaluate different criteria such as cost, efficiency and environmental impacts when selecting the most appropriate pesticide for pest management.

1.1.8. Climatic Factors

Climatic conditions directly impact the physiological processes of olive trees, influencing their growth, fruiting, and oil quality. Key meteorological parameters affecting olive production include:

- **Temperature (Min, Max, Average):** Affects flowering, fruit set, and oil accumulation (Perez-Lopez et al., 2008).
- **Humidity and Rainfall:** Influence disease susceptibility and irrigation requirements (Shirazi et al., 2011; Spooner-Hart et al., 2002).
- **Solar Radiation and UV Exposure:** Affect photosynthesis efficiency and fruit ripening (Bartolini et al., 2014; Georgiadou et al., 2010).
- **Wind Speed and Air Pressure:** Impact pollination, pest movement, and overall tree stability (Jimenez-Portaz et al., 2021).

Given the dependence of olive yield on these climatic variables, advanced machine learning models such as LSTM networks can be employed to establish predictive frameworks. These models analyse historical data to forecast yield variations, providing farmers and stakeholders with actionable insights for sustainable production.

1.1.9. Olive Cultivation

Olive cultivation is Mediterranean based agricultural activity which faces with

significant challenges as a result of climate change (Fraga et al., 2020). Olive cultivation is a term that mainly focuses on technical and systematic agricultural methods such as varieties and genetics of olive, soil or climate optimization. On the other hand, olive growing focuses on agricultural practices. For instance, planting olive trees, maintenance or irrigation activities belong to this definition. Olive production refers to the end-product such as olive harvesting or processing. The practice of conventional olive cultivation results in environmental issues that cause organic soil ingredients to dry up and lead to soil erosion and reduced water availability. Sustainable agricultural practices serve as a crucial solution to reduce these environmental issues. The recycling of organic materials together with balanced pruning methods enhances olive tree productivity while minimizing environmental impact (Michalopoulos et al., 2020). The impact of climate change on olive cultivation processes requires both immediate and future adaptation strategies. The strategies include water management, pest control and agricultural planning based on climate related predictions. The Mediterranean basin requires both the identification of suitable olive cultivation regions and adaptation measures to ensure agricultural sustainability (Villalobos et al. 2023).

Chapter 2

Literature Review

Creating a sustainable environment in the developing and changing world is very common in the literature and professional businesses. Although food sustainability is one of the basic needs, it can be said that it is important for humanity as it covers issues such as food safety. Within the scope of this study, it is planned to create an artificial intelligence-based innovative model of EWS and decision support mechanisms in the field of agriculture. Working specifically with olive trees will be held, and climate against management, prevention of yield losses and increasing food quality are the main targets. In line with achieving these goals, the discovery of sustainable ways is also prioritized. In agricultural processes, which constitute a significant part of food resources, a more recessive attitude may be displayed compared to other sectors due to the fact that the workforce involved in the process is mostly farmers.

Table 3

Taxonomy Table of Olive Related Studies

Author	Year	Problem Definition	Model/Approach	Future Research
Alshammari et al.	2023	Early diagnosis and categorisation of plant illnesses	Whale optimization algorithm (feature selection from dataset), Feed-forward neural network	-
Makhloufi et al.	2022	Early diagnosis of anomalies of the crop to increase its resilience	Development of ANN based on leaf area index, chlorophyll content, water content	Segmentation of trees
Brinkhoff et al.	2021	Identification of water stress level	Daily calibrated imagery	-

Table 3 (cont.d)

Bilgilioglu	2021	Land suitability for olive cultivation	AHP	-
Marques et al.	2020	Analyse the temperatures of the olive trees' canopy and soil surface while using various watering techniques	Thermal infrared images obtained by Unmanned Aerial Vehicle (UAV)	Creating relationships between the water status indicators and the thermal data analysis. Automatic estimate of olive plants using data from several sensors from UAVs
Noguera et al.	2020	In order to monitor water levels and measure olive tree canopy temperature, creation of a new low cost device based on an infrared (IR) thermal sensor	Infrared thermal sensor	Suitability for other products
Akcay et al.	2019	Examination of the reliability of the categorization of olive trees	Satellite images	-
Guine	2019	Use of ANN in food processing and its implications	Systematic review	-
Hafezalkotob et al.	2018	Olive harvesting machine selection	MCDM	-
Scalia et al.	2016	DSS for process of different olive groves	Fuzzy MCDM by remote sensing (RS) and geographic information system (GIS) to map olive groves	-
Funes et al.	2015	Use of ANN in food industry	Review	-
Torrecilla et al.	2008	Modelling olive oil mill wastes in a fluidized bed dryer	ANN	-

Table above indicates examples of studies from literature review of ANN and olive cultivation keywords. Continuous crop and tree tracking is essential for a sustainable agricultural output in order to have up to date data and create efficient

agricultural strategies (Akçay et al., 2019). One of the most frequently grown crops in the world, olives can be grown on every continent (Aftab Khan et al., 2018). One of the most important elements of crop yield can be considered as irrigation systems. For that reason, it is possible to encounter with that kind of studies in literature such as Brinkhoff et al. (2021)'s study about water stress level imagery conducted. In terms of irrigation optimization, another study is conducted by Marques et al. (2020). Aim of this study is to analyse various irrigation strategies about deficit in order to minimize climate change issues. During the analysis, the temperature of olive trees is based.

Another issue with olive trees' crop yield can be illnesses that result from different reasons such as plant type, situation and location of land, use of chemicals or other ingredients during the agricultural process, air pollution, global warming. In the literature, crop diseases are a trendy topic which is studied by different academic perspectives. Deep learning methods, specifically artificial neural networks are used to reach good forecasting results to improve accuracy. Alshammari et al. (2023)'s study is diagnosed early diseases of olive leaves. Firstly, in order to prevent data loss, they used a whale optimisation algorithm from the dataset to choose proper features. Then they continued with leaf disease categorisation by ANN. Masella et al. (2019) stated that harvesting efficiency may be viewed as the outcome of a complicated system with unknown interactions and nonlinear correlations between the input data. ANNs are a system that might be used in this case to solve the issue. Because artificial neural networks have been widely used to solve a variety of challenging real-world issues, there is growing interest in applying them as modelling tools in the field of food technology (Funes et al., 2015). Considering the use of ANN in food processing, study of Guine (2019) indicated significant facts as a result of systematic review of the article. In addition to the fact that the ANN method in food processing processes takes place in the literature with various studies as seen in Figure 2, it is understood that it is at a lower stage in product cultivation or growing.

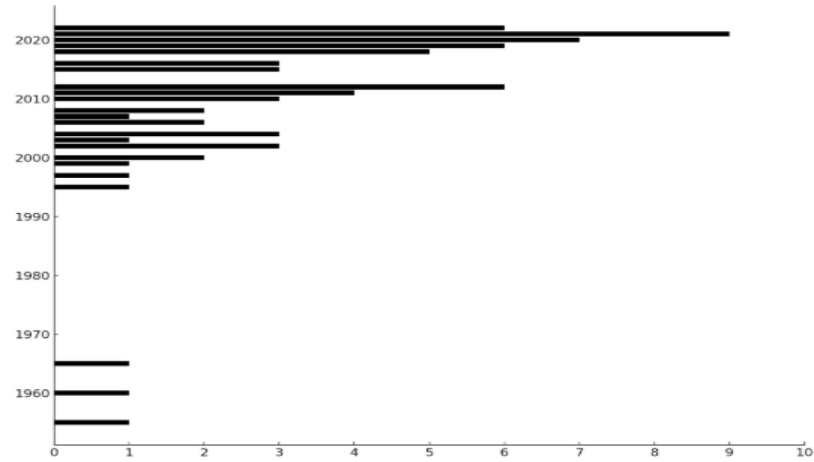


Figure 2. Number of studies related to olive fruit that cited by SCOPUS&WOS

In terms of crop yield, crop harvesting machines are also taking considerable significance in efficiency. For this reason, selection of oil harvesting machines can be done by MCDM methods. In order to reach this goal, study of Hafezalkotob et al. (2018) examined six potential machines using nine key criteria and divide them into three categories: advantageous, unfavourable, and target-based criteria. Specific to MCDM analysis, fuzzy MCDM method related to DSS for different olive groves was used in the study conducted by Scalia et al. (2016) on olive cultivation in the literature. In this study, images of plants were also taken by using RS and GIS. In another study conducted by Bilgilioğlu (2021), a suitable land analysis for olive cultivation was carried out using the AHP.

2.1 EWS

The implementation of EWS in olive cultivation enables farmers to obtain crucial information which leads to better disease control and resource management and improved agricultural techniques. Table 4 shows the examples of EWS in agricultural field. The research conducted by Romero et al. (2021) demonstrates that meteorological data analysis with logistic regression models generates effective early warnings for *Spilotea Oleagina* infections in olive tree plantations. The research led by Calderón et al. (2015) demonstrated how hyperspectral and thermal imagery works to detect *Verticillium Wilt* in olives during the early stages of infection. The early detection enables farmers to implement preventive actions that minimize disease

impacts. DSS that unite crop monitoring with soil evaluation according to Vanella et al. (2018) enabled educated management decisions which lead to rapid responses against new threats and better orchard health. The research proposed by Tanner et al. (2022) confirmed that sensor radiometry serves as a vital tool for detecting plant diseases prior to visible symptoms. The authors applied this concept by analysing Verticillium Wilt infections in olive tree cultivation.

Table 4

EWS in Agriculture

Identification and Control of Diseases	Decision Support Systems	Environmental Surveillance and Irrigation Enhancement	Incorporating Technology
Researchers have investigated novel approaches to detect illnesses in olive trees at an early stage. These methods include the use of hyperspectral and thermal photography (Calderón et al., 2015) as well as sensor radiometry (Tanner et al., 2022) to identify diseases like Verticillium Wilt. Early detection enables rapid treatment and disease management measures to mitigate the impact on olive crops.	DSS for the management of olive groves by combining different data sources, such as crop monitoring and soil assessment, with advanced technologies like soil electrical resistivity tomography (Vanella et al., 2018). These systems assist farmers in making well-informed decisions on interventions, allocation of resources, and general management of orchard health.	Emphasizes the importance of environmental monitoring in EWS. By incorporating meteorological data (Romero et al., 2021) and water potential data (Corell et al., 2016), one may enhance irrigation schedules, effectively handle water stress, and enhance overall water management methods in olive agriculture.	Incorporation of several technical tools, including remote sensing, imaging techniques, sensor networks and predictive analytics to establish comprehensive EWS. These systems utilize technology to observe environmental parameters, forecast disease outbreaks, and deliver immediate alerts to farmers, so improving the effectiveness and durability of olive farming operations.

EWS help farmers optimize irrigation methods and water management approaches for olive cultivation. Corell et al. (2016) emphasized that water potential data enables farmers to schedule olive tree irrigation precisely. Farmers can optimize water use by monitoring plant requirements which prevents water stress and leads to better crop yields. The implemented methods serve two purposes by protecting plants from diseases and supporting sustainable agriculture through minimized resource waste. The implementation of efficient EWS in olive cultivation enables farmers to respond swiftly to potential threats. The system strengthens resistance to diseases and adverse environmental factors while optimizing resource management and leading to better production results.

2.2 Machine Learning

The field of Machine Learning (ML) emerged in 1959 through Arthur Lee Samuel's research titled "Some Studies in Machine Learning Using the Game of Checkers". The research established ML as a specific area within artificial intelligence, more detailed clusters are shown in Figure 3. The definition of ML is expressed as the branch of science that enables computers to perform operations without the need for programmers to make changes to the software again (Samuel, 1959).

ML is a field that deals with the development of algorithms that enable computers to learn through experience (Carvalho & Cruz, 2020). The basis of this field consists of identification of patterns automatically from data and the model is capable of predictions through these patterns (Vellido et al., 2012; Hasan et al., 2014). At first, it was based on statistical methods and classical algorithms, but thanks to large data sets and improving computing power it has facilitated the development of much more complex models. Especially big data analytics and modern calculation techniques raise the performance of machine learning and created wider range of application areas (Condie et al., 2013).

ML initially worked with limited data and calculation power. Today, the power extended to DL and related methods with functioning big data and dataset (Kapoor et al., 2024). These improvements lead to important developments in a variety of fields such as health, economy and industrial. For instance, DL models' performance is over than human performance to solve complex problems such as image processing

and natural language processing. Furthermore, data mining and knowledge discovery techniques have helped the ML algorithms to make more accurate and optimal predictions.

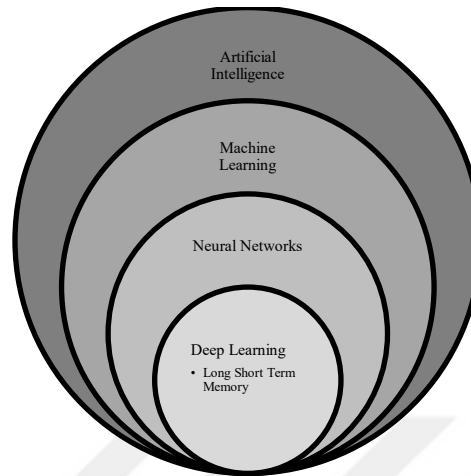


Figure 3. AI components (Musa, 2023)

Generally, ML techniques investigated into two main categories, which are supervised learning and unsupervised learning. While supervised learning works with labelled data sets and learns relationships between input and output, unsupervised learning focuses on discovering patterns and hidden structures in unlabelled data. In the practice, factors such as data collection, labelling costs, and complexity of data resulted in new learning approach developments.

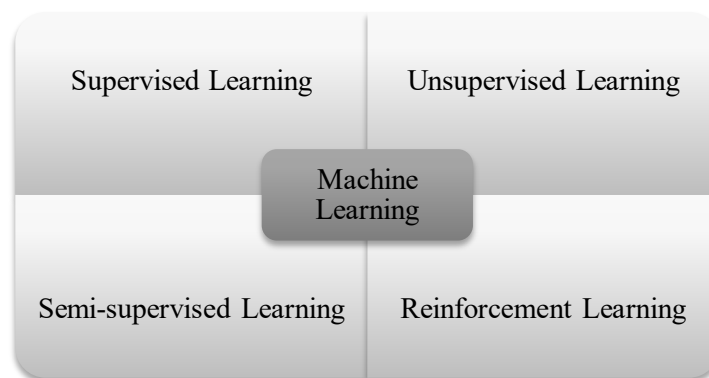


Figure 4. Learning types of ML

In this context, there have been developments in other approaches such as semi-supervised learning, additive learning, reinforcement learning, self-supervised

learning and online/incremental learning (Kapoor et al., 2024). Each of them presented in Figure 4 is a suitable solution for a particular problem area and comes with various benefits depending on the type of data and the way it is processed.

2.4.1 Supervised Learning

Supervised learning methods run with labelled data set to achieve the learning relationship between input and output data. This model aims accurate prediction of new data point with learning these relationships. Supervised learning is widely used in prediction and classification problems (Ayodele, 2010). For instance, these models can be used to create critical DSS in the field of agriculture, finance and health (Karthikeyan et al., 2020).

Supervised learning categorised into two:

- **Regression:** Models the prediction of continuous relationship. For instance, temperature prediction, prediction of investment value in the future.
- **Classification:** Based on categorisation of data (Sah, 2020). Classification plays an important role in medical diagnosis, spam detection and customer behaviour analysis.

2.4.2 Unsupervised Learning

The model focuses on identification of data structure without label information. this approach aims to natural grouping of data and bring out the hidden relationships. For the purpose of customer segmentation and genetic data analysis, unsupervised learning techniques are very effective. This learning is very common especially for pattern recognition and data identification in big data (Vellido et al., 2012).

Main categories of unsupervised learning:

- **Clustering:** Data separated into natural groups.
- **Dimensionality Reduction:** the most important factors are chosen from big data sets in order to increase the performance of the model. This technique used in especially for visualization and data preprocessing processes (Soberano et al., 2023).

2.4.3 Semi-Supervised Learning

Semi-supervised learning is a combination of both supervised and unsupervised learning techniques, where a small portion of the dataset is labelled, and a large portion is unlabelled. The model tries to extract information from unlabelled data using labelled data. This method is quite advantageous in cases where labelling costs are high, and one such case is in agricultural image analysis, where although an expert has only labelled some trees as diseased, the model can automatically classify other trees by learning this information. Biomedical image analysis and natural language processing are some of the most common areas in which semi-supervised learning is applied.

2.4.4 Reinforcement Learning

Reinforcement learning is implemented by the agent interacting with its environment. The agent gets rewards or punishments for the actions it performs in the environment and attempts to optimize its behaviour with repeated interactions. This method is used to optimize decision making processes in dynamic and complex systems (Kapoor et al., 2024). For instance, autonomous agricultural robots can employ reinforcement learning techniques to identify the most efficient path within the field. Reinforcement learning is of great importance in several application areas including robotics, game theory, and energy management. The different types enable machine learning to learn from multiple data sources and environments while providing unique advantages.

2.3 ML Applications in Agriculture

ANNs represent advanced tools which boost precision agriculture and crop management operations within agricultural research. The various ANN architectures serve to address unique agricultural challenges as seen in Table 5. The CNN architecture enables date palm tree segmentation and classification for inventory and monitoring purposes according to Gibril et al. (2021). Yarak et al. (2021) employed Faster-RCNN models to analyse high-resolution images for both oil palm tree health

status detection and classification.

Héctor García-Martínez et al. (2020) created ANN models which predicted maize yields through analysis of multispectral and RGB images. The research used plant density together with digitally predicted vegetation cover and multiple plant indices (NDVI and WDRVI) to forecast maize production. Neural network models generated accurate predictions of corn yields through high correlation between forecasted and actual results while maintaining low error margins. Elavarasan et al. (2020) used MLR-LSTM models as hybrid feature extraction methods for rice yield prediction. The method enhances prediction accuracy through the combination of environmental and spectral data. The research delivered better rice yield prediction accuracy than standard approaches while enhancing agricultural decision making systems. Wang et al. (2020) used weakly supervised LSTM networks to map rice fields through analysis of Sentinel-2 and Sentinel-1 optical and SAR images. The research achieved precise rice field spatial mapping through its analysis of time series data.

Table 5

Use of ANNs in Agriculture

Author	Year	Application	Objective	Neural Network Type	Key Features/Inputs	Performance Metrics
Pentos et al.	2022	Soil Compaction Prediction	Predict soil compaction in agriculture	RBF Neural Networks	Electrical Parameters (Eca MS)	Precision Agriculture Application
Gibril et al.	2021	Date Palm Tree Management	Manage date palm trees with computer vision	CNN Architectures	Crown Size, Colour, Density	Precision of Classification
Yarak et al.	2021	Oil Palm Tree Detection and Health Classification	Detect and classify health of oil palm trees	Faster-RCNN	Altitude, Crown Characteristics	F1 Scores
Shah et al.	2021	Weed Detection with Autonomous Robot	Develop autonomous weed detection robot	ANNs	Plant and Weed Identification	Classification Accuracy
Abraham et al.	2020	Soybean Harvest Prediction	Predict soybean harvest	ANNs	Yield, Production	Comparative Effectiveness

Table 5 (cont.d)

Boniecki et al.	2020				Mass, Equivalent Diameter, Humidity, Hardness	RMSE
		Grain Weevil Identification	Identify grain weevils	Radial Basis Function		
Niedbala et al.,	2020	Substance Concentration in Winter Wheat	Examine winter wheat yield based on biotic stress	Multilayer Perceptron (MLP)	Variety, Weather Conditions	Sensitivity Analyses, Mean Abs Value
Li and Chao	2020		Develop continual classification method in agriculture	CNN and GAN	Memory Storage, Retrieval	Knowledge Accumulation, Forgetting Alleviation
Aji et al.	2020	Dynamic Responses of Chili Pepper Plant Growth	Model dynamic responses of plant growth	Non-linear Autoregressive Model	Root Zone Temperature	RMSE, R ²
Garcia Martinez et al.	2020	Corn Grain Yield Estimation	Estimate corn grain yield	Neural Network Models	Vegetation Indices, Canopy Cover, Plant Density via	R ² , MAE, RMSE
Zhu et al.	2020	Cultivated Land Quality Evaluation	Evaluate cultivated land quality	GA-BPNN	Gross Primary Productivity (GPP)	Comparative Accuracy
Elavarasan et al.	2020	Paddy Crop Yield Prediction	Predict paddy crop yield	Hybrid Feature Extraction	Feature Selection Methods	Model Validation
Wang et al.	2020		Map paddy rice using weakly supervised learning			Accuracy with Limited Field Samples
		Weakly Supervised Paddy Rice Mapping		LSTM Network	Sentinel-2 Bands, Sentinel-1 SAR	
Parmley et al.	2019	Non-linear Machine Learning in Plant Breeding	Apply machine learning in plant breeding	Various	Genetic Diversity, Stress Assessment, Precision Agriculture	Application Overview

Niedbala et al. (2020) pointed out the use of ANN in agriculture field as a forecasting and statistical method. ANN is able to concurrently assess empirical data in a quantitative and qualitative manner because of the special characteristics of data

processing. These data cannot be obtained using traditional statistical approaches since they typically only provide for a quantitative interpretation of the investigated data. Li and Chao (2020) compared CNN and ANN. The findings demonstrate that conventional CNN are capable of handling a single task and classifying the categories but there is an issue with ongoing tasks. The improved continuous model can recognize all the categories from both old and new jobs without the forgetting problem thanks to the addition of memory storage and the retrieval mechanism such as including intelligent fruit picking robots that can identify and select various fruits and plant protection through the detection of diseases and pests that can continuously increase the detection range. Study of Abraham et al. (2020) compared ANN with classical linear function for soybean commodities. The findings show that while the conventional linear function continues to be more accurate at predicting soybean yield, ANN is the best method for predicting soybean harvest area and output. The model shows resilience through this result.

Gevrekçi et al. (2011) research demonstrated that ANN can predict multiple elements including goat milk production and olive cultivar results and corn and soybean yields and econometric model parameters. The research explored how ANNs together with multiple regression and probabilistic neural networks work to analyse chicken productivity and broiler ascites and grapevine genotypes. The application of ANNs enables researchers to analyse olive seed genetic diversity and detect experimental animal growth patterns and create herbicide application maps through fuzzy logic. The analysis of geotourism planning in landscape architecture makes use of ANN as an analytical tool.

There are various studies' data about ANNs in agricultural production prediction as seen below. The input data includes multiple variables which encompass climatic data together with weather indices and energy inputs and environmental factors and test day milk yields and age and peak yield and hybrid ML approaches. The output data includes predicted production amounts which can be evaluated through performance metrics such as R^2 and error percentage and accuracy and correlation coefficients.

ANNs studies that predict agricultural yield produce results as continuous values instead of binary outputs. The model-based continuous data characteristics enable the prediction of yield quantities which express expected harvest amounts in tons per

hectare or bushels per acre (Kulisz et al., 2023). The continuous output provides better insights into yield expectations which helps agricultural managers make informed decisions. The models work to minimize yield discrepancies by using performance metrics such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) for their evaluation (Deneshkumar et al., 2015).

2.4 Use of ML in Olive Cultivation

The study articles in Table 6 covered a number of subjects related to olive farming. These topics include the application of ANNs in different agricultural contexts, energy consumption in olive farming, genetic studies on olives, extraction of olive leaves, modelling and prediction of phenology, disease detection in olives, and cover crops identification. These papers identified some common concerns including the application of artificial intelligence and biotechnological methods in the cultivation of olives, climate change and its effects on olive production, the significance of proper classification in the olive oil industry, and the ability of deep learning in the identification of plant diseases. Some of the studies also indicated the relevance of the quantity and quality of the olive oil production with respect to the stage of maturity of the olives. In addition, these studies have identified the challenges related to disease diagnosis, pest management, and cover crop management in olive orchards. In addition, the studies discussed the use of machine learning, computer vision, and deep learning in automating some of the tasks that are labour-intensive in the cultivation of olives. The tasks included disease recognition, fruit sorting and recognition of cover crops. In addition, the study highlighted the need for energy use prediction, conservation of genetic diversity, and fast and unbiased identification of olive varieties. This information can be useful for the agriculture business to improve its decision making and predictive modelling. The papers were mainly based on solving the most pressing problems of olive cultivation. These issues include the impact of viral diseases on fruit yield, the significance of exact calculation of energy expenditure, and the need for proper identification and classification of olive varieties and diseases. In the course of the study, the authors always pointed at the potential of artificial intelligence, neural networks, and advanced modelling tools in addressing the problems and improving olive farming. In total, the papers indicated how these

technologies can revolutionize many aspects of olive production, such as pest management, fruit sorting, disease control, and fruit sorting within the particular categories. The research findings provide opportunities for the application of modern technologies in the agricultural sector which can improve the productivity, quality, and environmental friendliness of olive production.

Table 6

Use of ANN in Olive Cultivation

Author	Year	Description	ANN Type	Input	Parameter	Metrics	Location
Miho et al.	2024	Predicting olive varieties	custom (KDL) paradigm	72000 olives	-	-	Mediterranean
Tofeq et al.	2023	Predicting auger energy consumption	RBF	-	Temperature, precipitation, avg cloud, avg humidity	Soil moisture content, rotary speeds, hole depths	Iraq
Martinez et al.	2023	Identify olive orchards with varied intensification patterns using very high-resolution aerial orthophotographs	CNN	1187 olive groves	-	Accuracy, precision, receiver operating characteristics	Spain
Fazari et al.	2021	Detection of anthracnose disease in early stage	CNN	250 olives	-	Accuracy, sensitivity, F1 score	-
Galatali et al.	2021	Demonstration of potential benefits of AI and agriculture; detection of plant diseases	-	-	-	-	-

Table 6 (cont.d)

Author	Year	Description	ANN Type	Input	Parameter	Metrics	Location
Khosravi et al.	2021	Real-time potential and the robustness of the model to classify on-branch olives based on their ripening stages	CNN	-	-	-	-
Uğuz et al.	2021	Olive disease detection with a CNN	CNN	3400 olive leaves	-	Accuracy, precision, recall, F1 score	Türkiye
Milicevic et al.	2020	Determination of olive tree flowering phenophase	CNN	1400 images	-	-	Croatia
Ponce et al.	2019	Olive fruit variety classification as an image classification	CNN	2800 olives	-	-	-
Kavdır et al.	2018	Classifying green olives	Multi Layer BPNN	400 green olives	surface features	-	Türkiye
Aguilera Puerto et al.	2018	Classifying olives based on qualities	MLP	6325 olives	-	-	Spain
İlbay et al.	2014	Evaluation of the ultra-sound-assisted extraction (UAE) of polyphenols from olive leaves	RSM and Multi Layer Feedforward NN	Ph, time, temperature, solid/solvent ratio	-	-	Türkiye

Table 6 (cont.d)

Author	Year	Description	ANN Type	Input	Parameter	Metrics	Location
Gallo et al.	2013	Unsupervised artificial neural networks in the olive oil sector to classify farms, identify key features for effective communication and market success, and establish performance ratings and relationships among businesses using specialized computer software.	clustering analysis with neural network	81 companies	Company's headquarters diesel consumption for farming operations, Numeric Agricultural area, Numeric % of the area with olive trees, Numeric Varieties of olives produced, Categorical Product sold, Pruning sold	-	-
Cruz-Ramirez et al.	2012	Multi-objective neural network-based classification approach utilizing remote sensing data with enhancing accuracy	MLP	6000 instances	-	Olive trees, bare soil, and various cover crops	Spain
Gevrekçi et al.	2011	Use of ANN in agriculture			Plant and animal	-	-
Furferi et al.	2010	Evaluation of the ripening degree of olives	FFBP	60 lots of cultivars' olive	Colour, Sugar content, Oil content, Total phenolic	RI (ripening index)	Italy

Table 6 (cont.d)

Author	Year	Description	ANN Type	Input	Parameter	Metrics	Location
Bari et al.	2003	An analysis is conducted on the features gathered from the images of olive stones, which are then categorized using a neural network classifier method.	RBF	180 images	-	-	-
Mancuso et al.	2002	Predicting phenological event of olive	BPNN	288 inputs	8 climatic parameters	-	-
Mancuso and Nicese	1999	Identification of olive cultivars	BPNN	10 olive cultivars, 800 leaves	Leaf parameters	-	Italy

The research by Miho et al. (2024) introduced OliVaR as a DL model that identifies olive varieties through training with pictures of endocarps. The research team gathered a massive database of photographs amounting to 72,000 images from olive endocarps. The dataset contained 131 different olive varieties which originated from major olive-producing areas in the Mediterranean region. The model achieved more than 86% classification accuracy during its training and evaluation process with this dataset. The paper described the OliVaR architecture which uses knowledge-driven learning methods through expert models and knowledge-driven components.

Based on the study by Tofeq et al. (2023), ANNs improve decision making and predictive modelling in agricultural research. The article deals with olive production in Northern Iraq, the recent achievements of the Ministry of Agriculture, the difficulties in cultivation, and the application of agricultural mechanization to enhance productivity. The study employed radial basis function (RBF) neural networks to estimate energy consumption in olive farming. The analysis of energy use in olive production was done using RBF networks which took into account field operations, soil moisture, rotating speeds, and hole depths. RBF networks accurately forecasted energy consumption for diesel fuel treatments that need the highest amount of energy. The study highlighted the challenges associated with olive production, such as manual labour and the need for agricultural technology, in order to enhance output. The study

revealed that the process of cultivating olives in the field is arduous and time-consuming. Auger machines can be beneficial. Augers reduce labour for cultivating olives in nurseries. The discussion also includes the prediction of energy utilization in olive cultivation using RBF neural network. The accuracy of RBF energy consumption forecasts is evaluated by the examination of soil moisture levels, rotational velocities, and drilling depths.

The determination of olive stone features is challenging to accomplish objectively. Therefore, a mathematical technique was designed to extract the characteristics of the image. The utilization of a neural network technique allowed this system to accurately categorize crops with a success rate of 96%, exceeding the performance of traditional descriptors and statistical classifiers. The study also showed the displacement and diversity of Mediterranean olive cultivar origins. The improved technique shown effectiveness in distinguishing cultivars through the utilization of picture feature extraction. The neural network was modified using genetic algorithms with demonstration of the innovative technique's ability to differentiate between different cultivars.

Fazari et al. (2021) applied hyperspectral images and DL and CNNs to detect olive anthracnose at an early stage. Anthracnose is a severe fungal disease that affects olive production and causes major economic losses. The study used hyperspectral imaging and DL and CNNs to detect the disease early on. The improved ResNet101 architecture can detect sick olives in hyperspectral images with high sensitivity. Climate change impacts olives and diseases like anthracnose, which stresses the need for early detection. Due to the limitations of conventional detection methods, hyperspectral imaging and advanced modelling have been investigated. The study showed the proposed method may quickly diagnose anthracnose in olives, protecting the quality and value of olives and olive oil. The quality and market value of olives and olive oil improved. Hyperspectral imaging, DL, and CNN methods improved olive disease detection in the studied.

Galatali et al. (2021) examined the application of ML and AI in plant biotechnology with a focus on olive production and viral disease control. Demonstration of how AI can benefit agricultural practices in terms of viral diseases lead to decreased production of fruit while shortening plant life and deteriorating olive cultivar quality conducted. The research also demonstrated how AI serves to optimize

and select the most effective plant disease control approach and examines deep learning together with nonlinear and linear and supervised machine learning approaches in plant biotechnology. Research results demonstrated that AI should be used to determine the most effective biotechnological conditions for plant disease prevention. Additionally, how application requirements need adaptation based on plant species and variety while showing AI can reduce the process duration and select effective protocols demonstrated.

Uğuz and Uysal (2021) concentrated their research on understanding population growth demands and related nutritional problems. Plant diseases in Turkish olive production cause substantial damage which results in reduced agricultural yields. Researchers discovered *Aculus olearius* and Olive peacock spot infections in 3400 olive leaf samples which included healthy samples in addition to infected ones. The study stated that managing plant pests and diseases leads to higher agricultural yields. The text explored the various factors, including meteorological conditions, chemicals, fungi, bacteria, and viruses, that contribute to the occurrence of plant diseases. The implementation of early disease detection technologies is crucial in rural areas without medical facilities or specialized knowledge. They focused on developing deep learning architectures designed for detecting diseases in olive leaves. The evaluation of CNN model performance occurred through network assessment with and without data augmentation and optimization implementation.

On branch olive ripening is recognized in real time using deep CNNs and RGB photos in the research by Khosravi et al., (2021). The study developed a model to accurately detect Iranian olive cultivar ripening under natural orchard circumstances. The best model was M2+NewBN, with 91.91% accuracy. The study underlined olive oil's agricultural importance. The extraction method, cultivar, orchard management, and harvesting period affect olive oil amount and quality. Olive ripening phases affect oil amount and quality by influencing fatty acid composition, phenol levels, and oil stability. In precision applications like harvesting and chemical application, olive ripening phases must be visually identified in real time, according to the study.

The study revealed that climate change impacts olive tree cultivation and pest management. The paper by Milicevic et al. (2020), presented how climate change affects the production of olives in the Mediterranean region, the impact of phenology and geography on the blooming of olive trees, and the adaptability of pests to olive

trees. The research also provided the possibilities and effectiveness of deep learning approaches in phenological stages identification and pest control in agriculture. According to the study, the observation of olive tree growth stages and the prediction of climate change effects should be done through the use of mobile or permanent cameras and strong machine learning algorithms. The research revealed that deep learning systems are capable of identifying phenophase transitions correctly thus supporting integrated pest management. The study also looks at geographical factors as well as orchard factors such as tree age and micro location when looking at climate and olive blossoming. Pest adaptation to olive trees, specifically the olive moth is also discussed. The study uses deep learning technologies such as CNNs in classifying phenological stages and pest management. In the study, the network was designed by testing deep learning architectures and data augmentation techniques. This network achieved a classification accuracy of 0.9720 ± 0.0057 in fivefold cross-validation.

Concerning the automation of postharvest fruit classification, particularly the variety-based classification of olive fruits, the paper examined the difficulties the olive industry has encountered as a result of the rising demand for products derived from olives (Ponce et al., 2019). Machine vision, DL, and CNNs are used to achieve this goal. The researchers photographed 2,800 olive fruits from seven varieties. They then used image processing to examine the initial images and train six CNN architectures, which were externally validated. The Inception-ResnetV2 framework reached success rates and 95.91% precision. This technology offered an integrated way of handling and classifying olive fruits after harvesting when applied in industrial conveyor belts.

Aguilera Puerto (2019) presented an internet-based computer vision system that performs olive batch quality classification pre and post oil extraction. The technique distinguished between ground-harvested and tree-harvested olives which is essential for high-quality olive oil. The classification method used a feature vector with olive picture histograms from different colour spaces and texture values from three methods. The study reached 98.4% and 98.8% success rates using ANN and SVM classifiers before and after washing. Computer vision systems have the ability to enhance both quality and reliability of olive classification in olive oil production through precise categorization.

FT-NIR spectroscopy, ANN and statistical classifiers are used to distinguish undamaged olive fruit from those with bruising or fly problems. The study (Kavdır et

al., 2018) analysed classification success between two quality conditions (good vs. bruised, good vs. fly defect) and three quality conditions (good, bruised, and fly defect). The research found that ANN classifiers performed better than statistical classifiers. FT-NIR spectroscopy and ANN are used to distinguish olive fruit quality in the study which also presented ways to enhance classification performance and proposes method combination for better results.

İlbay et al. (2014) explored olive leaf polyphenol extraction and applications utilizing Response Surface Methodology (RSM) and ANNs. RSM and ANN were used to optimize ultrasound-assisted olive leaf polyphenol extraction by considering pH, extraction time, temperature, and solid-to-solvent ratio. The study indicated that ANN predicted better than RSM. The research discussed food plant polyphenols' antioxidant and antibacterial characteristics, health advantages, and uses in food supplements, cosmetics, and pharmaceuticals. Olive leaf extract's antitolerant, hypoglycaemic, and anticancer effects on adipogenesis and thermogenesis genes were also studied. The lack of study comparing RSM and ANN in olive leaf polyphenol extraction highlighted the need for such investigations. RSM and ANN models matched experimental data, suggesting they might be used in extraction.

Unsupervised ANNs are used to classify Apulian olive oil plantations in the paper of Gallo et al. (2013). The goal is to group similar organizations using common indicators to discover the best performers and their industry links. The study used digital marketing and mathematical models for market behaviour analysis to better corporate strategy and globalization. In addition to that, research explained why neural networks are used, highlighting their ability to learn from input-output data and classify data. Neural networks can analyse non-linear correlations and high-variability environmental processes without a model, unlike regression approaches. Olive oil industry software used to create an unsupervised neural network to analyse business, environmental, and market factors. The paper described the mathematical foundations and operation of neural networks, notably the MLP design. Olive oil companies were clustered using the suggested model and the online platform dataset. The results showed two clusters of enterprises with different energy efficiency, revenue, and employee counts.

Cover crops, olive trees, and bare soil in olive orchards are identified and classified using remote sensing data in the study of Cruz-Ramirez et al. (2012). The

suggested multi-objective neural network method improves seasonal classification. The paper also highlighted the usefulness of remote sensing data in agriculture and the difficulties of distinguishing cover crops, bare soil, and olive trees. Pattern recognition and Multi Objective Evolutionary Algorithm (MOEA) with MLP neural networks solve the multi objective classification problem.

The research of Furferi et al. (2010) presented how olive ripening influences olive oil production and quality. The manual, time consuming and environmentally sensitive RI measurement based on olive skin and pulp colour is discussed. The unique technology combined a Machine Vision system with an ANN algorithm to estimate the RI quickly, automatically, and objectively. The study explained olive ripening and how organoleptic characteristics and oil shelf life change. Testing the proposed approach on 40 olive samples shows a good correlation between the system's projected RI values and expert evaluations. The research presented a method for automatically forecasting olive RI using Machine Vision and ANN in olive oil production.

Bari et al. (2003) provided comprehensive descriptors that may be used for quick and automated description and recognition, with the goal of enhancing the utilization and preservation of olive genetic variety. The project aims to establish an unbiased method for distinguishing between different Mediterranean olive varieties. The current system based on morphological descriptions encounters challenges such as subjective assessment and duplication of cultivars. Novel techniques for extracting features from new pictures and classifying them using neural networks were developed as a solution to address these issues. The approach discovered five types from the west Mediterranean region.

The research of Mancuso et al. (2002) applied ANNs to predict olive phenology using climate factors in inland Tuscany. Phenology represented the scientific study of how biological events relate to time because it serves as a fundamental tool for both ecosystem analysis and climate change research. Olive tree growth responds strongly to changes in temperature. The research evaluated ANNs for their ability to predict olive phenology. The model accurately predicted these events using only climatic inputs and found that olive tree growth stages vary by variety and depend on local factors. The ANN model simulated olive phenology's response to climate change. Rising temperatures may advance certain phenophases. In addition, the ANN model showed that it can use meteorological data to forecast and understand plant phenology

effects of rising temperatures. So, the ANN model is important for agricultural management and climate change research.

2.5 MCDM in Agriculture

The process of decision making is a mental complex process which requires problem solving to reach desired results through multiple factor evaluation through rational or illogical methods which use implicit or explicit assumptions that come from physiological, biological, cultural and social elements (Taherdoost & Madanchian, 2023). The goal of MCDM problems to find the best possible results under these conditions. This approach is widely used and remain developments since 1950s (Dhiman & Deb, 2019). Additionally, the method has been used for years in complex decision problems that require the evaluation of alternatives according to multiple and often contradictory criteria. (Belton & Stewart, 2012). The development of MCDM methods has been directed to support various applications. Numerous techniques have been developed, and even slight modifications of existing techniques have resulted in the emergence of new fields of study (Velasquez & Hester, 2013). This technique continues to be a solution for decision making problems in order to make judgement for different alternatives such as policy, strategy, scenario, weightage and choice (Bhole & Deshmukh, 2018). Quantitative and qualitative criteria are important in MCDM methods. Quantitative criteria are based on numerical data, while qualitative criteria are based on more subjective evaluations. Since real world MCDM problems include both these quantitative and qualitative criteria, MCDM methods handle both (Nieto-Morote & Ruz-Vila, 2011). Thanks to this approach, decision makers can make more comprehensive decisions.

As MCDM are efficient and adaptable tools that may help with decision making when differentiating among a group of options under several criteria is necessary, these approaches are frequently employed in engineering practice (Benitez et al., 2019). As indicated in Table 7, farmers and other stakeholders who are directly or indirectly impacted by agricultural operations are the relevant decision-makers in the agricultural setting (Cinelli et al., 2014). Climate-smart agriculture (CSA) defined as a word that is widely used to describe advances in agriculture production that are designed to address climate change by Wassman et

al. (2019). CSA is often thought of as having three pillars, namely adaptation, food security, and mitigation which are also used as core criteria in that study to rank CSA technologies.

In the field of agriculture, Haseeb et al. (2020)'s framework reduced the ratio of energy consumption while improving data delivery performance. It also provided an intelligent decision for data routing. Sensors gather pertinent data and use a multi-criteria decision function to choose a set of cluster heads. For smart agriculture applications, drone selection based on data recording is done by Petkovics et al. (2017). The study is done by taking into account expert's opinions in the agriculture field by AHP method. Yazdani et al. (2021)'s risk study was suggested shown a successful application in evaluating various agricultural projects that claim to reduce the risks of flooding and their effects on crop regions. The approach may be used by agricultural businesses to pinpoint risk factors and find the best projects to lessen the worst effects of flooding threats in crop regions. The occurrence of new risks remains unavoidable, but they develop because of different factors. Uncertainty stands as one of the main causes of this situation. The authors of Schader et al. (2019) presented essential methodological guidelines to properly merge expert-based evaluations with multi-criteria assessment methods. The research provided to evaluate weight uncertainty from expert opinions while using this uncertainty to enhance SMART assessment results.

The assessment of multiple criteria in olive cultivation demands the use of MCDM approaches. These methods worked to enhance production levels while reaching sustainability targets. Environmental factors play a crucial role among these research aspects. Parra-López (2007) conducted research which used environmental indicators like soil erosion and water use and atmospheric pollution and biodiversity to evaluate organic olive cultivation systems against conventional olive cultivation systems. The evaluation criteria served to reduce environmental damage from olive production while maximizing ecosystem advantages.

The agronomic criteria consist of multiple elements which directly affect olive production levels. Zouaghi (2023) conducted a study to determine the most suitable sites for olive cultivation through evaluation of soil types combined with water availability and irrigation management practices. Caruso (2012) analysed agronomic factors such as olive varieties and planting patterns and mechanization levels to

enhance production quantities and quality levels. These parameters served to establish the most productive olive farm practices.

Table 7

Examples of MCDM Studies in Agriculture

Author	Year	Problem Definition	Model/Approach	Future Research
Yazdani et al.	2021	Analysis of risk factors like flood for different agricultural projects	SWARA and EDAS	Use of dynamic decision models
Haseeb et al.	2020	Bottlenecks among agriculture sensors	Multi criteria decision function	Analysis of mobile-based IoT network and Intelligent Transportation System
Wassman	2019	Climate smart agriculture; ranking system for different CSA technologies in rice lands	Criteria assessment	Taking into account national level, increasing number of farmers for interview
Schader et al.	2019	Uncertainty of agricultural decisions	Degree of Goal Achievement (DGA)	More number of attendees
Petkovics et al.	2017	Selection of right drone for precision agriculture based on data recording	AHP	-

The MCDM investigations heavily rely on economic and sustainability factors. The study by Stillitano (2017) evaluated different cultivation systems through economic analysis of production costs and yield per hectare and market value of olive oil. The research by Parra-López (2007) evaluated the long-term environmental performance between organic and integrated systems through environmental assessments. The conditions must be met to ensure olive production remains economically viable while minimizing environmental impact.

The production processes of agriculture involve multiple complex elements including climate change and efficient water resource management and sustainable

agricultural politics. For the purpose of managing these factors in balance, MCDM methods are commonly used in agriculture sector. In the study of Gomez-Limon et al. (2007) merged two different program management in order to optimise water management decisions in water used agriculture. Their study contributed to the policy development process for agricultural practices in Spain within the scope of the European Water Framework Directive. Similarly, in order to rank agricultural production regions in Türkiye in terms of performance, cluster analysis was integrated with MCDM to determine the regions with the highest production performance and to provide suggestions for local agricultural policies. These studies are important in terms of showing how MCDM methods can be used effectively in regional agricultural productivity assessments (Omurbek et al., 2021). AHP and TOPSIS methods are used to choose most efficient water management strategies in Iran by Golfam et al. (2019). The study also considered climate change-based management of agricultural water distribution in the country.

MCDM methods play critical role on decision for the use of IoT systems in agriculture and smart agriculture applications decision. For the optimisation of IoT platform selection process in agricultural activities, Ilieva and Yankova (2022) developed a fuzzy MCDM method. This method provided comprehensive method for decision makers to choose proper technology. Tolga and Başar (2022) analysed the efficiency of IoT and automation systems with the use of WEDBA and MACBETH methods in order to evaluate the smart agricultural systems. Supply chain model is developed by Chaudhari et al. (2024) with F-TOPSIS method in order to increase environmental sustainability in agricultural machine production

MCDM methods are also widely used in the evaluation of agricultural production sustainability and water management. Tork et al. (2021) applied AHP and COPRAS methods simultaneously to determine the most suitable scenario for the modernization of agricultural water distribution systems. In a similar way, another study conducted by Zamani et al. (2020) in order to identify best appropriate adaptation strategy to mitigate the impact of climate change in agricultural water management politics. In the study, both fuzzy TOPSIS and PROMETHEE II methods are used to indicate critical factors for adaptation of climate change.

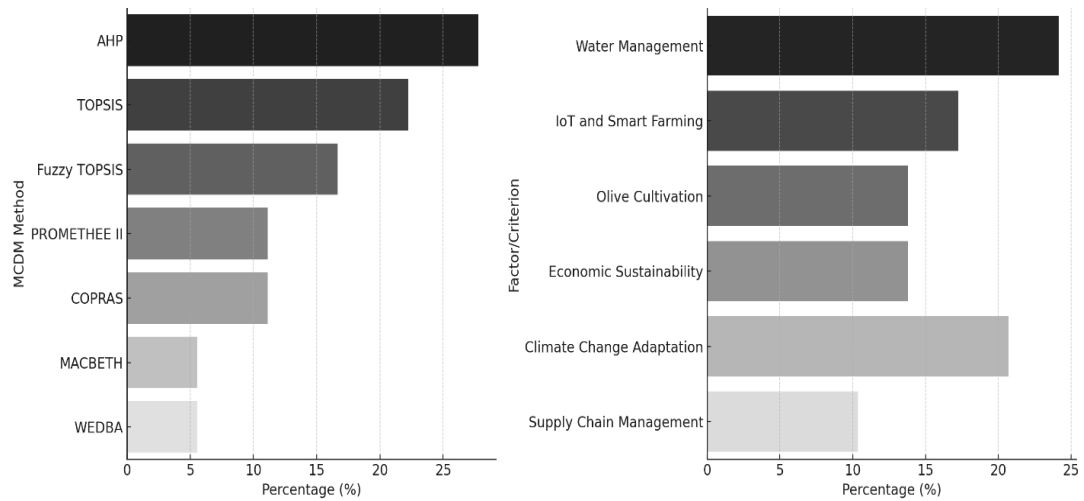


Figure 5. Distribution of methods and common criteria in agricultural MCDM

MCDM methods are also used in an efficient way for agricultural supply chain and product decision processes. Figure 5 indicates the distribution of methods and common criteria in agricultural MCDM. Taking into consideration of environmental factors in sustainable decision making is studied by Puska et al. (2022). Z-numbers based fuzzy MCDM methods are used to optimise green supplier selection in agricultural production. Moreover, Tirth et al. (2021) used MCDM methods to choose most sustainable agricultural crops in Saudi Arabia. The aim of the study is to develop sustainable agricultural policies that will utilize natural resources in the most efficient way.

2.6 Hesitant Fuzzy Sets in MCDM

Combining the FARE-CILOS approach and RATMI technique within an t-Spherical Probabilistic Hesitant Fuzzy (t-Spherical Probabilistic Hesitant Fuzzy) environment, Sandra et al. (2024) presented a fuzzy MCDM framework for sustainable weed control. Using robotics for focused weed eradication, precision weed management turns out as the best answer. The study offered useful information for regionalized weed control plans and stresses the need of sustainable substitutes for chemical pesticides.

To assess agricultural green development (AGD), Wan et al. (2023) constructed a model integrating the Gini coefficient with hesitant fuzzy MADM. Key dimensions impacting AGD are identified in the study as policy, science and technology,

awareness, and industry. Empirical study in Yantai City showed increasing AGD trends; policy green development shows the most notable expansion. Among the recommendations are raising consumer demand, government backing, and agriculture practitioners' knowledge.

Reviewing the EDAS approach, Torkayesh et al. (2023) underlined its application in MCDM in many sectors including supply chains management, energy, and construction. The paper addressed expansions of EDAS in fuzzy and probabilistic settings and makes recommendations for next directions including integration with machine learning and behavioural decision making theories.

For the choosing of investment policies, Ali et al. (2023) created a novel three-dimensional group choice model. The work sought to use hesitant fuzzy sets to enhance decision making procedures. The model enable decision-makers better control circumstances of uncertainty and doubt and hesitation. Particularly in difficult and multi-criteria decision issues, this method presented a good answer. In the axis of water, energy, food, and sustainability, Bai and Sarkis (2019) have evolved a multi-stakeholder and transdisciplinary strategy. The study intended to offer integrated solutions and improve understanding of the decision making the environment in several fields. Particularly the interactions among food systems, energy, and water and their effects on sustainability have been addressed. This method guaranteed the involvement of several stakeholders, therefore supporting more inclusive and efficient decision making. Summary of these studies are indicated in Table 8.

For decision making under uncertainty, Jantzi et al. (2021) presented an updated paradigm integrating Aczel-Alsina aggregation operators with intuitionistic hesitant fuzzy sets (IHFSs). The work introduced interval-valued equivalency classes for improved generalization by combining multiple attribute decision making (MADM) and three-way decision (3WD) methods. A case study showed the model handles conflicting and complicated information as well as how best to choose investments. Using aerial RGB photos, diachronic mapped occupying plants in the Pyrenees region in Southwestern France. The study also offered creative approaches for control and monitoring of the surroundings. Particularly, it is underlined how well remote sensing technologies monitor and stop the dissemination of invasive plants. This approach offered a major help for ecosystem management and environmental sustainability.

Emphasizing the importance of green spaces in offering physical, psychological, and social advantages, this Srdjevic et al. (2019) studied on urban sustainable development goals (USDGs) and the management of urban environments to provide Novi Sad, Serbia's environmental services top priority, the research presented a reluctant AHP for participative decision making. The results showed that, following regulating, cultural, and supporting services, provisioning services are the most important ones. Effective urban ecosystem management depends on transdisciplinary tools and citizen interaction as indicated in the study.

Table 8

Hesitant Fuzzy Related Studies in Agriculture

Author, Year	MCDM Methods	Criteria/Parameters
Burak et al., 2024	HF-AHP, HF-EDAS, PROMETHEE II	Initial investment cost, operation and maintenance cost, environmental impact, agricultural efficiency
Hezamm et al., 2024	CRITIC, Double Normalization-Based Multiple Aggregations (DNMA)	Employment, income, environmental impacts, cost of operations, agriculture development
Sandra et al., 2024	FARE-CILOS, RATMI, TOPSIS, EDAS, PROMETHEE-II	Weed density, cost, time consumption, precision weed control
Ali et al., 2023	Three-Way Decision-Theoretic Rough Set (DTRS), IHFS	Cost parameters, conditional probabilities, aggregation operators (e.g., IHFAAWA, IHFAOWA)
Torkayesh et al., 2023	EDAS, AHP, TOPSIS, SWARA, WASPAS	Various criteria in energy, construction, and technology applications
Wan et al., 2023	HF-MADM, Gini Coefficient	Policy green, industry green, science and technology green, awareness green
Bai & Sarkis, 2022	Joint Neighbourhood Rough Set (NRS), Interval-Valued Hesitant Fuzzy Set (IVHFS), Regret Theory	Water, energy, food sustainability nexus factors, stakeholder satisfaction degrees, regret-rejoice values

Table 8 (cont.d)

Author	MCDM Methods	Criteria/Parameters
Burak et al., 2022	HF-AHP-PROMETHEE II, HF-AHP-TOPSIS	Surface irrigation, furrow irrigation, sprinkler, mini-sprink, drip irrigation
Jantzi et al., 2021	IHFS, Aczel-Alsina Aggregation Operators	Market growth potential, financial stability, customer satisfaction, employee satisfaction
Narayanamoorthy, 2019	HF CRITIC, HF MAUT	Social acceptance, health risk, environmental feasibility, technical operation, economic
Srdjevic et al., 2019	H-AHP	Ecosystem services: provisioning, regulating, cultural and supporting
Joshi and Kumar, 2017	Hesitant Fuzzy Weighted Aggregation Operator (HFWAO), Preference Relations	Human resource development criteria

Under uncertainty, Hezamm et al. (2024) created an integrated decision making model to assess irrigation systems. The study analysed environment friendly irrigation systems. The model guaranteed that more sustainable and balanced decision making with including social, environmental and financial aspects. Especially about the efficient management of the water source and the agricultural output, this strategy shows an important answer. Burak et al. (2024) listed the request of cotton irrigation recycling with using the techniques named MCDM. The project is observed Söke Plain's water management techniques. It helped to create more sustainable and successful solutions with considering some of the criteria. That method put variety of contribution to agricultural sustainability and preservation of water sources. Another study conducted by Burak et al. (2022) in order to analyse the irrigation method for cotton crop in the Söke Plain. It is indicated that modern irrigation techniques increase the efficiency of water use and better to keep up environmental stress against traditional methods. Joshi and Kumar (2017) created a computer method for the difficulties of hesitant fuzzy group decision making. The study took the collective

decision making procedures to the highest level. It suggested creative algorithms for dealing with especially for the uncertainty and hesitation. This approach created more efficient answers and helps to understand the group dynamics under hard decision making situations. Narayanamoorthy et al. (2019), presented a sustainable evaluation for choosing the best solution with the MCDM techniques. This study indicated an important view for sustainability and efficient use of water resource management. Through consideration of social, environmental, and economic elements, the model guarantees more balanced and efficient decision making.

2.9 Quality in Olive Cultivation

As it comes to olive crops, there are a number of critical aspects that have an important impact on the process and the quality of the olives that are produced throughout both the planting and harvesting phases:

Location selection: One of the most important aspects of planting is selecting a location that is suitable for the plants. According to Paoletti et al. (2023), the success of olive tree development and subsequent fruit production is heavily dependent on a number of factors, including the type of soil, drainage, slope, and exposure to sunshine.

Techniques of planting: Planting methods determine how olive trees establish themselves and grow during their early stages. The establishment of olive trees depends on planting hole dimensions and root ball preparation as well as tree spacing (Paoletti et al. 2023).

Soil management: The preparation of soil combined with nutrient additions through fertilization and soil conditioning before planting significantly affects tree growth according to Gucci et al. (2012).

Timing of harvest: The moment of harvest controls olive oil quality because it establishes when to harvest the olives based on their stage of ripeness. Harvesting olives at the right stage of maturity ensures the proper chemical composition and sensory attributes of the oil (Salas et al., 1999; Dib, 2021).

Methods of harvesting: The technique of harvesting affects both the processing convenience and the final quality of the harvested fruit. The olive harvest includes both manual collection and automated machinery harvesting methods. The process of mechanical harvesting becomes faster with proper management to avoid damaging the fruit according to Bendini et al. (2007).

Conditions of harvesting: Multiple environmental elements during harvesting operations affect fruit quality including weather conditions and temperature factors. The method of olive preservation through seasonal harvesting during cooler times or through temperature protection measures (Mafrica et al., 2021).

The establishment of olive trees along with maximum fruit quality needs proper parameter management during planting and harvesting stages to achieve successful results in olive products such as olive oil.

2.10 Evaluation of Current Studies and Contribution

The UN FAO together with the World Meteorological Organization (WMO) announced multiple statements about the 2030 development agenda in 2017. The two organizations recommended the following highlights to enhance agro-meteorological services and their availability to farmers and fishermen in their statements:

- The worldwide and regional specific monitoring system for the purpose of detection and respond to high impact occurrences such as droughts,
- Developing countries experience more than 80% of their drought related damage and losses through agricultural sectors,
- The strategies aim to connect farmers with advanced technologies which will enable them to manage their operations better,
- Creating options for farmers that want to change their approach from reactive to proactive.

While this statements in overall draw attention to being more resistant to climate change in agricultural processes and production, another report of FAO pointed the potential of Türkiye's digital technologies for agriculture. The report highlighted the capacity of agriculture in Türkiye and there is a limited use of digital farming practices which may result from small farmer dominance in the field.

Moreover, The Ministry of Agriculture and Forestry's 2024-2028 strategic plan gave place the integration of use of AI technologies in agriculture, climate friendly agricultural processes and more use of smart agricultural planning. The strategic plan manual aligns with Türkiye's 11th and 12th development plan. 11th and 12th plans include following statements which indicates the contribution of this thesis study:

- Increasing efficiency in agriculture,

- Decreasing risk of climate change,
- Integration of digital technologies in agriculture,
- More use of AI technologies,
- Climate based production planning,
- Creation of scenarios related to climate change.

In this respect, the proposed methodology of AI based production prediction model will contribute to increasing efficiency with more efficient use of sources. MCDM approach in agriculture will provide more data related background to farmers for agricultural production planning.

The studies in the literature about the use of EWS with LSTM indicates that the focus mostly on climate prediction, disease management and crop efficiency predictions (Nurraharjo et al., 2024). However, the application of LSTM in specific agricultural fields such as olive cultivation is limited. Recent studies propose hybrid models and hyperparameter modification to raise LSTM accuracy in time series data (Macherera & Chimbari, 2016). However, these models are not fully integrated into tools that help cultivators make decisions.

Hesitant Fuzzy AHP, become prominent as an efficient method for uncertainty and multi criteria related issues. In the agricultural related studies, use of this method can be seen as limited. It is pointed out that this method provides flexibility for decision makers for modelling uncertainties and group decision making processes. Together this, there is a need to investigate more in the process of determining and weighting criteria in agricultural practices (Akram et al., 2023; Öztayşi et al., 2015). Studies are significant to indicate that efficiency of MCDM methods considering regional agricultural efficiency. For the purpose of developing integration of EWS and decision support mechanisms, MCDM methods are seen useful tools. For this reason, literature provides insights for identification of climatic and environmental factors related systems. Identification of most proper management strategies and understand the impact of water and climatic management on agricultural practices efficiency. These studies lead the way to determination of best varieties in olive growing and sustainable crop production strategies. In addition to that, there is additional research for criteria determination and weight processes for agricultural applications (Mousavi et al., 2014).

The literature shows that the integration of LSTM and Hesitant Fuzzy AHP in

olive cultivation can be an innovative approach. LSTM is a good tool for time series data and Hesitant Fuzzy AHP is a good tool for decision making processes during uncertainty (Mateo-Sanchis et al., 2023; Öztayşı et al., 2015). This thesis sought to address the gap in the application of these methodologies in olive cultivation for the purpose of more efficient and comprehensive decision support mechanism.



Chapter 3

Methodology

As stated in the previous sections, the study will be carried out on olive tree cultivation processes in the field of agriculture.

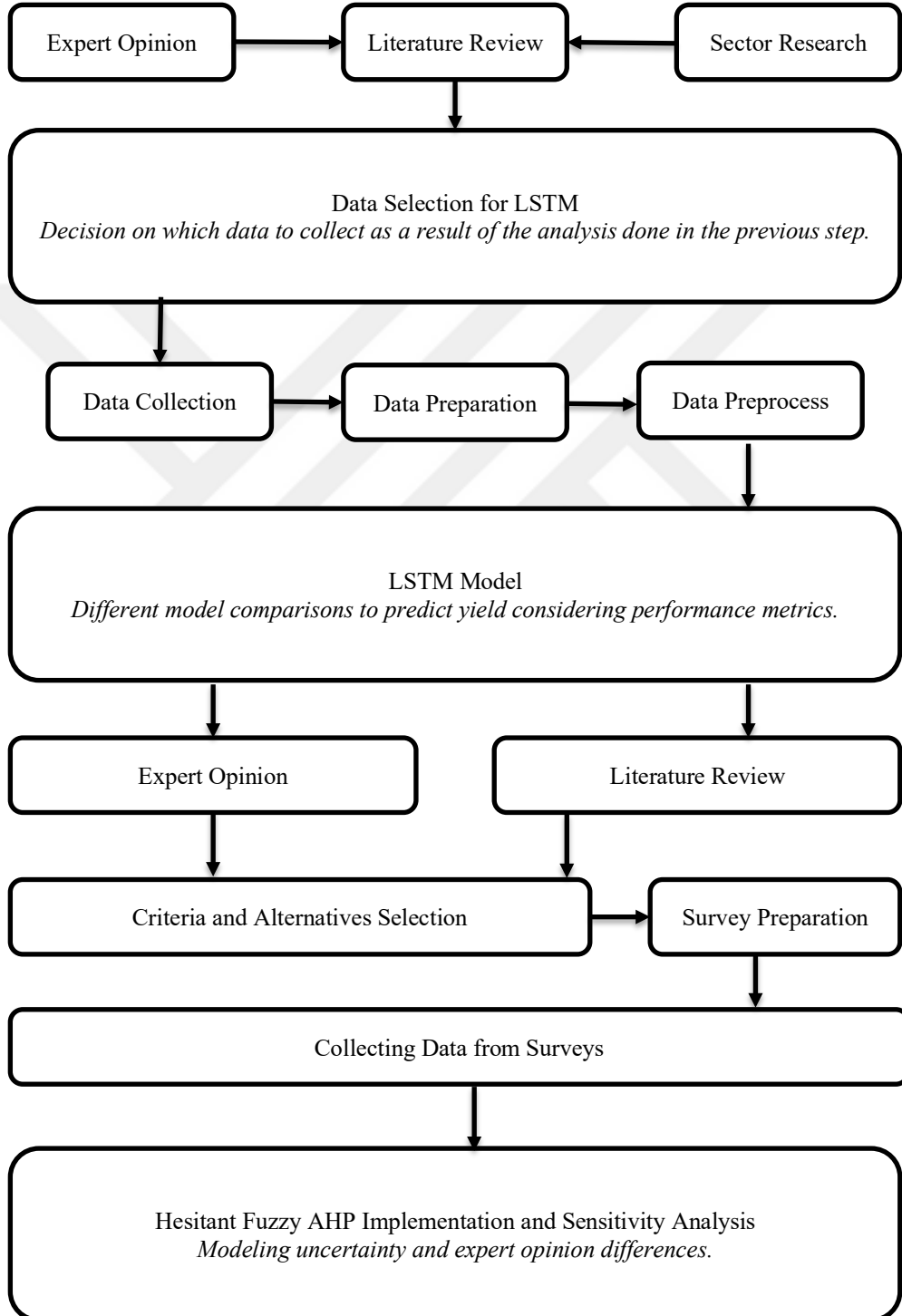


Figure 6. General flow of the methodology

Increasing the efficiency in agricultural production, challenge of climate change and integration of digital technologies in agriculture are defined as a prior field in Turkish Development Plan. In this context, integrated smart olive cultivation system design planned to make predictions with using meteorological data. LSTM and MCDM methods will be used to make predictions for the purpose of efficient use of sources and maintaining yield efficiency. LSTM based prediction mechanisms provide contribution to data based politics creation processes and increasing wide use of sustainable agricultural practices.

As it is known, farmers are usually involved in the execution of these processes. The role of farmers in olive tree cultivation; in other words, the role of farmers from the aspects covered by this study is in line with their own knowledge and experience. In other words, they become aware of the fact that they encounter any undesirable situation in the processes from planting trees to development, from development to harvesting. Then they take action according to their observations. These observations can consist of various damages in the development of plants, diseases, drought, soil moisture, and the current state of the product. In these cases, it is preferred that the actions they take or take should be by considering the environmental and biological factor effects due to their work in rural areas.

Through the methodological flow, selection and preparation of meteorological and yield data will be obtained. After the application of LSTM model, criteria and alternatives will be determined by literature review and expert opinions. With these alternatives and criteria, MCDM survey will be prepared and data from participants through surveys will be collected. Result of Hesitant Fuzzy AHP, sensitivity analysis will be completed.

With the system planned to be put forward within the scope of this study which is seen in Figure 6, it is expected that the role and effect of expert researchers will be involved in agricultural fields. It causes the quantitative characteristics of the crop to be obtained from olive trees to reach the optimum level, and it is also for the use of researchers in terms of improving production and food safety.

3.1 Research Design

Time series analysis and multicriteria decision making techniques bring

together for the purpose of improving olive crop prediction and decision support processes. Through this context, two different methods integrated. First of all, with the use of deep learning based LSTM model, olive crop prediction for future years aimed. After this implementation, Hesitant Fuzzy AHP method used to identify best strategic actions considering predictions.

Under the quantitative research techniques, this work was designed following an experimental modelling procedure. First, meteorological and agricultural data were collected for particular years and made ready for the forecast procedure by subjecting them to LSTM model processing. Then the multi criteria decision making model was employed to evaluate the forecast findings and the decided on agricultural guidelines.

LSTM model that used in the research is the type of Artificial Neural Network which is commonly used in the literature for time series predictions and have a high capacity to learn, especially long term dependencies (Hochreiter & Schmidhuber, 1997). Other types of ANNs are indicated in Figure 7. The time period agricultural data changes can be properly modelled by using LSTM to create a suitable structure and architecture. The method proved successful in literature to reveal the strong relationship between climate related variables and agricultural crop predictions (Jiang et al., 2020; Mateo-Sanchis et al., 2023).

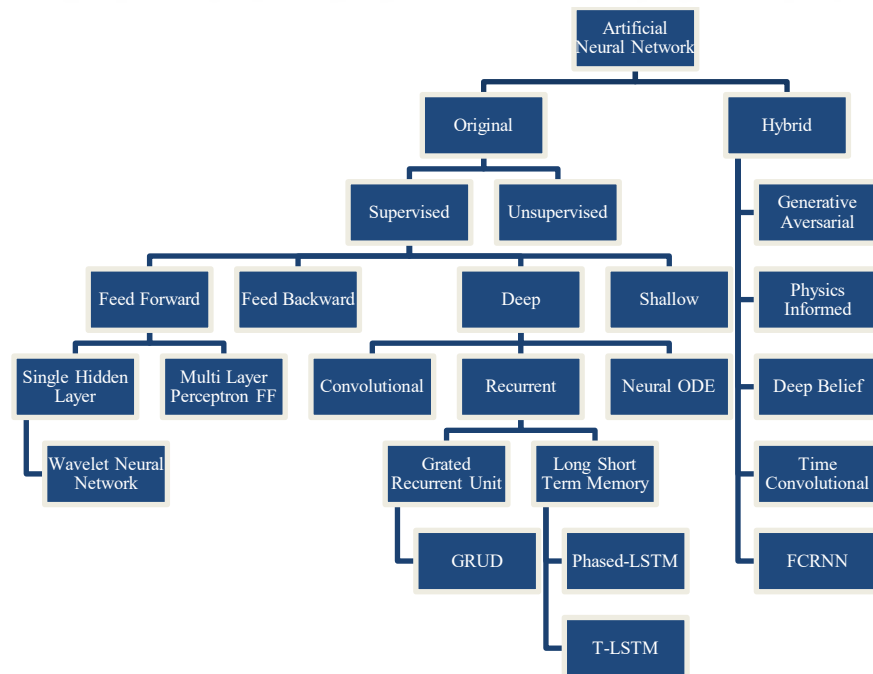


Figure 7. Different types of continuous time series modelling in Neural Network
(Habiba, 2022)

The Hesitant Fuzzy AHP method was developed by Torra (2010) to evaluate situations that include uncertainties in multi criteria decision making, in addition to LSTM. AHP is one of the most widely used methods in multi criteria decision making that provides a systematic quantitative view of decision makers' subjective evaluations. On the other hand, Hesitant Fuzzy Sets allow decision makers to evaluate more than one possibility. Considering classical AHP, Hesitant Fuzzy Sets bring more flexible application during uncertainty (Liao et al., 2014). During this research, climate suitability, soil quality, production yield and other factors took into consideration. There are four primary steps or stages of the implementation process of the research:

- The development of the dataset, including its preprocessing procedures.
- Application of the LSTM model to the forecasting of time series.
- The implementation of Hesitant Fuzzy AHP and sensitivity analysis.
- The analysis of the model and the interpretation of the findings.

This systematic framework also aims to increase the accuracy of the predictions and to create a DSS in agricultural production, among others. All of the particulars of the research have been explained in detail in the subsequent subsections.

3.2 Machine Learning

Evolution of machine learning, starts with classical statistical approaches, continues with artificial neural networks, goes through advanced deep learning models such as LSTM. This process eased to understand not only the superficial features of data, but also complex relationships through the time. Supervised, unsupervised, semi-supervised, additive, reinforcement learning approaches, each learning technique provides solution to different kinds of problems. Success of LSTM models, especially in long-term dependencies resulted in high quality of research for time series analysis.

At the present time, data analytics and prediction models in a variety of fields thanks to flexibility and capacity of non-linear relationship capturing with LSTM. In the future, these methods form a basis to develop more complex and hybrid models. These developments, especially for the situation where there is a real time data flow and continuously changed environmental conditions implementations, give an

opportunity to more reliable and accurate predictions. Thereby, the process through machine learning to LSTM doesn't only stand for technological transformation, but also pioneer for data based decision making processes and essential changes.

3.2.1. General definition of LSTM. Recurrent Neural Networks (RNN) seen as an important step in the literature. RNNs have a capacity to include the information from past time to next step of calculations. Thanks to this capacity, these networks are able to model dependencies in sequences (Parcollet et al., 2018). This feature considering time series data bring a huge advantage for applications that contain recurrent data such as natural language processing (NLP), voice recognition and video analytics. In addition to that, there are such problems like gradient loss or exploding gradient (Bengio et al., 1994; Jin et al., 2024). These problems lead to performance decrease of the capacity to learn relationships in long sequences (Lechner and Hasani, 2020). In order to cope with these problems, LSTM developed (Hochreiter & Schmidhuber, 1997). This model improves RNN structure and able to learn long term relationships in efficient way for certain circumstances. LSTM consists of three main gates for each time step which are forget gate, input gate and output gate (Greff et al., 2015; Jin et al., 2024). These gates allow model to decide which information will be hold, which information will be learnt, and which information will be used as an output. This model increases the learning capacity of long-term dependencies in a large scale.

3.2.2. LSTM elements and structure. LSTM is a kind of RNN that is designed to learn long term dependencies in sequence learning. The structure of LSTM designed has a special design to process data properly through the time. The structure consists of gates and cell state elements as seen in Figure 8.

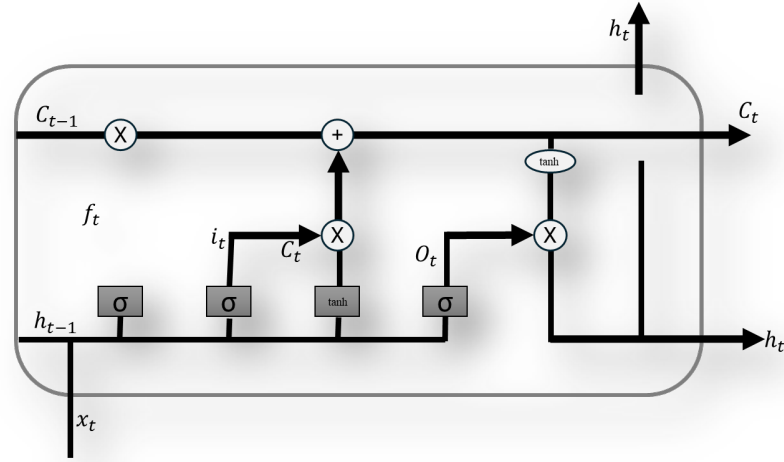


Figure 8. General structure of LSTM (Jiang et al., 2019)

Cell State: This element is the long-term memory of LSTM. Transfers data through the time and updates the data thanks to gates. Cell state has an impact of model's decision with emerging past and current data.

Forget Gate: This gate decides what kind of information from past will be held in the memory. Unrelated or incorrect information prevented in the model that provides more efficient use of the memory. For example, for financial market analysis (Shakawi & Shabri, 2025), past and invalid price information can be forgotten.

Input Gate: Controls the addition of new information to the memory. This gate decides whether which new information will be learnt by the model. For example, for weather forecasting (Karevan & Suykens, 2018), current temperature and humidity data can be added to the memory.

Output Gate: Decides whether which information of the memory will be used as an output. This gate controls which information will be focused during the forecasting. For example, only critical sensor data of the production line can be used as an output in the processes of industrial.

Hidden State: Represents the data which is transferred to next time step or last prediction of LSTM.

Activation Functions: LSTM executes sigmoid function for gates and tanh activation function for cell state. Sigmoid function normalizes data between 0-1. On the other hand, tanh activation function limits between -1 and 1.

x_t : input at current time step

h_t : output of the lstm block at time step t

c_t : cell state (memory) at time t

$\tilde{c}_t$: candidate for cell state at time t

f_t : forget gate

i_t : input gate

O_t : output gate

w_t : weights of respective gate (x) neurons

b_x : biases for the respective gates

σ : sigmoid function

A_t : internal cell state

Equations of gates: The input, forget and output gates are processed by three fully connected layers with sigmoid activation function to calculate their values. As a result, the values of the three gates are in the range of 0 to 1. Equation 1 refers to the input gate that tells the information which will be stored in the cell state. Equation 2 is for forget gate to remove information from the cell state. Equation 3 used to make activation of LSTM block's last output at time 't' for output gate.

Mathematically, the input is x_t and the hidden state of the previous time step is h_{t-1} . Accordingly, the gates in the time step are defined as: Input gate i_t (equation 1), forget gate f_t (equation 2) and output gate is o_t (equation 3). These are calculated as follows:

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (1)$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (2)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (3)$$

where w_i, w_f, w_o are the weight parameters and b_i, b_f, b_o are the additional input parameters.

Equations of cell state: At this stage, the design of the memory cell takes place. Since the action of the various gates has not yet been specified, the candidate memory cell is first included in equation 4. The calculations are similar to those for the three gates (Equation 1, equation 2 and equation 3) described above but use a function with a value range between -1 and 1 as the activation function. This is included in the following equation in the time step:

$$\tilde{c}_t = \tanh(w_c[h_{t-1}, x_t] + b_c) \quad (4)$$

Equation of memory cell: LSTMs have two special gates for the purpose of providing a mechanism to manage input and forgetting (or skipping). i_t controls how much of the new data is taken into account via the input gate $\tilde{c}_t$, and f_t controls how much of the old memory cell content c_{t-1} is retained. If the forget gate is always approximately 1 and the input gate is always approximately 0, past memory cells are saved with time c_{t-1} and passed to the current time step. This design is used to alleviate the vanishing gradient problem and better capture long-range dependencies within sequences. Equation 5 expresses this memory cell:

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (5)$$

Equation of hidden state: Finally, the calculation of the hidden state h_t is given in the following equation 6. This is where the output gate comes into play. Basically, in LSTM, it is the gated version of the memory cell with tanh. This ensures that the h_t values are always within the range of -1 to 1. When the output gate approaches 1, it effectively transfers all memory information to the predictor, whereas for an output gate close to 0, it only stores all the information in the memory cell and does not perform any further processing.

$$h_t = o_t * \tanh(c^t) \quad (6)$$

3.2.3. LSTM learning process. Learning flow of LSTM methodology is provided in Table 9. Sequence learning defines the process of data through time and brings out meaningful patterns or relationships. This learning process is especially used for time series such as text, speech or biological sequencing (DNA/RNA).

Table 9

Learning Flow of LSTM

Aspect	Description
Data Flow	One step at a time, LSTM processes input sequences. In each step, the cell state and the hidden state are also updated. This process is useful for capturing dependencies between elements in a sequence.
Gating Mechanism	The forgetting gate is used to forget some information from the cell state. The input gate lets new information in. Only some information from the cell state is chosen to be used by the output gate. These gates are responsible for selecting the relevant information in the learning process.
Gradient Flow	The cell state in LSTM is maintained across timesteps to solve the vanishing gradient problem. This makes learning long term dependencies possible.
Training	LSTM is trained with the Backpropagation through time (BPTT) algorithm which is BPTT algorithm is specifically designed for sequences of data. This algorithm updates the weights by looking at all the timesteps. The model is quantized based on the loss function.
Goal	It identifies patterns and relationships in sequential data to perform the task of prediction, classification or any other similar task.

Loss function is expressed in equation 7:

$$L = \frac{1}{N} \sum_{t=1}^T (y_t - \hat{y}_t)^2 \quad (7)$$

where y_t

is real value and $\hat{y}_t$ is prediction of the model and T is the sum of all time steps

Gradient calculation:

$$\frac{\partial L}{\partial W} = \sum_{t=1}^T \frac{\partial L}{\partial h_t} \frac{\partial h_t}{\partial W} \quad (8)$$

where W are the weights of LSTM.

Weight update:

$$W = W - \eta * \frac{\partial L}{\partial W} \quad (9)$$

where η is learning rate.

With the help of the modelling the long term correlation of the time series, LTSM is preferred in various areas:

- Weather Forecast: LSTM can analyse the previous weather data to predict future temperature, moisture, precipitation which directly has positive impact on the critical decision making (Siarni-Namini et al., 2019).
- Financial Market Analysis: LSTM learn the long term relation with the share prices, exchange rate and other financial indicators. For this reason, it enables to develop investment strategies (Qiu et al., 2020).
- Industrial Processes: Sensor data on the production line is analysed by the LSTM to use important processes such as failure prediction, quality control and process optimization.
- Natural Language Programming (NLP): LSTM can learn long term dependence of the text data which can be used for constructing language model, classifying text and translate (Gavrishchaka et al., 2019).

The wide application areas of the LSTM can offer ideal solution to the long-term dependencies with the help of the gate mechanisms, LSTM models can learn both short term and long-term relationships. For this reason, it can be identified that LSTM becomes powerful tool for the consecutive data analysis. Main features of sequence learning divides into three. The first feature is called time dependency. The relationship of time and sequencing between data is very crucial. The second one is modelling. Generally, RNN, LSTM and Transformer models are using sequence learning. Considering application fields, as indicated before, NLP, speech recognition, prediction and other time series related areas are common.

3.2.4. Advantages of LSTM. The LSTM network is a type of RNN that can grasp connections compared to basic recurrent units, by preserving gradient errors with a memory cell introduced by Hochreiter and Schmidhuber to address the vanishing/exploding gradient issue in RNN training. Model utilizes three gates (forget, input and output) allowing information retention, across cycles well (Kong et al., 2024). LSTM networks might offer benefits, over RNNs. Certain studies indicate that LSTM networks exhibit a convergence rate compared to RNNs because LSTM does not always require updates to its past memory cells and certain weights during training leading to delayed activation of gradient updates, in those weights until the training data triggers them. While this method proves effective, for fluctuating data sets; it simply results in delayed activation in the majority of scenarios observed in the experiment conducted showed that the memory cells activation, within the LSTM network is significantly lower compared to the activation of input and recurrent weights, indicating that the memory cell exerts an impact. Different versions of LSTM layers have been. Tested to evaluate their effectiveness, in building a final machine learning model structure. This encompasses the LSTM well as the proposed LSTM formulation mentioned in the research. (Kent & M.Salem, in 2019) utilized feed forward back propagation batch training with LSTM to potentially enhance the performance accuracy of LSTM models. Many used LSTM neural network toolkits and applications are believed to have originated from these LSTM models. In practice it is common to set the drop out seed between 0.6-0.9 for forget gates, within these models. When selecting a model to use as the standard, for a system the decision is guided by options and these structures will be applied in a way similar to those previously studied in. The capacity to grasp relationships, over extended periods is one of the strengths.

Understanding the mechanisms underpinning the ability of LSTM networks to capture long-term dependencies is a long-standing problem in the field of computational neuroscience, artificial intelligence and complex systems. LSTM networks branch out from neural networks to address this challenge and have lately shown remarkable progress and gained popularity across various fields of application. The concept of long-term dependence has been effectively captured through memory processes. Has been applied in creating commonly used models, in engineering like autoregressive moving average models and fractional Brownian motions. Questions

still linger regarding the capacity of LSTM networks to grasp long term dependencies due to their intricate structure.

The LSTM network has gained popularity, for addressing the challenge of long-term memory. Has seen success in real world applications. It is widely believed that by incorporating transfer functions within a unit. Allowing input at a given time step to influence the internal memory without having to pass through numerous time steps. The network becomes adept at capturing long term dependencies. However, the intuitive explanation falls short in justifying why LSTM outperforms RNN in scenarios since a vanilla RNN, with a transfer function can exhibit similar characteristics with the right parameters set in place. This contentious viewpoint is also supported by studies that highlighted the significance of network depth, over the choice of LSTM units. The raised issue is whether networks lacking internal memory components are capable of learning long term dependencies; examples show that certain new memory units, with designs possess this ability well. Resistance to the vanishing gradient issue of 32 is shown by the network.

One common issue encountered during the training of a reservoir type or fully trainable RNN is its high sensitivity, to the initial hyperparameters selected for initialization purposes. Choosing a distribution can frequently result in a model that either produces zero values or infinite values. Another notable drawback of this architecture is its learning pace when compared to the echo state network. Although this problem has not been completely resolved yet the model has displayed some degree of resilience against the vanishing gradient problem.

According to a study, by Ghojogh and Ghodsi in 2023 LSTM models have excelled in network tasks due to their capability to manage long range dependencies effectively. It is widely believed that LSTM addresses the issue of vanishing gradients and possesses an ability to retain long term memory.

RNN and LSTM networks have become popular, for handling sequences of data over time or space. However, there's still a challenge in training RNN models to remember long term dependencies. Currently there isn't a theory that explains how the structure of a model relates to its memory capacity, including any biases in architecture design. Research indicates that the information stored in points within these models may not be crucial for processing sequences of data. This new study takes an approach, to understanding how information an RNN or LSTM model can retain over time.

There has been growing interest in LSTM networks due to their performance across different applications when compared to basic RNN. LSTM networks are equipped with memory capabilities that allow them to efficiently learn and retain long-term dependencies by utilizing four gates. Input gate; forget gate; output gate; and internal memory cell. Although the exact mechanisms, for learning these long-term dependencies have not been explicitly demonstrated. When it comes to analysing data LSTM networks prove to be highly efficient (Zhao et al., 2020). Sequential data has been extensively utilized and has led to technological breakthroughs, in various domains like forecasting and modelling sequential data as well as classifying and generating it; however long-term sequential dependency modelling within a fixed time frame presents challenges due to the vanishing gradient phenomenon hindering further learning, by traditional RNNs. To address this issue researchers have explored styles of RNNs. One of the architectures that stands out is the LSTMs. LSTMs are a type of neural network that has shown to be successful in capturing extensive contextual information, for certain NLP. Recent research has revealed that deep neural networks can approximate a version of the input data they receive (Tai et al., 2015). The results indicated that the output produced by LSTM cells helps to stabilize the input data and reduces its reliance on information. This implies that in deeper LSTM networks exponents of the input are forgotten at a rate and they discard parts of the input that occur frequently above a threshold level of frequency which raises concerns about the effectiveness of deep LSTM models. One of the progressions in networks and machine learning is the introduction of the LSTM layer that allows training networks with temporal connections over longer periods of time effectively. This has resulted in the integration of LSTM-based networks into applications, like language translation, speech processing and video analysis that rely heavily on understanding context. Although the LSTM cell contains gating components there have been simplified versions introduced that may not perform as well. Three new versions have recently been introduced to analyse the design aspect of any LSTM based unit computationally.

The key benefits of the LSTM unit compared to its RNN counterpart come from its gating mechanisms and memory cell design that allow it to capture relationships, across extended periods of time effectively. The ability to retain information over time steps resides in the long-term memory component of the LSTM architecture. LSTM represents progression following the limitations of RNN in

grasping long term dependencies and continues to make advancements in this area. Understanding the timescale of acquired characteristics becomes crucial in developing empirically reliable models, for learning such prolonged dependencies. In addition, the learning principles in models. The interest in developing models that can accurately capture the persistent evolution of temporal characteristics over extended periods has sparked inquiries about the long-term memory capabilities of RNNs and LSTMs. While this query may seem broad and ambiguous. It can be explored from angles such as asymptotic trends, state quantities and temporal durations. (Zhao et al., 2020).

3.2.5. Disadvantages of LSTM. This part discusses the advantages and drawbacks of utilizing LSTM networks. The drawback of LSTM networks is their long-term memory capacity despite being popular, for modelling sequences due to their effectiveness, in capturing long term dependencies statistically speaking. LSTM networks need to retain input details in order to exhibit long term memory capability; however, this can adversely affect their training efficiency. Developed to investigate this concept is a unique type of LSTM known as LSTM. An adjustment is implemented in the traditional LSTM structure to maintain memory stability and prevent decay by ensuring that the memory remains relatively consistent, over time. The study shows how the consistent LSTM impacts training efficiency and memory retention while enhancing the capacity for generalization, in tasks that involve processing sequences.

Structure Complexity: The introduction of LSTM architecture marked an advancement, in the realm of RNNs. Its capacity to grasp long term relationships has positioned LSTM as the pick for addressing time sequence challenges. Contrary to RNN designs, LSTM boasts a memory state that does not capture but also retains dependencies spanning distant timesteps. Despite its advantages there are apprehensions surrounding the intricacies of LSTMs structure and its learning mechanisms. One key concern revolves around the complexity, in LSTM architecture. In comparison, to types of RNN models there the structure of LSTM is quite complicated. Even though options, like Simple RNN exist, LSTM surpasses Simple RNN by a degree.

One reason why LSTM architecture is better at learning compared to networks is because of the chain structure it has in place. Calculations in LSTM that carry the

gradient error back through time are distinct from what the memory state holds. Since LSTMs learn from errors moving back from the output gap the difference between these two quantities can make it challenging to grasp how LSTMs are trained. Many self-taught individuals are often cited as examples of how LSTMs learn through implication, then demonstration. In this version released now shows a demonstration of how LSTMs learn in a scenario. In the LSTM design architecture show that the memory states derivative concerning the error becomes zero when the output gate shuts down.

Training Time: LSTM networks were created to address the challenge of capturing long term relationships that the Gated Recurrent Unit (GRU) struggled with initially. Although designed LSTM network can effectively store and recall input sequences, a model, with this capacity can easily become too specialized for use. Extensive testing across tasks has revealed that achieving an LSTM model behaviour to this theoretical perfection demands meticulous calibration of the forget bias, in each scenario. Training a model like this can be tough because minor adjustments in the training process or environmental factors can make the forget bias less effective. Zhao et al., (2020) discussed a drawback of the LSTM network known as the forget bias problem that will be covered in this chapter.

The LSTM based RNN with its forget gate has become popular for various applications including language modelling and other fields because of its recurrent architecture. LSTM networks have the theoretical capability to handle long term dependencies but in practice, dealing with sequences is challenging because the network tends to focus on local information rather than contextual cues by continuously forgetting past information. The LSTM network demonstrates difficulties in learning long-term dependencies according to experimental results.

Large Dataset: The neural network model known as LSTM functions as a type of RNN to analyse temporal and spatial sequence patterns effectively. The model maintains its ability to understand enduring information patterns without running into gradient explosion or vanishing problems. Creating an LSTM model requires advanced expertise because it needs multiple components such as forget gates and input gates and input modulation and output gates and output modulation functions. Four nested matrix multiplication operations make up its structure. Comprising the state product of input and output values with a weight matrix, along with an element

activation function added in the mix for measure. LSTM networks have proven effective in handling data sets across different fields like natural language processing and time series data analysis. However, the overall cost associated with LSTM models might pose limitations on platforms.

Challenges of Tuning Hyperparameters: Determining the learning rate, for optimizing performance or setting an epoch limit can be challenging in practice. Researchers discovered that numerous LSTM models experience NaN losses when using Smooth and Hyperbolic Medium activations compared to other model variants. This issue typically arises within the fifty epochs of training. It is believed to be related to a sudden increase in input gradient rather than any specific activation threshold. One way to address this issue is to monitor it at each training cycle and make parameter adjustments; accordingly, although doing so would involve checking the training status while the model is running a task that's not feasible, in practice. Alternatively, we could establish a cap of 50 epochs. Inform the user if the early stopping criteria are met. Even though NaN accumulations may still happen they wouldn't disrupt the programs operation allowing the model to continue working within the set limit. Usually early stopping leads to enhanced performance. However, having few epochs can lead to reduced accuracy while having too many may not fully utilize the resources of the layers in the models training process. A model that has been trained for 100 epochs usually shows performance; however, aiming for 4 epochs goes beyond this threshold by a significant margin.

After going through the training data of 100 models, with layer variations and configurations in depth analysis was done to estimate the performance of the best model compared to the average top performing models' validation accuracy within a 5% range assuming the correct training of the latter initially happened as intended. The standard layer seems to be the option, among all others considered. Out of the 12 instances tested with a fixed 50 epoch limit and learning rate set at 0.1, only 7 managed to achieve a validation accuracy below 50. In general, the LSTM variant labelled LSTM2 tends to show the performance, among the three tested variants. If all other factors are held constant or equal in this context it might be recommended to explore variations of the LSTM layer labelled as LSTM3; for instance, ones with reduced forget bias and increased output units. This adjustment could potentially lead to enhancements in accuracy per epoch and average loss figures. However, it is worth

noting that these modified models may face challenges, to those encountered with activations and learning rates.

Limited Interpretability: Hochreiter and Schmidhuber introduced the LSTM network which has gained popularity in DL applications and holds significant roles across different fields of use today. Originally designed to address issues with vanishing and exploding gradients, the LSTM network excels at capturing short term dependencies in input sequences. Effectively capturing long term dependencies still poses a challenge that requires exploration.

In a study by Zhao et al. (2020), it is noted that natural languages often have memory structures requiring the use of LSTM based models in natural language processing tasks like handwriting recognition and machine translation among others. However, in practice one often needs to grasp the workings and weights of a trained model to apply it to different problems or make modifications as necessary. Unfortunately interpreting both LSTM and bidirectional LSTM models can be challenging due to their gated structures. RNNs including LSTM models and their variations have seen application in tasks dealing with data analysis. There is a perception that RNNs and LSTM are capable of capturing the past associations in the input data; however, such relationships tend to weaken over time intervals as they progress. Despite their effectiveness in applications the precise reasons, behind the success of RNNs and LSTMs, have not been fully elucidated. Some researchers believe that RNN and LSTM can remember information for a time; however, this study shows that statistically speaking they do not have long memory capabilities. The use of fixed weights in LSTM is practice. A basic version of binary RNN has also been presented in this study.

3.3 As a Novel MCDM model: Hesitant Fuzzy AHP

AHP is a kind of multi criteria decision making technique that develops complicated problems with systematic analysis. Hesitant Fuzzy AHP goes beyond traditional AHP that provides more flexible structure to decision makers during uncertainty and less information situations. Considering this opportunity, the method integrates fuzzy logic principles. If criteria and alternatives are not specified properly, this methodology provides more meaningful and valid decision making processes.

Main function of the methodology is modelling complicated relationships of elements which are locating in decision making processes. Through the process, different opinions of decision makers took into consideration with the help of fuzzy set theory. This is why decisions are made in a less uncertain environment. Hesitant Fuzzy AHP provides tools to decision makers to support ranking and preference steps with considering impact of uncertain factors. This approach brings together both a dynamic and flexible decision making process and considers subjective judgements of decision-makers more systematically.

AHP is a systematic technique which is developed to structure and manage complex decision making processes by Thomas L. Saaty during the end of 1970s. In order to make more effective decision analysis, the methodology is structured by alternatives and criteria in a hierarchical way. AHP reduces the uncertainty and confusion that decision makers face when making choices, allowing them to make more conscious and rational choices. This process organizes a large number of basic elements used in the decision making process in a hierarchical structure and evaluates them within an analytical framework, making it possible to compare selection criteria. Main principles are indicated Table 10 below:

Use of AHP is accepted through most of the sectors, in a wide range of fields such as risk analysis, Project management and source allocation. Flexibility of AHP processes make possible to optimize decision making processes of users from different disciplines. In today's world, it is integrated to fuzzy logic to manage uncertainties better and continues to developments of Hesitant Fuzzy AHP and related methods.

Fuzzy Logic:

Fuzzy logic provides a system that evaluates uncertainties with passing through classical logic based on certainty principle. This approach is modelled by Lotfi Zadeh in 1965 for the purpose of modelling real world problems during uncertainty situations with rating membership between 0 and 1. The approach provides efficient solutions especially in the field of engineering, health and artificial intelligence. This system provides applicable and more flexible framework with imitating human thoughts closer when classical methods are not enough.

Table 10

Principles of AHP

Principle	Definition	Explanation
Hierarchical Structure	Brings the decision problem into a gradual structure	The main goal is organized as sub-goals, criteria and alternatives. This structure allows the problem to be examined systematically.
Pairwise Comparison	Each criterion or alternative is compared with others in pairs	The decision maker's preferences are numerically converted with comparisons on a scale of 1-9. The relative importance of each element is determined with this method.
Consistency	Ensuring consistency in comparisons	The consistency rate is calculated to evaluate how consistent the decision maker's judgments are. When the threshold value is exceeded, the comparisons are reviewed again.

Fuzzy Sets:

Fuzzy sets offer structures that stretch the binary structure of classical set theory and define the degree of belonging of an element to a particular set between 0 and 1. This approach is quite suitable for modelling uncertainties in real-world events. It especially provides more accurate analysis of subjective concepts such as “high” and “young”. The degree of membership of each element indicates how much it belongs to the set, and thus fuzzy sets contribute to more realistic analyses in decision making processes. Considering classical logic of 0 or 1, fuzzy sets smooth that situation and model uncertainties better. Fuzzy logic is based on fuzzy set theory which is supported by membership functions. Some of the fuzzy logic includes also non-membership functions and hesitation.

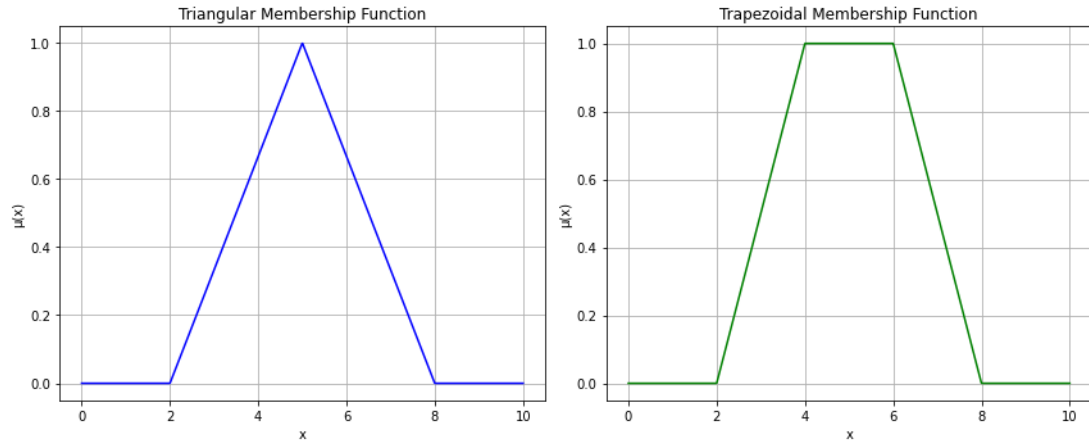


Figure 9. Triangular and trapezoidal (Grigoras & Cartina, 2011)

Together with the membership functions, the degree of membership to each set is determined for each element. Membership functions for fuzzy sets define generally as a triangular or trapezoidal (Figure 9). These functions make ease the calculations and adaptable to real world situations. For triangular membership function, the range of membership values increase first. When the value reaches to the top, membership value falls. On the other hand, different than triangular form, trapezoidal membership functions have flat top. That indicates the interval with full membership values. It is frequently preferred in areas that involve uncertainty such as economics, engineering and social sciences.

Applications of Fuzzy Logic:

Fuzzy logic provides practical applications when uncertainties are high. Most common application fields are control system. For instance, the logic provides optimal comfort with evaluating temperature and humidity variables. AI and ML supports decision making processes based on information. As an example, during the diagnosis and treatment processes, this approach supports related experts. In this context, fuzzy logic comes front as an approach which provides powerful and flexible solutions for variety of disciplines from health to engineering.

Hesitant Fuzzy AHP:

Hesitant Fuzzy AHP is a method that integrates fuzzy logic and classical AHP which results in efficient management of uncertain and subjective evaluations. This approach brings opportunities to decision makers to make evaluations with fuzzy expressions rather than net numerical values (Mardani et al., 2017). Multi criteria

decision making process supported by hierarchical structured model with survey and expert opinions related data. This method produces efficient results especially in the fields of engineering, environment management and finance.

Hesitant Fuzzy AHP is applied in decision making processes where there is uncertainty and subjectivity in the decision making process (Ashtiani & Azgomi, 2016). As a basic contribution to the classic AHP, the notion of hesitant fuzziness is a significant contribution particularly when there is uncertainty in data used in decision making process. Hesitant fuzziness is the situation where the decision maker has information but cannot give a direct result. This introduces a new level of complexity in the manner in which the participants state their preferences according to the type of thoughts and judgments that people make (Thuong et al., 2018). Hesitant Fuzzy AHP operates according to the traditional AHP framework which consists of three main steps. The problem statement defines the criteria for evaluation. The hierarchy structure emerges from comparing criterion relationships through hesitant fuzzy number assessments. The final ranking of solutions occurs through analysis of the collected data. Decision makers achieve better control over uncertain situations while addressing individual decision complexity through this process.

Hesitant Fuzzy AHP demonstrates two key strengths by allowing decision makers to work with ambiguous and conflicting information sets. Through this method decision makers can perform evaluations with greater flexibility (Öztaysi et al., 2015). The method allows for the systematic inclusion of personal instincts together with individual preferences. The hesitant fuzzy structure enables better rational decision making because it minimizes emotional and irrational influences during the decision process (Alharbi et al., 2024). Hesitant Fuzzy AHP provides an effective solution to reduce uncertainty in complex system decision making processes while enhancing group decision rationality.

The Hesitant Fuzzy AHP developed with considerations of uncertainty and hesitation while keeping the main principles of fuzzy logic. Since the approach enables decision makers to give more institutional opinions (Kumar et al., 2020), the results are mostly more accurate. The basis of this structure is integrated into the layered structure of the classical AHP, where data with uncertainty and fuzziness are used. It is created to provide an analytical framework for multi dimensional decisions. Hesitation is related to the uncertainty brought by the fact that an option

is not definitely stated as a preference or decision under a certain criterion. In this context, evaluating options using hesitant fuzzy numbers allows decision makers to make a more flexible and realistic analysis.

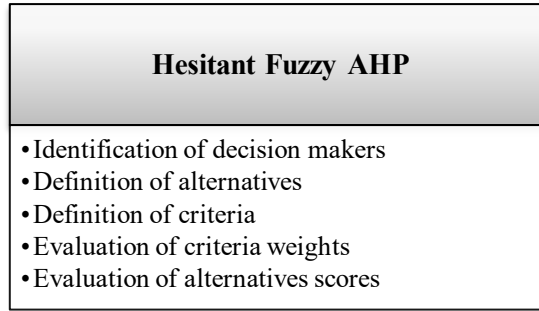


Figure 10. General steps of Hesitant Fuzzy AHP

As a first step of the problem, decision makers identify the alternatives and criteria in order to reach the final goal. General steps of Hesitant Fuzzy AHP are indicated in Figure 10. After the definition process, criteria and alternatives are evaluated by hesitant fuzzy values as indicated in Table 11. Here, decision makers put the importance of each alternative and criteria as a hesitant fuzzy matrix.

Table 11

Linguistic Scale for Hesitant Fuzzy AHP (Öztaysi et al., 2015)

	Linguistic Term	Abbreviation	Triangular Fuzzy Number
1	Absolutely High Importance	AHI	(7, 9, 9)
2	Very High Importance	VHI	(5, 7, 9)
3	Essentially High Importance	ESHI	(3, 5, 7)
4	Weakly High Importance	WHI	(1, 3, 5)
5	Equally High Importance	EHI	(1, 1, 3)
6	Exactly Equal	EE	(1, 1, 1)
7	Equally Low Importance	ELI	(0.33, 1, 1)
8	Weakly Low Importance	WLI	(0.2, 0.33, 1)
9	Essentially Low Importance	ESLI	(0.14, 0.2, 0.33)
10	Very Low Importance	VLI	(0.11, 0.14, 0.2)
11	Absolutely Low Importance	ALI	(0.11, 0.11, 0.14)

Step 1: Pairwise comparison matrices of alternatives and criteria preparation and evaluation of linguistic variables collection. Linguistic variables transform into triangular fuzzy number with the use of Table 11.

$$\hat{A}^k = \begin{bmatrix} 1 & \cdots & \hat{a}_{1n}^k \\ \vdots & \ddots & \vdots \\ \hat{a}_{n1}^k & \cdots & 1 \end{bmatrix} \quad (10)$$

Where $\hat{a}_{ij}^k$ represents the evaluation value of expert k by comparing element i with element j. these values are fuzzy numbers.

Step 2: Accuracy of each fuzzy pairwise comparison matrices are done by taking average of matrices in equation 11.

$$A = \frac{l+4*m+u}{6} \quad (11)$$

Step 3: If there is a conflict between experts' opinions, decision makers re-evaluate again.

Step 4: All values from evaluations bring into together from decision makers with fuzzy envelope approach which is developed by Liu and Rodriguez (2014).

$$a = \min\{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\} = a_L^i \quad (12)$$

$$d = \max\{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\} = a_R^i \quad (13)$$

The scale in Table 11 ranks from lowest to highest. Decisions of decision makers vary between s_i and s_j such as $s_o \leq s_i < s_j \leq s_g$.

Parameters and fuzzy membership values are calculated in equation 12, equation 13, equation 14 and equation 15.

Process of OWA requires weighted vector which calculated in equation 16 and equation 17.

$$b = \begin{cases} OWA_{W^2} \left(a_m^i, \dots, a_m^{\frac{i+j}{2}} \right), & \text{if } i+j \text{ is even} \\ OWA_{W^2} \left(a_m^i, \dots, a_m^{\frac{i+j-1}{2}} \right), & \text{if } i+j \text{ is odd} \end{cases} \quad (14)$$

$$c = \begin{cases} a_m^{i+1} \text{ if } i+1 = j \\ OWA_{W^1} \left(a_m^j, a_m^{j-1}, \dots, a_m^{\frac{i+j}{2}} \right), & \text{if } i+j \text{ is even} \\ OWA_{W^1} \left(a_m^i, a_m^{j-1}, \dots, a_m^{\frac{i+j-1}{2}} \right), & \text{if } i+j \text{ is odd} \end{cases} \quad (15)$$

$$w_1^1 = a2, w_2^1 = a2(1 - a2), \dots, w_n^1 = a2(1 - a2)n - 2 \quad (16)$$

$$w_1^2 = a_1^{n-1}, w_2^2 = (1 - a1)a_1^{n-2}, \dots, w_n^2 = (1 - a1) \quad (17)$$

where $a_1 = \frac{g-(j-i)}{g-1}$ and $a_2 = \frac{(j-i)-1}{g-1}$, g is the number of terms in the rating scale, j is the highest rating rank of the given range, and i is the lowest rating value rank of the given range.

Step 5: Creating comparison matrix $\hat{C}$ in equation 18.

$$\hat{C} = \begin{bmatrix} 1 & \cdots & \hat{c}_{1n} \\ \vdots & \ddots & \vdots \\ \hat{c}_{n1} & \cdots & 1 \end{bmatrix} \quad (18)$$

$$\hat{c}_{ij} = \hat{c}_{ij1}, \hat{c}_{ijm1}, \hat{c}_{ijm2}, \hat{c}_{iju}$$

$$\hat{c}_{ij} = (\frac{1}{\hat{c}_{iju}}, \frac{1}{\hat{c}_{ijm2}}, \frac{1}{\hat{c}_{ijm1}}, \frac{1}{\hat{c}_{ijl}})$$

Step 6: Calculation of geometric mean is done for each row $\hat{r}_i$ by equation 19.

$$\hat{r}_i = (\hat{c}_{i1} \otimes \hat{c}_{i2} \dots \otimes \hat{c}_{in})^{1/n} \quad (19)$$

Step 7: For each criterion or alternative, fuzzy weights are calculated as equation 20.

$$\hat{w}_i = \hat{r}_i \otimes (\hat{r}_1 + \hat{r}_2 \dots + \hat{r}_n) - 1 \quad (20)$$

Step 8: Previous all steps are repeated for each pairwise comparison matrices and latest fuzzy value of each alternatives are calculated as in equation 21.

$$\tilde{S}_i = \sum_{j=1}^n \tilde{W}_j \tilde{S}_j, \text{ for all } i. \quad (21)$$

where $\tilde{S}_i$ is the fuzzy performance value of alternative i , $\tilde{W}_j$ is the weight of criteria j and $\tilde{S}_j$ is the performance score of alternative j .

Step 9: Defuzzification of each fuzzy numbers in equation 22.

$$D = \frac{c_1 + 2c_{m1} + 2c_{m2} + c_u}{6} \quad (22)$$

Step 10: Ranking all alternatives based on defuzzied values. The alternative that has highest score is the best alternative.

3.3.1 Advantages of Hesitant Fuzzy AHP. Hesitant Fuzzy AHP brings a variety of advantages especially for complicated decision making processes. This method comes into front with the ability of managing uncertainty and subjective judgements. At the same time, the method provides more flexibility during comparison of alternatives. The evaluation process is wealthy to let decision makers express their opinions, on the other hand traditional AHP is stricter. Decision making

processes become more natural and humanized when hesitancy and fuzziness are included in the decision making process. The method of Hesitant Fuzzy AHP provides both high suitability and deep depth for multi-criteria decision analysis. Decision makers gain objectivity in their choices through alternative evaluation under uncertain conditions. The situation promotes the development of systematic and thoughtful approaches to decision making processes.

The user-friendly structure of Hesitant Fuzzy AHP represents a significant benefit of this method. The method enables all partners to express their various perspectives and hesitancies which strengthens group dynamics. The approach enables effective decision making process management while building a collaborative environment. The methodology delivers substantial benefits for uncertainty management while providing an adaptable framework for decision making processes.

3.3.2 Disadvantages of Hesitant Fuzzy AHP. Hesitant Fuzzy AHP requires additional calculations and data processing when compared to traditional AHP. The consideration of decision makers' hesitancy with more than one membership degree makes the comparison of alternatives more complicated. The evaluation time of the problem becomes longer especially for big, scaled projects due to this situation. The evaluation of decision makers' more than one value for each criterion may result in difficulty to reach meaningful data.

The interpretation of results can be more complicated than with classical methods. It is also possible that the results contain several hesitant values, which can be a problem for decision makers to build clear and concise decisions.

The Hesitant Fuzzy AHP is a relatively new and advanced method and therefore does not have widespread and user friendly software support like the classical AHP. This may reduce the use of the method. The use of hesitant values requires rethinking of the consistency analysis used in classical AHP in the hesitant context. This may make the evaluation of consistency a more technical and difficult process.

3.4 Application

This thesis study was planned considering the preparation and support for smart agricultural applications aimed at improving and developing agricultural processes.

Olive cultivation is of great importance both in Türkiye and the World for various reasons. The cultivation process is completely related to climate and mostly prefers the Mediterranean regions. On the other hand, global warming and climate crisis issues are increasing the effects due to different reasons nowadays. Considering all these reasons, in order to make yield and production predictions using the LSTM model and to determine which actions would be better for decision makers to take regarding certain criteria, a DSS was aimed to be created by continuing with the Hesitant Fuzzy AHP method.

3.4.1 LSTM Model Data Collection.

As a result of literature review and expert interviews, it was decided to apply the LSTM model due to the fact that olive cultivation and agricultural processes are generally time-dependent and that it gives better results in time-dependent processes. Again, due to similar reasons, the data in the list below was requested from the General Directorate of Meteorology of the Republic of Türkiye due to the great importance of climate parameters in agricultural processes in this process. The explanations of these parameters will be explained in the subheadings and will be used as input in the LSTM model.

According to the Ministry of Agriculture and Forestry, TÜİK 2022-2024 reports, the provinces where the models will be created were determined. These provinces consist of the provinces where the majority of olive production in Türkiye takes place. The 13 provinces included in the reports of recent years are the cities where 90% of Türkiye's olive production, and sometimes even more, is realized. In addition to the climate data obtained from the General Directorate of Meteorology of these cities (Table 12), the olive grove area, production and yield data (Table 13) of these provinces were obtained from the Turkish Statistical Institute (TÜİK), which is also a state institution, via their online systems (MEDAS). The time period was determined as 2010-2024 as a 15 years of time period. In addition, some social parameters in these 13 provinces have been determined under the title of "social parameters". These parameters include the universities in the relevant provinces and years, the relevant university departments, and the scientific, social or financial activities carried out by institutions such as public institutions, unions or non-governmental organizations in the provinces.

Table 12

Definition of Climatic Parameters from General Directorate of Meteorology

	Parameter	Definition for MGM	Relevance to Olive Cultivation
1	Max Actual Pressure (hPa)	The highest atmospheric pressure recorded during a specific period.	High pressure often indicates clear and dry weather. Prolonged high pressure may lead to drought stress for olive trees.
2	Average Actual Pressure (hPa)	The average atmospheric pressure over a given time period.	Indicates general weather patterns; pressure fluctuations can affect plant stress levels.
3	Min Actual Pressure (hPa)	The lowest atmospheric pressure recorded during a specific period.	Low pressure is associated with rainy and unstable weather; excess rainfall during flowering can harm yields.
4	Max Wind Direction	The direction from which the highest wind speed is observed (e.g., north, south).	Strong winds can damage branches or knock down fruits; wind direction is important for designing windbreaks.
5	Max Wind Speed (m/s)	The highest wind speed recorded.	Sudden or extreme winds may cause physical damage to trees and fruit loss.
6	Max Temperature	The highest daily temperature measured.	Extreme heat (above 40°C) can stress trees, reduce fruit set, and lower oil quality.
7	Min Temperature	The lowest daily temperature measured.	Temperatures below -7°C can damage or kill olive trees, especially young ones.
8	Average Max Temperature	Average of daily maximum temperatures.	Reflects heat stress during critical growth periods; affects flowering and fruit development.
9	Average Max Relative Humidity (%)	Average of the daily highest relative humidity levels.	High humidity may increase fungal disease risk, especially during fruit development.
10	Average Min Relative Humidity (%)	Average of the daily lowest relative humidity levels.	Low humidity can cause water stress and sunburn, affecting yield and fruit quality.
11	Average Relative Humidity (%)	Overall average relative humidity.	Influences plant transpiration and water demand; ideal levels are critical for healthy growth.

Table 12 (cont.d)

	Parameter	Definition for MGM	Relevance to Olive Cultivation
12	Average Wind Speed (m/s)	The average wind speed during a certain period.	Persistent winds can dry out leaves and flowers, leading to lower pollination and fruit set.
13	Total Precipitation (mm or kg/m ²)	Total amount of precipitation recorded during a given period.	Ideal rainfall for olives is 600–800 mm annually; too much may cause root rot, while too little requires irrigation.
14	Monthly Number of Frost Days	Number of days in a month with temperatures falling below 0°C.	Frost can damage flowers and young shoots; late spring frost is especially harmful to fruit formation.
15	Monthly Max Soil Temp at 10 cm	Highest temperature recorded at 10 cm soil depth.	Affects root activity and nutrient uptake; optimal range is between 15°C and 30°C.
16	Monthly Min Soil Temp at 10 cm	Lowest temperature recorded at 10 cm soil depth.	Low soil temperatures slow down root metabolism and water/nutrient absorption.
17	Monthly Minimum Temperature Above Soil	Minimum temperature just above the soil surface.	Helps detect surface frost risk, which is crucial in early spring for flower and bud protection.
18	Total Sunshine Duration (hours)	Total hours of sunshine reaching the ground during a certain period.	Olive trees require high sunlight exposure; long sunshine durations improve flowering, fruit set, and oil accumulation.

The cultivation of olives responds strongly to multiple meteorological elements which deliver essential information about the growing conditions. The stability of weather conditions depends on atmospheric pressure. The weather remains dry and calm under higher pressure values which restricts water access for olive trees, but low-pressure systems deliver necessary rainfall that can become damaging when it exceeds during critical flowering or fruiting times. Wind characteristics are equally important. The direction and speed of the wind can affect the physical structure of olive trees. The risk of disease reduction through moderate wind exposure is counteracted by strong winds which break branches and cause fruit drop and create uneven pollination conditions. Knowledge of prevailing wind patterns enables farmers to create better

orchard arrangements and install wind protection barriers. Every developmental stage of olives requires temperature data which includes maximum values and minimum values and average values. Summer high daytime temperatures damage fruit development and oil quality when water stress exists. Conversely, low night-time temperatures, especially those approaching or falling below freezing, pose a major threat to both young trees and flowering stages. Relative humidity, particularly when averaged over different periods, gives insight into the plant's evaporative demand and potential disease pressure. High humidity levels increase the risk of fungal infections, whereas extremely low humidity may cause dehydration stress or sunscald on developing fruit. Precipitation data indicate the quantity of water supplied naturally to the orchard. While olives are relatively drought-tolerant, they still require a baseline level of annual rainfall (ideally between 600 and 800 mm) for stable productivity. Excess rainfall, however, may lead to root diseases or poor soil aeration. Soil temperature, both at 10 cm depth and just above the surface, is also important. It affects root metabolism, nutrient absorption, and the risk of frost at ground level. Cold soil slows down root activity, which can hinder the tree's ability to absorb water and nutrients, especially in early spring. Finally, sunshine duration reflects the total light exposure that olive trees receive, directly influencing photosynthesis, flower induction, and oil accumulation. Prolonged sun exposure is generally beneficial, particularly in ripening periods, though extreme conditions may still require protective strategies.

Table 13

Definition of Area and Output Parameters from TÜİK

Parameter	Definition	Relevance to Olive Cultivation
1 Cultivated Area (decare)	The total area used for olive cultivation. Reported in decares.	Indicates the production potential and investment scale of the region. As the area increases, the total production potential increases.
2 Production Quantity (ton)	Total annual olive production in tons (1 ton = 1,000 kg).	Total amount of olives obtained in a year (in tons). It shows regional production efficiency. Climatic changes or applications have a direct effect on production.

Table 13 (cont.d)

3	Yield (kg/fruit-bearing tree)	The average amount of olives harvested per fruit-bearing tree.	Average amount of olives obtained from each fruit-bearing olive tree. It is directly related to the health of the tree, environmental conditions and maintenance activities. It reflects the effects of quality and climate.
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The following agricultural production parameters are obtained from the Turkish Statistical Institute (TÜİK) and are critical for analysing olive cultivation across regions. These variables are numerical and are commonly used in yield, area, and productivity assessments. Cultivated area used as a parameter in order to understand prevalence degree and economical value. Production gives insights into the dimension of agricultural outputs that may use for regional or annual comparisons. Yield parameter is ideal in order to realize the direct impact of climate, soil, irrigation and other factors to olive trees.

3.4.2 LSTM Model Data Preparation.

Previous research on data-related topics has revealed that over sixty percent of the time spent on applications is allocated to the process of organizing and preparing the applications' data. Furthermore, in order to bring about an increase in the artificial neural network's consistency, it is recommended that inter-input and input-output correlation analyses be carried out. An understanding of the connections that exist between the data is acquired as a consequence of the analysis.

During the analysis, meteorological data collected from 13 cities between 2010-2024 and annual yield and production information were used. Figure 11 indicates the yield and production trend of selected cities for 15 years. While the input variables included parameters such as area, max/average/min actual pressure, wind direction, max wind speed, temperature, average min/max relative humidity, average relative humidity, average wind speed, precipitation, monthly number of frost days, soil temperature, total sunshine duration, the output variables were determined as yield (kg/fruit-bearing tree) and production (ton). In the data preprocessing stage, missing data were filled manually, then the dataset was normalized. Olive yield is affected by climatic factors such as temperature, humidity, precipitation, and this interaction

usually shows a linear relationship. For example, as the temperature increases, the yield usually changes at a certain rate; or as precipitation increases, the yield may also tend to increase. Heatmap is created to understand correlations between inputs and input-output relationships (Figure 12). As seen from the figure, production and yield indicates mid-level of relationship for most of parameters. For yield, min temperature, soil temperature min, surface min temperature, average humidity and soil temperature max are top parameters with values of 0.62, 0.60, 0.53, 0.49 and 0.47.

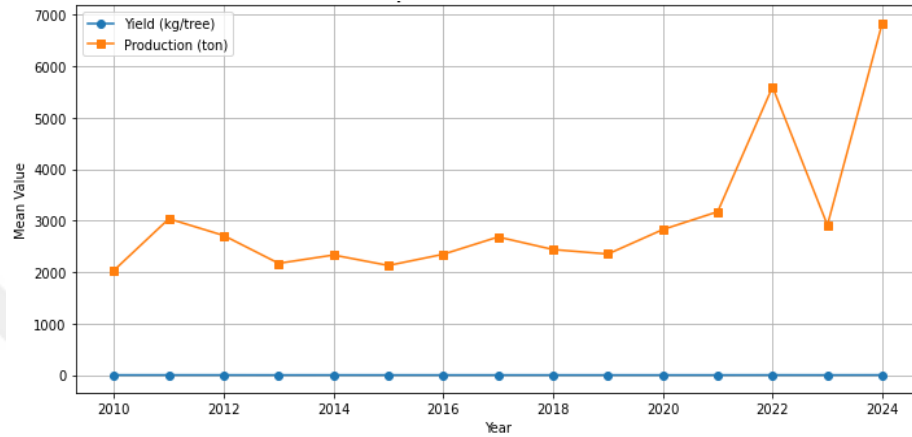


Figure 11. Trend of yield and production over time

In addition to yield output, production indicates very high correlation with area (decare) with 0.84 as an expected relation. Remaining correlations are not very high such as soil temperature min is 0.37, max pressure and soil temperature max are 0.36 and min temperature is 0.35.

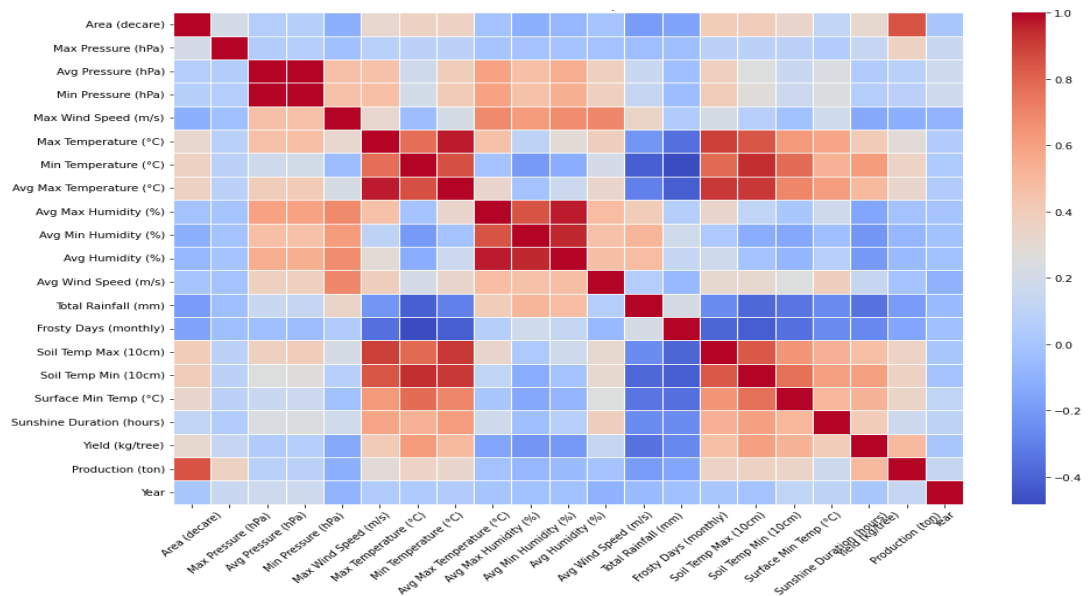


Figure 12. Heatmap

Outlier analysis is also done for 2010-2024 data in order to analyse the changes for input and output data (Figure 13). The analysis is conducted by considering z-values. For parameters which are above 3 and below 3 are considered as an outlier. Since the ratio between number of observations and number of outlier points are low, there is no cleaning or extra steps are done in order to avoid these outliers.

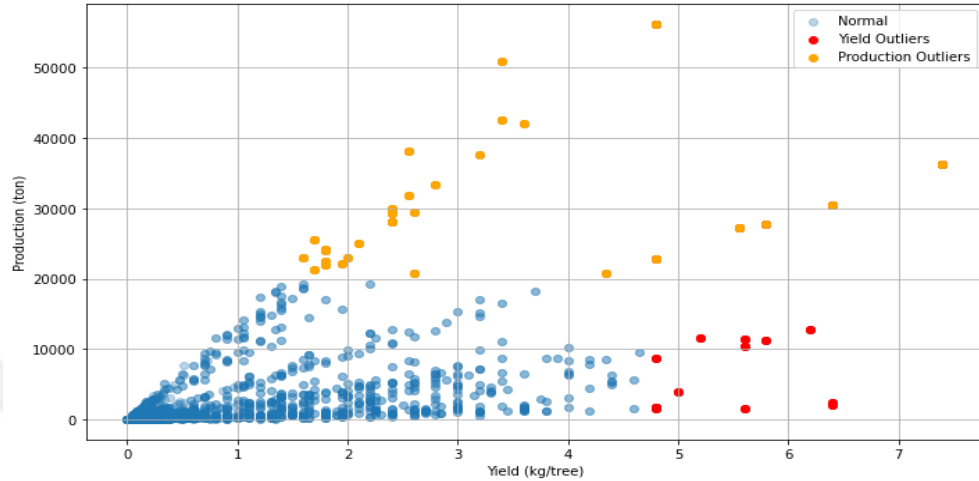


Figure 13. Outlier results

Table 14

Feature Selection Results

Feature	F-score	p-value	F-score	p-value
	Yield		Production	
Min Temperature (°C)	1460,45	1E-248	330,58	3E-69
Soil Temp Min (10cm)	1342,53	1E-232	361,70	4E-75
Surface Min Temp (°C)	910,92	3E-169	309,32	4E-65
Avg Max Temperature	752,18	8E-144	281,29	1E-59
Soil Temp Max (10cm)	657,63	5E-128	338,06	1E-70
Max Temperature (°C)	465,21	3E-94	205,88	8E-45
Sunshine Duration (hours)	429,21	1E-87	67,41	4E-16
Total Rainfall (mm)	316,23	2E-66	94,45	6E-22
Area (decare)	250,77	1E-53	5831,87	0E+00
Frosty Days (monthly)	186,02	8E-41	56,24	9E-14
Avg Min Humidity (%)	120,15	3E-27	12,84	3E-04
Avg Humidity (%)	102,04	2E-23	7,13	8E-03
Avg Max Humidity (%)	59,67	2E-14	0,57	5E-01
Max Pressure (hPa)	47,08	9E-12	343,41	1E-71
Avg Wind Speed (m/s)	44,94	3E-11	0,17	7E-01
Max Wind Speed (m/s)	43,78	5E-11	28,69	9E-08
Min Pressure (hPa)	7,80	5E-03	16,54	5E-05
Avg Pressure (hPa)	4,48	3E-02	13,79	2E-04
Year	0,32	6E-01	48,02	5E-12

Before the model construction, feature selection is applied to parameters in order to reach better prediction and increase the generalization ability (Table 14). For this purpose, F-test is used. The F-Test is crucial in feature selection as it determines the value of each feature in enhancing the model (Pirbazari et al., 2019). In this context, for each parameter F-score is calculated to indicate the power of explain the variance on the target variable. Higher F score means that feature contributes to model. In this thesis, F score accepting value is above 10. In addition to F score, p-value is also used to show this relation is not coincidental. P-value which is lower than 0.05 indicates that statistically there is significance. As a feature selection, $F\text{-score} > 10$ and $p\text{-value} < 0.05$ is accepted. As a result of the analysis, it was determined that almost all parameters had a significant effect in terms of yield and production. Although this condition was not met for only 3 parameters, for more and various parameters to better capture the pattern, all of them were included in the model when evaluated individually. The reason for this is that the significance of two parameters on yield and one parameter on production was low because an aggregated model will be made.

During the application, 4 different models are created which are explained in section 3.4.3. The main model is based on annual data which predicts yield and production at the same time. The other models differ with the output since one of the models just predicts production amount and the other one predicts just yield. This differentiation is done in order to analyse the performance since units' of outputs are in quite different scales. The last model differs for time window of data. The data is prepared for monthly basis. Since climate data is provided on a monthly basis, various calculations have been made in order to make it comparable to annual production. Due to the suitability of the methodology, it was found more appropriate to perform analyses monthly. For this reason, while climate data was kept as is, annual production data was combined with the opinions of experts and the suitability of the literature and arranged monthly.

Some missing or erroneous observations were detected in the data set. These values generally originated from the months when measurements were not made at the relevant stations of the MGM and especially from deficiencies in some provinces. These deficiencies were left missing in a way that would not disrupt the structure of the model and were filled in reasonably within the model.

Since the vast majority of climatic variables are numerical, they are directly

suitable for modelling. However, some categorical structures such as wind direction were transformed in order to make them usable in the analysis. Similarly, social parameters were filled in as “1” if they were a parameter realized in the relevant year and city, and as “0” if they were not.

3.4.3 LSTM Model.

The proposed flow of LSTM model is indicated in Figure 14. All variables of input and output data are scaled between 0 and 1 with MinMaxScaler. LSTM models give an opportunity to model the impact of previous years, with the time window method application applied. For instance, for each observation the data for the last 3 years data used as a sequence such as for the prediction of 2013, the data between 2010-2012 windowed. For monthly based models, time is used as a single step and modelled with each year’s 12 month’s average or total value. For each model, test and train sets are divided into 80-20 and 2024 data are just used for prediction purposes and not included in any of these test and train sets. This differentiation provided model to the test data evaluation which is not available during training process. So that, during the training phase just 2010–2023-time horizon is used. 2024 data is not used to just indicate the general performance of the model but also to provide real foresight. Considering time series modelling, data shuffle is used. Although it confuses time information to a certain extent, one of the main targets of the model is to understand and learn the impact of climatic data on yield and production. This use of the model also contributed to the model’s capability of generalization. On the other hand, use of time window in the model tried to stabilize this situation.

Model 1: This model is aggregated annual data used model. Train and test data separated into 80-20 ratio. 3 years’ time window created so each observation is represented by 3 years block. Data is prepared sequentially but train and test split is shuffled.

Model 2: Aggregated monthly data used with targeting to predict both production and yield. The data separated into 80-20 ratio again with shuffle.

Model 3: Monthly data used with just one target output as a production. Similarly, data is prepared sequentially but during train and test processes, it is shuffled with 80-20 ratio.

Model 4: Last model has same processes with only difference as an output. The only

output targeted here is yield prediction. The data is separated with a ratio of 80-20 with shuffle.

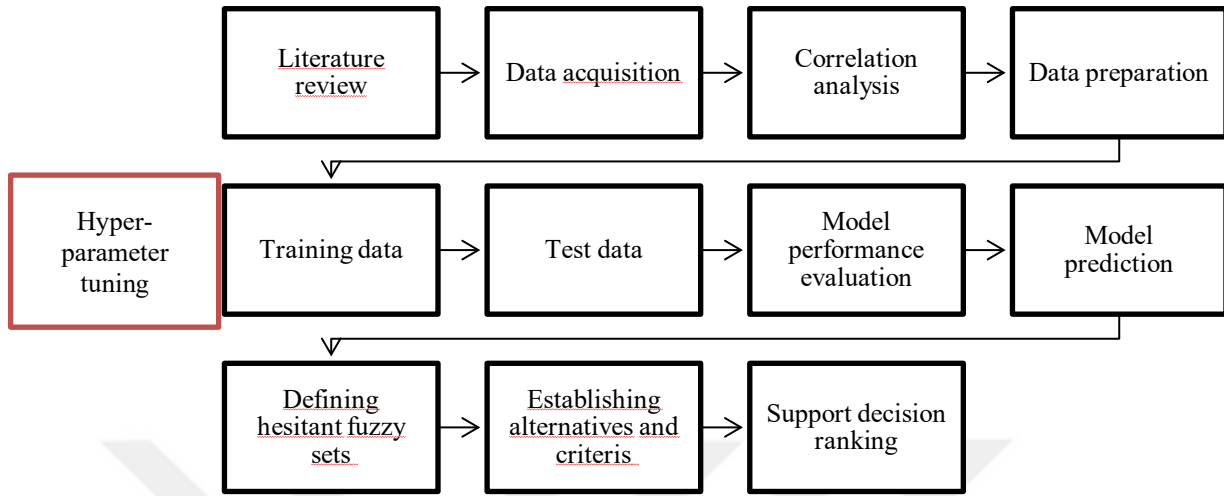


Figure 14. Proposed LSTM Flow

During the model optimization processes, all LSTM structures have quite similar architectures. For training process, adam optimization algorithms and mean square error loss function used. In order to avoid overfit problems which, occur because of over learning, early stopping method is used. If the model doesn't develop during consecutive 15 steps, the training is stopped. Output layers are designed as one or two neurons depending on the target variable.

Two metrics are planned to use model performance and Table 15 provides the related research's metrics. Performances of the models' evaluations are achieved by R^2 and Root Mean Squared Error (RMSE). R^2 is a statistical tool that indicates the extent to which the model explains the variance of the dependent variable and it reflects the relation between real data and predicted data. When R^2 value gets close to 1, the model has high capability to predict. On the other hand, values which are close to zero or negative reflect that model has low performance. In addition to R^2 , RMSE is an error metric that evaluates the errors of prediction. Lower RMSE value means model has more accurate predictions. Magnitude of RMSE may vary on the unit of the parameter.

Table 15

Similar Performance Metrics in the Literature

Study	Machine Learning	Parameters	Performance Metrics
Applying Machine Learning for Analysis and Forecasting of Agricultural Crop Yields	Random Forest, Decision Tree, SVM	Weather data, crop yield data	R ² , RMSE
Prediction of Soil Organic Carbon Using Machine Learning Techniques	Random Forest, SVM, Adaptive Boosting, k-NN	Soil organic carbon, geospatial data	R ² , RMSE
Field-Scale Precision: Predicting Grain Yield of Diverse Wheat Breeding Lines Using High-Throughput UAV Multispectral Imaging	Random Forest, Decision Tree, Gradient Boosting, XGBoost	NDVI, NDRE, G-NVDVI data	R ² , RMSE
Weight Prediction of Durum Wheat Grains Using Computer Vision and Machine Learning	ANN	Length, width, thickness, projection area	R ² , RMSE
Improving Soil Salinity Prediction in Semi-Arid Areas Using Machine Learning Models	XGBoost, SVM, Random Forest	Soil salinity data	R ² , RMSE
Evaluating Performance of Machine Learning Models to Predict Climate Zone-Based Crop Yields	Random Forest, XGBoost, RNN, ANN, LSTM, k-NN	Temperature, rainfall, pesticide usage	R ² , RMSE

3.4.4 Hesitant Fuzzy AHP Data Collection.

This thesis is used Hesitant Fuzzy AHP method in order to strength the multi-dimensional decisional support system of olive cultivation. In the previous sections, theoretical frameworks of classical AHP which is widely used in literature and calculation steps are explained. The research group in this thesis study mainly consists of farmers or agriculturalists and the agricultural processes have very dynamic structure. In this context, there is a high possibility of encountering hesitations during evaluation procedures. For this reason, Hesitant Fuzzy AHP method is preferred.

The evaluation form, which includes the comparative evaluations of the prepared criteria and alternatives, was prepared with the processes in the previous sections. These evaluation forms were shared with three experts, two engineers and one farmer. This evaluation form provided which has pairwise comparison matrices for decision makers. These comparison matrices include both criteria-criteria and criteria-alternatives comparisons to understand preferred actions through different criteria list. The importance degree comparison evaluations are asked under linguistic terms. This process is conducted by very common 11 level linguistic scale in literature (Öztaysi et al., 2015). This scale is between “Extremely Very Important” and “Absolutely Low Importance”. Experts are able to choose more than one linguistic term during the evaluation to construct structure that they can express their doubts and uncertainties.

Hesitant Fuzzy AHP Data Preparation. Hesitant Fuzzy AHP method gives the possibility to experts to choose more than one value while comparing two criteria. This possibility of uncertainty and evaluation differences impact the model’s value. Criteria and alternatives of the study organized by both the literature and olive experts. First of all, the basement of the criteria and alternatives are formed by literature. From previous studies about agricultural, olive, multi criteria decision making, from AHP to Hesitant Fuzzy AHP related studies are searched step by step. After that, the draft of the list is discussed by olive experts and re-organized. As a last step, a reorganized list is reviewed by academicians to finalize the criteria and alternatives of the methodology for the sake of applicability (Table 16 and Table 17).

Table 16

Definition of Criteria List

Criteria	Explanation	Reference
C1: Climate Suitability	Rainfall/Soil/Temperature amounts are taken into consideration.	Vanitha and Padma, 2021; Altan et al., 2020; Chary et al. 2014; Breuil et al., 2000
C2: Infrastructure/Resource Status	As an example, if water is limited, drip irrigation or efficient methods can be suggested.	
C3: Government Subsidies and Incentive Plans	Structural incentive programs can be implemented to ensure sustainability of production and reduce fluctuations in the medium and long term.	Otiende et al., 2024; Ghosh and Roy, 2010
C4: Input and Maintenance Planning	The use of agricultural inputs such as fertilizer, pesticide, and water should be optimized according to the expected yield and market conditions.	Otiende et al., 2024; Vanitha and Padma, 2021
C5: Labor and Equipment Planning	If necessary, additional workers can be hired before the harvest season or more harvesting machines can be rented to ensure that all products are collected on time and without loss.	Ghosh and Roy, 2010
C6: Pest/Disease Risk	If the probability of disease is high, agricultural control is mandatory.	Otiende et al., 2024
C7: Cost Impact	Economic constraints can affect the farmer's decisions.	Otiende et al., 2024; Raju and Duckstein, 2004
C8: Market Conditions	Production and price expectations can shape marketing and storage decisions.	Otiende et al., 2024
C9: Processing Time and Shift Planning	In order for olives to be processed quickly during the harvest period, increasing the working hours in the facilities and switching to a shift system may be on the agenda.	-

Table 17

Definition of Alternatives List

Alternative	Explanation	Reference
A1: Irrigation Strategy	Covers the tendency of climate change to alternative irrigation strategies.	Vanitha and Padma 2021; Çakmakcı et al., Narayanamoorthy et al., 2019; Alwan and Aziz, 2019; Chary et al., 2014
A2: Fertilization Program	Addresses plant nutrients, fertilization methods and basic principles of fertilization.	-
A3: Crop Growth and Health Management	Covers pruning timing and intensity, agricultural control.	-
A4: Harvest Time Planning	Effects of various actions on harvest time planning can be examined.	Otiende et al., 2024
A5: Soil Management and Maintenance	Soil processing and maintenance techniques are considered.	Atlı, 2024; Vanitha and Padma, 2021; Raju and Duckstein, 2004; Breuil et al., 2000
A6: Marketing and Storage Strategy	Marketing and storage strategies can also be addressed along with productivity increase strategies.	

These criteria represent the main factors that influence the efficiency of olive cultivation. Each of these criteria plays an important role in decision making processes from farmers' perspective and requires decision support structure weight of the system.

After the completion of the LSTM prediction model, the decision making methodology will be passed. The predictions made with the LSTM model will be used as input in the decision making process. The integration of LSTM outputs provides a framework for enhancing decision making processes in yield risk management. Membership degrees will be calculated using a combination of factors, including model accuracy, expert opinions, and prediction uncertainty. The framework evaluates both numerical and non-numerical aspects of predictions through this complete methodology.

The framework uses membership degrees to accomplish two essential goals. The framework enables yield risk classification through a three-tiered risk assessment system which distinguishes between high and medium and low risk levels. The risk

severity classification helps stakeholders understand risk levels so they can properly focus their intervention efforts. The framework enables organizations to create prevention and assistance plans which match the risk severity levels. The plans establish warning systems together with resource management plans and support protocols to reduce risks and build agricultural resilience. This integrated approach combines advanced predictive modelling with expert driven insights, creating a robust system for proactive and effective yield risk management.

3.4.5 Hesitant Fuzzy AHP Model.

In this study, Hesitant Fuzzy AHP method was applied to manage uncertainties in the decision making process for olive production. Figure 15 indicates the hierarchy structure of proposed Hesitant Fuzzy AHP method.

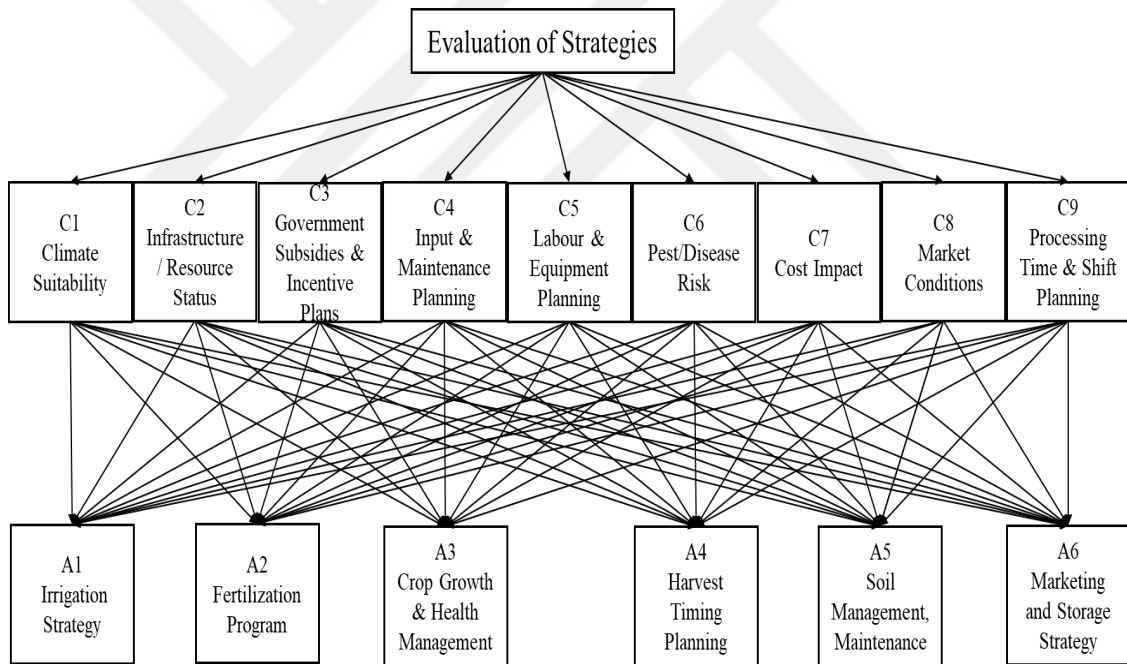


Figure 15. Hierarchy structure

The application process includes the steps in Figure 16. After its creation through an online platform the initial draft of the evaluation form with criteria and alternatives comparison was sent to three experts. The expert group includes a farmer with thirty years of experience in the business. The second expert has maintained their academic focus for an extended period while dedicating their professional work to

agriculture during the last five years. The third expert is food engineer at the Agriculture and Food Directorate has worked within the department for nineteen years as a food engineer. The evaluators have not faced any time restrictions or completion limitations for the forms. The first feedback form was found on the online platform and the other two were received in printed format. The replies from the form have been manually transferred to the environment represented by Microsoft Excel. The experts recorded criterion and alternatives evaluations at the beginning of this process as numerical values instead of linguistic terms on the first sheet of the workbook. The alternative evaluations received the same treatment by being entered on the second sheet of the Excel book. The evaluation responses on each page are organized into multiple columns which correspond to the appropriate expert. The worksheet relevant to this discussion includes the implementation of the formulas and matrices that were discussed previously.

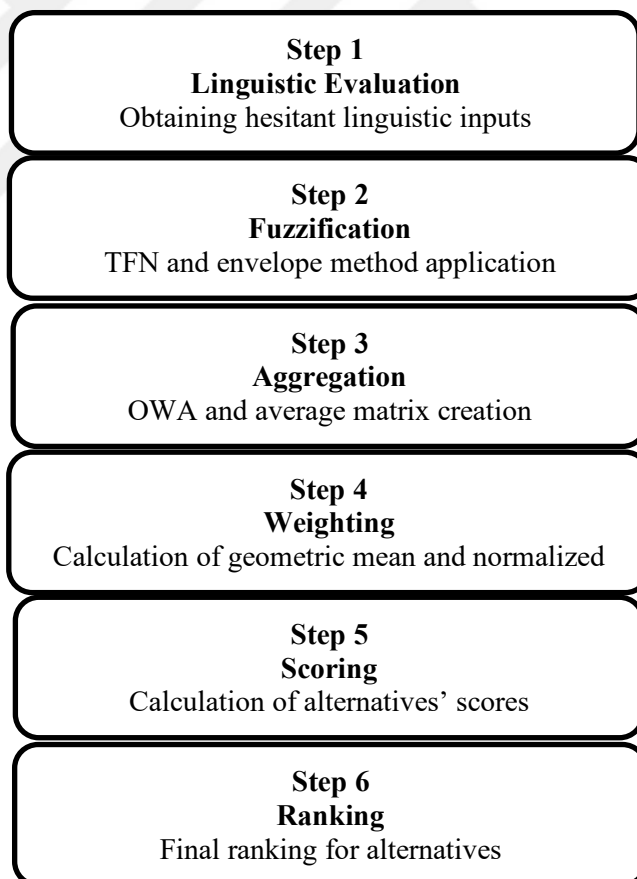


Figure 16. Application process of Hesitant Fuzzy AHP (Adapted from Candan, 2020)

HFA operators aggregated expert evaluations through the Hesitant Fuzzy Aggregation method. The experts' fuzzy value assessments for each criterion underwent combination while the criteria weights were determined. The HFSs underwent aggregation through calculation by using their minimum and maximum and average values. The defuzzification method was used to sharpen and normalize the criterion weights. The evaluation of alternative performances occurred within Hesitant Fuzzy Set format for each criterion before combining them with criterion weights. The aggregation process involved multiplying alternative performance scores for each criterion by their respective weights then summing these values across all criteria. The final decision model ranked alternatives based on their total performance scores. The Python program used the Spyder interface to execute subsequent actions.

Chapter 4

Findings

This section of the thesis provides results of the methodologies that explained in detailed before. Results and performances of prediction model will be provided through R^2 and RMSE values. Comparison tables of different models, their metrics will be indicated through LSTM models' outputs. These methods are crucial to provide reliable output for agricultural related studies' performance. In addition to findings of LSTM models, Hesitant Fuzzy AHP results will be indicated. These findings bring together from different experts' opinions by surveys. These surveys created considering hesitancy and uncertainty possibilities of experts since the agriculture field itself has quite uncertain and dynamic structure.

4.1 Findings of LSTM

The LSTM model was selected due to its ability to learn long-term dependencies in time series. The model consists of an input layer, multiple LSTM layers, and an output layer. The hyperparameters used include learning rate, epoch number, and batch size. Appropriate time windows were created for time series analysis and the data were separated into training, validation, and test data sets. In addition, correlation analysis was performed between different features in the data set. During the model training process, performance measures such as RMSE were used.

The model was optimized on the training data set and its performance was tested with the validation data set. Table 18 indicates the general structure of the created models. The performance of each model was evaluated based on these hyperparameters, and each model was trained with different combinations of epochs (from 8 to 32) and batch sizes (from 150 to 300). The performance of the models has been evaluated independently on both training and test datasets by using R^2 (coefficient of determination) and RMSE metrics. In addition, production and yield projections for each model for the year 2024 have been documented.

Table 18

Developed General Structure of Models

Layer	Component	Explanation	Model
1st Layer	Input Layer	Takes the input data.	Climate data
	Hidden Layer	Contains LSTM cells.	Varies
2nd Layer	Input Gate	Decides which new values to input.	Yield and production
	Forget Gate	Decides which information to forget.	Past info, allows the model to remember long-term dependencies.
3rd Layer	Output Layer	Outputs of results	Yield and production

Throughout this thesis parameters were established which led to multiple model development. The first model was created through monthly data collection because the density of data helped learning and added detailed information to the model in a positive way. From the General Directorate of Meteorology, monthly basis for climate parameter collection has been done with request. TÜİK's online database used for obtaining data about the area size and yield and production levels of the crop. The information was collected on an annual basis. The monthly data distribution followed olive development stages to preserve the model's monthly structure. The model needed this approach for its continuation. The initial ratios were established using literature before receiving input from olive growers and oil producers and agricultural engineers and other field professionals for their finalization.

Table 19 presents monthly based model output forecasts together with their yield results and performance metrics. The R^2 values for production forecasts on test data from the first model ranged from 0.828 to 0.84 while RMSE values spanned from 2040 to 2115 tons. The R^2 values for yield predictions on test data spanned from 0.50 to 0.55 and the RMSE values extended from 0.75 to 0.79 kg. The predicted production quantities for 2024 varied between 447,107 tons and 492,023 tons while the yield

predictions for the same year fell between 1.66 - 1.68 kg/tree.

The annual production and yield forecasting models were evaluated through five different hyperparameter combinations in Table 20. The R^2 values for production prediction on test data spanned between 0.81 and 0.893 while RMSE values spanned from 9,409 tons to 12,550 tons. The R^2 values for yield predictions during testing showed a range from 0.024 to 0.388 while the RMSE values spread from 4.36 kg to 5.50 kg. The projected output for 2024 spanned between 554,888 tons and 1,035,678 tons while yield forecasts spanned from 11.05 kg to 16.49 kg for each tree. The training data output results showed similar patterns to each other. The R^2 values for production prediction on the training data spanned from 0.583 to 0.823 but yield R^2 values spanned from 0.031 to 0.408. The RMSE values for production in the training set varied from 17,562 to 29,672 tons, whereas the RMSE values for yield ranged from 4.95 to 6.33 kg.

The evaluation of target variables' yield and production values occurred both separately and together. The training process occurred in specific models where only one output variable existed either for production or efficiency. The single-output modelling structure was selected because it may provide stronger focused learning than multi-output models. The model structure allows better observation of performance changes. Two separate model groups exist based on the established conditions because one group focuses exclusively on production output and the other group focuses exclusively on efficiency output.

Table 21 indicates the model results that just focuses on production output. The R^2 values in the test data were found to be in the range of 0.84 - 0.897 and the RMSE values were in the range of 9,258-11,513 tons. The R^2 values for production forecast on training data were in the range of 0.659 to 0.766 and the RMSE values were in the range of 20,197 to 24,398 tons. The production forecasts for 2024 from these models were between 500,373 tons and 1,045,200 tons. Since yield estimation was not conducted, the performance measurements related to yield have not been reported in these models.

Table 19

Findings of Monthly Basis Model

		Train						Test			
		2024		Production		Yield		Production		Yield	
Batch Size	Epochs	Production	Yield	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE
150	32	447107.91	1.66	0.807	2188.19	0.553	0.76	0.834	2074.27	0.54	0.76
150	16	479550.38	1.68	0.81	2172.15	0.571	0.74	0.84	2040.57	0.55	0.75
300	32	474731.66	1.66	0.801	2221.48	0.507	0.8	0.828	2115.87	0.5	0.79
300	16	478336.31	1.67	0.808	2184.47	0.555	0.76	0.835	2068.79	0.54	0.76
300	8	492023.56	1.7	0.81	2173.38	0.572	0.74	0.841	2035.66	0.55	0.75

Table 20

Findings of an Annual Model

		Train						Test			
		2024		Production		Yield		Production		Yield	
Batch Size	Epochs	Production	Yield	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE
150	32	923511	12.14	0.583	29672.62	0.031	6.33	0.81	12550.88	0.02	5.5
150	16	917913	13.02	0.733	21565.54	0.148	5.93	0.893	9409.4	0.18	5.04
300	32	554888	11.68	0.624	256.14	0.052	6.26	0.868	10470.7	0.07	5.38
300	16	956507	11.05	0.78	19591.66	0.137	5.97	0.824	12075.35	0.15	5.14
300	8	1035678	16.49	0.823	17562.99	0.408	4.95	0.857	10879.18	0.39	4.36

Table 21

Findings of an Annual Model with Production Output

		2024		Train		Test	
Batch Size	Epochs	Production	Yield	R ²	RMSE	R ²	RMSE
150	32	952637	NA	0.766	20197	0.876	10133
150	16	817713	NA	0.748	20958	0.875	10185
300	32	916846	NA	0.714	22322	0.84	11513
300	16	500373	NA	0.659	24398	0.889	9586
300	8	1045200	NA	0.759	20487	0.897	9258

Table 22

Findings of an Annual Model with Yield Output

		2024		Train		Test	
Batch Size	Epochs	Production	Yield	R ²	RMSE	R ²	RMSE
150	32	NA	155	0.034	6.32	0.02	5.51
150	16	NA	178	0.082	6.16	0.07	5.38
300	32	NA	158	0.106	6.08	0.09	5.31
300	16	NA	195	0.161	5.89	0.18	5.03
300	8	NA	211	0.495	4.57	0.36	4.44

The R² values on the test data were between 0.021 and 0.281, and the RMSE values were between 4.44 and 5.51 kg in the model developed solely for yield prediction.

The R² values on the training data range from 0.034 to 0.495, and the RMSE values range from 4.57 to 6.32 kg. The yield predictions for this model for the year 2024 ranged from 155 to 211 kg/tree. Production estimates were not made, so production related metrics were not evaluated in these models as seen in Table 22.

4.1.1 Improvement trials. The yield model did not generate reasonable results compared to other models so multiple testing models were implemented because the model was incompatible with other models. The yield data contains values that span from 0 to 37 with most points clustered around zero. The subsequent model was tested after narrowing the value range by removing data points below 3. The log transformation was used for normalization purposes before testing a different model. Additionally, it is used to gain suitable data and stabilize the variance. Simpler model has been created during the work with dense layers. The test results are presented in Table 23 which is available below.

Table 23

Trial Results of Yield Output Related Model

Trial	1	2	3	4	5
Log Transformation	Not used	Used	Not used	Used	Not used
Yield > 3 Filter	Not used	Not used	Not used	Used	Used
Dense Layers	64-32-1	64-32-1	32-16-1	32-16-1	32-16-1
R ² (Train/Test)	0.034 / 0.021	-0.084 / -0.122	-0.049 / -0.041	-0.084 / -0.122	0.028 / -0.047
RMSE (Test)	5.51	5.90	5.68	5.90	7.02
Yield Prediction	159 kg/tree	206 kg/tree	138 kg/tree	206 kg/tree	146 kg/tree

The initial test of the 64-32-1 structure without log transformation or filtering resulted in poor accuracy with $R^2_{\text{test}} = 0.021$, $\text{RMSE} = 5.51$. The model performance worsened after applying log transformation during the second trial with the result of $R^2_{\text{test}} = -0.122$. The third trial utilized a 32-16-1 structure, but it did not perform well. The fourth trial combined filtering with log transformation yet the test performance failed to improve. The fifth trial removed only low-performance records from the data without applying log transformation which resulted in a small improvement on the training data which is $R^2_{\text{train}} = 0.028$. The model achieved limited generalization capacity because test data success remained at a low level with $R^2_{\text{test}} = -0.047$. The current model produced more authentic results than previous models by predicting 146 kg/tree for 2024.

4.1.2 Loss function. Functions used for regression models from the TensorFlow library were used. Neural networks heavily rely on loss functions because they determine how the model adapts to training data when combined with optimization functions. A loss function measures the difference between actual and

predicted output values to evaluate how well the neural network models the training data. The main goal during training involves minimizing the difference between actual and predicted output values. The hyperparameters serve to minimize the mean loss value.

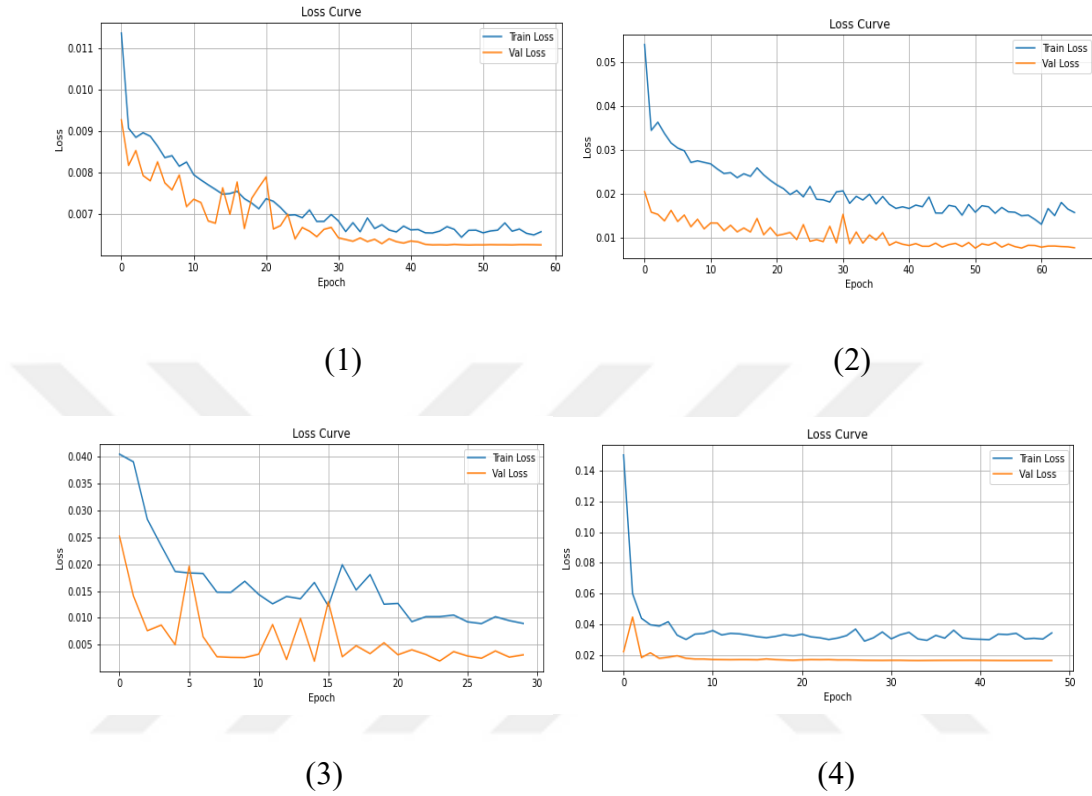


Figure 17. Loss curves of monthly (1), annual (2), production focused (3) and yield focused (4) models

As seen in Figure 17, for each model, there is a sharp decrease in loss value for first couple of epochs. This trend indicates that model tries to adapt to data at the beginning of the process. For all models, there isn't any overfitting issues. Since validation loss is always below the train loss or very close to train's loss curve. After 10 to 20 epoch, all trends of loss curves are steady, and loss levels are preserved without certain fluctuations.

In terms of first model which reflects monthly basis model, since the validation loss is less than train loss model shows the good capability of generalization without overfitting risk. After the 10th epoch, the figure stabilised, and both curves are stabled. For the annual based model, there is a stable learning observed especially until 50th epoch. Both curves go parallel for long time. However, train loss is above the

validation loss. This situation indicates there is more successful output during validation. Production focused annual model has stable learning process since losses are close and steady. Especially after 30th epoch it is almost stable. There is a possibility that the model found the appropriate weights there. As a last model which is yield based annual mode has distinct lower validation loss than train loss. This may be the sign of underfitting or lower variance since the model has better performance for train data. Learning curve has stabilised quickly but in total the curve continues with low levels of accuracy.

4.2 Findings of Hesitant Fuzzy AHP

Hesitant fuzzy (HF) is a concept used in fuzzy logic and decision making processes. It is used especially in cases where a decision maker may express more than one rating or hesitation regarding an object or situation. Advantages of hesitant fuzzy sets are It expresses uncertainty and indecision better. It is suitable for integrating multiple expert opinions. It offers a more flexible structure in decision making processes.

The pairwise comparison values obtained from experts are expressed with triangular fuzzy numbers corresponding to predefined linguistic terms such as, “Absolutely High Importance” = (7, 9, 9), “Exactly Equal” = (1, 1, 1). Table 24 indicates three experts’ evaluations. Since the criteria list includes 9 inputs, snapshot of evaluations provided. Criteria are listed as (C1) climate suitability, (C2) infrastructure/resource status, (C3) government subsidies and incentive plans, (C4) input and maintenance planning, (C5) labour and equipment planning, (C6) pest/disease risk, (C7) cost impact, (C8) market conditions, (C9) processing time and shift planning. The study followed by consistency analyses which relied on the criteria comparison matrices that experts provided. The calculation of the consistency ratio (CR - Consistency Ratio) from the defuzzified matrices that each expert created. The CR calculation resulted in matrix acceptance when the consistency ratio fell below 10% according to Saaty’s method. The second expert’s comparison matrix proved to be the only one that met the consistency requirement ($CR < 0.10$). The comparison matrices of the first and third experts showed inconsistency because their CR values fell between 0.10 and 0.15. The TFN values in the two expert matrices were

defuzzified to produce numerical matrices which enabled GMIR weight calculations using the average formula $(l + m + u)/3$. Each matrix received new CR values which resulted in CR measurements below 0.10. The Hesitant Fuzzy AHP process continued after verifying consistency with the enhanced matrices.

Pairwise comparison matrices are provided in Table 24 that evaluated by experts for criterion. For each criterion, experts are able to provide more than one TFN value.

Table 24

A Snapshot of Criteria Pairwise Comparisons by Expert 1, 2, 3 (in linguistic terms)

<i>E1</i>	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	EE	ESHI	EE	EE	EE	Between ELI and WLI	WLI	ESHI	EE
C2		EE	EHI	EE	EE	Between ELI and WLI	Between ELI and WLI	ESHI	EE
C3			EE	WHI	ESHI	EE	EE	ESHI	WHI
C4				EE	EE	EE	EE	EE	EE
C5					EE	EE	EE	WHI	WHI
C6						EE	EE	WHI	WHI
C7							EE	WHI	EE
C8								EE	EE
C9									EE

<i>E2</i>	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	EE	EE	EE	EE	EE	EE	EE	EE	EE
C2		EE	EE	EE	EE	EE	EE	EE	EE
C3			EE	EE	WLI	WLI	EE	EE	EE
C4				EE	EE	EE	EE	EE	EE
C5					EE	EE	WLI	WLI	EE
C6						EE	EE	EE	EE
C7							EE	EE	EE
C8								EE	EE
C9									EE

Table 24 (cont.d)

<i>E3</i>	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	EE	WHI	EE	WHI	EE	EE	EE	EE	EE
C2		EE	ESHI	EE	EE	EE	ESHI	EE	WHI
C3			EE	EHl	ESHI	WHI	WHI	EE	ESHI
C4				EE	EE	EHl	EHl	EE	EE
C5					EE	EE	EE	WHI	EE
C6						EE	EE	EE	EE
C7							EE	WHI	EHl
C8								EE	EE
C9									EE

The values obtained from experts for each criterion pair are converted to combined TFN using Liu & Rodriguez's (2014) envelopment approach. The range is expanded during this process by taking the minimum lower end and the maximum upper end while the middle values are subjected to weighted average with OWA operators. For this model, no weighting is applied for Expert 2. The evaluation includes 3 experts who hold equal weight in the assessment.

Table 25

Fuzzy Envelopes of the Evaluations

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	EE	ESHI	VHI	VHI	VHI	WHI	ESLI	AHI	AHI
C2		EE	VHI	ESHI	ESLI	ESLI	ESLI	ESHI	AHI
C3			EE	ESHI	ESHI	ELI	ELI	AHI	ESHI
C4				EE	ELI	ELI	ELI	AHI	VHI
C5					EE	ELI	EE	AHI	AHI
C6						EE	ELI	AHI	AHI
C7							EE	VHI	EE
C8								EE	EE
C9									EE

Calculation example of Criteria1-Criteria2 for 3 experts' evaluation as indicated in Equations between 12-14:

$$a = \min \{1, 3, 5\} = 1$$

$$d = \max \{7, 5, 3\} = 7$$

$$\alpha_1 = (10-8)/9 = 0.222$$

$$\alpha_2 = (8-4)/9 = 0.444$$

$$b = 0.222 \times 3 + 0.444 \times 1 = 1.11$$

$$c = (2 \times 1.77) - 1.11 = 2.44$$

Result: (0.33, 1.11, 2.44, 7)

Table 26

Trapezoidal Fuzzy Sets of Criteria

	C1	C2	C3
C1	(1, 1, 1, 1)	(0.33, 1.11, 2.44, 7)	(1, 1, 3.22, 9)
C2	(0.143, 0.41, 0.901, 3.03)	(1, 1, 1, 1)	(1, 1.11, 8.89, 9)
C3	(0.111, 0.311, 1.0, 1.0)	(0.111, 0.112, 0.901, 1.0)	(1, 1, 1, 1)
C4	(0.111, 0.2, 1.818, 1.0)	(0.111, 0.196, 1.124, 1.0)	(0.2, 0.451, 1.0, 1.0)
C5	(0.111, 0.111, 0.312, 0.948)	(0.2, 0.901, 1.124, 1.0)	(0.143, 0.479, 1.802, 5.0)
C6	(0.111, 0.21, 1.0, 3.03)	(0.143, 0.188, 1.493, 3.03)	(0.143, 0.506, 2.049, 5.0)
C7	(0.143, 0.291, 1.818, 9.091)	(0.143, 1.205, 5.882, 9.091)	(0.2, 0.743, 4.202, 9.091)
C8	(0.111, 0.21, 0.82, 7.143)	(0.143, 0.709, 1.695, 5.0)	(0.2, 0.743, 4.202, 9.091)
C9	(0.111, 0.21, 1.0, 7.143)	(0.2, 0.901, 1.124, 3.03)	(0.2, 0.743, 4.202, 9.091)
	C4	C5	C6
C1	(1, 0.55, 5, 9)	(1.055, 3.21, 9, 9)	(0.33, 1, 4.77, 9)
C2	(1, 0.89, 5.11, 9)	(1, 0.89, 1.11, 5)	(0.33, 0.67, 5.33, 7)
C3	(1, 1.0, 2.219, 5)	(0.2, 0.555, 2.089, 7)	(0.2, 0.488, 1.976, 7)
C4	(1, 1, 1, 1)	(0.14, 0.294, 4.0, 9)	(0.2, 0.703, 1.026, 3)
C5	(0.111, 0.25, 3.401, 7.143)	(1, 1, 1, 1)	(0.33, 0.898, 1.33, 1)
C6	(0.333, 0.975, 1.422, 5.0)	(1.0, 0.752, 1.114, 3.03)	(1, 1, 1, 1)
C7	(0.333, 1.151, 1.623, 9.091)	(1.0, 0.77, 1.225, 5.0)	(1.0, 0.578, 3.704, 7.143)
C8	(0.111, 0.31, 0.745, 9.091)	(0.2, 0.442, 0.913, 5.0)	(0.2, 1.0, 3.448, 7.143)
C9	(0.143, 0.355, 1.001, 9.091)	(0.2, 0.485, 1.013, 5.0)	(0.2, 0.588, 3.448, 7.143)
	C7	C8	C9
C1	(0.11, 0.55, 3.44, 7)	(0.14, 1.22, 4.77, 9)	(0.14, 1, 4.77, 9)
C2	(0.11, 0.17, 0.83, 7)	(0.2, 0.59, 1.41, 7)	(0.33, 0.89, 1.11, 5)
C3	(0.11, 0.238, 1.346, 5)	(0.11, 0.238, 1.346, 5)	(0.11, 0.238, 1.346, 5)
C4	(0.11, 0.616, 0.869, 3)	(0.11, 1.342, 3.226, 9)	(0.11, 0.999, 2.814, 7)
C5	(0.2, 0.816, 1.298, 1)	(0.2, 1.095, 2.264, 5)	(0.2, 0.987, 2.063, 5)
C6	(0.14, 0.27, 1.73, 1)	(0.14, 0.29, 1.0, 5)	(0.14, 0.29, 1.7, 5)
C7	(1, 1, 1, 1)	(1, 1.333, 4.667, 5)	(1, 1.0, 1.0, 3)
C8	(0.2, 0.214, 0.75, 1.0)	(1, 1, 1, 1)	(1, 0.55, 1.45, 1)
C9	(0.333, 1.0, 1.0, 1.0)	(1.0, 0.69, 1.818, 1.0)	(1, 1, 1, 1)

Step 6: Calculation of Criteria Weights.

After the taking geometric mean of each row, normalized values of geometric means are calculated. Crisp weights are calculated by $\frac{a+2b+2c+d}{6}$. Calculation examples of first row are indicated below as seen in Table 27.

$$a_g = (1 + 0.33 + 1 + 1 + 1.055 + 0.33 + 0.11 + 0.14 + 0.14)^{\frac{1}{9}} = 0.397$$

$$b_g = (1 + 1.11 + 1 + 0.55 + 3.21 + 3.21 + 1 + 0.55 + 1.22 + 1)^{\frac{1}{9}} = 1.030$$

$$c_g = (1 + 2.44 + 3.22 + 5 + 9 + 4.77 + 3.44 + 4.77 + 4.77)^{\frac{1}{9}} = 3.706$$

$$d_g = (1 + 7 + 9 + 9 + 9 + 9 + 7 + 9 + 9)^{\frac{1}{9}} = 6.667$$

$$a_w = \frac{0.397}{9} = 0.044$$

$$b_w = \frac{1.030}{9} = 0.114$$

$$c_w = \frac{3.706}{9} = 0.411$$

$$d_w = \frac{6.667}{9} = 0.740$$

Table 27

Criteria Weights

	Trapezoidal Weight	Crisp Weight
C1	(0.0441,0.1145,0.4118,0.7408)	0.1954
C2	(0.0457,0.0725,0.2105,0.5601)	0.1246
C3	(0.0228,0.0410,0.1551,0.3501)	0.0813
C4	(0.0183,0.0583,0.1770,0.2869)	0.0825
C5	(0.0237,0.0662,0.1525,0.2349)	0.0740
C6	(0.0259,0.0456,0.1492,0.3287)	0.0791
C7	(0.0533,0.0917,0.2512,0.5956)	0.1419
C8	(0.0268,0.0549,0.1500,0.4016)	0.0891
C9	(0.0303,0.0664,0.3493,0.3799)	0.1320

Same calculations are followed for 6 alternatives as computed below.

Comparison Matrix of Alternatives. Each criterion received alternative comparisons from each expert, TFNs were calculated and then combined with OWA in Table 28.

Table 28

A Snapshot of Alternative Comparisons for Criteria 1, 8, 9 (in linguistic terms)

C1	A1	A2	A3	A4	A5	A6
A1	EE	Between WHI and VHI	Between EHI and ESHI	Between ELI and EHI	Between EHI and ESHI	Between VHI and AHI
A2		EE	Between WLI and ELI	Between VLI and ESLI	Between WLI and EE	Between EHI and WHI
A3			EE	Between ELI and EE	Between EE and EHI	Between ESHI and AHI
A4				EE	Between ESHI and AHI	Between ESHI and AHI
A5					EE	Between EHI and ESHI
A6						EE

C8	A1	A2	A3	A4	A5	A6
A1	EE	Between WLI and EE	Between WSL and ELI	Between VLI and WLI	Between ESLI and ELI	Between ALI and VLI
A2		EE	Between ESLI and WLI	Between ALI and ESLI	Between ELI and EHI	Between VLI and WLI
A3			EE	Between WLI and ELI	Between ESLI and ELI	Between ESLI and ELI
A4				EE	Between VLI and WLI	Between WLI and EE
A5					EE	Between VLI and WLI
A6						EE

C9	A1	A2	A3	A4	A5	A6
A1	EE	Between WLI and EE	Between ESLI and ELI	Between ALI and ESLI	Between ESLI and ELI	Between WLI and EE
A2		EE	Between ESLI and ELI	Between ALI and ESLI	Between VLI and WLI	Between ESLI and ELI
A3			EE	Between WLI and EE	Between EE and WHI	Between WLI and ELI
A4				EE	Between ESLI and ELI	Between EHI and ESHI
A5					EE	Between EHI and ESHI
A6						EE

Calculating and Normalizing Trapezoidal Weights. All alternatives had trapezoidal weights calculated and normalized based on each criterion. As an example, rows are calculated as follow, expert1 and expert3 with envelopment result of values related to A1 under C1, expert1 and expert3 with envelopment result of values related to A1 under C2, expert1 and expert3 with envelopment result of values related to A1 under C3.

Calculation of Final Scores (Trapezoidal Weighted Total). The criterion-based trapezoidal weights of each alternative were multiplied by the respective criterion weights, results are indicated in Table 29.

The weighted value of A1 under K1 is calculated as follows: $(0.034 \times 0.045, 0.081 \times 0.077, 0.086 \times 0.111, 0.146 \times 0.16) \approx (0.001, 0.006, 0.009, 0.023)$

Table 29

Trapezoidal Alternative Priorities for Each Criterion

	C1	C2	C3
A1	(0.120,0.280,0.311,0.530)	(0.145,0.280,0.374,0.578)	(0.133,0.305,0.325,0.602)
A2	(0.031,0.050,0.079,0.120)	(0.084,0.109,0.162,0.315)	(0.084,0.131,0.162,0.343)
A3	(0.080,0.125,0.156,0.251)	(0.051,0.107,0.138,0.200)	(0.042,0.088,0.096,0.209)
A4	(0.160,0.274,0.297,0.480)	(0.026,0.040,0.085,0.111)	(0.026,0.057,0.086,0.111)
A5	(0.046,0.077,0.083,0.167)	(0.058,0.074,0.096,0.248)	(0.061,0.090,0.113,0.248)
A6	(0.020,0.027,0.035,0.058)	(0.032,0.063,0.081,0.111)	(0.031,0.059,0.063,0.120)
	C4	C5	C6
A1	(0.092,0.170,0.177,0.455)	(0.070,0.130,0.136,0.289)	(0.044,0.091,0.097,0.169)
A2	(0.078,0.195,0.205,0.277)	(0.049,0.084,0.085,0.189)	(0.111,0.235,0.247,0.461)
A3	(0.064,0.144,0.146,0.302)	(0.070,0.092,0.111,0.251)	(0.228,0.402,0.446,0.577)
A4	(0.032,0.088,0.096,0.160)	(0.042,0.084,0.092,0.133)	(0.038,0.065,0.068,0.174)
A5	(0.084,0.149,0.158,0.329)	(0.133,0.235,0.323,0.546)	(0.037,0.072,0.081,0.184)
A6	(0.017,0.025,0.026,0.077)	(0.027,0.065,0.068,0.092)	(0.021,0.034,0.041,0.070)
	C7	C8	C9
A1	(0.145,0.303,0.349,0.586)	(0.022,0.039,0.052,0.084)	(0.023,0.053,0.058,0.092)
A2	(0.051,0.138,0.151,0.266)	(0.032,0.045,0.052,0.145)	(0.027,0.041,0.044,0.120)
A3	(0.036,0.074,0.079,0.174)	(0.044,0.075,0.122,0.200)	(0.064,0.129,0.164,0.277)
A4	(0.029,0.044,0.051,0.111)	(0.070,0.149,0.189,0.302)	(0.115,0.204,0.221,0.418)
A5	(0.055,0.108,0.124,0.289)	(0.064,0.156,0.164,0.368)	(0.084,0.243,0.259,0.423)
A6	(0.042,0.090,0.094,0.209)	(0.145,0.306,0.339,0.602)	(0.058,0.088,0.116,0.262)

Final Trapezoidal Score and Ranking. The total trapezoidal scores of the alternatives were obtained by adding all the weighted values as seen in Table 30.

The final scores are determined by multiplying alternative priorities with their criterion weights and then summing the weighted priorities to get the overall score of alternatives. The weighted priority of first alternative in relation to first criteria is computed as follows:

$$0.120*0.0442, 0.280*0.1145, 0.311*0.411, 0.530*0.740 = 0.005, 0.032, 0.128, 0.393$$

Table 30

Total Trapezoidal Scores

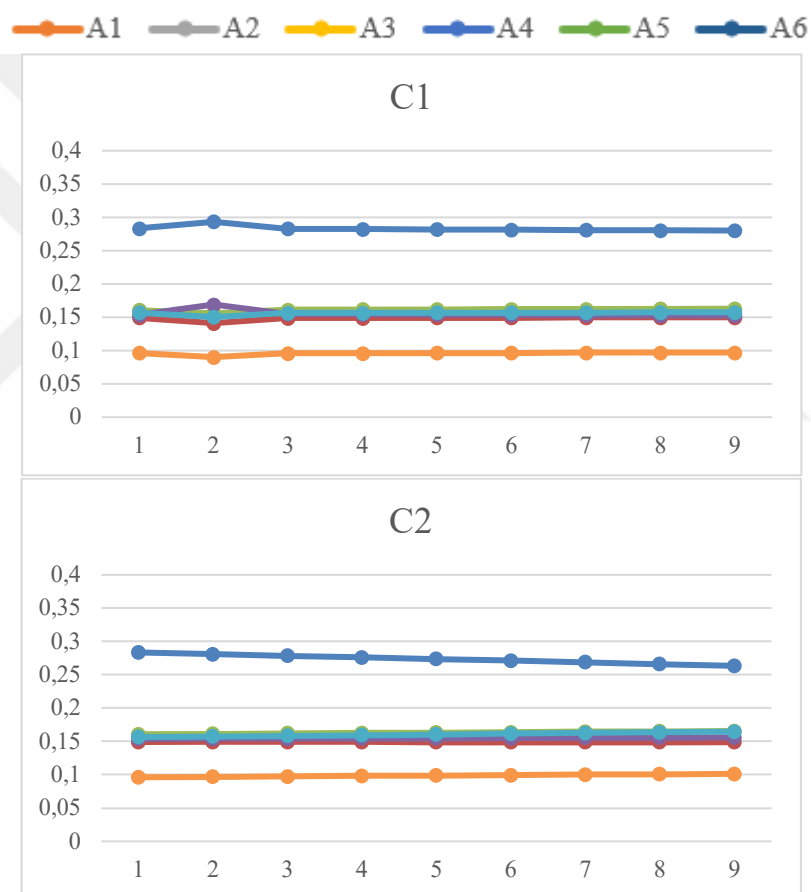
	C1					C2					C3	
A1	0.00534	0.03211	0.12839	0.39335	0.00665	0.02034	0.07882	0.32386	0.00305	0.01252	0.05052	0.21107
A2	0.00138	0.00574	0.03277	0.08963	0.00389	0.00796	0.03414	0.17679	0.00194	0.00540	0.02515	0.12031
A3	0.00355	0.01441	0.06444	0.18644	0.00234	0.00776	0.02914	0.11257	0.00097	0.00365	0.01493	0.07337
A4	0.00708	0.03150	0.12233	0.35615	0.00121	0.00294	0.01802	0.06224	0.00060	0.00237	0.01344	0.03890
A5	0.00205	0.00882	0.03454	0.12397	0.00266	0.00539	0.02024	0.13918	0.00140	0.00371	0.01768	0.08699
A6	0.00090	0.00313	0.01474	0.04365	0.00149	0.00460	0.01713	0.06224	0.00071	0.00246	0.00978	0.04236
	C4					C5					C6	
A1	0.0017	0.0100	0.0315	0.1306	0.0017	0.0086	0.0208	0.0681	0.0012	0.0042	0.0146	0.0557
A2	0.0014	0.0114	0.0365	0.0796	0.0012	0.0056	0.0130	0.0446	0.0029	0.0107	0.0369	0.1516
A3	0.0012	0.0084	0.0259	0.0867	0.0017	0.0061	0.0169	0.0591	0.0059	0.0184	0.0667	0.1898
A4	0.0006	0.0052	0.0170	0.0460	0.0010	0.0056	0.0141	0.0314	0.0010	0.0030	0.0102	0.0574
A5	0.0016	0.0087	0.0281	0.0944	0.0032	0.0156	0.0493	0.1284	0.0010	0.0033	0.0121	0.0607
A6	0.0003	0.0015	0.0048	0.0221	0.0006	0.0044	0.0104	0.0217	0.0006	0.0016	0.0061	0.0233
	C7					C8					C9	
A1	0.0078	0.0279	0.0878	0.3493	0.0006	0.0022	0.0079	0.0341	0.0007	0.0035	0.0203	0.0352
A2	0.0027	0.0127	0.0381	0.1586	0.0009	0.0025	0.0078	0.0584	0.0008	0.0027	0.0154	0.0460
A3	0.0020	0.0068	0.0201	0.1039	0.0012	0.0042	0.0184	0.0807	0.0020	0.0086	0.0575	0.1056
A4	0.0016	0.0041	0.0129	0.0662	0.0019	0.0082	0.0284	0.1214	0.0035	0.0136	0.0773	0.1588
A5	0.0030	0.0100	0.0312	0.1726	0.0017	0.0086	0.0247	0.1479	0.0026	0.0162	0.0908	0.1611
A6	0.0023	0.0083	0.0238	0.1248	0.0039	0.0169	0.0509	0.2421	0.0018	0.0059	0.0406	0.0998

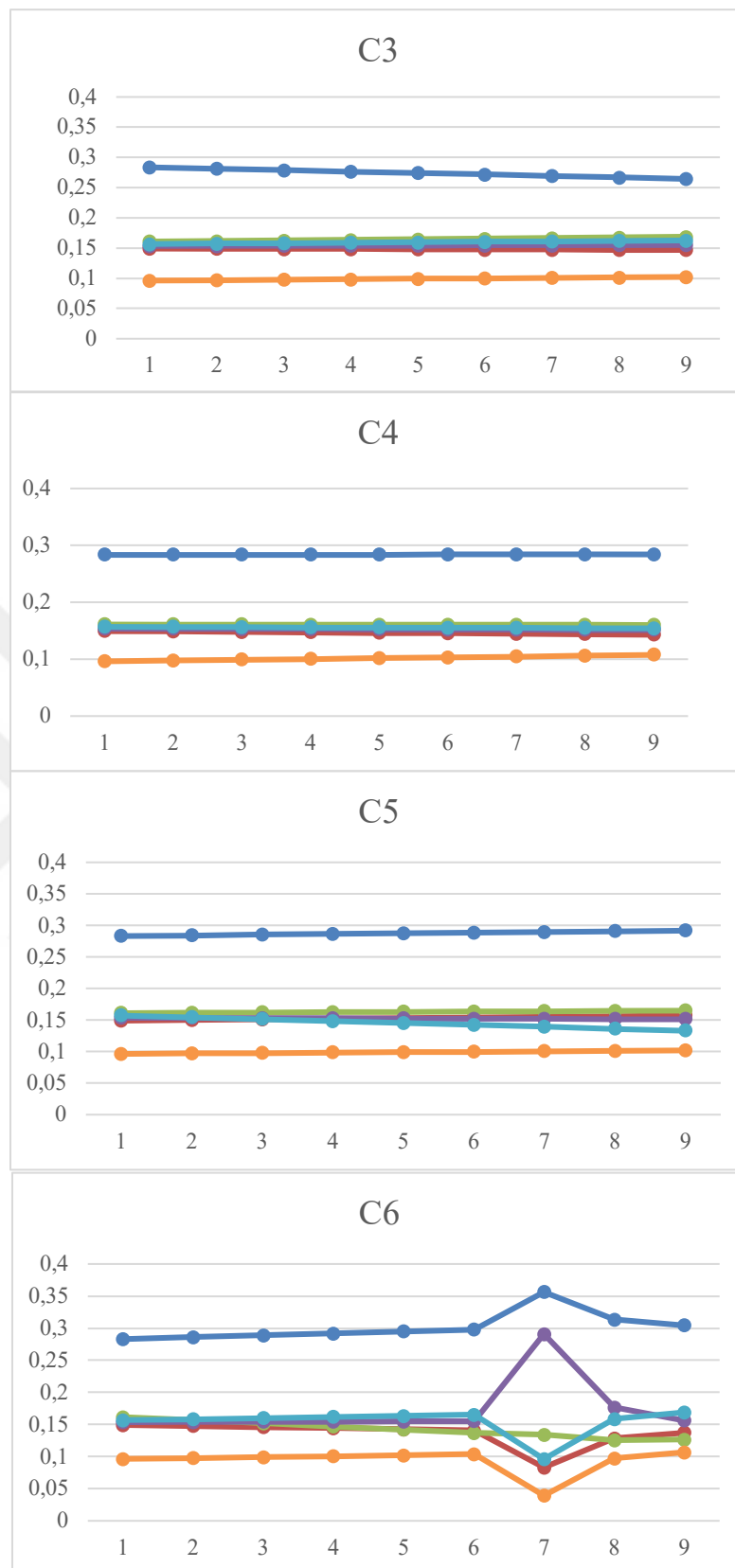
The weighted priorities are aggregated to determine the overall ratings of the alternatives. The second column of Table 31 shows the scores of the choices as trapezoidal fuzzy sets. The numbers are then defuzzified and normalized to get the final score for each choice.

Table 31

Final Scores

	<i>Fuzzy Scores</i>				<i>Crisp Score</i>
<i>A1</i>	0.0287	0.1213	0.4406	1.6013	0.2525
<i>A2</i>	0.0171	0.0648	0.2399	0.9255	0.1423
<i>A3</i>	0.0208	0.0783	0.3141	0.9983	0.1654
<i>A4</i>	0.0185	0.0765	0.3138	0.9384	0.1593
<i>A5</i>	0.0191	0.0803	0.3086	1.1153	0.1753
<i>A6</i>	0.0126	0.0486	0.1783	0.6822	0.1053





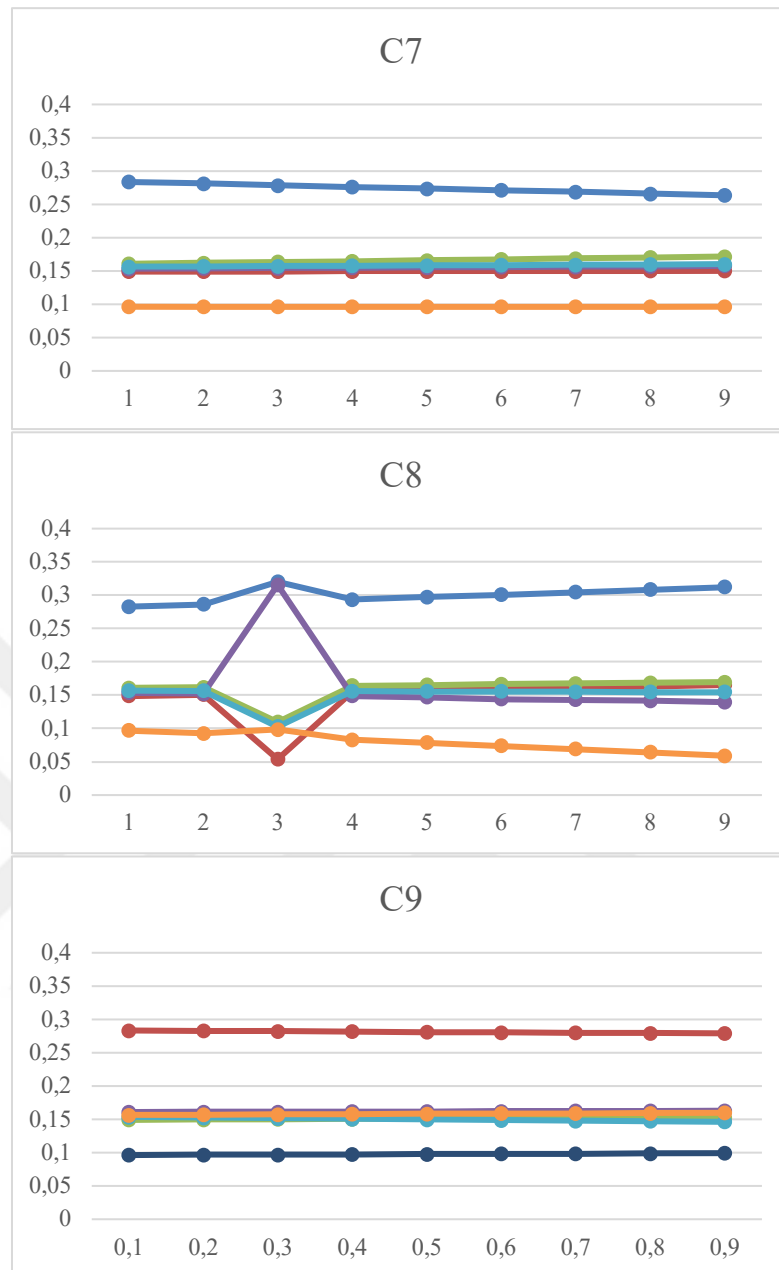


Figure 18. Sensitivity Analysis for Criteria

The sensitivity analysis results in Figure 17 demonstrate that modifications to the criteria weights of Pest/Disease Risk (C6) and Market Conditions (C8) resulted in substantial changes to alternative strategy rankings. These criteria demonstrate how crucial they are for decision making. The weight modifications of criteria including “Climate Suitability (C1)” and “Government Support (C3)” failed to influence the ranking order. The model stability regarding these criteria confirms the reliability of the obtained results.

Chapter 5

Discussions and Conclusions

5.1 Discussion

The results include the performance of the model, the characteristics of the dataset, and the error rates of the predictions. All of the findings presented in this section are necessary in order to accomplish the primary objective of the study, which is to lay the groundwork for recommendations about future enhancements. After conducting a comprehensive analysis into the data, significant insights have been obtained that can be used to improve the accuracy and reliability of models used in agricultural production projections.

5.1.1 LSTM

The present study is focused on comparing the forecasting abilities of four different LSTM models constructed (combined model with monthly data, combined model with annual data, model with only production output and model with only yield output) using common regression metrics such as R^2 , RMSE and MSE. The findings reveal that the results of the models differ based on the input data structure and model architecture.

The monthly-based LSTM model demonstrated a very good performance in the production prediction due to its more detailed description of the time series. The R^2 values obtained for production in the test data set were in the range of 0.834-0.841, while the RMSE values remained between 2040-2115 tons. The test R^2 values for the yield output of the same model were between 0.50-0.55, and the RMSE values were approximately 0.75 kg/tree. These results show that the modelling performed at the monthly level is extremely successful in terms of production prediction but offers limited explanatory power for yield prediction.

The model created with annual data again exhibited high performance for production output but produced weaker results for yield output. In the test data set, the R^2 value for production varied between 0.802-0.857, while the RMSE values remained in the 9400-10879. On the other hand, the R^2 value in yield estimation was between 0.35-0.39, and the RMSE was approximately 4.36-5.51 kg/tree. This may be due to the fact that annual averages did not adequately reflect the natural variation in yield.

The annual model, which focused only on production output, produced the highest test R^2 values (0.84-0.897) and the RMSE values remained between 9258-11513 ton. This type of model can be used especially for future scenario analyses and strategic production planning. The absence of yield output ensured that the model did not make measurements in this direction, and did not cause any loss of accuracy.

The model focusing only on yield output showed the lowest performance level. In the test data set, R^2 values remained in the range of 0.02-0.36 and RMSE values were found at the level of 4.44-5.51 kg/tree. This result suggests that the yield variable is not as predictable as production and that some external factors not included in the model (soil quality, disease prevalence, pruning time and so on) may be effective. The high RMSE and MSE values are particularly related to the production data being in “tons”. In other studies, the use of “thousand tons” or “normalized production” data shows lower RMSE values. Indeed, since the model outputs are given in tons in this study, model accuracy should be evaluated more fairly with R^2 . The effects of various batch sizes (150 and 300) and number of epochs (8, 16 and 32) used in each of the four different LSTM models used in the study on the model performance was systematically analysed.

When evaluated in total, the highest performance in production estimation was obtained in the annual model targeting only production output. However, the most balanced results in terms of model generalization capacity and sensitivity to time series structure were observed in the combined model structured in monthly format. The predictive power for yield output remained low due to the limited data available. This situation can be explained by the fact that the yield variable depends on more biological and agronomic factors. Therefore, in order to increase the yield estimation performance in future studies; it is recommended to include additional explanatory parameters such as soil structure, tree age, olive variety, maintenance practices into the model. The predictive performance for yield output was limited due to the limited explanatory variables in the current data set. Yield is affected by biotic and abiotic factors more than production; especially when agronomic details such as tree age, olive variety, soil structure, maintenance-irrigation practices are not included in the model, the estimation accuracy decreases. Therefore, in future studies, it is recommended to integrate such additional explanatory variables into the model for yield estimation; It is also recommended that the models be tested at a more micro data level, not on a

provincial basis, but on a field or parcel scale. In this way, both the statistical performance of the models can be increased, and they can be made functional in terms of agricultural DSS. As stated in the previous sections, the social parameter prepared for use in the data set is also included. The social parameter was added to the most successful models in comparison and its effect was examined. In the annual production-only model, there was a 1% decrease in performance metrics, and in the annual combined model, there was a 4-5% decrease in test and train performances. The production quantity estimate was low in both models.

5.1.2 Hesitant Fuzzy AHP

The hesitant fuzzy logic approach is an important component of the Hesitant Fuzzy AHP method that was adopted in the study. This method provides higher levels of accuracy in situations where the opinions of experts are ambiguous. The construction of trapezoidal fuzzy numbers (TFN) and their aggregation through various aggregation procedures, especially the Liu & Rodríguez ranking and OWA operators, is the result of the equations that are used in the methodological steps. These equations are based on direct expert ratings. The Hesitant Fuzzy AHP method was used in this research to assist in the decision making process. This was done in the context of the development of an integrated Smart Olive Cultivation System. The Hesitant Fuzzy AHP technique has enabled the consideration of the hesitant and multiple evaluations of decision-makers. This is achieved by the removal of the certainty assumption, which is one of the major limitations of the conventional AHP approach. In particular, in the context of agricultural decision making processes, the opinions of experts are often characterized by uncertainty, and Hesitant Fuzzy AHP provides a framework that is very well suited to modelling this uncertainty.

The Hesitant Fuzzy AHP methodology was used to analyse six distinct strategic alternatives and each of these choices was evaluated based on nine variables that have an effect, either directly or indirectly, on the olive process. The model selects the alternative with the highest benefits by evaluating this alternative against specific criteria within a multi-criteria framework. The selection process provides the individual with a structured approach to evaluate which approach is more suitable for practical application. The method provides insights into present conditions as well as

potential future uncertainties which include climate change together with market volatility and agricultural possibilities.

The weights of criteria which resulted from the Hesitant Fuzzy AHP method show that Climate Suitability (C1) has the highest priority weight of 19.54%. This shows that the most basic factor that directly affects production and quality of olive production is climate, which includes factors such as temperature, rainfall, humidity, and other similar weather characteristics. This conclusion is also consistent with the LSTM predicting model that was made in the previous study; this is because the model has indicated that the prediction power of climatic data is relatively high. Therefore, it can be seen that the climate adaptability is the most crucial aspect that should be considered in the planning of olive production.

The Cost Impact (C7) criterion is the second most important criterion with a weight of 14.19%. This conclusion shows that agricultural output decisions had to be considered not only from the viewpoint of environmental sustainability but also from the viewpoint of economic sustainability. As be more specific, factors such as the costs of inputs, the amount of labour, and the amount of energy consumed are directly affecting the choice of production strategies. As a result, it is even more crucial that the system is integrated not only in terms of the environment but also in terms of the economy.

Among the criteria, Labor and Equipment Planning (C5) has the lowest importance with a score of 7.40%. The next highest low level of priority is Pest/Disease Risk (C6), which has a score of 7.91%. The current circumstance reveals that decision makers assigned a lower weight to the criteria that have a limited capacity to directly affect yield in the short run. On the other hand, this conclusion may pose the need for reconsidering the situation especially with regards to the effects that EWS for disease risk have in the long run. Based on the research that have been conducted in the sector of agriculture about machine learning, it is found that many approaches are used in the detection of pests and diseases of different crops. Based on the analysis made, it is possible to consider this tendency as contradictory to the fact that it is at low levels.

Also, the analysis of the weights of criteria has shown that there is a significant gap between the first four criteria and the last five criteria. The first four criteria have a weight of 19% to 12% of everything. On the other hand, the weights of the last five

criteria range from 8% to 7% of the total available weight. It is thought that the criteria within the two extremes grouped together are quite similar; however, there is a noticeable level of difference between the groups.

Among the normalized ratings of the alternatives, Irrigation Strategy seems to be the most important, with a score of 25.25%. This shows that irrigation is an important factor in the determination of efficiency especially in the regions with Mediterranean climate. From the results of Hesitant Fuzzy AHP, the Irrigation Strategy is the most critical alternative. However, this is contrary to the notion that olive tree is a drought resistant species, and that water irrigation is not necessary. Though this situation may look a bit unusual at the first glance, it shows that deliberate and planned irrigation measures are quite effective, particularly in terms of yield and quality management. This has become important in the current production context including factors such as oil quality, size and uniformity which are beyond the ordinary resilience. Water management in olive production can be more significant due to climate change, which has brought about high temperatures and dry spells. MCDM process shows that irrigation, among other factors, is crucial in achieving the production goals. This is the case even though the experts do not consider irrigation to be necessary. This conclusion was reached by the Hesitant Fuzzy AHP model by taking into consideration the impact of irrigation projects not only on climatic feasibility but also on cost and resource planning. This means that this result may have been achieved. This could mean that the integrated decision making approach offers a more extensive assessment than the conventional approaches.

The Soil Management and Maintenance category, which ranked the second with 17.53%, is considered to be very important. Based on detailed assessment, it was determined that this alternative has a very high level of interrelation, especially with the C1 (climate suitability) and C4 (input and maintenance planning) criteria. This conclusion is also supported by the fact that the LSTM model uses soil properties (temperature), that these parameters are frequently cited in the review articles, and that both of these factors are closely related to production.

Marketing and Storage Strategy is the choice with the lowest importance, and it received 10.53% of the response weight. From this conclusion, it can be deduced that the managers pay less attention to processes that do not have any direct impact on production performance in the short run. Nevertheless, when looking at the long-term

effects of such strategies on revenue growth and market sustainability, it can be safe to say that experts may hold more weight in other contexts. The Fertilization Program has a score of 14.23%, which puts it among the low priority options. One possible implication of this situation is that farmers should treat fertilization methods in existing operations as a well established and optimized component.

5.2 Conclusion

A deep learning method has been implemented for estimating production and yield using olive production and climatic data from different provinces of Türkiye. Time series estimations were performed by the successful LSTM network which resulted in four separate models for annual and monthly data while the modelling procedure included various structures and parameter combinations.

The evaluation of model performance was conducted using R^2 and RMSE. The annual model which focused solely on production variables demonstrated the highest R^2 value of 0.85 for production estimation which led to its success in production prediction. The combined model targeting yield and production along with monthly formatting produced the most generalizable and balanced structure. The model shows superior performance in EWS because it reacts to climatic scenarios, so it was determined as the most suitable choice.

The insufficient performance of yield estimation models stems from insufficient explanatory data within the model. Olive yield results from a combination of climatic factors and agricultural elements which include tree age, soil structure and olive variety together with maintenance processes. Future studies should include these explanatory variables in the model according to the recommendation.

The Hesitant Fuzzy AHP method produces these prioritization results which demonstrate an integrated smart system design approach that combines environmental and economic factors. The alternatives receive performance rankings through weighted criteria assessment and yield oriented and climate based applications stand out as prominent results. The framework enables both historical data-based estimation and future strategy guidance through multi criteria evaluation which is tailored to olive production.

During modelling both estimations and usability assessment through Hesitant

Fuzzy AHP were conducted to develop a DSS. A large number of criteria assessed by expert opinions received weightings through alternative comparisons which resulted in production estimate compatible agricultural action rankings. The research served both academic modelling requirements and provided an operational DSS.

The actual production data for 2024 revealed that the model predicted an estimated total annual production of around 1,066,000 tons which matched the observed production closely. The research results indicate that the developed model demonstrates excellent performance in its field and strong potential for future use.

This thesis evaluates data driven agricultural planning together with climate-sensitive prediction systems and multi criteria decision support mechanisms in an integrated manner. The research presents a powerful example of AI and decision support integration into agricultural practices.

5.3 Recommendations

Agricultural systems modelling has an importance especially with the use of time series meteorological data since this approach consists long term insights. DL models similar to LSTM provides successful results for yield and production predictions. However, rather than using just statistical models, integration with MCDM methods like Hesitant Fuzzy AHP which includes experts' opinions, make ease the theoretical applications become practical. Evaluation of objective data related models with subjective expert knowledge can result in more successful especially for agricultural studies. Also, comparison of more than one model for these kinds of models can be more useful.

One of the most important results of this study highlights that with the continuous and efficient use of climate data it is possible to increase yield. Reports of institutions reveal that in Türkiye, most of the agricultural activities are done by small or medium scaled producers. Besides the advantage of this situation, use of smart agricultural applications is limited. For this reason, being more proactive rather than reactive during agricultural plannings through climate change challenges. AI based model may be helpful for this purpose. On the other hand, MCDM methods can make possible for farmers to adapt new challenges through climate change scenarios. Investments of smart farming activities in order to make data based decisions are

suggested for the long term yield success.

Considering the reality of agriculture field, sector consists of high knowledge and experienced experts. This situation may end up with more challenges for changes of traditional production practices in terms of digitalization, relying on data and planning. This is why, climate resistant farming transition can be also more challenging. Since the first step of these transition starts with analysis of data, governmental level data systems play crucial role. In order to sustain regional data infrastructure, new mechanisms can be developed to bridge data. Together with holistic agricultural planning, digital agriculture transformation politics can be prioritised.



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