T.C
IZMIR DEMOKRASI UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

MASTER THESIS

ELECTRICAL AND ELECTRONICS ENGINEERING DEPARTMENT

Investigation of the Applicability of IoT and Machine Learning Approaches in Smart Coffee Roaster Design

Serhat AKTAŞ

Supervisor:
Assoc. Prof. Dr. Kemal AVCI

IZMIR-2025

Serhat
AKTAŞ

INVESTIGATION OF THE APPLICABILITY OF IOT AND MACHINE LEARNING APPROACHES IN SMART COFFEE ROASTER DESIGN

2025

COMMITMENT

I hereby declare that this thesis has been written in accordance with academic and ethical rules at the Graduate School of Natural and Applied Sciences at Izmir Democracy University, and that all the literature sources used have been properly cited in the thesis.

Serhat AKTAŞ

CONTENTS **Page**

LIST OF ICONS AND ABBREVIATIONS

AC	Alternating Current
ANN	Artificial Neural Network
CO	Carbon monoxide
CO2	Carbon dioxide
DC	Direct Current
DHT	Digital Humidity and Temperature
DOI	Digital Object Identifier
FOPDT	First Order Plus Dead Time
GLCM	Gray-Level Co-occurrence Matrix
Gr	Gram
HMI	Human-Machine Interface
Hz	Hertz
IC	Integrated Circuit
IDE	Integrated Development Environment
IoT	Internet of Things
Kg	Kilogram
LPG	Liquefied Petroleum Gas
MATLAB	MATrix LABoratory
MKR	Maker
ML	Machine Learning
NOx	Nitric oxides
PID	Proportional Integral Derivative
RH	Relative Humidity
SO2	Sulfur dioxide
SVM	Support Vector Machine
WLAN	Wireless Local Area Network

LIST OF FIGURES

Page

LIST OF TABLES

Page

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Assoc. Prof. Dr. Kemal AVCI for his invaluable guidance and support throughout my studies, sharing his extensive knowledge and experience. My sincere thanks also go to my fellow electrical and electronics engineers, Tuğrul Yiğit EFE and Burak ESENLİK, for their valuable contributions. I am truly grateful to my family for their unwavering support and constant presence by my side. Finally, I extend my thanks to BESCA Roasters for providing a conducive environment for my research.

Serhat AKTAŞ
İZMİR, 2025

ABSTRACT

M.Sc. Thesis

Investigation of the Applicability of IoT and Machine Learning Approaches in Smart Coffee Roaster Design

Serhat AKTAŞ

İzmir Demokrasi University
Graduate School of Applied and Natural Sciences
Department of Electrical and Electronics Engineering

Supervisor: Assoc. Prof. Dr. Kemal AVCI

Coffee is one of the most popular beverages worldwide, enjoyed by millions of people. The primary goal of the coffee industry is to produce high-quality coffee products with diverse taste and aroma profiles. In this process, roasting process plays a critical role. When the roasting duration and temperature profile are carefully controlled, different roasting levels can be achieved, significantly affecting the final aroma of the coffee. Therefore, producing high-quality coffee is directly related to the type of beans used and the applied roasting process. The design of coffee roasting machines is a key factor in ensuring high-quality coffee production and is, therefore, of great importance to the industry. This study examines the applicability of Internet of Things (IoT) and Machine Learning, two of today's significant technological approaches, in the design of coffee roasting machines. As part of the IoT study, a small-scale prototype coffee roasting machine was designed and implemented. The system, based on an Arduino MKR Wi-Fi 1010, was equipped with various sensors and electrical components and was successfully managed in real time through an interface developed on the Arduino Cloud platform, enabling data visualization. Additionally, a mobile user interface developed using the MIT App Inventor platform allowed the system to be controlled from mobile devices via Bluetooth communication, with real-time data displayed. In the Machine Learning study, coffee roasting machines with four different capacities (0.5 kg, 6 kg, 15 kg, and 30 kg) were used to collect sound samples during the coffee roasting process. Subsequently, these raw sound data were processed through the steps of data preprocessing, feature extraction, and machine learning model development. For each group of coffee roasting machines, seven different machine learning models were tested to recognize the coffee bean cracking sounds, which play a crucial role in the roasting process, and their performance was compared. The SVM model achieved the highest success rate of 95.5% for all the sounds. This study, offering significant findings to guide future developments, concludes with various recommendations for the design of smart coffee roasting machines.

Keywords: Coffee, coffee roasting machine design, smart control, internet of things, machine learning

2025, 89 pages

ÖZET

Yüksek Lisans Tezi

Akıllı Kahve Kavurma Makinesi Tasarımında IoT ve Makine Öğrenimi Yaklaşımlarının Uygulanabilirliğinin İncelenmesi

Serhat AKTAŞ

İzmir Demokrasi Üniversitesi
Fen Bilimleri Enstitüsü
Elektrik ve Elektronik Mühendisliği Ana Bilim Dalı

Danışman: Doç. Dr. Kemal AVCI

Kahve, dünya genelinde milyonlarca insanın severek tükettiği en popüler içeceklerden biridir. Kahve endüstrisinin temel amacı, farklı tat ve aroma profillerine sahip yüksek kaliteli kahve ürünleri üretmektir. Bu süreçte kahve çekirdeklerinin kavrulma süreci kritik bir rol oynar. Kavurma süresi ve sıcaklık profili dikkatlice kontrol edildiğinde, farklı kavurma seviyelerine ulaşılır ve bu durum kahvenin nihai aromasını büyük ölçüde etkiler. Bu nedenle, kaliteli kahve üretimi, kullanılan çekirdek türü ve uygulanan kavurma işlemi ile doğrudan ilişkilidir. Kahve kavurma makinelerinin tasarımı, kaliteli kahve üretiminde önemli bir etkendir ve bu nedenle sektörde büyük öneme sahiptir. Bu çalışmada, Nesnelerin İnterneti ve Makine Öğrenmesi gibi günümüzün önemli teknolojik yaklaşımlarının, kahve kavurma makinesi tasarımında uygulanabilirliği incelenmiştir. Nesnelerin İnterneti çalışması kapsamında, küçük ölçekli bir kahve kavurma makinesi prototipi tasarlanmış ve gerçekleştirilmiştir. Çeşitli sensörler ve elektrik donanımlarıyla donatılmış Arduino MKR Wi-Fi 1010 tabanlı sistem, Arduino Cloud platformu üzerinden oluşturulan bir arayüz ile gerçek zamanlı olarak başarıyla yönetilmiş ve veri görüntülenmesi sağlanmıştır. Ayrıca, MIT App Inventor platformunda hazırlanan bir mobil kullanıcı arayüz sayesinde sistem, Bluetooth iletişimi kullanılarak mobil cihazlardan kontrol edilmiş ve anlık veriler görüntülenebilmiştir. Makine Öğrenmesi çalışmasında ise, öncelikle dört farklı kapasiteye sahip endüstriyel kahve kavurma makineleri (0,5 kg, 6 kg, 15 kg ve 30 kg) kullanılarak kahve çekirdeklerinin kavrulma sürecindeki ses örnekleri toplanmıştır. Daha sonra bu ham ses verileri üzerinde veri ön işleme, öznitelik çıkarma ve makine öğrenmesi modeli geliştirme adımları gerçekleştirilmiştir. Her bir kapasitedeki kahve kavurma makinesi grubu için, kavurma sürecinde önemli rol oynayan kahve çekirdeği çıtlama seslerinin tanınması amacıyla yedi farklı makine öğrenmesi modeli test edilmiş ve performansları karşılaştırılmıştır. SVM modeli, tüm sesler için %95,5 ile en yüksek başarı oranına ulaşmıştır. Gelecekteki geliştirmelere ışık tutacak önemli bulgular sunan bu çalışma, akıllı kahve kavurma makinelerinin tasarımı için yapılabilecek çeşitli önerilerle sonlandırılmıştır.

Anahtar Kelimeler: Kahve, kahve kavurma makinesi tasarımı, akıllı kontrol, nesnelerin interneti, makine öğrenmesi

2025, 89 sayfa

1. INTRODUCTION

Globally, coffee is a leading choice among beverages, and meeting consumers expectations in terms of taste and aroma is of great importance. The coffee roasting process is a crucial stage that determines the taste and aroma of coffee, enjoyed by millions of people around the globe. At this point, the nature of the green coffee beans and the roasting processes of these beans play a vital role.

The coffee plant originated in the Ethiopian highlands, where Coffee Arabica first thrived, and in the forests of West and Central Africa, home to Coffee Robusta (Canephora). By the 14th century, coffee had become a well-known beverage in Yemen, from where it expanded to other Middle Eastern regions in the 15th century and crossed the Arabian Sea to India. Today, coffee is widely grown and consumed across tropical regions worldwide [1].

Figure 1.1 demonstrates the sequential transformation of coffee beans during the roasting process [2]. The beans start with a green color, gradually turning light brown, then dark brown, and finally reaching a black shade as the roasting progresses. This color change is the result of the Maillard reaction and other chemical processes occurring during roasting. Additionally, the beans rich aromatic characteristics and flavor profiles are developed throughout this process.

Figure 1.1. Adventure of Green Coffee Beans in Roasting Process

When the roasting time and temperature profile are controlled, the aroma of the resulting coffee is greatly influenced, leading to different roasting levels. The design of coffee roasters (or roasting machines) is a significant issue in the industry to achieve high-quality coffee associated with roasting processes. Obtaining a consistent process to achieve the desired taste and aroma profile in coffee roasting is an important problem. Professional coffee roasters guide the coffee roasting process based on intuition and experience. A data-driven and remotely controlled coffee roasting process is an important consideration in obtaining the final coffee roasting profile. Therefore, it is important to integrate new technology-based developments into such systems. In this thesis, the applicability of Internet of Things (IoT) and Machine Learning (ML) approaches are investigated in the design of coffee roasters.

This thesis consists of six main chapters.

Chapter-1. Introduction – This chapter outlines the main motivation behind the research, the purpose of the study, and the overall structure of the thesis.

Chapter-2. General Information – This chapter provides an overview of coffee roasting machines, Internet of Things, and machine learning, serving as a foundation for understanding the research context.

Chapter-3. Literature Review – In this chapter, previous scientific studies related to coffee roasting machines and coffee field are reviewed and categorized based on the type of research conducted.

Chapter-4. Materials and Method – This chapter details the hardware and software tools utilized in the research, along with the methodologies applied throughout the study.

Chapter-5. Research Results and Discussion – This chapter presents the analysis and key findings of the research.

Chapter-6. Conclusion and Future Studies – The final chapter summarizes the major outcomes of the thesis and provides suggestions for future research directions.

2. GENERAL INFORMATION

In this section, general information about coffee roasters, Internet of Things, and machine learning is provided.

2.1. About Coffee Roasters

Coffee roasters are devices that roast green coffee beans at specific temperatures and durations to create unique flavor and aroma profiles. These machines enable exact management of factors such as temperature, time, and airflow, ensuring consistent and high-quality coffee. Modern roasters are equipped with advanced technologies and automation features. They can be classified based on capacity and operation.

2.1.1. Types of Coffee Roasters Based on Capacity

Coffee roasters can indeed be classified into various types such as sample, shop, and industrial according to their intended use and capacity [3].

2.1.1.1. Sample Type Coffee Roasters

Sample roasters are small-scale coffee roasting machines with a typical capacity ranging from 50 to 500 grams. They are primarily used to evaluate the quality and potential of newly sourced or imported coffee beans. By enabling the development of optimal roasting profiles on a smaller scale, sample roasters help refine settings before transitioning to larger roasting machines. Their affordability allows for efficient testing without the need for large quantities of beans. Additionally, these machines are ideal for training purposes, serving as valuable tools for learning and teaching roasting techniques.

Figure 2.1 illustrates a compact sample roaster with a 200-gram capacity, designed for testing coffee beans and developing precise roasting profiles [4]. Equipped with adjustable temperature and airflow controls, it is ideal for small-scale roasting experiments commonly conducted in cafes or coffee labs.

Figure 2.1. A Sample-Type Coffee Roaster Machine

2.1.1.2. Shop Type Coffee Roasters

Shop-type coffee roasters are larger-capacity devices designed for commercial applications, commonly used in coffee shops, cafes, and small roasting facilities. These machines typically handle batches ranging from 1 kg to 15 kg of coffee beans, making them well-suited for medium- to large-scale operations.

Designed for commercial efficiency, they offer faster roasting speeds and the ability to produce large quantities while maintaining consistency. Users can save specific roasting profiles, ensuring repeatable and precise results with every batch.

Figure 2.2 shows a shop-type coffee roaster designed for medium-scale operations [5]. Ideal for coffee shops and small roasting businesses, it provides precise control over temperature and airflow, guaranteeing consistent quality and flavor in each batch. Its durable construction and efficient performance make it a dependable choice for professional roasters.

Figure 2.2. A Shop-Type Coffee Roaster Machine

2.1.1.3. Industrial Type Coffee Roasters

Industrial coffee roasters as shown in Figure 2.3 [6] are high-capacity machines designed for large-scale production and commercial use. They are commonly utilized by coffee producers, large coffee brands, and industrial roasting facilities. Engineered to meet high production demands, these machines deliver efficient performance while maintaining consistent quality across large batches. Built for high efficiency and consistent results, they are equipped with advanced automation, precise temperature control, and rapid cooling systems.

Figure 2.3. An Industrial-Type Coffee Roaster Machine

2.1.2. Types of Coffee Roasters Based on Operation

Based on their operating principles, coffee roasters can be classified into two main types: drum roasters and fluid bed roasters.

2.1.2.1. Drum Coffee Roasters

In a drum roaster, coffee beans are placed inside a rotating drum that is typically positioned horizontally and externally heated. In most drum roasters, the heat source, typically a flame or electric heating element, is located beneath the drum, ensuring the beans are evenly roasted as they tumble within the chamber [7]. Both the rotation speed and temperature are adjustable, allowing precise control over the roasting profile to achieve the desired flavor and quality.

Figure 2.4 gives an illustration related to a drum roaster [8]. The coffee rotates inside the drum and is roasted by the flame beneath it.

Figure 2.4. A Drum Roaster

2.1.2.2. Fluid Bed Coffee Roasters

Fluid bed roasters use hot air to roast coffee beans by circulating it evenly around them, ensuring uniform heat distribution. Fluid bed roasters are defined by their continuous use of a fan to ensure even heating. Hot air is blown from the center of the cylinder, and as the hot air flows through the roaster, it creates enough force to lift and suspend the beans in midair, forming a "bed" of heated air. This unique process is the origin of the term "fluid bed roasting" [9]. These roasters are typically smaller and designed for small-batch roasting.

Figure 2.5 provides an example related to the fluid bed roaster [10]. The coffee is roasted inside the chamber by hot air blown from below.

Figure 2.5. Fluid Bed Roaster

2.1.3. Hardware Components of Coffee Roasters

The components of a coffee roaster machine typically include several key parts as explained below. These components are shown on a shop type coffee roaster as in Figure 2.6 [11].

- **Hopper:** The container where green coffee beans are placed before roasting.
- **Hopper Gate:** A mechanism that releases the green beans into the roasting drum.
- **Roasting Drum:** The chamber where the roasting process occurs.
- **Sample Spoon:** Used to check the roasting progress and assess the maturity level of the beans during roasting.
- **Roasting Check Window:** Allows visual monitoring of the beans to observe changes in color and texture throughout the roasting process.
- **Cooling Tray:** The area where roasted coffee beans are cooled immediately after roasting.

- **Electrical Control Box:** Functions as the system controller, regulating various parameters such as temperature, airflow, and rotation speed.

Figure 2.6. Components of a Shop-Type Coffee Roaster

2.2. About Internet of Things

Internet of Things refers to a network of physical items that are integrated with sensors, software, and various technologies, allowing them to connect and exchange information with other devices and systems over the internet. These items can include everything from daily household products to complex industrial equipment [12].

The foundation of IoT concept was laid in the 1970s with the idea of autonomous devices communicating with each other. In 1982, a group of researchers at Carnegie Mellon University improved an internet connected Coca-Cola vending machine. This device could monitor the temperature of the drinks and check stock levels, making it one of the first examples of IoT. IoT began to gain traction in the 2000s and started becoming popular in the 2010s. Today IoT has become an ecosystem of billions of connected devices, integral to everyday life.

As shown in Figure 2.7 [13], IoT is a vast network that collects data on device usage and the surrounding environment, allowing for remote operation from any location. This enables users to easily control IoT-based devices, regardless of their physical location.

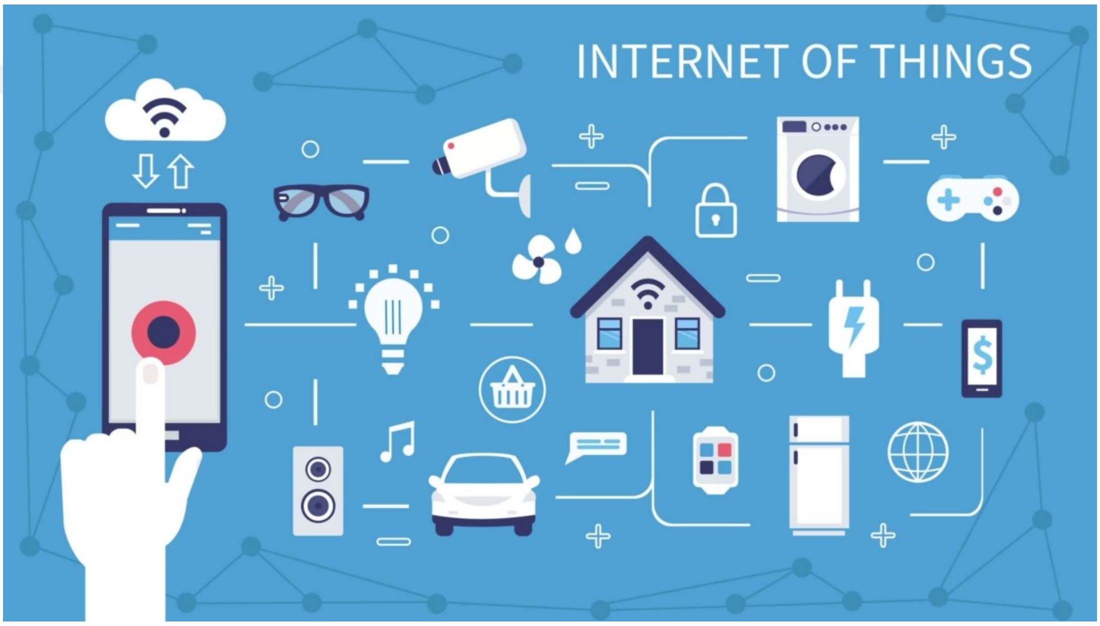


Figure 2.7. Internet of Things

The functionality of IoT relies on the integration of several key technologies which can be listed as below:

- **Sensors and Actuators:** Devices that gather data from the physical environment and interact with it.
- **Connectivity Technologies:** Communication protocols that enable devices to connect and exchange data, such as Wi-Fi, Bluetooth, and 5G.
- **Cloud Computing:** Provides scalable storage and processing power for managing large volumes of data.

- **Large-Scale Data Analysis:** Analyzes the collected data to generate insights and support decision-making processes.
- **Data Security and Privacy Solutions:** Protects sensitive information and ensures the secure transmission of data across networks.

2.3. About Machine Learning

Machine learning is a subset of artificial intelligence (AI) focused on developing models that enable computers to learn from data and make predictions or decisions. Instead of being explicitly programmed to perform specific tasks, machine learning systems are trained on large datasets, allowing them to recognize patterns, draw inferences, and improve their performance over time without requiring human intervention. Figure 2.8 illustrates the capabilities of machine learning and the various areas it is connected to [14].

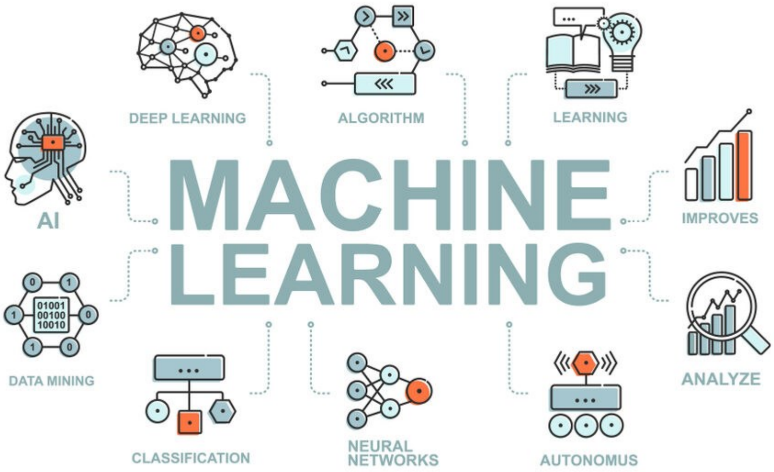


Figure 2.8. Machine Learning Capabilities

Machine learning is primarily divided into three main branches:

- **Supervised Machine Learning:** In this approach, the model is trained using labeled data, where the input-output pairs are known. The algorithm learns to map inputs to the correct outputs and improves its accuracy over time, making it ideal for tasks such as classification and regression.
- **Unsupervised Machine Learning:** This model works with unlabeled data, where the system tries to identify patterns, relationships, or hidden structures

within the data. It is commonly used for clustering, anomaly detection, and dimensionality reduction.

- **Reinforcement Machine Learning:** In this approach, the model learns through trial and error by interacting with its environment. It receives feedback in the form of rewards or penalties, helping it optimizes decision-making over time, as seen in applications like game playing and robotics.

Although numerous machine learning methods exist, their core concepts remain largely similar. The process begins with **data collection**, where relevant data is gathered and prepared for training and testing. The next step is **feature extraction and selection**, which involves identifying key features from the data that will be used to train the model. Following this, **model selection** takes place where an appropriate algorithm is chosen, trained on the data, and its performance is evaluated to ensure accuracy and effectiveness [19].

Although machine learning algorithms are widely applied across various industries, they come with specific challenges and considerations. One key challenge is the heavy reliance on data quality—flawed, inaccurate, or biased data can result in unreliable models. Additionally, some complex models, such as deep learning, lack interpretability, making it difficult to understand how decisions are made. Other important concerns include addressing bias in models, ensuring data privacy, and managing potential societal impacts when deploying machine learning systems [15].

Figure 2.9 presents examples of machine learning applications in the modern world [16]. The areas depicted in the illustration highlight key examples of how machine learning is utilized across various domains.

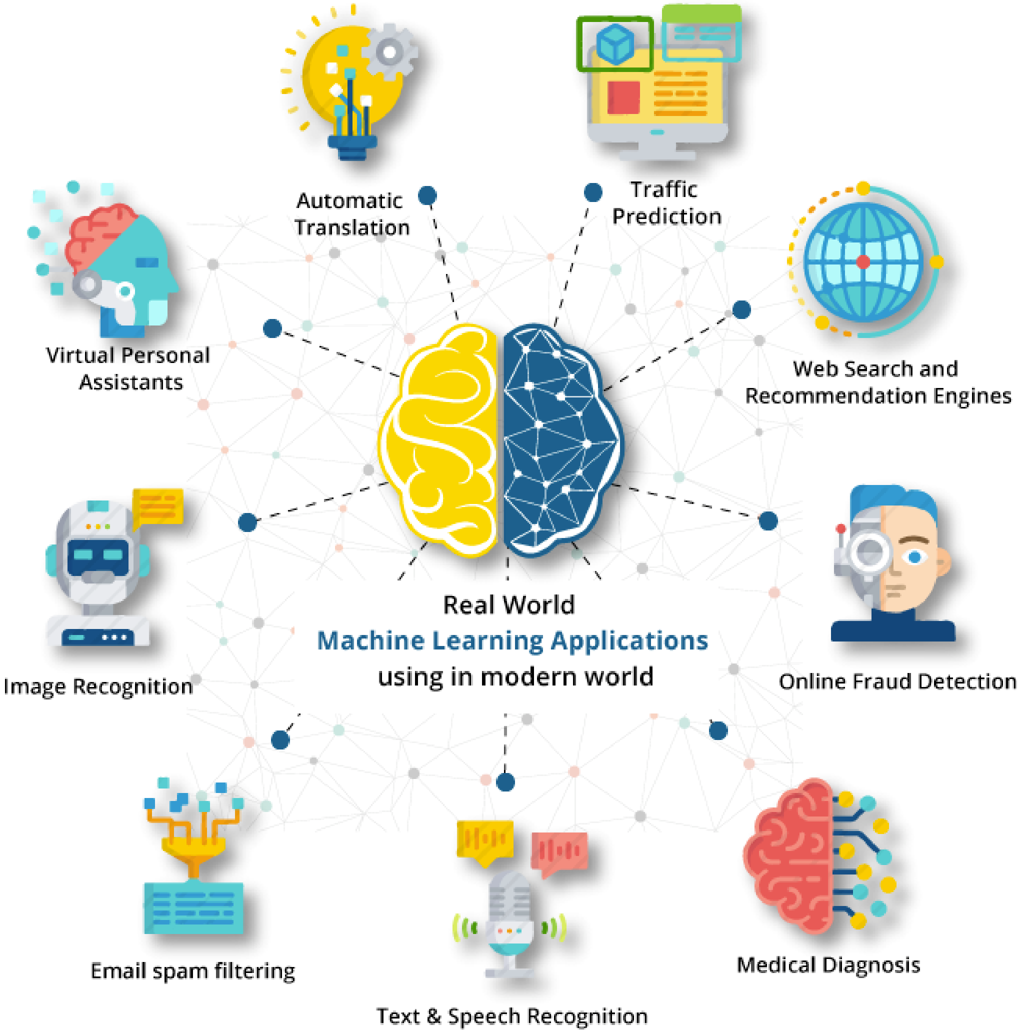


Figure 2.9. Machine Learning Applications in the Modern World

3. LITERATURE REVIEW

This chapter presents scientific studies on coffee roasting machines, categorized according to the type of research conducted. Additionally, studies related to IoT and ML in the field of coffee are also presented.

3.1. Studies Related with Coffee Roaster Design

This section reviews previous studies on coffee roaster design, highlighting the technological advancements, engineering approaches, and design principles used to improve roasting efficiency, and coffee quality. The section is divided into three subheadings: studies unrelated to IoT and ML, IoT-related studies, and ML-related studies. It's observed that most of the studies focused on the design and development of small-scale coffee roasting machines.

3.1.1. None IoT and None ML Related Studies

This section reviews studies on designing coffee roasting machines that do not incorporate IoT or ML technologies. The primary goal of these studies is to examine the features, benefits, and limitations of traditional coffee roasting machines that operate without the need for advanced digital technologies.

Cristo and his colleagues (2006) [17] conducted a study focused on the design of a cylindrical drum and the movement of coffee beans within it. They tested changes in movement by varying key parameters, such as angular velocity, drum radius, and gravitational force, using the Froude number formula. Their objective was to analyze how the drum's physical structure and rotational speed affect the performance of the roasting machine. Additionally, they investigated the relationship between heat transfer within the drum and the drum's speed. Through experimental results, they demonstrated that the movement of coffee beans and effective heat transfer significantly influence the overall roasting process.

Hadzichan and his colleagues (2013) [18] designed and built a solar-powered coffee roaster using an open-source Scheffler solar reflector to concentrate sunlight onto a roasting drum. They developed a 25 cm diameter rotating drum to ensure proper mixing of the coffee beans, achieving uniform roasting. The drum was made of stainless steel, chosen specifically for its food-safe properties. The team tested the roaster by successfully roasting 1 kg of coffee in 24 minutes. For cooling, they used a vacuum cleaner to cool the roasted beans efficiently. Additionally, they shared insights and experiences gained during the design process of the coffee roaster.

Hsu and Lo (2014) [19] developed an innovative coffee roaster based on a gas-fueled roasting method. To enhance energy efficiency, they utilized premixed fuel and direct-fired baking technologies, allowing the premixed flame to directly contact the coffee beans inside a vertically rotating drum. They also integrated a touch screen controller with a machine interface for managing roasting modes and procedures. The design included a specialized roasting chamber equipped with a thermocouple to monitor and control the chamber's temperature. Their design proved to be eco-friendly, improved energy efficiency, minimized smoke emissions, and ensured a consistent roasting quality.

Purwantana and his colleagues (2018) [20] designed a coffee roaster machine specifically for home-based industries, with a roasting capacity of up to 2 kg. They tested the machine at a temperature of 225°C, experimenting with different roast levels: light, medium, and dark. Various parameters, including energy consumption, roasting time, moisture content, roasted bean color (Lab* values), bean density, and the percentage of grain cracking, were measured and compared across the three roast levels. The machine used LPG as its heat source, and all tests were successfully completed.

Xu and his colleagues (2018) [21] developed a smart home coffee roaster design that integrates monitoring of key parameters, such as bean temperature, bean cracks, and carbon monoxide levels, while offering the operator full remote control. The design prioritizes operator safety by protecting them from health risks, such as headaches, dizziness, or lung issues, which can arise from prolonged exposure to harmful gases during roasting. Inspired by the Behmor 1600 coffee roaster model, their system successfully monitored the first and second cracks, roasting profiles, and carbon monoxide levels. The study concluded that remote roasting reduces the side effects of the coffee roasting process while ensuring successful and safe coffee roasting.

Nasution and his colleagues (2018) [22] developed an automatic coffee roasting machine capable of producing various roast levels with control via a smartphone. The system, built using an Arduino Uno microcontroller, operates through an Android smartphone application using Bluetooth connectivity. A thermocouple was used to monitor temperature, and Android Studio was employed for software development. The team observed and shared insights on how roasting duration affects the aroma and color of the beans, with longer roasting times leading to sharper aromas and darker bean colors. They provided practical guidance on adjusting the roasting duration and shared their experiences with optimizing the roasting process.

Ogunjiri and his colleagues (2019) [23] designed and built an electrically powered coffee roasting machine. Their work focused on constructing the machine by designing and dimensioning its key components. They analyzed and shared temperature variations based on different heat power settings. The team conducted successful roasting tests and contributed their findings to the literature. The developed machine had a capacity of 25 kg, and during testing, they roasted 10 kg of green coffee in 20 minutes.

Daywin and his colleagues (2020) [24] designed a coffee roasting machine with a capacity of approximately 500 grams. Their design process involved reverse engineering and the application of engineering design methods. The machine's design was inspired by the SCR-300 model roaster, and they detailed the arrangement and dimensions of its components. They conducted roasting tests and shared the results, highlighting the relationship between roasting time and temperature.

Fachruddin and his colleagues (2021) [25] investigated the effect of heat transfer within a horizontal cylindrical drum. They used SolidWorks Flow Simulation software to model heat transfer within the drum, while actual temperature measurements, taken with a thermocouple, were simulated using Surfer software. Their study demonstrated the distribution of heat across the lower, middle, and upper sections of the drum. During the trials, key parameters such as the weight of green coffee beans, roasting temperature, and bulk density were monitored, showing consistent changes throughout the process. Roasting trials with 5 kg of beans were conducted, and the corresponding roasting durations were recorded. The results revealed that the degree of bean darkening was directly related to the roasting duration.

Wibowo and his colleagues (2022) [26] provided a review of smart coffee roaster systems, focusing on electronics, design, and artificial intelligence (AI). It explored the components of a smart coffee roaster, including sensors (temperature, sound, gas), controllers (Arduino, ESP32), and actuators (motors for drum rotation and cooling systems). The study highlighted the role of AI in detecting roasting maturity levels, such as identifying the crack sound during roasting. Additionally, it compared manual and automatic roasting systems, emphasizing how AI and IoT technologies enhance consistency, accuracy, and automation in coffee roasting. The review aimed to help researchers and industry professionals understand key specifications for developing an efficient smart coffee roaster.

Agustian and his colleagues (2022) [27] designed an automatic coffee bean roaster based on the Arduino Uno microcontroller to enhance roasting consistency. The system integrated temperature sensors to monitor and control the roasting process, ensuring optimal conditions for different roast levels. A PID (Proportional-Integral-Derivative) control system was implemented to regulate the temperature dynamically, reducing fluctuations. The system automated the roasting process by adjusting fan speed and heating elements based on real-time sensor data. The results demonstrated that the automated roaster provides more consistent and precise roasting levels compared to manual methods

Bonilla (2024) [28] developed a prototype for an automated home-use coffee roaster. The study focused on key aspects such as maximizing automation, optimizing energy efficiency and production costs, designing a user-friendly interface, ensuring efficient dimensions and weight, and achieving predictable coffee roasting results. The research adopted a mixed-method approach, quantitatively analyzing independent variables such as temperature, relative humidity, revolutions per minute, timer settings, and the gas opening angle. A control program was developed to manage the roasting process through an HMI (Human-Machine Interface) screen. The prototype was constructed by integrating its various sections, including electrical, mechanical, structural, and software systems.

3.1.2. IoT Related Studies

In this section, studies on the use of IoT technologies in coffee roasting machines are reviewed. As far as it has been determined, no English or Turkish studies on the design of an IoT-based coffee roasting machine have been found in the literature. Only two studies written in Indonesian were identified [29, 30].

Pratama and his colleagues (2022) [29] designed and implemented a smart coffee roasting machine based on ESP32 microcontroller. The system automatically controlled temperature and roasting time using a K-type thermocouple sensor (MAX6675) and a gas heating system with solenoid valves. The roasting process could be monitored and controlled wirelessly through a web-based interface accessible via smartphone or laptop over a local WLAN connection. The system allowed users to select the desired roasting level (light, medium, dark) and automatically adjusted heating cycles based on sensor readings. The study claims to use IoT technology in the smart coffee roasting system. However, its IoT implementation is quite limited in scope, as it only supports local operation and lacks cloud integration.

Oematan and his colleagues (2024) [30] developed a portable ESP32 microcontroller based electronic system to monitor and control the roasting process in a semi-automatic manner. The system integrated a K-type thermocouple sensor (MAX6675) for temperature measurement and a push button to set the roasting time. The roasting process could be controlled and monitored via a smartphone application (Blynk). The study claims to use IoT technology in the smart coffee roasting system; however, while details about the IoT section were provided, there was no figure or sufficient section describing the system's use in coffee roasting tests.

3.1.3. Machine Learning Related Studies

In this section, studies on the application of ML technologies in coffee roasting machines are reviewed. These studies investigate how machine learning algorithms are applied to optimize roasting parameters, enhance operational efficiency, and improve the overall quality of roasted coffee.

Winjaya and his colleagues (2017) [31] developed a coffee roasting system that identifies crack sounds to optimize the roasting process. They used an oven-shaped roaster equipped with an IC MAX 6675 module and a K-type thermocouple to monitor temperature, which was regulated through a PID controller integrated into the microcontroller system. Key components of the setup included a microphone, heater, heating driver, temperature sensor, and DC motor. The Arduino UNO acted as the main controller, processing sensor data and controlling the temperature accordingly. For sound recording, they utilized a Soundcrest EM 610 condenser microphone. To identify the crack sounds of the coffee beans, they applied a Neural Network algorithm. The system was designed to measure and analyze these sounds, enabling precise temperature adjustments and ensuring optimal roasting quality.

Fauziyah and her colleagues (2018) [32] developed a temperature control system for a coffee roaster using a fuzzy logic algorithm. Recognizing the critical role of temperature control in achieving optimal roasting, they designed a fuzzy logic-based algorithm to regulate the process. A block diagram of the coffee roaster system was presented, and a PT100 sensor was used to measure the temperature due to its high stability and accuracy. The system employed a servo motor, whose position was adjusted using PID control to maintain the desired temperature. MATLAB was used for simulation and control system implementation. The experimental results demonstrated high precision, with a minimal error rate of only 0.52%.

Samodro and his colleagues (2019) [33] developed a coffee roasting machine with temperature control based on fuzzy logic algorithms. A thermal camera was installed inside the drum to monitor the coffee beans during roasting and detect any uneven roasting. The system utilized an ATMega 32 microcontroller with embedded fuzzy logic, which controlled the speed of the drum motor and the fuel valve to achieve the desired roast level. The fuzzy logic system ensured precise adjustments based on real-time conditions to maintain consistency and quality. This coffee roaster was specifically designed for farmers and medium-scale coffee industries, providing a practical and efficient solution for roasting coffee beans.

3.2. IoT and ML Studies Related with Coffee Field

This section explores the expanding research on the integration of IoT and machine learning in the coffee industry. IoT facilitates continuous data collection throughout coffee production using sensors and connected devices, while machine learning processes this data to offer advanced tools for optimizing processes, improving quality, and performing predictive analysis.

3.2.1. IoT Related Studies on Coffee Field

For this section, only one study was found from the literature. This study focused on transferring parameters related to the characteristic properties of coffee during the washing stage to the cloud, enabling remote monitoring and data analysis.

Rutayisire and his colleagues (2017) [34] developed a system to assess the quality of green coffee beans and transmit the collected data using IoT technology. The system utilized moisture, pH, humidity, and temperature sensors to monitor the beans throughout the process. Their goal was to help the coffee market in Rwanda prevent fraud and ensure quality standards. The system monitored coffee cherries during both the washing and drying stages, with the pH levels showing distinct variations across different phases. They employed WROOM 02 and Node MCU 8266 microcontrollers, integrated with a Wi-Fi module, to transmit the collected data to a nearby access point and upload it to the cloud platform Ubidots for analysis and monitoring.

Terano and his colleagues (2019) [35] analyzed users' lifestyles through the IoT-based coffee roasting service, "The Roast." By comparing IoT device usage data with survey results, the study identified differences in lifestyle trends between subscribed and non-subscribed users. It was observed that coffee roasting habits vary based on users' lifestyles, and differences were found between those who continued the service and those who quit. The study introduced a service continuity index and suggested strategies to enhance service retention based on lifestyle analysis.

Rodriguez and his colleagues (2021) [36] presented IoT-Agro, a smart farming system designed for Colombian coffee farms. The system is based on a three-layer architecture: Agriculture Perception, Edge Computing, and Data Analytics. In the Agriculture Perception Layer, different IoT technologies (Omicron, Libelium, and Intel) were evaluated based on criteria like price, sensor connectivity, and communication protocols. The Edge Layer focuses on outlier detection and data reliability using Machine Learning algorithms, with Isolation Forest performing best for detecting anomalies. The Data Analytics Layer uses AI algorithms to estimate coffee production, with XGBoost achieving the lowest error rates. The system was validated through a Colombian coffee farm case study, demonstrating its usability and effectiveness in providing weather monitoring, coffee production estimation, and IoT infrastructure management.

Sujiwa and Santoso (2022) [37] developed an IoT-based automatic coffee maker to improve the efficiency and cleanliness of coffee preparation. By integrating an ESP8266 microcontroller, they enabled remote control of the coffee-making process. Their system managed different components, including DC stirring motors, to dispense coffee, milk, and sugar for various beverages, such as non-sugar coffee, sweet coffee, milk, and milk coffee. The testing revealed that the system performed well, with an overall error rate of less than 4% when preparing different drinks. Their design demonstrated how IoT can enhance both efficiency and hygiene in coffee preparation processes.

Imammuddin and his colleagues (2023) [38] proposed an IoT-based coffee grinding system using fuzzy logic to determine the roasting maturity level. Traditional methods rely on manual expertise, whereas this system utilizes capacitive sensors and color sensors to classify coffee beans into light, medium, and dark roast levels. The capacitance value, influenced by the moisture content of the beans, is combined with color intensity readings to determine roasting levels more accurately. The fuzzy logic system processes the data and sends it to an Android application via Arduino with Wi-Fi and Firebase. The system was tested 10 times, achieving 100% accuracy, demonstrating its potential for automating coffee classification and grinding

Syamsiana and his colleagues (2024) [39] implemented an IoT-based monitoring system for coffee bean drying equipment to improve efficiency and quality. The system measured temperature (0°C - 70°C) using DHT22 sensors and electrical energy consumption (kWh) using PZEM-004T, with real-time data displayed on the ThingSpeak dashboard. The temperature monitoring system showed an average error of 2.1%, while the energy monitoring system had a 0% error rate. The study compared manual (on/off) control and fuzzy logic control, demonstrating that fuzzy logic improved temperature stability and reduced operational costs by 11.2%. The system enabled remote monitoring, providing coffee farmers with an efficient drying process.

Minoli and his colleagues (2024) [40] introduced an IoT-based technology for monitoring and analyzing the coffee drying process of small farmers. The system collected real-time data on grain moisture, air temperature, and humidity using a portable set of sensors, enabling farmers to make informed decisions. A three-phase methodology was used: designing the IoT framework, developing the software for data transmission and visualization, and conducting a case study with a female coffee farmer association in Génova, Quindío, Colombia. The results showed that this system helped visualize drying trends and patterns, allowing farmers to optimize drying conditions and improve coffee quality. The study highlighted the impact of IoT in agriculture, enhancing efficiency and sustainability for smallholder farmers.

Sagita and his colleagues (2024) [41] developed a low-cost IoT-based multichannel spectral acquisition system for evaluating roasted coffee beans. The system used an 18-channel spectral sensor (AS7265X) covering a 410–940 nm wavelength range and costs around $114 USD, making it accessible for small and medium-scale coffee enterprises. It classified the degree of roasting (very light, light, medium, dark) using machine learning models, with Random Forest (RF) achieving the best performance (validation accuracy of 98.8%). The system offered a real-time, non-invasive, and objective method for coffee roasting evaluation, potentially improving quality control and automation in coffee production.

3.2.2. Machine Learning Related Studies on Coffee Field

This section reviews studies on the application of machine learning technologies for coffee field. It was found that the studies are related to coffee bean processing. The studies focus on utilizing machine learning algorithms for tasks such as predicting coffee bean quality, optimizing roasting processes, and classifying coffee beans.

Faridah and her colleagues (2011) [42] developed a system for assessing the grade of coffee beans, recognizing the critical role of green coffee quality in production. They created a color detection program to evaluate the beans and presented a block diagram in the study, showing the use of light sources and a digital camera to identify key features of beans. By applying image processing techniques, they monitored differences in size, shape, color, defects, and other quality indicators. The system tested various camera and light source angles to identify the optimal setup, demonstrating the impact of positioning on detection accuracy. Using robusta coffee beans as samples, they successfully determined the coffee grades, showcasing the system's effectiveness.

Turi and his colleagues (2013) [43] developed a computer algorithm for analyzing and categorizing coffee beans using image processing techniques. Their system automatically classified four different types of green coffee beans found in Ethiopia. An artificial neural network (ANN) was employed to perform the classification based on key features, including color, morphology, texture, and a combination of color and morphology. The study demonstrated that Ethiopian coffees grown in different regions could be effectively classified according to their botanical origins using image analysis. The results highlighted that imaging techniques are among the most effective methods for assessing coffee bean quality, particularly for export purposes.

Nasution and his colleague (2017) [44] developed a method for recognizing the roast levels of coffee beans by processing digital images. As an initial step, they trained and tested the images, followed by scaling them for consistency. Using the Gray-Level Co-Occurrence Matrix (GLCM) method, they extracted key features from the images. These features were then normalized using a decimal scale and classified. The backpropagation method was applied to identify the different roast levels of the coffee beans. The system successfully categorized the beans into six levels: green, begins to pale, early yellow, yellow-tan, light brown, and brown. Their study demonstrated that backpropagation neural networks are effective for accurately classifying coffee bean roast levels.

Arboleda and his colleagues (2018) [45] developed an alternative method for identifying coffee beans from various regions around the world. The study focused on distinguishing between different coffee species, including Robusta, Excelsa, and Liberica. A Sony camera was used to capture images of coffee beans, which were then processed using a computer and analyzed in MATLAB. The beans were categorized based on their shapes, and the classification phase was carried out using a Neural Network. The network structure consisted of four layers: an input layer, a first hidden layer, a second hidden layer, and an output layer. Additionally, the nearest neighbor method was applied, and the classification results for each coffee species were presented separately, demonstrating the effectiveness of the approach.

Akbar and his colleagues (2020) [46] applied machine learning techniques to identify and classify green coffee beans. They categorized the beans into five grades: specialty, premium, exchange, below grade, and off grade, using Arabica coffee as the sample. A mini studio was set up for capturing images, where a camera took photos of the beans under controlled conditions. Given the large variety of coffee beans globally, they demonstrated that machine learning and visual feature selection could significantly speed up the classification process. The study utilized both the random forest classifier and the K-nearest neighbors (KNN) classifier. The results showed promising accuracy, with test values reaching around 88%.

Okamura and his colleagues (2021) [47] analyzed the coffee roasting curve by collecting data from roasted coffee beans and associating it with the roasting curve using machine learning techniques. They first explained the key phases of the coffee roasting process: the drying phase, Maillard phase, and development phase. They also introduced basic roasting terms, including roasting time, end temperature, and input temperature. Neural Network, Support Vector Machine (SVM), and Random Forest methods were employed to identify and analyze the data. The results were compared across different stages, including before grinding, after grinding, and based on color differences, providing valuable insights into how these factors impact the overall roasting process.

Simbro and his colleagues (2022) [48] developed a system based on deep learning models to automatically identify the tariff code of coffee for import and export by analyzing digital images in real time. The system generates a detailed report for customs brokers, streamlining the classification process. They tested the system using four different coffee types: Arabica, Excelsa, Liberica, and Robusta, categorizing the coffee into three types for tariff purposes. The results indicated that Robusta was the easiest to classify accurately. Users can upload coffee images through the system, and the corresponding tariff report is automatically generated. As a final step, a web page was created, and the models were successfully integrated for user access and functionality.

4. MATERIALS AND METHODS

In this chapter, the materials used and the methodology employed are explained. As the study focuses on two different topics, this chapter is divided into two sections to address each topic separately.

4.1. Materials and Methods for IoT Study

4.1.1. Materials for IoT Study

The hardware materials used in this study include the Arduino MKR Wi-Fi 1010, K-type thermocouple, DHT11 sensor, cooling fan, single-channel relay module, and heat gun. The software materials consist of the Arduino Cloud and Arduino IDE. A brief explanation of each material is provided below.

4.1.1.1. Arduino MKR Wi-Fi 1010

The Arduino MKR Wi-Fi 1010 is a compact and powerful microcontroller board designed for IoT applications, offering built-in Wi-Fi and Bluetooth connectivity. It is powered by the SAMD21 Cortex-M0+ 32-bit low-power ARM MCU and features the u-blox NINA-W102 module for wireless communication. The board operates at 3.3V logic level and includes 256KB of Flash memory and 32KB of SRAM, making it suitable for real-time applications. With 8 digital I/O pins, 7 PWM outputs, analog inputs, and support for secure communication using the ECC508 crypto chip, it provides a robust solution for connected projects. Figure 4.1 illustrates the physical appearance of the Arduino MKR Wi-Fi 1010 [49].

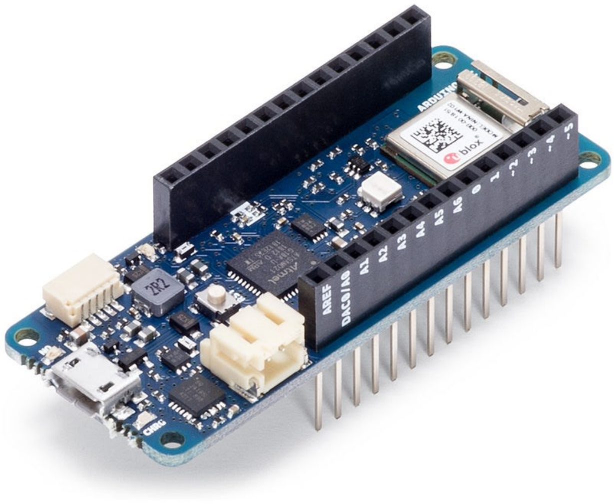


Figure 4.1. Arduino MKR Wi-Fi 1010

4.1.1.2. K-Type Thermocouple

A thermocouple is a temperature measurement device that works based on the Seebeck effect, which is a fundamental principle of thermoelectricity. It consists of two dissimilar metal wires joined at one end, creating a junction where a voltage is generated. This voltage is proportional to the temperature difference between the junction and a reference point, allowing accurate temperature measurement. Thermocouples are widely used due to their simplicity, durability, and cost-effectiveness, making them ideal for a range of industrial and scientific applications [50]. Figure 4.2 shows the K thermocouple [51] used in the IoT study.

Figure 4.2. K-Type Thermocouple

K-type thermocouples are commonly used in coffee roasting machines due to their numerous advantages. The reasons for their preference in coffee roasting machines are as follows:

- Wide Temperature Range: Capable of measuring a broad range of temperatures, typically from -200°C to 1,260°C, making them suitable for the high-temperature requirements of coffee roasting.
- Durability and Reliability: Resistant to wear, oxidation, and corrosion, ensuring reliable performance in the high-heat and demanding environment of a coffee roaster.

- Cost-Effectiveness: Affordable and readily available, providing an economic option without compromising performance.
- Accuracy and Stability: Offers consistent and precise temperature measurements, crucial for achieving optimal roasting profiles.
- Rapid Response Time: Quickly detects temperature changes, allowing for immediate adjustments and better control of the roasting process.
- Compatibility with Roasting Equipment: Easily integrates with various roasting machines and control systems, making them highly adaptable to different setups.

4.1.1.3. DHT11 Humidity and Temperature Sensor

The DHT11 sensor is a basic, low-cost digital sensor designed to measure both temperature and humidity. Known for its simplicity, low power consumption, and affordability, it is commonly used in various applications, including environmental monitoring, home automation, and IoT projects [52]. Figure 4.3 displays the physical appearance of the DHT11 sensor and its connection pins.

The key features of the DHT11 sensor include a temperature range of 0°C to 50°C with an accuracy of ±2°C, a humidity range of 20% to 90% RH with an accuracy of ±5% RH, single-wire digital interface communication, a power supply range of 3.3V to 5.5V, and a sampling rate of 1 reading per second (1 Hz) [53].

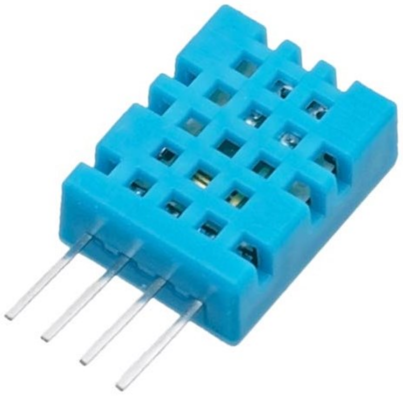


Figure 4.3. DHT11 Sensor

4.1.1.4. Cooling Fan

A 220V AC fan shown in Figure 4.4 [54] was used to cool down the roasted coffee beans. The 220V fan was selected for its compatibility with standard mains voltage, eliminating the need for an additional power converter. This fan plays a crucial role in rapidly reducing the temperature of the roasted beans to preserve their flavor and quality.

Figure 4.4. 220V AC Cooling Fan

4.1.1.5. Single-Channel Relay Module

A single-channel relay is an electronic component that functions as a switch, activated by a low-power control signal, such as one from an Arduino microcontroller. When integrated with an Arduino board, the relay module enables remote control of high-power devices, including lights, motors, or appliances, through a computer or mobile device [55]. Figure 4.5 shows the physical appearance of the relay module along with its connection pins [56].

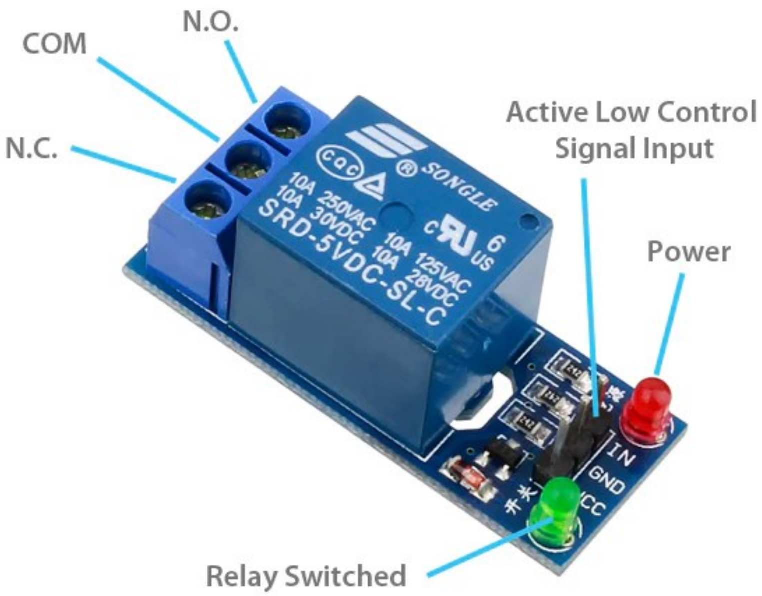


Figure 4.5. Single-Channel Relay Module

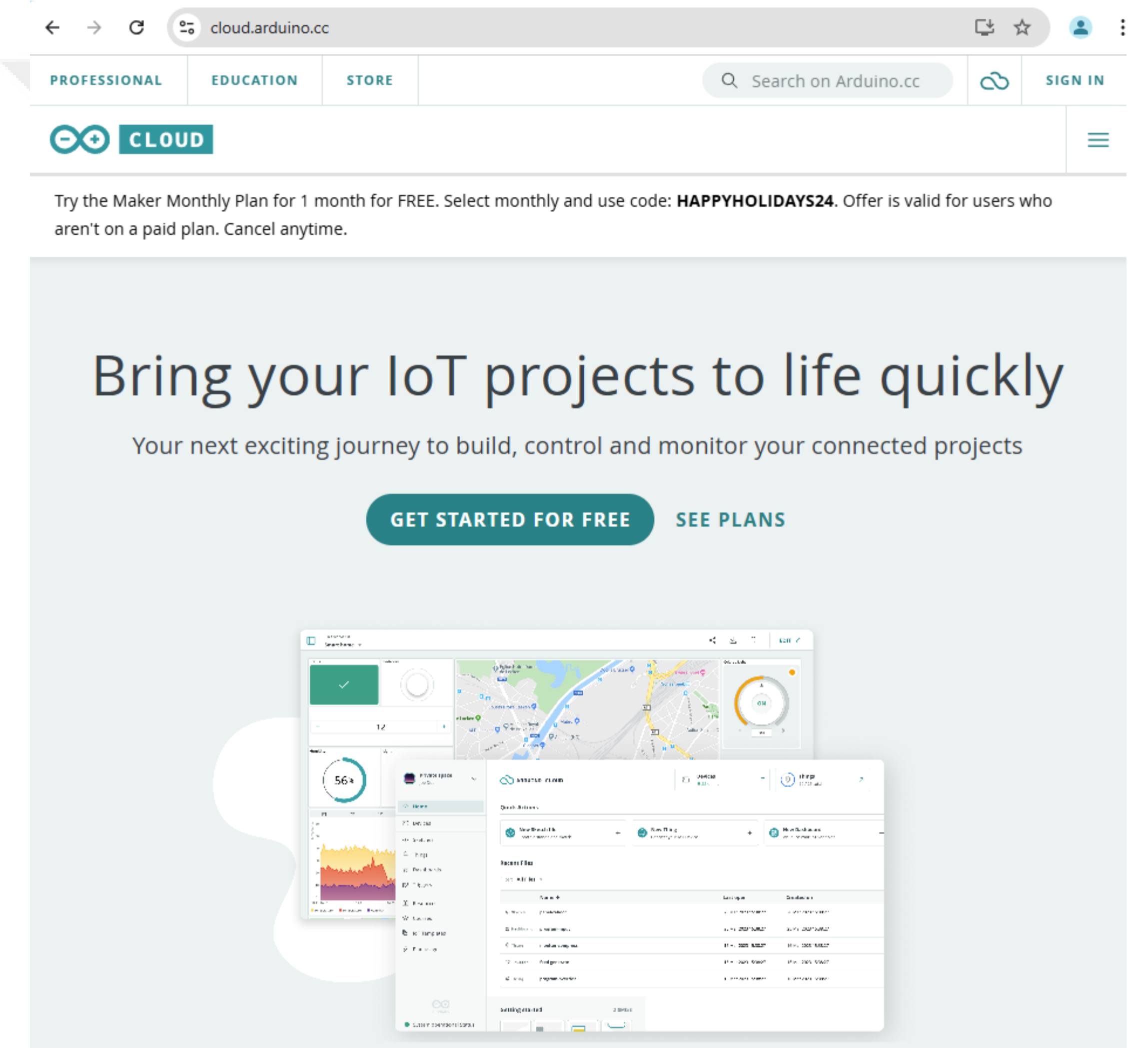
4.1.1.6. Heat Gun

Heat guns are portable electric devices designed to blow hot air at adjustable temperatures, making them useful for a wide range of applications, including surface treatment, drying, shaping materials, paint stripping, soldering, and welding. They operate by heating air using an electrically powered heating element and directing the hot air through a nozzle. Both the temperature and airflow can be adjusted, providing versatility and precision for various tasks. Figure 4.6 shows the heat gun used to heat the coffee beans in the IoT-based study [57].

Figure 4.6. Heat Gun

4.1.1.7. Arduino Cloud

Arduino Cloud is an online platform designed to streamline the development, deployment, and monitoring of IoT projects. It provides secure connectivity with Arduino boards using various communication methods, including Wi-Fi, LoRaWAN, Ethernet, and Cellular networks [58]. Figure 4.7 shows the main page of Arduino Cloud. The platform offers an Integrated Development Environment (IDE) for programming, a backend service for synchronizing data from Arduino boards, a graphical dashboard for real-time monitoring and control, and additional tools such as REST APIs and a command-line interface for automating tasks on a larger scale.



Try the Maker Monthly Plan for 1 month for FREE. Select monthly and use code: **HAPPYHOLIDAYS24**. Offer is valid for users who aren't on a paid plan. Cancel anytime.

Bring your IoT projects to life quickly

Your next exciting journey to build, control and monitor your connected projects

Figure 4.7. Arduino Cloud Main Page

4.1.1.8. Arduino IDE

The Arduino Integrated Development Environment (IDE) is a user-friendly platform that includes a text editor for writing code, a message area for displaying errors and feedback, a text console for monitoring outputs, and a toolbar with quick-access buttons for common tasks. It also features various menus for managing sketches and tools. The IDE allows users to upload programs to Arduino hardware and establish communication with connected devices [59].

Figure 4.8 illustrates the Arduino IDE interface, highlighting its key components and labels [60].

```
/*
  AnalogReadSerial

  Reads an analog input on pin 0, prints the result to the Serial Monitor.
  Graphical representation is available using Serial Plotter (Tools > Serial Plotter menu).
                 in of a potentiometer to pin A0, and the outside pins to +5V and ground.

  This example code is in the public domain.

  https://www.arduino.cc/en/Tutorial/BuiltInExamples/AnalogReadSerial
*/

// the setup routine runs once when you press reset:
void setup() {
  // initialize serial communication at 9600 bits per second:
  Serial.begin(9600);
}

// the loop routine runs over and over again forever:
void loop() {
  // read the input on analog pin 0:
  int sensorValue = analogRead(A0);
  // print out the value you read:
  Serial.println(sensorValue);
```

Figure 4.8. Arduino IDE

4.1.2. Methods for IoT Study

The implementation of the Internet of Things-based coffee roaster machine proposed in this study involves eight distinct steps. Each step is designed to ensure efficient and accurate operation of the system. Figure 4.9 illustrates the steps of the proposed system, providing a visual representation of the process flow.

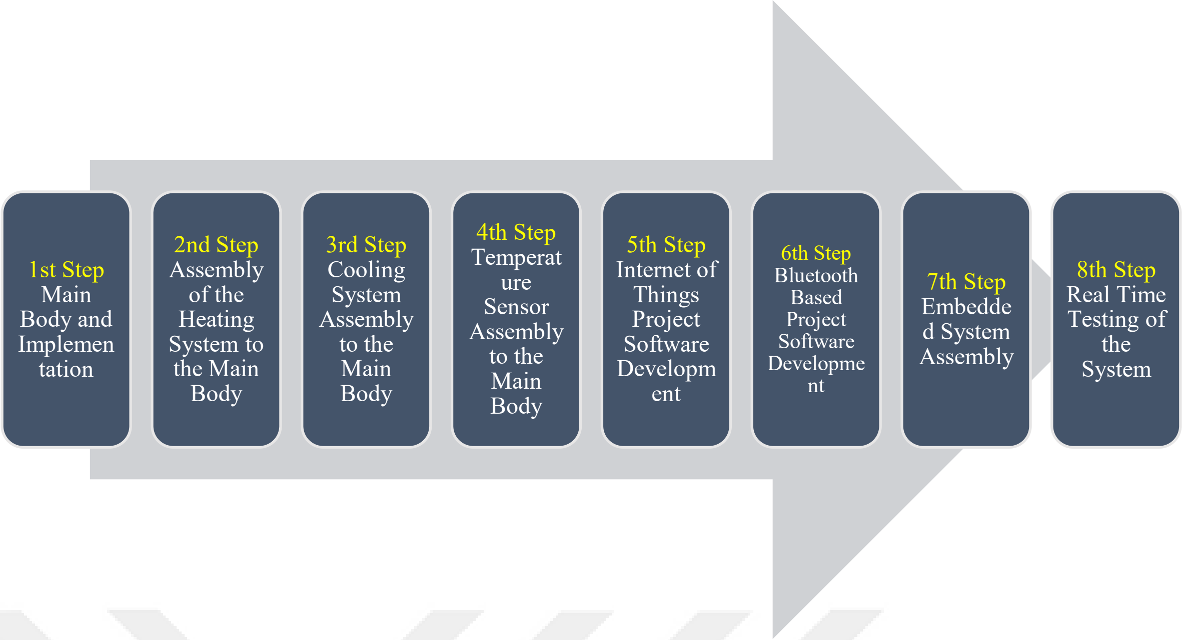


Figure 4.9. Steps of the Proposed IoT System Development

(1) The first step involves the design and construction of the main body of the coffee roaster machine. The structure will be built using heat-resistant chrome to ensure long-term durability and suitability for food-grade applications. For example, the design will feature a cylindrical structure. The main body will consist of a roasting chamber where the coffee beans are roasted and a heat source compartment below it.

A perforated chrome sheet will be placed at the bottom of the roasting chamber to facilitate efficient heat transfer. Chrome is chosen for this component due to its rust resistance and food-safe properties. An opening will be incorporated into this section to allow easy removal of the roasted coffee beans. An exhaust outlet will be designed with an outward-facing partition to prevent chaff from re-entering the chamber during roasting. Additionally, a perforated lid made of chrome will be used to cover the top of the chamber.

To provide structural stability, a rectangular support structure will be created beneath the roasting area, ensuring that the chamber remains securely in place.

(2) The second step involves installing the heating system into the main body of the coffee roaster. A hot air gun is used as the primary heat source. The placement and design of the hot air inlet are critical to achieving efficient and high-quality roasting. To ensure uniform heating of all the coffee beans, the heating system is positioned at the bottom of the main body. This design keeps the beans suspended in the air and in continuous motion, promoting even heat distribution and consistent roasting. One significant advantage of this setup is the reduced risk of scorching or over-roasting the beans. For maximum efficiency, the hot air inlet is sealed, with an opening only at the designated point where the hot air enters the system. This optimized airflow design ensures that the beans are roasted evenly and homogeneously, while also minimizing energy consumption and improving overall roasting performance.

(3) The third step involves the installation of the cooling pan and fan system on the main body of the coffee roaster. Once the beans reach the desired roast level, they must be quickly cooled to halt the roasting process at the precise moment. Rapid cooling is essential to stop chemical reactions, such as the Maillard reaction and caramelization, which occur during roasting. If cooling is delayed, these reactions may continue, leading to overdevelopment of the beans, resulting in undesirable flavors and increased bitterness.

The cooling tray is made of chrome material, chosen for its durability, food safety, and resistance to rust. It features a perforated design to allow airflow and efficient cooling. The tray is positioned at the outlet of the roasting area, with a cooling fan installed underneath. This setup ensures effective heat dissipation, preserving the desired roast profile and maintaining the beans’ optimal flavor and aroma.

(4) In the fourth step, the K-type thermocouple sensor will be installed to measure the core temperature during the coffee roasting process. The K-type thermocouple is ideal for this application due to its fast response time, making it suitable for the dynamic environment of coffee roasting. It provides reliable and accurate temperature readings, which are crucial for maintaining consistency and ensuring the quality of the roasted beans.

The placement of the thermocouples is essential for precise temperature monitoring. The bean thermocouple will be positioned just above the perforated chrome sheet inside the roasting chamber, where it can accurately measure the temperature as the coffee beans move around. The exhaust thermocouple will be installed in the airflow direction on the upper part of the main body, allowing it to monitor the exhaust air temperature and provide insight into the heat transfer within the roasting chamber.

To read the temperature data from the K-type thermocouple, the MAX6675 module will be used. This module performs cold-junction compensation and digitizes the thermocouple’s signal, ensuring accurate temperature readings.

Additionally, to measure the ambient temperature in the roasting environment, a DHT11 temperature sensor will be installed, further enhancing the control and monitoring of the roasting process.

(5) The fifth step involves transferring sensor data and controlling the system through the Arduino Cloud platform using the Arduino MKR Wi-Fi 1010 board. The platform will allow real-time monitoring and control of key operations, ensuring an efficient and automated roasting process.

The system will control and monitor the following operations:

Power On/Off Function: The overall system’s power will be turned on or off remotely via the cloud interface.

Cooling Fan System: The cooling fan will be controlled to enable swift and efficient cooling of the roasted beans.

Temperature Monitoring and Roasting Control: Temperature readings from the K-type thermocouple will be used to regulate the roasting process and maintain optimal conditions.

Hot Air Control: The hot air system will be monitored and adjusted to prevent overheating or other unwanted conditions during roasting.

To achieve this, variables, devices, and network configurations will be defined on the Arduino IoT Cloud platform. A user-friendly interface will be created on the dashboard using appropriate widgets to enable easy control and monitoring. The program for sending and saving data to the cloud will be developed using the Arduino IDE and uploaded to the Arduino MKR Wi-Fi 1010 board, ensuring seamless integration of hardware and software.

(6) In the sixth step, a mobile application for the Android operating system will be developed to enable mobile control and monitoring of the coffee roasting system through Bluetooth connectivity. The mobile app will facilitate real-time tracking of the roasting process, allowing users to monitor key parameters such as temperature, in real-time directly from their smartphones. This feature will enhance the user experience by providing convenient, remote control and data flow tracking of the system.

(7) The seventh step involves assembling the embedded system by connecting all the hardware components. This includes establishing the necessary electrical connections for the Arduino MKR Wi-Fi 1010 board, K-type thermocouple sensor, cooling system, relays, DHT11 sensor, and the system on/off button. The integration of these components ensures proper communication and functionality, enabling real-time monitoring and control of the coffee roasting process.

Figure 4.10 illustrates the circuit design, created using Fritzing, to provide a visual representation of the wiring and connections in the system.

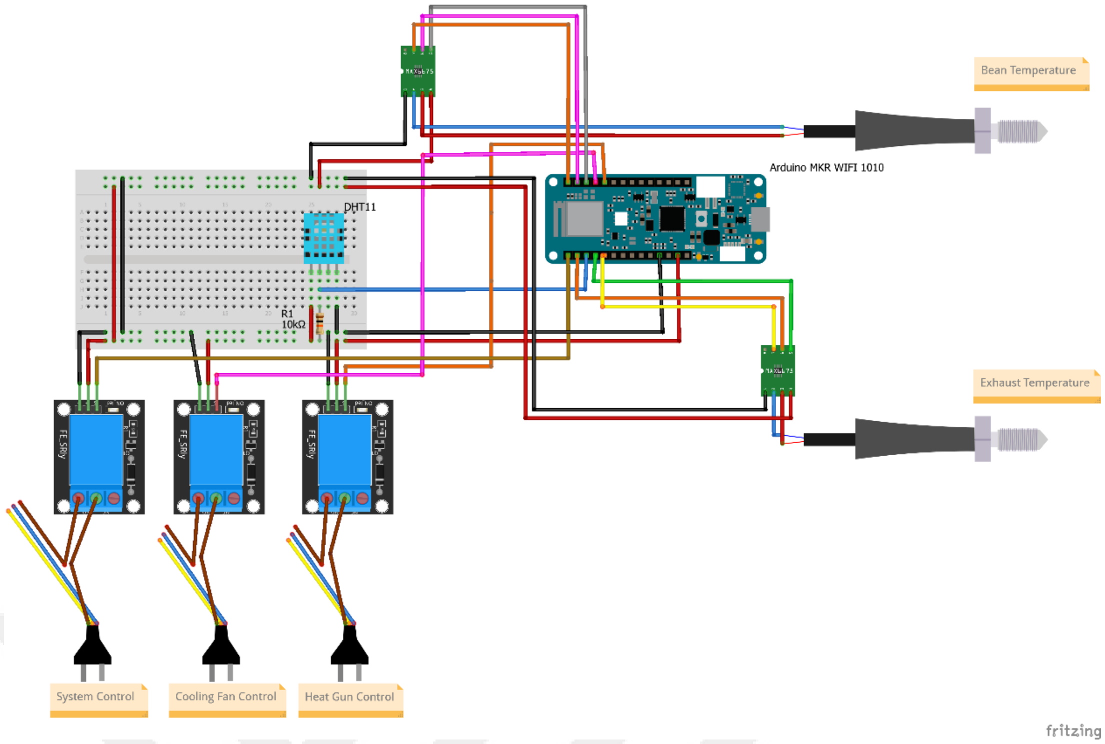


Figure 4.10. Circuit Design Drawn in Fritzing

(8) In the final step, real-time testing of the Internet of Things-based coffee roaster machine will be conducted to evaluate its performance and functionality. During the roasting process of green coffee beans, the system will continuously generate and transfer data to the Arduino Cloud platform and mobile phone. The data flow will include key parameters such as temperature.

Additionally, the reliability and effectiveness of the internet-connected cloud platform and the Bluetooth-connected mobile platform will be tested for remote control and monitoring. This step ensures that the system operates as intended, providing seamless data flow and control. Figure 4.11 presents the flowchart of the IoT-based study, outlining the overall process and interactions within the system.

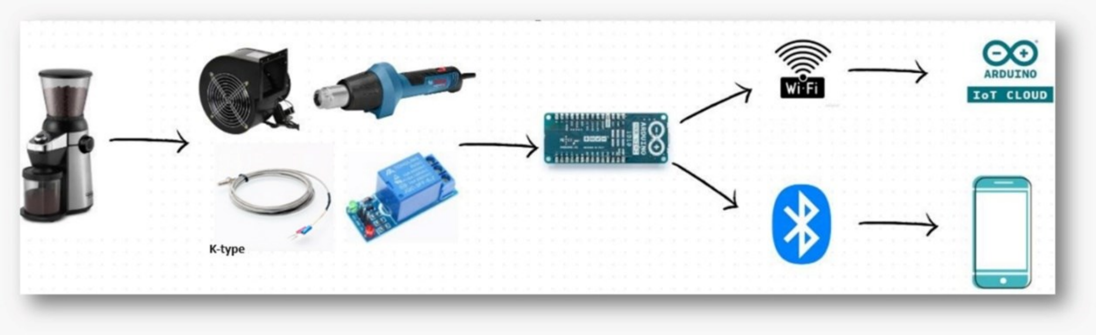


Figure 4.11. Smart Coffee Roaster Flow for the IoT Study

4.2. Materials and Methods for Machine Learning Study

4.2.1. Materials for Machine Learning Study

In the study, different types of microphones were used as hardware material, including a lavalier microphone, dynamic microphone, and mobile phone microphone. As for the software materials, Google Colab and Python programming language with additional libraries were used. The materials are briefly explained below.

4.2.1.1. Microphones

A microphone is a transducer that converts sound waves into electrical signals. There are various types of microphones, each suited for different applications. In the machine learning study, lavalier microphones, dynamic microphones, and mobile phone microphones were used to record sound for data collection to create a dataset.

A lavalier microphone is a small, clip-on microphone typically attached to the body or clothing, making it convenient for hands-free use. Its compact design and proximity to the sound source ensure clear audio capture. Figure 4.12 shows the appearance of a lavalier microphone attached to clothing [61].

Figure 4.12. Lavalier Microphone

Dynamic microphones are one of the most used types of microphones, known for their durability and versatility. Most dynamic microphones are unidirectional, meaning they primarily capture sound from the front while minimizing background noise, making them ideal for live performances, speeches, and studio use. In fact, when people think of a typical microphone, a dynamic microphone often comes to mind. Figure 4.13 illustrates the appearance of a typical dynamic microphone [62].

Figure 4.13. Dynamic Microphone

Mobile phones are commonly preferred as practical recording devices due to their portability, ease of use, and accessibility in daily life. Additionally, modern mobile phones come equipped with high-quality microphone systems, making them suitable for capturing audio with sufficient clarity for research and academic studies. In this study, the Redmi Note 9 Pro was used for audio recording, as shown in Figure 4.14 [63].

Figure 4.14. Mobile Phone Used in This Study

4.2.1.2. Google Colab

Google Colab (Colaboratory) is a web-based Python programming environment provided by Google. It allows users to write, execute, and share Python code, making it a popular choice for machine learning, data analysis, and artificial intelligence projects [64].

Google Colab offers several advantages:

- Cloud-based Computing: It runs code on Google's servers instead of the user's local machine, enabling complex computations without the need for powerful local hardware.
- Access to GPUs and TPUs: Users can access free GPU and TPU resources for limited periods, making it ideal for computationally intensive projects like deep learning.

- Cloud Integration: Projects can be easily integrated with Google Drive, allowing data storage and access in the cloud.
- Jupyter Notebook Compatibility: It supports Jupyter Notebook format, allowing seamless transition of projects between local Jupyter environments and Colab.
- Collaboration: Projects can be shared with others, like Google Docs, supporting real-time collaborative work.

As for Library Support:

- Google Colab supports popular libraries, including TensorFlow and PyTorch, for machine learning and deep learning projects.
- It is compatible with libraries like Pandas, Matplotlib, and Seaborn, making it effective for data analysis and visualization.
- Colab is ideal for experimental research, such as testing new algorithms or models, and is widely used for creating online educational materials and projects.

4.2.1.3. Phyton Programming Language

Python is a high-level, interpreted programming language renowned for its simplicity, versatility, and ease of readability. Created by Guido van Rossum and first released in 1991, Python has become one of the most popular languages globally. Its widespread adoption is due to its extensive standard library, support for multiple programming paradigms (such as procedural, object-oriented, and functional programming), and a large, active community that continuously contributes to its growth and development [65].

Python is commonly used in the following areas:

- Web Development
- Data Science and Machine Learning
- Scripting and Automation
- Scientific Computing
- Game Development
- IoT and Robotics

4.2.2. Methods for Machine Learning Study

The system proposed in this study is divided into four steps as illustrated in Figure 4.15.

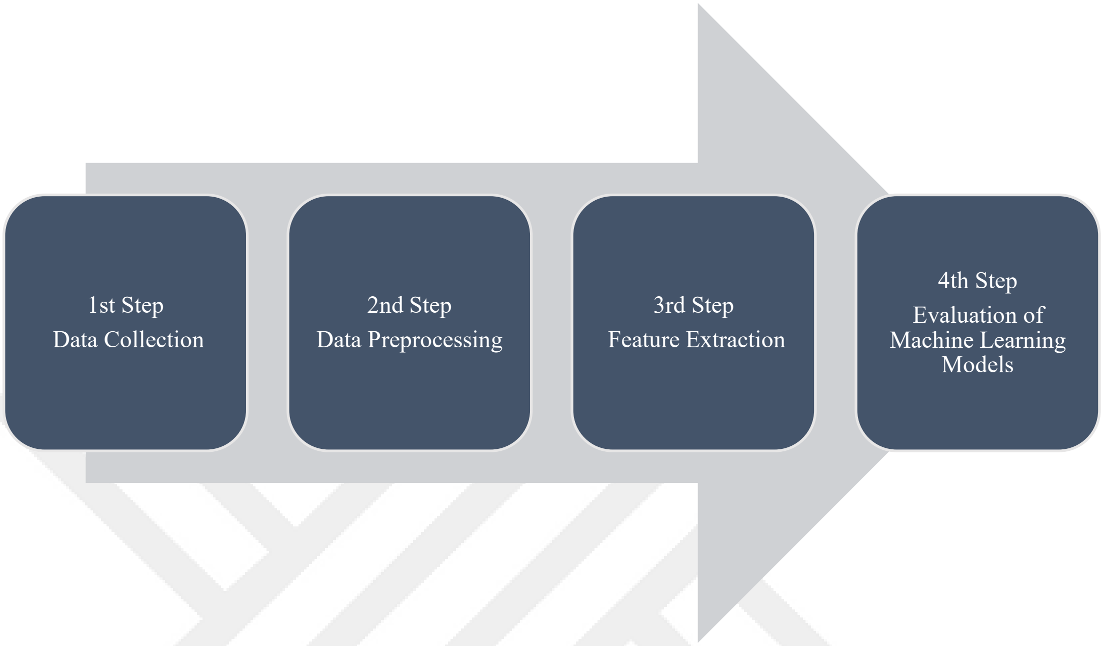


Figure 4.15. Steps of the Machine Learning Study

(1) The first step involves the data collection process for the study. Industrial coffee roasting machines, designed and produced by BESCA ROASTERS in Izmir, is used to capture audio data during the coffee bean roasting process, specifically during the testing phase. The recordings include the sounds of coffee bean cracking, machine noise, and other ambient sounds. In addition to the audio data, the manually observed starting and ending times of the first and second crack sounds are recorded, providing essential reference points for further analysis.

(2) The second step involves preprocessing the data collected in the first step. This step focuses on analyzing, segmenting, and reducing noise from the audio recordings to isolate the coffee bean cracking sounds. The preprocessing is conducted in a computer environment using relevant software tools and toolboxes designed for audio processing.

(3) In the third step, following the preprocessing step, feature extraction is applied to the raw audio data. A set of features, derived from both the time and frequency domains, is utilized based on established methods from literature. This process helps identify key characteristics of the audio signals, such as amplitude, duration, and spectral properties. As a result, a comprehensive dataset containing labeled default, first and second crack sounds is generated.

(4) In the fourth step, a supervised machine learning model is developed for the automatic detection of coffee bean cracking sounds. Well-known classification methods from the literature, including Adaptive Boosting, Decision Tree, Gradient Boosting, K-Nearest Neighbors (K-NN), Naive Bayes, Random Forest, and Support Vector Machines (SVM) will be employed for supervised classification. The performance of each model will be evaluated and presented to determine the most effective approach. For this purpose, the dataset obtained in the third step is divided into training and testing sets to ensure reliable model training and performance assessment. For performance evaluation of the machine learning model, the confusion matrix and four well known metrics are used. These are briefly explained below:

The confusion matrix is a matrix that shows the results of actual classification and predictions with the size of LxL, where L is the number of labels/classification classes [66]. In this study, the confusion matrix used was 3x3 because it had three labels/classes. For a classification task with three classes as shown in Figure 4.16.

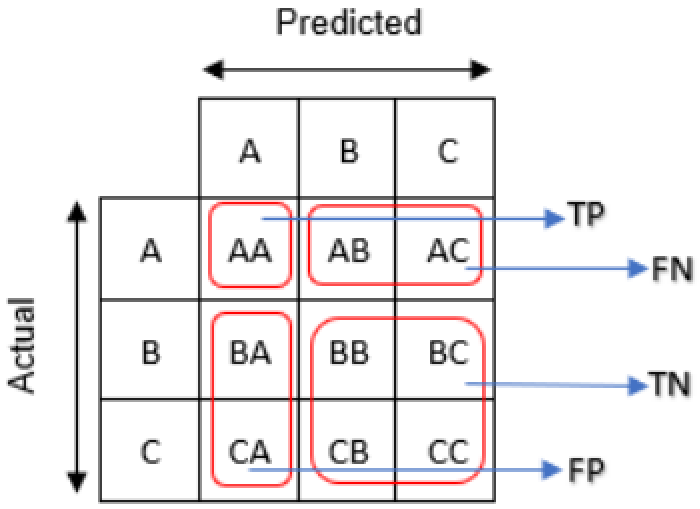


Figure 4.16. 3x3 Confusion Matrix

The scores of accuracy, precision, recall, and f1-score can be calculated by the following equations (4.1) – (4.4).

$$\text{Accuracy } = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{4.1}$$

Accuracy is the proportion of correctly classified instances among all instances. It measures overall model performance.

$$\text{Precision } = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{4.2}$$

Precision is the proportion of correctly predicted positive instances among all predicted positives. It helps minimize false positives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{4.3}$$

Recall is the proportion of correctly predicted positive instances among all actual positives. It helps minimize false negatives.

$$\text{F1 Score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{4.4}$$

F1 Score is the harmonic mean of precision and recall, balancing both metrics for imbalanced datasets.

The overall structure of the system for ML study is given in Figure 4.17.

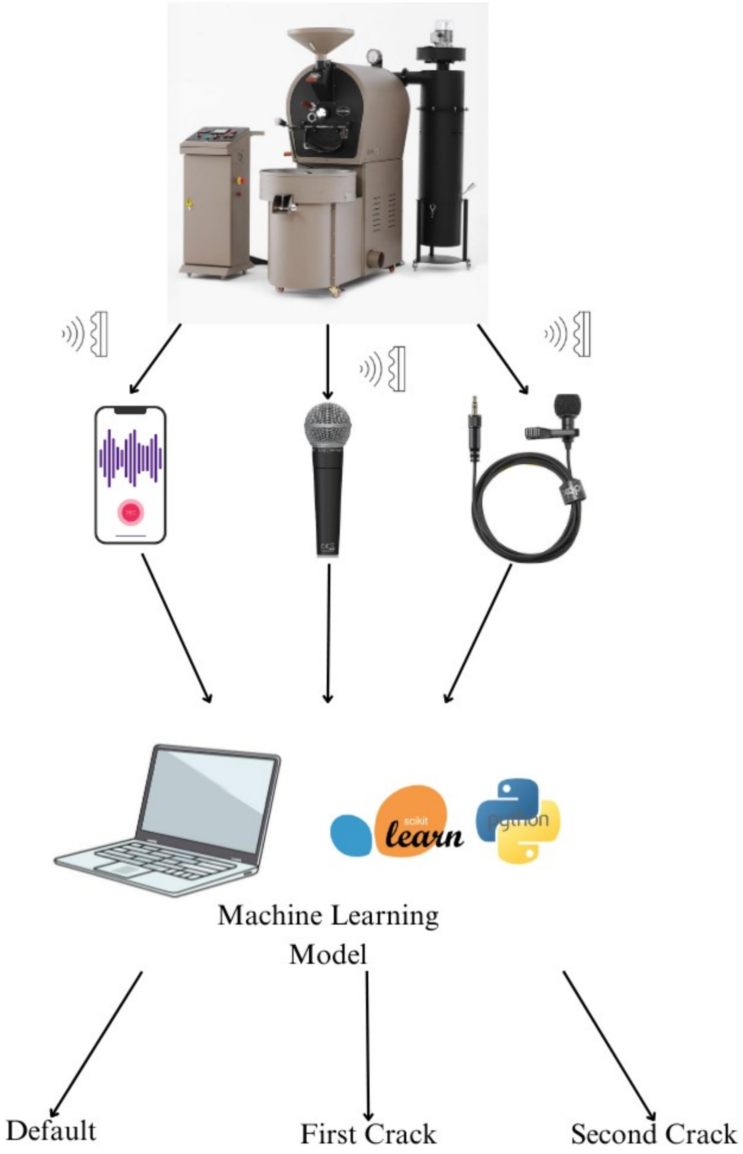


Figure 4.17. System for Machine Learning Study

5. RESEARCH RESULTS AND DISCUSSION

5.1. Results for IoT Study

In this section, the successful completion of the assembly and construction steps of the proposed IoT-based coffee roaster machine is presented.

5.1.1. Main Body Design and Implementation

The main body structure and the roasting chamber of the machine have been successfully constructed according to the design specifications, as shown in Figure 5.1. The installation and assembly of the heating system, cooling system, thermocouple sensors, and exhaust outlet have been completed, meeting the target requirements and ensuring optimal performance for the coffee roasting process.

Figure 5.1. Main Body Structure

The perforated sheet was successfully designed and implemented in alignment with the coffee flow, as shown in Figure 5.2. The perforated design was specifically chosen to allow the hot air from the heat gun to efficiently pass through and reach the coffee beans, ensuring even and effective heat distribution. The sheet was constructed using chrome material, selected for its durability, resistance to rust, and suitability for food-grade applications.

Figure 5.2. Perforated Sheet

5.1.2. Hot Air Gun Placement

The hot air gun was installed directly beneath the roasting chamber, as shown in Figure 5.3. The inlet of the hot air was sealed, with an opening left only at the designated point to direct the airflow effectively. The Bosch GHG 20-60 hot air gun was used to ensure that the coffee beans on the perforated chrome sheet received heat evenly, promoting uniform roasting. Mounting the hot air gun underneath the chamber was a strategic choice, as the vertical hot air flow enhances the roasting process by improving heat distribution and maintaining consistent bean movement.

Figure 5.3. Hot Air Gun Placement

5.1.3. Cooling Pan and Cooling Fan Placement

The cooling pan was positioned at the outlet side of the main body, with the cooling fan installed directly beneath it, as shown in Figure 5.4. Once the coffee beans reach the desired roast level, they are rapidly cooled using the fan system. This quick cooling is crucial to halt the roasting process at the precise moment, preventing overdevelopment of the beans and preserving their optimal flavor and aroma.

Figure 5.4. Cooling Pan and Cooling Fan

5.1.4. Thermocouple Sensor Placement

The thermocouples were positioned as shown in Figure 5.5. The bean thermocouple (the one located below) collected temperature data directly from the coffee beans, while the exhaust thermocouple (the one located above) measured the temperature of the hot air. Both thermocouples were connected to the Arduino MKR Wi-Fi 1010 board using a special interface sensor, the MAX6675 module, to ensure accurate data collection.

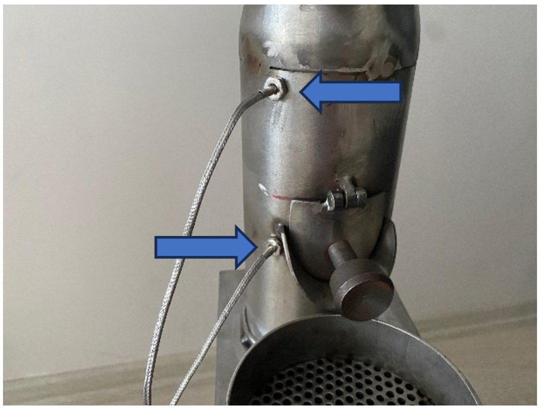


Figure 5.5. Thermocouple Locations on the Main Body

Monitoring temperature is crucial during the coffee roasting process, as it helps determine the roasting stage and ensures consistency in a closed environment. The precise placement of the thermocouples was essential to accurately reflect the true conditions within the roasting chamber, providing reliable feedback on the beans' temperature and airflow conditions for optimal control of the roasting process.

5.1.5. Creating User Interface and Software on Arduino Cloud

Widgets were created on the Arduino Cloud platform to monitor the real-time temperatures of the coffee beans, exhaust air, and ambient environment. Switches were integrated into the interface to provide control over key functions, including:

- Turning the entire system on and off.
- Enabling or disabling the thermocouple data acquisition.
- Remotely controlling the hot air gun (on/off).
- Controlling the cooling fan.

The software program to be uploaded to the Arduino MKR Wi-Fi 1010 board was developed using web editor of Arduino IDE from Arduino Cloud, and temperature data from the sensors was successfully transferred and displayed on the platform. The DHT11 temperature sensor was used to measure and monitor the ambient temperature.

The switches and control functions were tested, and remote operation was confirmed, demonstrating the system's reliability. The created interface is shown in Figure 5.6, while a specific segment of the program code uploaded to the board is shown in Figure 5.7.

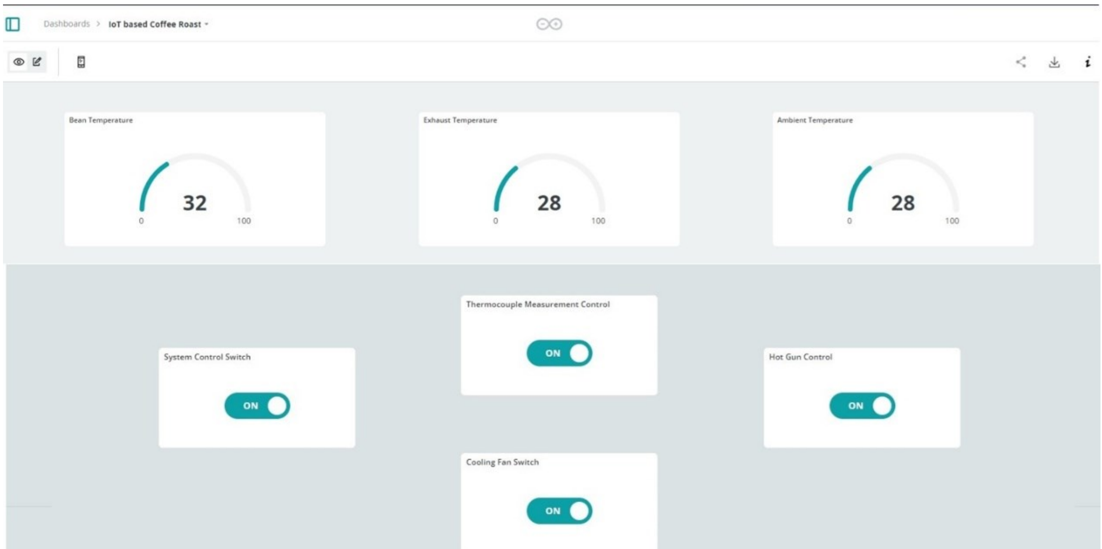
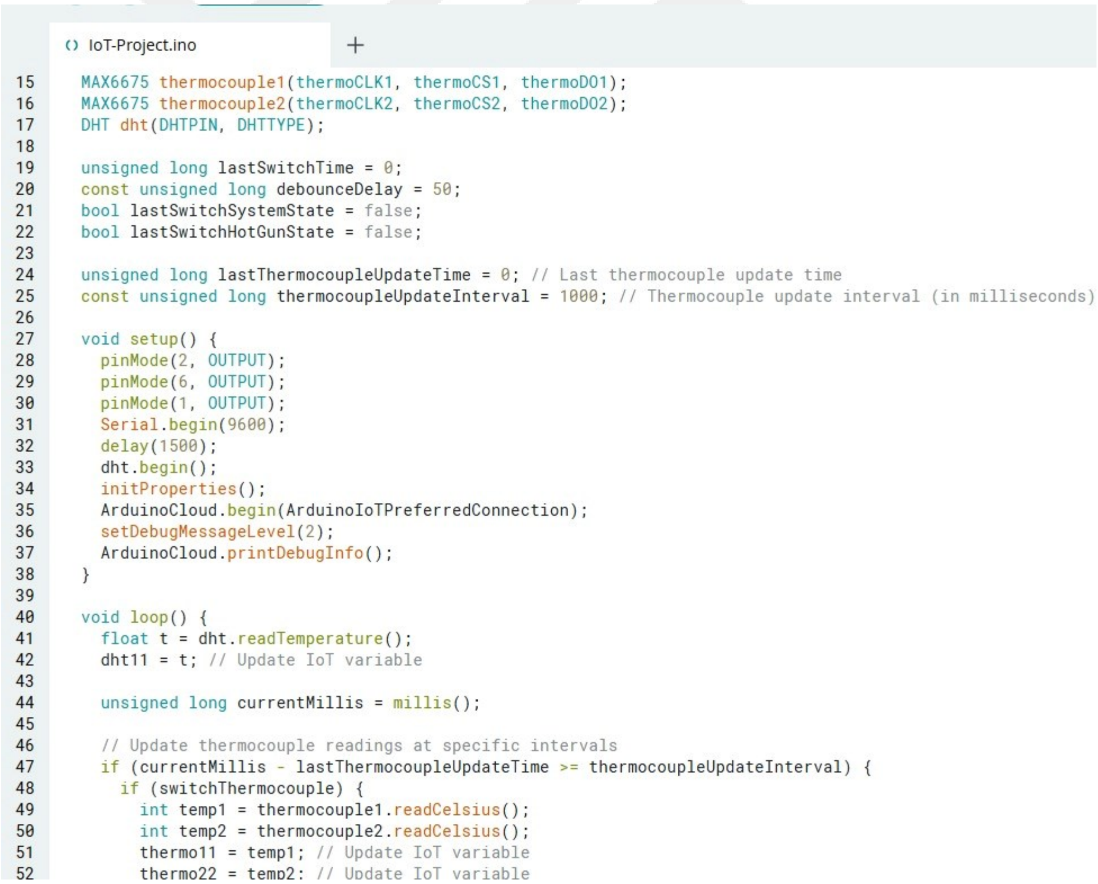


Figure 5.6. User Interface on Arduino Cloud



```
MAX6675 thermocouple1(thermoCLK1, thermoCS1, thermoDO1);
MAX6675 thermocouple2(thermoCLK2, thermoCS2, thermoDO2);
DHT dht(DHTPIN, DHTTYPE);

unsigned long lastSwitchTime = 0;
const unsigned long debounceDelay = 50;
bool lastSwitchSystemState = false;
bool lastSwitchHotGunState = false;

unsigned long lastThermocoupleUpdateTime = 0; // Last thermocouple update time
const unsigned long thermocoupleUpdateInterval = 1000; // Thermocouple update interval (in milliseconds)

void setup() {
  pinMode(2, OUTPUT);
  pinMode(6, OUTPUT);
  pinMode(1, OUTPUT);
  Serial.begin(9600);
  delay(1500);
  dht.begin();
  initProperties();
  ArduinoCloud.begin(ArduinoIoTPreferredConnection);
  setDebugMessageLevel(2);
  ArduinoCloud.printDebugInfo();
}

void loop() {
  float t = dht.readTemperature();
  dht11 = t; // Update IoT variable

  unsigned long currentMillis = millis();

  // Update thermocouple readings at specific intervals
  if (currentMillis - lastThermocoupleUpdateTime >= thermocoupleUpdateInterval) {
    if (switchThermocouple) {
      int temp1 = thermocouple1.readCelsius();
      int temp2 = thermocouple2.readCelsius();
      thermo11 = temp1; // Update IoT variable
      thermo22 = temp2; // Update IoT variable
```

Figure 5.7. Software Program Created on Arduino Cloud

5.1.6. Development of Mobile Application Software for System Control and Data Flow with Bluetooth

The mobile application software was developed, and the user interface was designed using MIT App Inventor. The application enabled real-time analysis and sharing of temperature data. Communication between the Arduino MKR Wi-Fi 1010 board and the mobile device was successfully established via Bluetooth.

The application featured a login screen, as shown in Figure 5.8, which included two primary buttons: "System Control" and "Data Monitoring".

Figure 5.8. Bluetooth Application Entry Screen

System Control: When the "System Control" button was clicked, the user was directed to a screen displaying switches for general system control, hot air gun control, cooling fan control, and thermocouple measurement control as illustrated in Figure 5.9.

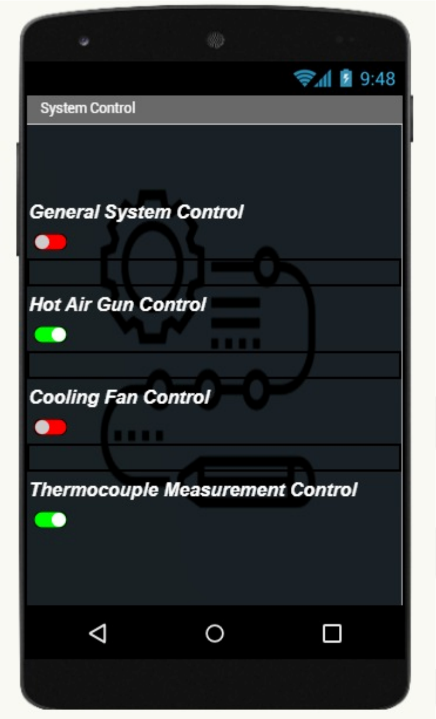


Figure 5.9. Bluetooth Application System Control Screen

Data Monitoring: When the "Data Monitoring" button in Figure 5.8 was clicked, the user could view the real-time temperature data of the coffee beans, exhaust air, and ambient environment. The data was displayed in a clean and organized format, as shown in Figure 5.10, allowing users to monitor the roasting process effectively.

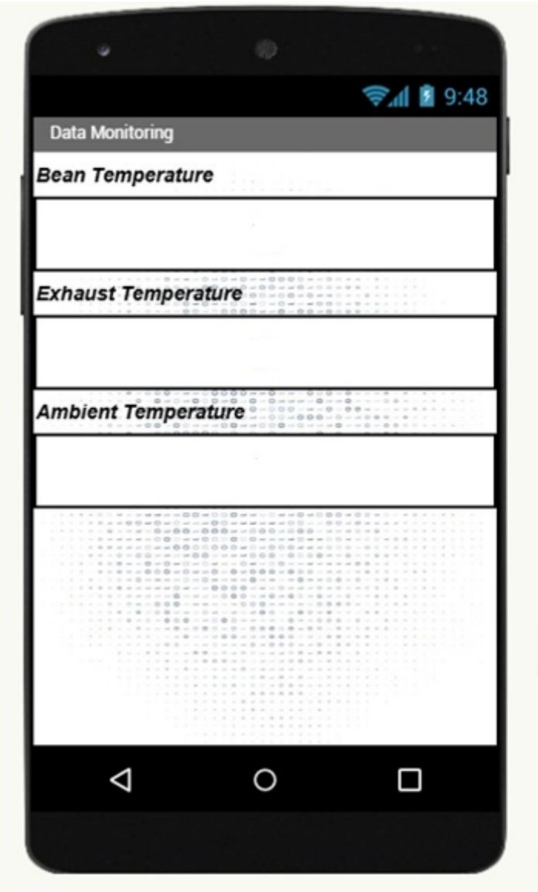


Figure 5.10. Bluetooth Application Data Monitoring Screen

5.1.7. Creating an Electronic Circuit

The connection between the Arduino MKR Wi-Fi 1010 board and the K-type thermocouples was established using the MAX6675 sensor, ensuring accurate temperature readings. For controlling the system components, modifications and relay connections were made as follows:

- The hot air gun’s cable was cut, and a 10-amp relay was inserted between the plug and the hot air gun to allow for on/off control.
- The same process was applied to the cooling fan’s cable and the system general control cable, enabling independent control of each system component.
- A total of three relays of the same model were installed, with their electrical connections successfully established to the Arduino MKR Wi-Fi 1010 board.
- The cloud system was set up to enable remote on/off control for each component via relay switches.

The DHT11 temperature and humidity sensor was integrated into the interface to measure the ambient temperature, ensuring that environmental factors were accounted for during the roasting process. The complete electronic circuit design is shown in Figure 5.11.

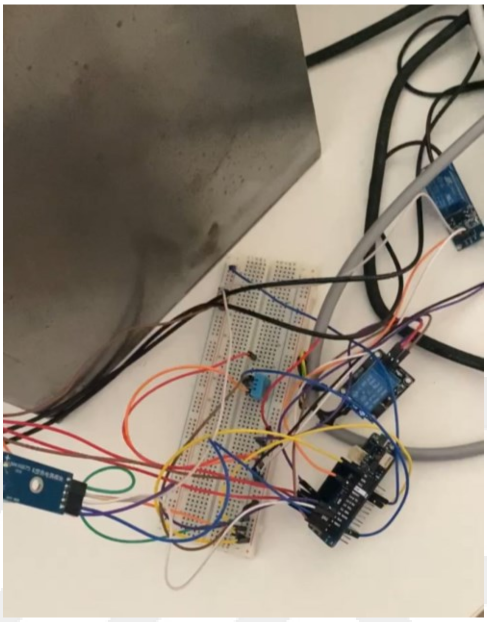


Figure 5.11. Electronic Circuit for IoT Study

5.1.8. Test Result of Coffee Roasting Process

The coffee roasting process was successfully tested on the designed machine, with the beans roasted to the desired level, as shown in Figure 5.12. During the roasting process, key temperature parameters, including the ambient temperature, bean temperature, and exhaust temperature, were accurately measured and monitored. Data collection and analysis were successfully carried out in both the Arduino Cloud environment and the Bluetooth-connected mobile application.

The connected relays enabled remote on/off control of critical components, including the entire system, cooling fan, and hot air gun, through the cloud interface. The machine demonstrated its effectiveness by roasting the coffee beans as targeted and efficiently cooling them during the cooling phase. The overall data flow and system performance were successfully established, confirming the machine's functionality and integration of all key components.

Figure 5.12. Coffee Roasting Trial

Figure 5.13. Exhaust Outlet

The exhaust outlet was designed with an outward partition to effectively prevent chaff from re-entering the roasting chamber, as shown in Figure 5.13. This design ensured that the chaff, which could negatively impact the flavor and quality of the coffee beans, was expelled efficiently and did not interfere with the roasting process. During the roasting process, the temperature data collected from the cloud platform and the control interface used to monitor and manage the system are displayed in Figure 5.14.

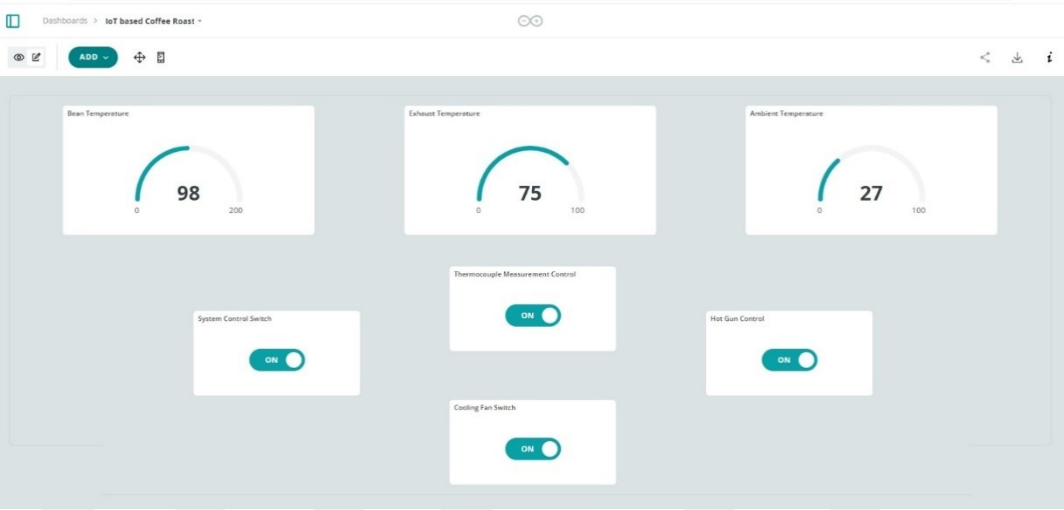


Figure 5.14. Data Results and Control During Roasting

The coffee roasting process was tested nine times with different bean weights: 50 grams, 100 grams, and 150 grams. The durations for medium-level roasting of coffee beans for each weight are given in Table 5.1. The heat gun was operated at a fixed level, and when the time measurement was completed, the bean temperature was recorded as around 150°C. The trials were conducted using Brazil Rio Minas green coffee beans, as shown in Figure 5.15. These beans, from the Arabica variety, are grown in high-altitude mountainous regions, known for their rich flavor and quality.

Table 5.1. Roasting Times at Different Capacities

No	Coffee Weight	Roasting Time
1	50 gr	1 min. 40 sec. - 1 min. 50 sec.
2	100 gr	2 min. 50 sec. - 3 min. 5 sec.
3	150 gr	3 min. 40 sec. - 3 min. 55 sec.

Figure 5.15. Green Coffee Beans Before Roasting

Among the trials, the best results were achieved with the 100-gram test, as shown in Figure 5.16. After this trial, the coffee beans experienced a 15% weight loss, which is typical during the roasting process due to moisture evaporation and chemical transformations. The findings suggest that 100 grams provided optimal roasting consistency and flavor development compared to the other tested weights.

Figure 5.16. The Coffee Roasting Trial

5.2. Results for Machine Learning Study

This section presents the machine learning-based results for detecting coffee bean crack sounds recorded during the roasting process of industrial coffee roasting machines with varying capacities. The study was conducted through the following stages: data collection, data preprocessing, feature extraction, and the evaluation of machine learning models.

5.2.1. Data Collection

At this stage, industrial type coffee roasting machines (BESCA) with different capacities (0.5 kg, 6 kg, 15 kg, and 30 kg.) were used, and sound recordings were captured during the roasting process for each machine, forming the basis of the data collection. Various types of microphones, including a lavalier microphone, dynamic microphone, and phone microphone, were selected to ensure diversity and enhance the quality of the sound data. Figure 5.17 shows the images taken during the sound recording process for each type of roasting machine.

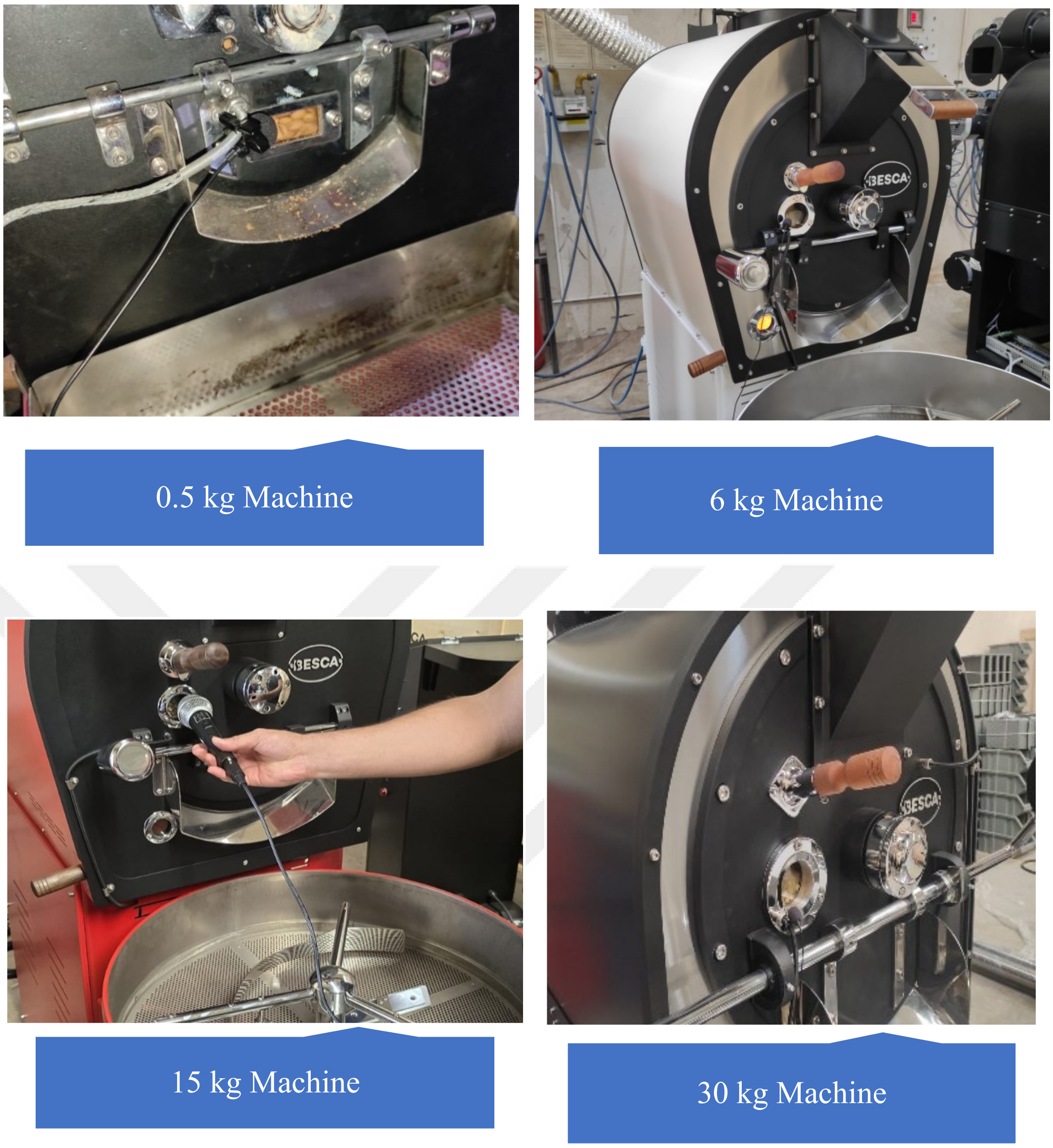
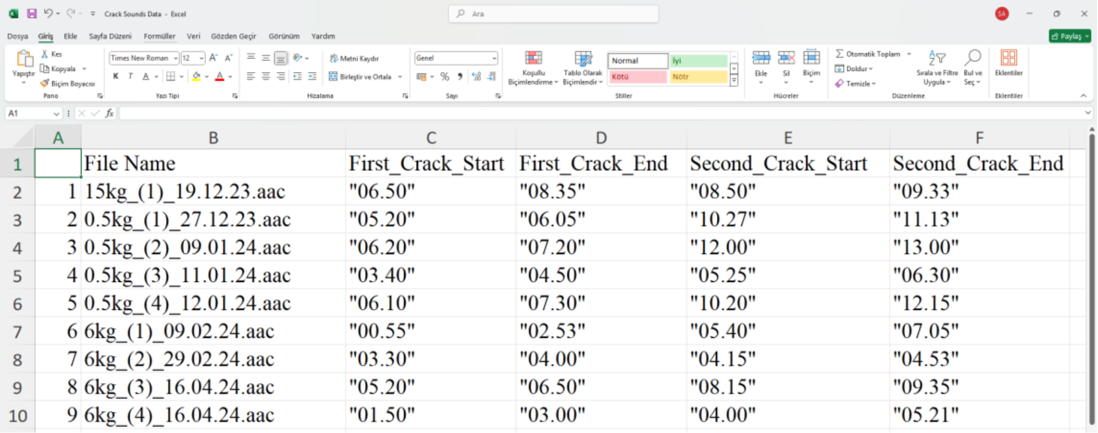


Figure 5.17. Different-Sized Machines Used for Data Collection

Roasting tests were conducted on different days using coffee roasting machines with varying capacities. During each sound recording, the durations of key events—"First Crack Start," "First Crack End," "Second Crack Start," and "Second Crack End"—were also identified by an expert test engineer from BESCA, and their corresponding time points are presented in Figure 5.18. As a result, a total of 29 sound recordings were obtained as shown in Figure 5.19. These raw data collected will be utilized in subsequent steps.



	File Name	First_Crack_Start	First_Crack_End	Second_Crack_Start	Second_Crack_End
1	15kg_(1)_19.12.23.aac	"06.50"	"08.35"	"08.50"	"09.33"
2	0.5kg_(1)_27.12.23.aac	"05.20"	"06.05"	"10.27"	"11.13"
3	0.5kg_(2)_09.01.24.aac	"06.20"	"07.20"	"12.00"	"13.00"
4	0.5kg_(3)_11.01.24.aac	"03.40"	"04.50"	"05.25"	"06.30"
5	0.5kg_(4)_12.01.24.aac	"06.10"	"07.30"	"10.20"	"12.15"
6	6kg_(1)_09.02.24.aac	"00.55"	"02.53"	"05.40"	"07.05"
7	6kg_(2)_29.02.24.aac	"03.30"	"04.00"	"04.15"	"04.53"
8	6kg_(3)_16.04.24.aac	"05.20"	"06.50"	"08.15"	"09.35"
9	6kg_(4)_16.04.24.aac	"01.50"	"03.00"	"04.00"	"05.21"

Figure 5.18. A Fragment of Table Showing Cracking Times Detected by the Test Expert from BESCA for Each Roasting Machine

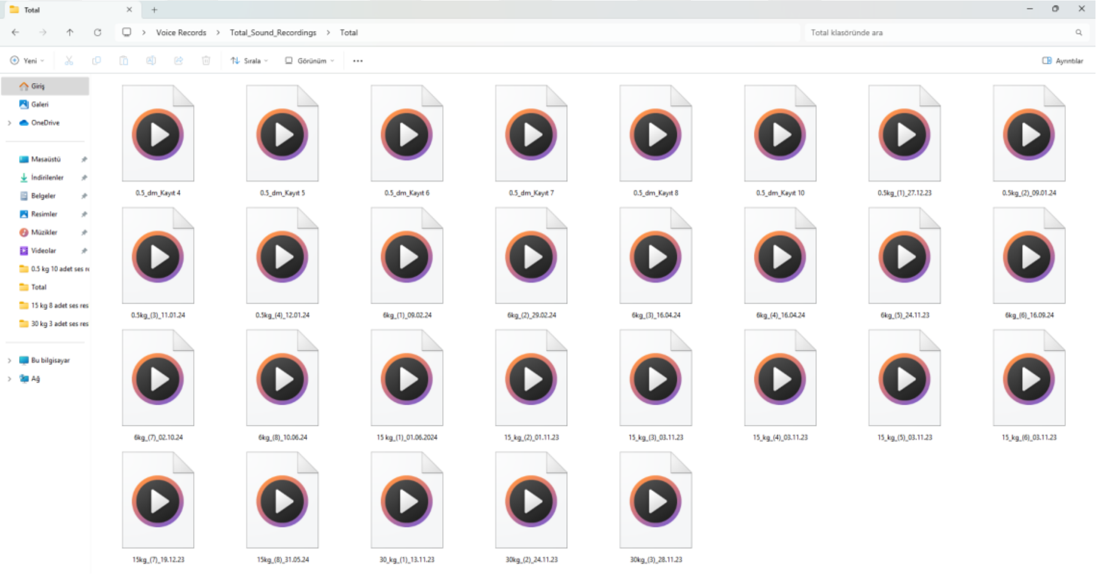


Figure 5.19. Collected Sound Recordings During Coffee Roasting

5.2.2. Data Preprocessing

During this stage, noise reduction and data segmentation processes were carried out to optimize the audio data for subsequent analysis. These processes were executed using tools such as NumPy, Pandas, and Librosa within the Google Colab environment, providing an efficient and scalable framework for audio signal processing. NumPy is a powerful Python library used for numerical computations and working with large, multi-dimensional arrays and matrices. Pandas is a data manipulation and analysis library that provides easy-to-use data structures like

DataFrames and Series for handling structured data. Librosa is a widely used Python library designed for audio signal processing and analysis. It is particularly valuable for loading audio files, extracting meaningful features such as MFCC (Mel-Frequency Cepstral Coefficients) and Mel-spectrogram, and performing various audio analyses through its extensive range of built-in functions. This makes it an essential tool for preparing audio data in machine learning applications.

Figures 5.20 and 5.21 show the spectrum and spectrogram of the roasting sound recorded from a 0.5 kg capacity roasting machine, respectively. Both figures reveal that the dominant noise primarily occurs below 5000 Hz. To reduce background noise—such as human speech, environmental sounds, and machine operating noise—numerous empirical tests were conducted. Based on auditory observations, a Butterworth high-pass filter with a cutoff frequency of 5000 Hz was selected for noise reduction as shown in Figure 5.22. After the denoising process, the cracking sounds became audibly clear.

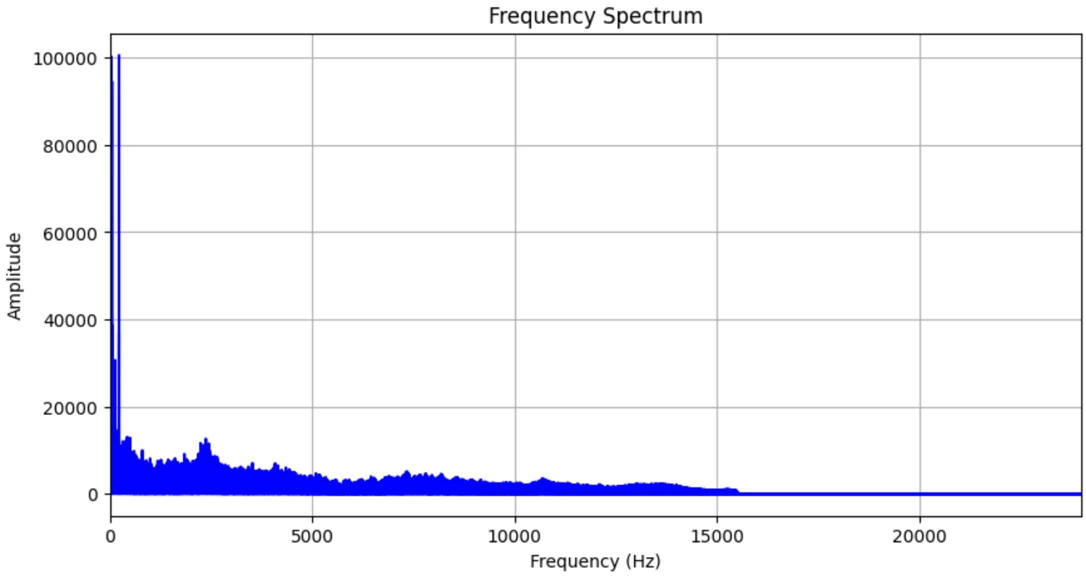


Figure 5.20. Spectrum of the Noise Sound Recording From a 0.5 kg Capacity Roasting Machine

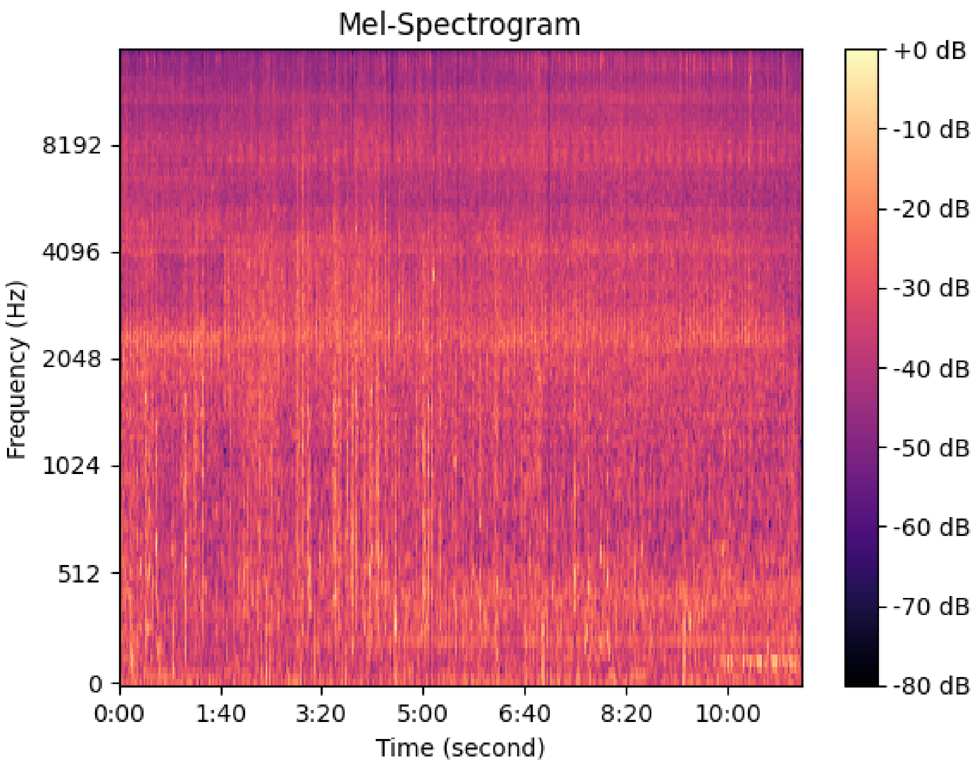
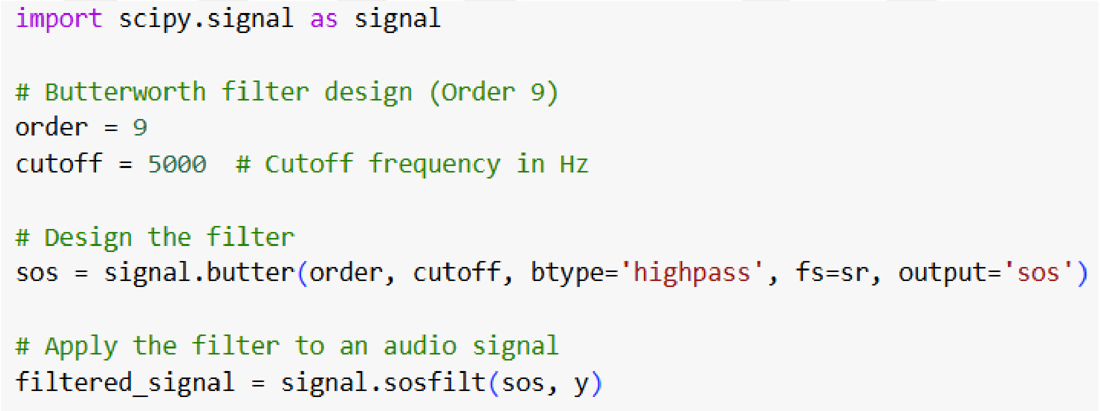


Figure 5.21. Spectrogram of the Noisy Sound Recording from a 0.5 kg Capacity Roasting Machine



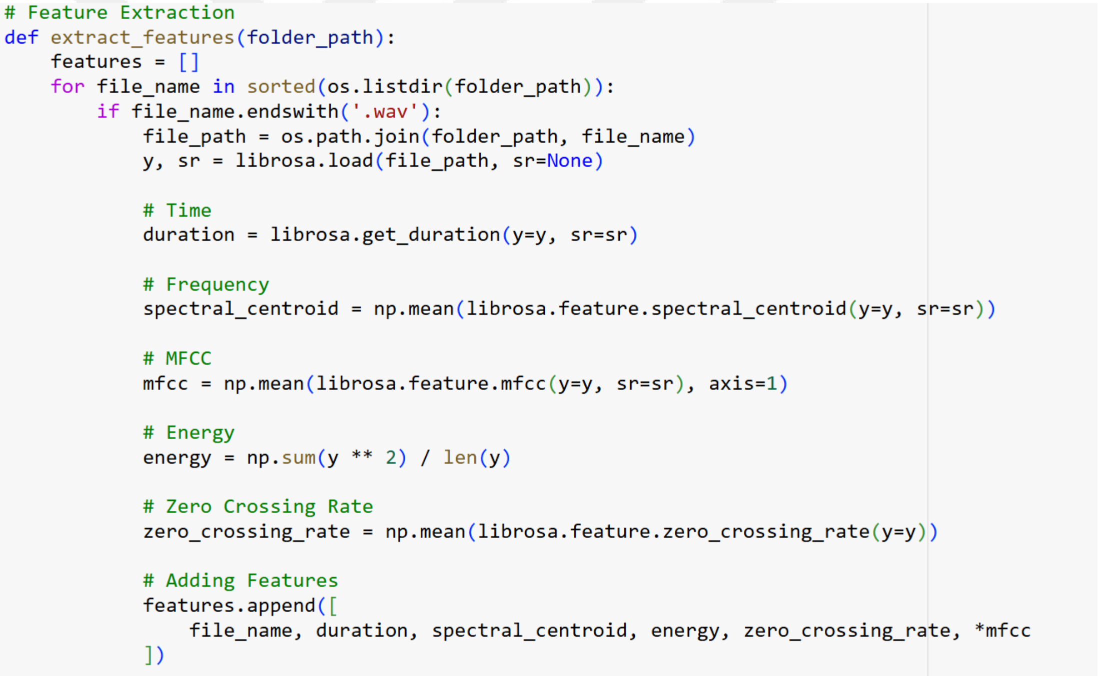
```
import scipy.signal as signal

# Butterworth filter design (Order 9)
order = 9
cutoff = 5000  # Cutoff frequency in Hz

# Design the filter
sos = signal.butter(order, cutoff, btype='highpass', fs=sr, output='sos')

# Apply the filter to an audio signal
filtered_signal = signal.sosfilt(sos, y)
```

Figure 5.22. Code Section for Filtering the Noisy Signal Using a Butterworth High-Pass Filter

Following noise reduction, all 29 denoised audio recordings were divided into three subcategories: Crack-1, Crack-2, and Default (i.e., no crack), based on the cracking times shown in Figure 5.18. These partitions were further segmented into 500 ms intervals and labeled accordingly. The dataset derived from a single sound recording (0.5 kg capacity) was segmented using durations of 20 ms, 50 ms, 100 ms, 500 ms, and 1000 ms, and the results were tested. The findings indicated a significant decrease in machine learning test performance for segment lengths exceeding 500 ms. Consequently, a segmentation length of 500 ms was chosen for audio segmentation.

5.2.3. Feature Extraction

At this stage, features commonly used in audio processing applications were selected. The feature set consists of time-domain, frequency-domain, MFCC, energy, and zero-crossing rate features. During the feature extraction process, widely used Python libraries, including Librosa and NumPy were utilized, as illustrated in Figure 5.23. Then, the features were normalized to the range of 0 to 1 using the MinMaxScaler from sklearn.preprocessing.

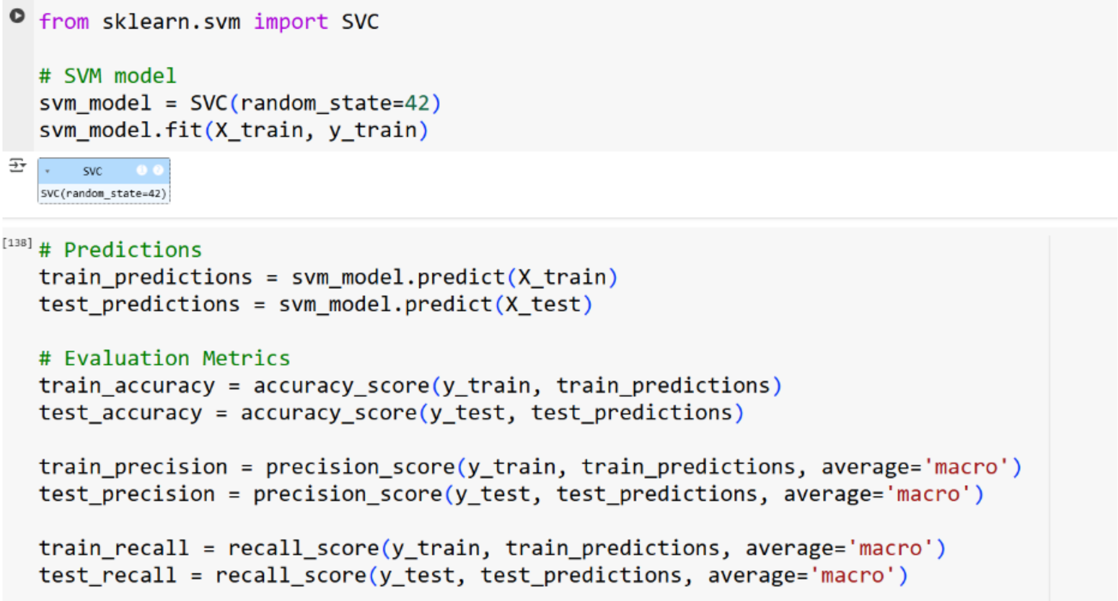


```
# Feature Extraction
def extract_features(folder_path):
    features = []
    for file_name in sorted(os.listdir(folder_path)):
        if file_name.endswith('.wav'):
            file_path = os.path.join(folder_path, file_name)
            y, sr = librosa.load(file_path, sr=None)

            # Time
            duration = librosa.get_duration(y=y, sr=sr)

            # Frequency
            spectral_centroid = np.mean(librosa.feature.spectral_centroid(y=y, sr=sr))

            # MFCC
            mfcc = np.mean(librosa.feature.mfcc(y=y, sr=sr), axis=1)

            # Energy
            energy = np.sum(y ** 2) / len(y)

            # Zero Crossing Rate
            zero_crossing_rate = np.mean(librosa.feature.zero_crossing_rate(y=y))

            # Adding Features
            features.append([
                file_name, duration, spectral_centroid, energy, zero_crossing_rate, *mfcc
            ])
```

Figure 5.23. A Fragment of Python Code for the Feature Extraction Process

5.2.4. Evaluation of Machine Learning Models

To facilitate the development of machine learning models, the scikit-learn and Seaborn libraries—commonly used in Python for machine learning and data visualization—were employed. A code section of the Python program for Support Vector Machine (SVM) model is shown in Figure 5.24.



```
from sklearn.svm import SVC

# SVM model
svm_model = SVC(random_state=42)
svm_model.fit(X_train, y_train)
```

```
SVC
SVC(random_state=42)
```

```
# Predictions
train_predictions = svm_model.predict(X_train)
test_predictions = svm_model.predict(X_test)

# Evaluation Metrics
train_accuracy = accuracy_score(y_train, train_predictions)
test_accuracy = accuracy_score(y_test, test_predictions)

train_precision = precision_score(y_train, train_predictions, average='macro')
test_precision = precision_score(y_test, test_predictions, average='macro')

train_recall = recall_score(y_train, train_predictions, average='macro')
test_recall = recall_score(y_test, test_predictions, average='macro')
```

Figure 5.24. A Fragment of Python Code for Model Training and Testing of the SVM Model

Standard machine learning practices were followed, ensuring that the dataset was properly preprocessed and ready for model training and evaluation. the dataset was divided into 75% for training and 25% for testing, ensuring a robust evaluation of the models. The dataset classes were labeled as First Crack, Second Crack, and Default (representing no crack).

The prepared datasets were tested using seven different machine learning models to compare performance and identify the most effective algorithm for crack detection:

- **Adaptive Boosting (AdaBoost):** A boosting technique that combines weak classifiers to form a strong classifier by focusing on misclassified instances.
- **Decision Tree:** A simple, interpretable model that uses a tree structure to make decisions based on feature splits.
- **Gradient Boosting:** A more advanced boosting technique that optimizes prediction errors iteratively.
- **K-Nearest Neighbors (K-NN):** A non-parametric algorithm that classifies samples based on their nearest neighbors in the feature space.

- **Naive Bayes:** A probabilistic classifier based on Bayes' theorem, assuming feature independence.
- **Random Forest:** An ensemble learning method that constructs multiple decision trees and aggregates their predictions for improved accuracy.
- **Support Vector Machine (SVM):** A powerful algorithm that seeks to find the optimal hyperplane to separate different classes in the feature space.

Initially, machine learning algorithms were applied on the dataset belonging to 10 sound recordings of 0.5 kg machine with dynamic and lavalier microphones for 500 ms segmentation. The results for each algorithm are given below.

5.2.4.1. Adaptive Boosting Classification Results

In Figure 5.25, the classification prediction values provided by the Adaptive Boosting method for the test dataset are displayed using a confusion matrix. Table 5.2 presents the test performance metrics obtained from the Adaptive Boosting method at each fundamental step. When the Adaptive Boosting method was applied to the dataset, the average accuracy and recall rates were observed to be 94.8% and 91.6%, respectively.

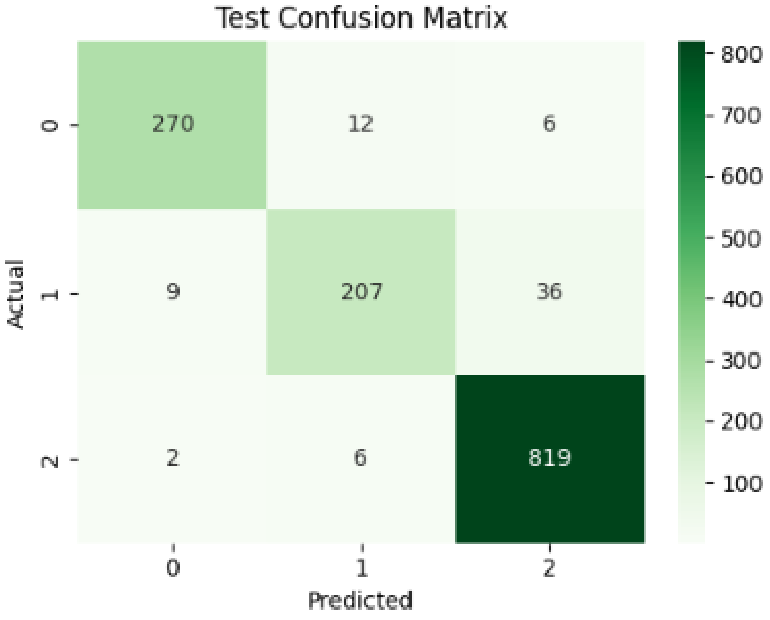


Figure 5.25. Confusion Matrix of the Test Data for the Adaptive Boosting Model

Table 5.2. Results for the Adaptive Boosting Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

Adaptive Boosting					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.978	0.960	0.937	0.949
1	Second Crack	0.953	0.920	0.821	0.867
2	Default	0.962	0.951	0.990	0.970

5.2.4.2. Decision Tree Classification Results

In Figure 5.26, the classification prediction values provided by the Decision Tree method for the test dataset are displayed using a confusion matrix. Table 5.3 presents the test performance metrics obtained from the Decision Tree method at each fundamental step. When the Decision Tree method was applied to the dataset, the average accuracy and recall rates were observed to be 96.2% and 95.2%, respectively.

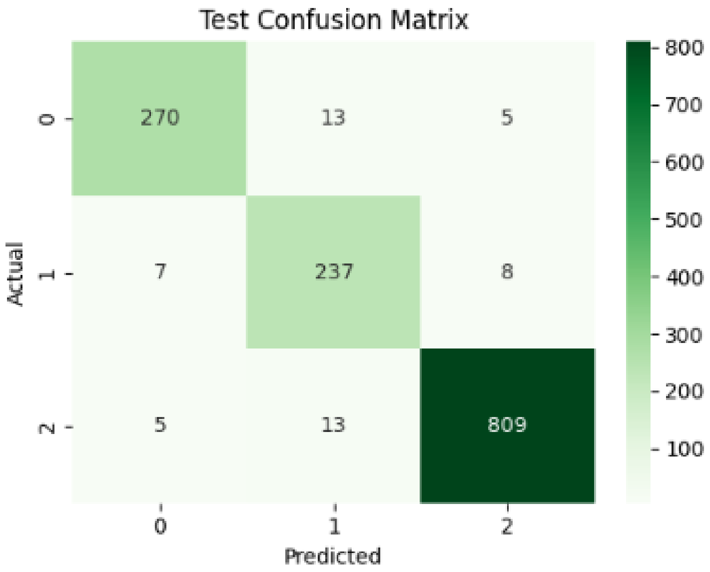


Figure 5.26. Confusion Matrix of the Test Data for the Decision Tree Model

Table 5.3. Results for the Decision Tree Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

Decision Tree					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.977	0.957	0.937	0.852
1	Second Crack	0.968	0.901	0.940	0.854
2	Default	0.976	0.984	1.000	0.978

5.2.4.3. Gradient Boosting Classification Results

In Figure 5.27, the classification prediction values provided by the Gradient Boosting method for the test dataset are displayed using a confusion matrix. Table 5.4 presents the test performance metrics obtained from the Gradient Boosting method at each fundamental step. When the Gradient Boosting method was applied to the dataset, the average accuracy and recall rates were observed to be 99.2% and 99.0%, respectively.

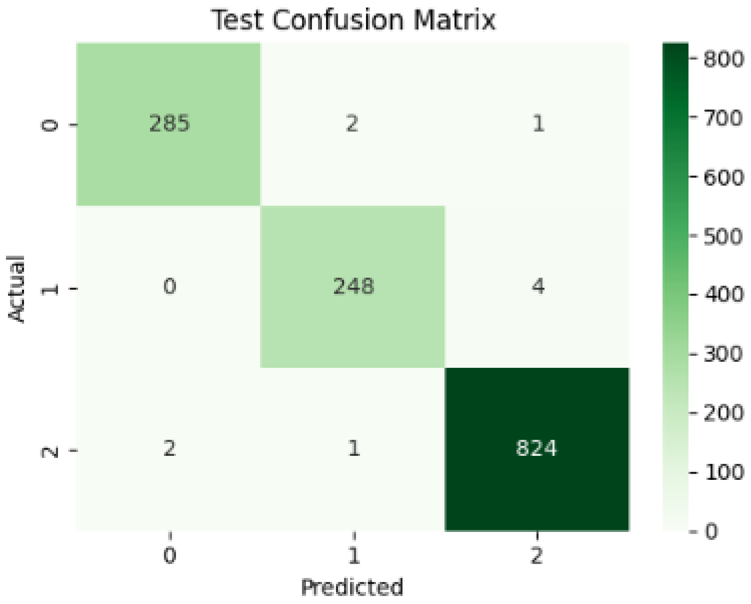


Figure 5.27. Confusion Matrix of the Test Data for the Gradient Boosting Model

Table 5.4. Results for the Gradient Boosting Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

Gradient Boosting					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.996	0.993	0.989	0.991
1	Second Crack	0.994	0.988	0.984	0.986
2	Default	0.994	0.994	0.996	0.995

5.2.4.4. KNN Classification Results

In Figure 5.28, the classification prediction values provided by the KNN classification method for the test dataset are displayed using a confusion matrix. Table 5.5 presents the test performance metrics obtained from the KNN classification method at each fundamental step. When the KNN classification method was applied to the dataset, the average accuracy and recall rates were observed to be 99.1% and 98.8%, respectively.

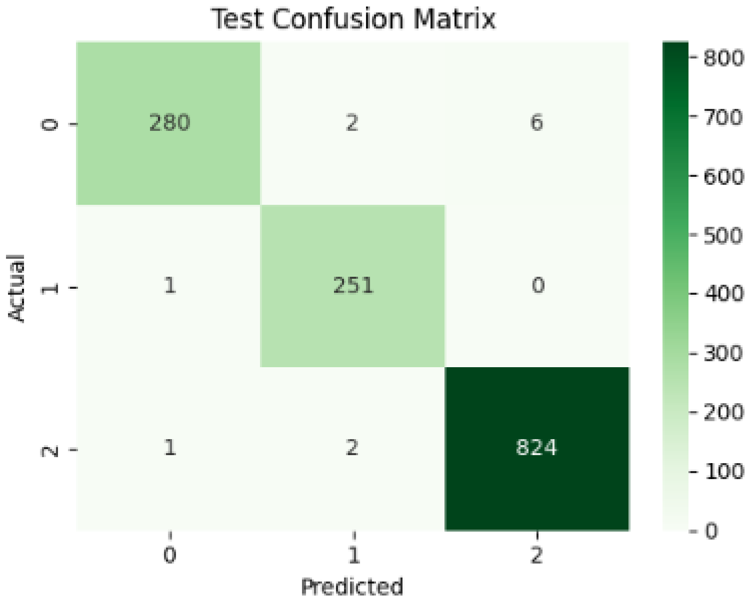


Figure 5.28. Confusion Matrix of the Test Data for the KNN Model

Table 5.5. Results of the KNN Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

KNN					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.992	0.992	0.972	0.982
1	Second Crack	0.996	0.984	0.996	0.990
2	Default	0.993	0.992	0.996	0.994

5.2.4.5. Naive Bayes Classification Results

In Figure 5.29, the classification prediction values provided by the Naive Bayes method for the test dataset are displayed using a confusion matrix. Table 5.6 presents the test performance metrics obtained from the Naive Bayes method at each fundamental step. When the Naive Bayes method was applied to the dataset, the average accuracy and recall rates were observed to be 52.1% and 48.1%, respectively.

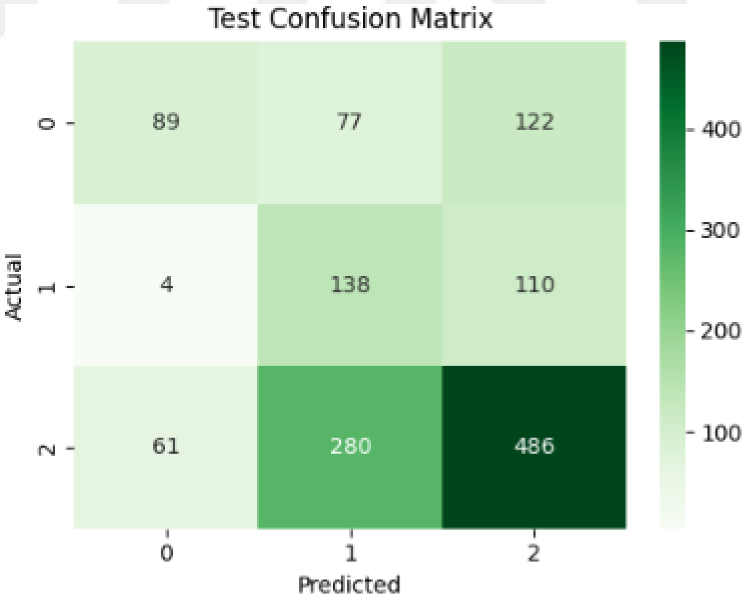


Figure 5.29. Confusion Matrix of the Test Data for the Naive Bayes Model

Table 5.6. Results of the Naive Bayes Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

Naive Bayes					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.729	0.577	0.309	0.402
1	Second Crack	0.602	0.278	0.547	0.369
2	Default	0.554	0.676	0.587	0.629

5.2.4.6. Random Forest Classification Results

In Figure 5.30, the classification prediction values provided by the Random Forest method for the test dataset are displayed using a confusion matrix. Table 5.7 presents the test performance metrics obtained from the Random Forest method at each fundamental step. When the Random Forest method was applied to the dataset, the average accuracy and recall rates were observed to be 99.5% and 99.3%, respectively.

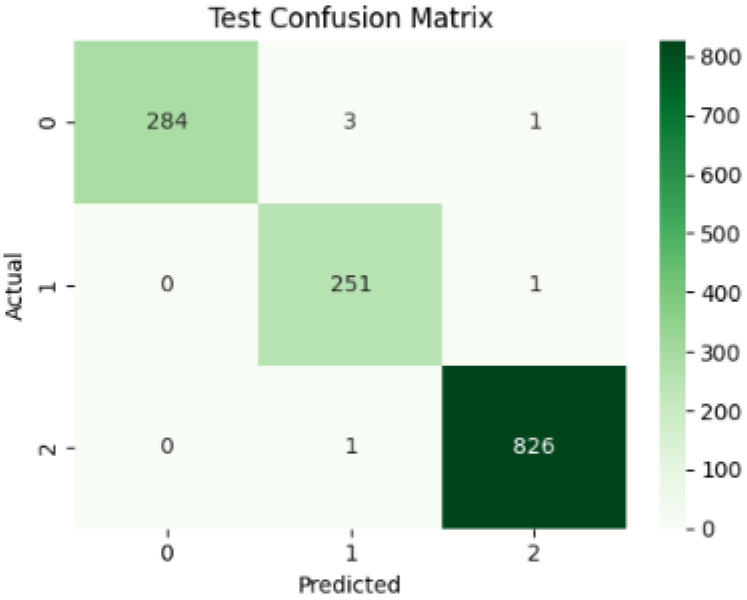


Figure 5.30. Confusion Matrix of the Test Data for the Random Forest Model

Table 5.7. Results of the Random Forest Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

Random Forest					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.997	1.000	0.986	0.993
1	Second Crack	0.996	0.984	0.996	0.990
2	Default	0.997	0.997	0.998	0.998

5.2.4.7. SVM Classification Results

In Figure 5.31, the classification prediction values provided by the SVM method for the test dataset are displayed using a confusion matrix. Table 5.8 presents the test performance metrics obtained from the SVM method at each fundamental step. When the SVM method was applied to the dataset, the average accuracy and recall rates were observed to be 99.7% and 99.7%, respectively.

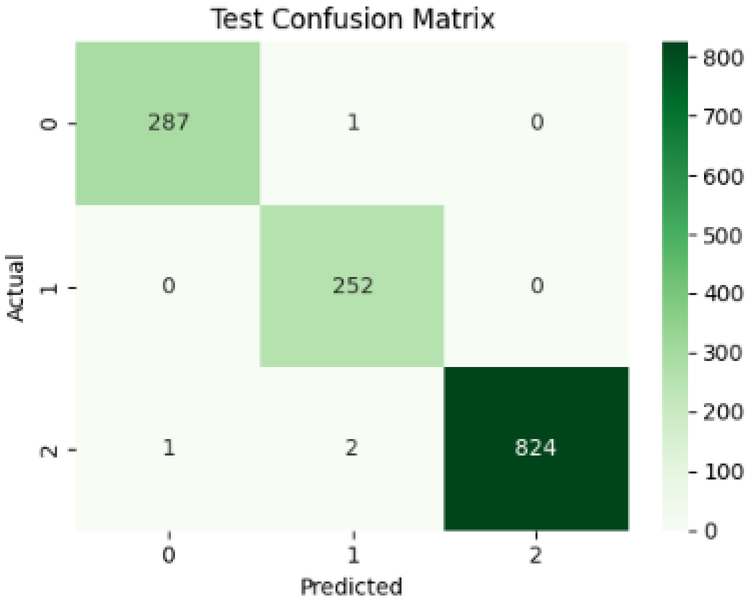


Figure 5.31. Confusion Matrix of the Test Data for the SVM Model

Table 5.8. Results of the SVM Model for 10 Coffee Roasters with a 0.5 kg Capacity Using 500 ms segmentation

SVM					
Class No	**Class**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
0	First Crack	0.998	0.996	0.996	0.996
1	Second Crack	0.997	0.988	1.000	0.994
2	Default	0.997	1.000	0.996	0.998

5.2.4.8. Overall Classification Results for Coffee Roasters of Different Capacities

There were 29 sound recordings for four different roasting machine groups in terms of capacity.

Ten coffee roasters with 0.5 kg capacity roast sound were recorded, and machine learning models were evaluated based on their performance in analyzing these sound recordings. SVM achieved the highest accuracy (99.7%), followed by Random Forest (99.5%), and Gradient Boosting (99.2%), KNN (96.6%). These models demonstrated strong classification abilities and effectively identified patterns in the sound recordings. Naive Bayes had the lowest accuracy (52.1%). Overall, SVM, Random Forest, and Gradient Boosting were the best-performing models, while Naive Bayes was the least effective due to the limitations of its feature representation as in Table 5.9.

Table 5.9. Overall Scores for Sound Recording of 10 Coffee Roaster with 0.5 kg Capacity for 500 ms segmentation

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Adaptive Boosting	0.948	0.944	0.916	0.929
Decision Tree	0.962	0.947	0.952	0.949
Gradient Boosting	0.992	0.991	0.990	0.990
KNN	0.991	0.990	0.988	0.989
Naive Bayes	0.521	0.511	0.481	0.467
Random Forest	0.995	0.994	0.993	0.993
SVM Model	0.997	0.994	0.997	0.996

Eight coffee roasters with 6 kg roast sound were recorded, and machine learning models were evaluated based on their performance in analyzing these sound recordings. SVM achieved the highest accuracy (99.6%), followed by Random Forest and KNN (both at 98.5%). Gradient Boosting and Decision Tree also performed well, with 98.4% and 97.9%, respectively. These models effectively identified patterns in the sound recordings. Naive Bayes had the lowest accuracy (89.5%). Overall, SVM, Random Forest, and Gradient Boosting were the best-performing models, while Naive Bayes was the least effective as shown in Table 5.10.

Table 5.10. Overall Scores for Sound Recordings of 8 Coffee Roasters with 6 kg Capacity Using 500 ms Segmentation

Model	Accuracy	Precision	Recall	F1 Score
Adaptive Boosting	0.946	0.929	0.908	0.918
Decision Tree	0.979	0.963	0.970	0.967
Gradient Boosting	0.984	0.984	0.975	0.979
KNN	0.985	0.983	0.980	0.982
Naive Bayes	0.895	0.845	0.807	0.818
Random Forest	0.985	0.981	0.984	0.983
SVM Model	0.996	0.994	0.992	0.993

Eight coffee roasters with 15 kg capacity roast sound were recorded, and machine learning models were evaluated based on their performance in analyzing these sound recordings. SVM achieved the highest accuracy (98.8%), followed by Gradient Boosting (98.6%), KNN (98.5%), and Random Forest (98.4%). These models effectively identified patterns in the sound recordings, demonstrating strong classification capabilities. Naive Bayes had the lowest accuracy (79.7%). Overall, SVM, Gradient Boosting, KNN, and Random Forest were the best-performing models, while Naive Bayes was the least effective as in Table 5.11.

Table 5.11. Overall Scores for Sound Recordings of 8 Coffee Roasters with 15 kg Capacity Using 500 ms Segmentation

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Adaptive Boosting	0.949	0.867	0.867	0.864
Decision Tree	0.956	0.890	0.882	0.886
Gradient Boosting	0.986	0.981	0.978	0.979
KNN	0.985	0.976	0.976	0.976
Naive Bayes	0.797	0.633	0.585	0.587
Random Forest	0.984	0.973	0.971	0.972
SVM Model	0.988	0.985	0.986	0.986

Three coffee roasters with 30 kg capacity roast sound were recorded, and machine learning models were evaluated based on their performance in analyzing these sound recordings. SVM achieved the highest accuracy (98.8%), followed by Gradient Boosting (96.6%), KNN (96.6%), and Random Forest (95.7%). These models demonstrated strong classification abilities and effectively identified patterns in the sound recordings. Naive Bayes had the lowest accuracy (85.6%). Overall, SVM, Gradient Boosting, and KNN were the best-performing models, while Naive Bayes was the least effective as in Table 5.12.

Table 5.12. Overall Scores for Sound Recordings of 3 Coffee Roasters with 30 kg Capacity Using 500 ms Segmentation

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Adaptive Boosting	0.935	0.895	0.862	0.877
Decision Tree	0.933	0.877	0.858	0.867
Gradient Boosting	0.966	0.962	0.936	0.948
KNN	0.966	0.966	0.936	0.950
Naive Bayes	0.856	0.742	0.775	0.757
Random Forest	0.957	0.945	0.907	0.925
SVM Model	0.988	0.985	0.985	0.985

All various coffee roasters with 0.5 kg, 6 kg, 15 kg, and 30 kg capacities were recorded, and machine learning models were evaluated based on their performance in analyzing these sound recordings. SVM achieved the highest accuracy (95.5%), followed closely by Decision Tree (95.0%), KNN (94.9%), Gradient Boosting

(94.7%), and Random Forest (94.8%). These models effectively identified patterns across different coffee roaster capacities, demonstrating strong classification capabilities. Naive Bayes had the lowest accuracy (75.3%), likely due to its reliance on a 3×3 feature matrix and the assumption of feature independence, which may have limited its ability to capture complex relationships in the data. Adaptive Boosting also showed lower performance compared to other models, with an accuracy of 88.9%. Overall, SVM, Decision Tree, and KNN were the best-performing models, while Naive Bayes was the least effective due to the limitations of its feature representation as shown in Table 5.13.

Table 5.13. Overall Scores for Sound Recordings of All Various Coffee Roasters with 0.5 kg, 6 kg, 15 kg, and 30 kg Capacities Using 500 ms Segmentation

Model	Accuracy	Precision	Recall	F1 Score
Adaptive Boosting	0.889	0.831	0.810	0.812
Decision Tree	0.950	0.928	0.928	0.928
Gradient Boosting	0.947	0.946	0.945	0.945
KNN	0.949	0.949	0.949	0.949
Naive Bayes	0.753	0.666	0.660	0.663
Random Forest	0.948	0.948	0.947	0.947
SVM Model	0.955	0.952	0.951	0.951

The results in Table 5.14 show the performance of machine learning models on sound recordings without noise reduction. The impact of noise on model accuracy and overall performance is evident, because all models performed worse in noisy conditions. Comparing Table 5.13 (with noise reduction) and Table 5.14 (without noise reduction) highlights the importance of pre-processing techniques like noise filtering to enhance model accuracy.

Table 5.14. Overall Scores for Sound Recordings of All Various Coffee Roasters with 0.5 kg, 6 kg, 15 kg, and 30 kg Capacities Using 500 ms Segmentation Without Noise Reduction

Model	Accuracy	Precision	Recall	F1 Score
Adaptive Boosting	0.780	0.720	0.690	0.710
Decision Tree	0.700	0.660	0.670	0.660
Gradient Boosting	0.740	0.720	0.740	0.730
KNN	0.780	0.760	0.800	0.780
Naive Bayes	0.680	0.620	0.670	0.630
Random Forest	0.760	0.720	0.760	0.740
SVM Model	0.800	0.790	0.800	0.790

5.3. Discussion

As a first study, an IoT based sample-type coffee roaster was successfully developed using Arduino MKR Wi-Fi 1010 board and Arduino Cloud platform. With the integration of the IoT, the coffee roaster machine has been equipped with several advanced features such as remote control, data monitoring, and data collection. Also, since the roasting process can be monitored and controlled remotely, it is beneficial for protecting respiratory health by reducing exposure to smoke and particles released during roasting.

The developed smart roaster design offers several advantages. The exhaust outlet was designed with an outward partition to prevent chaff from re-entering the roasting chamber, ensuring it did not affect the flavor of the coffee beans. The cylindrical design and adjustable heat gun minimized the development of undesirable flavors during roasting by promoting even heat distribution. The cooling fan rapidly cooled the roasted beans, effectively preserving their optimal roasting level and preventing overdevelopment. Accurate measurements of ambient temperature, coffee bean temperature, and exhaust temperature were achieved using the thermocouple and DHT11 sensor. Temperature data from the coffee beans, exhaust, and ambient conditions were monitored simultaneously through the Arduino Cloud system, ensuring real-time feedback and control. Additionally, remote control of the heat gun and cooling fan enabled faster and more efficient operation, enhancing the overall precision and consistency of the roasting process.

The proposed system can be further improved by integrating a heat gun with adjustable temperature control. One of the challenges encountered was the use of a 2000 W heat gun, which proved to be overly powerful for this design. As a result, sometimes unwanted burns and spots form on the coffee beans during the longer roasting process. Since even roasting is critical to achieving the desired aroma and flavor, this uneven heat distribution negatively affects the overall taste of the coffee. However, by incorporating a heat gun with adjustable temperature settings, it would be easier to prevent these issues and ensure a more controlled and uniform roasting process.

As a second study, machine learning approach was used to identify the cracking sounds of the coffee beans during roasting process for industrial-type coffee roasters. In the coffee roasting process, the roasting stage is typically determined by the roast master. The first and second crack points are crucial phases in the roasting process, and the roast master needs to hear these sounds with their own ears. The machine learning study aimed to automatically detect cracking sounds without requiring the user to listen. In the machine learning study, sound was successfully recorded, and data were collected from coffee roasting machines with different capacities.

It was observed that clear sound data was more easily obtained from machines with smaller capacities, likely due to reduced background noise and better sound isolation in smaller machines.

Three types of microphones—dynamic, lavalier, and phone microphones—were used during the audio recording process. To identify the optimal recording location, the microphones were placed at various points on the roasting machine, including the back of the machine, the front cover, the front casting mirror, and the observation glass. Given the machine was closed during the roasting process, different positions were tested to minimize noise interference and maximize sound clarity. The observation glass was found to provide the best results, as it captured clear sound signals from the coffee bean cracks. Among the microphones tested, the dynamic microphone produced the best performance. Its directional nature, which captures sound primarily from the front while minimizing background noise, made it ideal for isolating the critical cracking sounds. This optimization of microphone selection and placement played a significant role in ensuring high-quality sound recordings, which were essential for effective machine learning predictions and analysis.

Challenges during the sound recording process are listed below:

Noise from the drum mechanism: Since the study was conducted on drum-type roasting machines, the rotating drum generated significant noise, which impacted the clarity of the audio recordings and made it challenging to isolate the coffee bean cracking sounds.

Factory environment noise: The recordings were made while the machines were operating in a factory environment, where external noise, such as machinery and ambient sounds, had a significant impact on the quality of the sound data.

Sound insulation from the cast iron front mirror: The front mirror section of the roasting machine was made of cast iron, which provided a high level of sound insulation. This made it more difficult to capture the cracking sounds effectively, as the cast iron blocked much of the acoustic signal.

Microphone placement limitations due to high temperatures: The high operating temperatures inside the roasting machine restricted the placement of the microphone. Placing the microphone too close to the cast iron could have caused damage. For example, during the sound recording process on a 6 kg machine, the temperature reached 68.8°C, requiring careful consideration to avoid overheating the microphone.

6. CONCLUSION AND FUTURE STUDIES

This thesis explored the integration of Internet of Things and Machine Learning technologies in the design and implementation of a smart coffee roaster. The research provided valuable insights into how these emerging technologies can be utilized to optimize coffee roasting processes, enhance control mechanisms, and improve the overall quality of roasted coffee.

For IoT study, a small-scale prototype coffee roaster was developed using Arduino MKR Wi-Fi 1010 board and Arduino Cloud platform, successfully demonstrating real-time remote control, data monitoring, and data collection through cloud-based and mobile interfaces.

The following recommendations are suggested for future work to improve and expand the current IoT-based coffee roaster design:

- **Utilizing a heat gun with a wider temperature range:** Improving control over the roasting process by using a heat gun with a broader adjustable temperature range can help minimize undesirable outcomes such as uneven roasting or burnt beans.
- **Incorporating a heat gun with a built-in cooling feature:** If the heat gun used in the design includes a cooling function, the need for a separate cooling fan can be eliminated, simplifying the overall system design and reducing component requirements.
- **Enhancing control over the heat gun's temperature:** Currently, only the on/off functions of the heat gun are controllable. By enabling communication between the circuit and the heat gun, temperature levels can be adjusted dynamically, allowing for precise and fully remote control of the roasting process.
- **Scaling up the design for larger machines:** The current design can be adapted to larger coffee roasting machines. In this scaled-up version, a temperature sensor would monitor only the internal temperature of the machine, and the roasting process could be carried out efficiently. Additionally, a more powerful fan for the heat gun could be selected to create sufficient airflow, allowing the coffee beans to float and achieve even roasting throughout the chamber.

In the machine learning study, a total of 29 different sound recordings were collected and labeled into three categories: **first crack, second crack, and default**. Machine learning models were developed to analyze the audio data collected from industrial-type coffee roasting machines with varying capacities (0,5 kg, 6 kg, 15 kg, and 30 kg), using a segmentation window of 500 ms.

- **0.5 kg Machine:** Ten different recordings were analyzed, with the Support Vector Machine (SVM) model achieving the highest accuracy, while the Naive Bayes model demonstrated the lowest performance.
- **6 kg Machine:** Eight recordings were analyzed, and the SVM model achieved the highest accuracy of 99%.
- **15 kg Machine:** The same process was applied to eight recordings, where SVM achieved an accuracy of 98%.
- **30 kg Machine:** In the industrial machine category, three recordings were collected, and the SVM model once again demonstrated the highest accuracy.
- **Overall Machines:** A total of 29 audio recordings from different machine types were subjected to seven different machine learning models. It was observed that accuracy rates decreased across all models. The highest success rate was achieved by the SVM model with 95.5% accuracy, while the Naive Bayes model had the lowest success rate at 75.3%.

However, as the machine size increased, data collection became more challenging. Larger machines generated more background noise due to the drum's rotation and operating sounds, making it more difficult to capture the cracking sounds clearly. As a result, the accuracy of the machine learning models declined with increasing machine size. This observation highlights the need for improved noise reduction techniques and optimized sensor placement to maintain high accuracy in larger-scale coffee roasters.

The following recommendations are suggested for future work to get improved data quality for ML-based study:

- **Utilizing a fluid bed type roasting machine:** Replacing the drum-type roasting machine with a fluid bed type could simplify the sound recording process by reducing mechanical noise interference, leading to clearer audio capture of the coffee bean cracking sounds.

- **Minimizing external ambient noise:** Implementing soundproofing measures or conducting the recordings in a controlled acoustic environment would help reduce external noise, resulting in clearer audio data and improved machine learning performance.
- **Integrating the microphone inside the machine:** Embedding the microphone within the roasting machine and positioning it closer to the coffee beans would allow it to capture the crack sounds more clearly and accurately, improving the quality of the audio data used for training the machine learning models.
- **Using a high-temperature-resistant microphone:** Selecting a microphone designed to withstand high temperatures would prevent overheating and potential damage during the roasting process, ensuring reliable and consistent data collection.
- **Exploring alternative methods for detecting crack stages:** In addition to sound analysis, the detection of the first and second crack stages could be enhanced by monitoring the release of various gases produced during the coffee roasting process. By analyzing these gases, a complementary system could be developed to independently verify and detect key roasting milestones, providing a more robust and accurate solution.

REFERENCES

[1] Habtamu M. A. Image Analysis for Ethiopian Coffee Classification. Addis Ababa University, Faculty of Informatics Department of Computer Science, Addis Ababa, 2008, 99 pages (Master Thesis)

[2] Roast Phase: https://jahaniandassociates.com/ja-report-coffee-processing-how-roasting-affects-taste/

[3] https://www.darycoffee.com/post/how-to-choose-roaster-coffee-roaster-types-and-notable-coffee-roaster

[4] About Sample Roasters: https://www.roestcoffee.com/products/sample-roasters

[5] About Shop Type Roasters: https://bescaroasters.com/product/bsc-06-gen-ii-specialty-coffee-roasters/

[6] About Industrial Roasters: https://www.scottrao.com/blog/2020/4/8/how-to-choose-a-roasting-machine

[7] Drum Roasters: https://www.wakacoffee.com/blogs/coffeepedia/what-is-a-drum-roaster?srsltid=AfmBOoqf0K8E4bdXhxD9zuCQzbBFNBP-nlLv0hfAhQawUyv_Y_vysYOY

[8] Roasting Animating: https://www.youtube.com/watch?v=F3rB2zLSnjQ

[9] About Fluid Bed Roasters: https://perfectdailygrind.com/2021/05/a-guide-to-fluid-bed-coffee-roasters/

[10] About Fluid Bed Roasters: https://www.toper.com/en/fluid-bed-coffee-roasters/

[11] Parts of Coffee Roaster: https://coffeeroastco.com/blogs/coffee-roast-co-blog/parts-of-a-coffee-roaster

[12] Internet of Things: https://www.ibm.com/topics/internet-of-things

[13] Internet of Things: https://network-insight.net/2017/10/24/internet-of-things-access-technologies/

[14] Machine Learning: https://www.fsm.ac.in/blog/an-introduction-to-machine-learning-its-importance-types-and-applications/

[15] Özüdoğru F. Drone Propeller Recognition Through Machine Learning with Millimeter Wave Radar. Eskişehir Technical University, Department of Electrical and Electronics Engineering Eskişehir, 2024, 76 pages, (Master Thesis)

[16] Machine Learning: https://www.goodfirms.co/blog/machine-learning-in-mobile-app-development

[17] Cristo H. P., Martins M. A., Oliveira L. S., and Franca A. S. Transverse Flow of Coffee Beans in Rotating Roasters. Journal of Food Engineering 75, 2006, Vol. 75 page 142–148
doi: 10.1016/j.jfoodeng.2005.04.010

[18] Hadzicha M., Veynandt F., Delcolb J., Hadzichb L. M., Pérezb J. P., and Vergarab S. Design of a Solar Coffee Roaster for Rural Areas. ISES Solar World Congress, 3 to 7 November, 2013, Cancun-Mexico (Energy Procedia 57 (2014) 3215 – 3224)
doi: 10.1016/j.egypro.2015.06.071

[19] Hsu H. C. and Lo R. C. A High Efficiency Coffee Roaster Development Based on Gas Baking Technology for Home Use. Applied Mechanics and Materials, 2014, Vol. 681 page 23-28
doi: 10.4028/www.scientific.net/AMM.681.23

[20] Purwantana R. B., Alamsyah R. P., and Prawira H. D. Design of Portable Coffee Roaster for Home Industry. IOP Conf. Series: Earth and Environmental Science, 13-14 November, 2018, West Sumatera-Indonesia (Earth and Environmental Science Vol. 327, 2019)
doi: 10.1088/1755-1315/327/1/012019

[21] Xu Y., Shaull J., Bavar T., and Tan L. Smart Coffee Roaster Design with Connected Devices. 2018 IEEE International Conference on Consumer Electronics (ICCE), 2-5 September, 2018, Berlin-Germany
doi: 10.1109/ICCE.2018.8326177

[22] Nasution T. H., Putramas A., Soeharwinto S., Fahmi F., and Siregar I. Automatic Coffee Roaster Design Using Arduino. The 6th International Conference on Manufacturing, Optimization, Industrial and Material Engineering AIP Conf. Proc. 2044, 24-25 March, 2018, Bandung-Indonesia
doi: 10.1063/1.5080068

[23] Ogunjiri O. A., Odeniyi O. M., Olubo A. S., Farounbi A. J., Ola O. A., and Adeleke S. A. Design and Construction of an Electrically Powered Coffee Roasting Machine. IOP Conf. Series: Earth and Environmental Science, 14 August, 2019, Bogor-Indonesia (Earth and Environmental Science Vol. 445, 2020)
doi: 10.1088/1755-1315/445/1/012009

[24] Daywin F. J., Doaly C. O., Gozali L., Kosasih W., and Taek G. Improving the Quality of Coffee Shops in Jabodetabek Area by Application and Modification of Coffee Roaster Machine Capacity 400-600 Gram Coffee Beans Using the Reverse Engineering and Engineering Design Method. IOP Conf. Series: Materials Science and Engineering, 3-4 August, 2020, Jakarta-Indonesia, (Materials Science and Engineering Vol.1007, 2020)
doi: 10.1088/1757-899X/1007/1/012132

[25] Fachruddin F., Syafriandi S., and Fadhil R. Temperature Coverage Simulation of Horizontal Cylinder Type Coffee Roasting Machine. IOP Conf. Series: Earth and Environmental Science, 21 September, 2021, Banda Aceh-Indonesia, (Earth and Environmental Science Vol. 922, 2021) doi: 10.1088/1755-1315/922/1/012031

[26] Wibowo J. W., Munandar A., Mahendra O., Josary J. V., Ningrum D. I. S., and Sejati B. A Review of a Smart Coffee Roaster: Electronics, Design, and Artificial Intelligence. IOP Conference Series: Earth and Environmental Science, 9-10 August, 2022, Sumatra-Indonesia (Earth and Enviromental Science Vol. 1116, 2022)
doi: 10.1088/1755-1315/1116/1/012011

[27] Agustian R., Bintoro A., Rosdiana R., Jannah M., Salahuddin S., and Al-Ani W. K. A. Design of Automatic Coffee Bean Roaster Based on Arduino Uno Microcontroller. International Journal of Advances in Data and Information Systems. 2022, vol 3, page 49-57.
doi:10.25008/ijadis.v3i2.1238

[28] Bonilla E. S. D. Prototype for an Automated Home-use Coffee Roaster. 22nd LACCEI International Multi-Conference for Engineering, Education, and Technology,17 – 19 July, 2024, San Jose – COSTA RICA
doi: 10.18687/LACCEI2024.1.1.1692

[29] Pratama Y., Basuki B. M., and Melfazen O. Smart Coffee Roaster Berbasis IoT. Science Electro. 2022, vol 15

[30] Oematan, A., Kelen, Y. P., Baso, B., and Sucipto, W. Rancang Bangun Mesin Roasted Biji Kopi Timor Portabel Berbasis Internet of Things (IoT) dengan Mikrokontroler ESP32. Krisnadana Journal. 2024, vol 3, page 155-165.
doi: 10.58982/krisnadana.v3i3.606

[31] Winjaya F., Rivai M., and Purwanto D. Identification of Cracking Sound During Coffee Roasting Using Neural Network. International Seminar on Intelligent Technology and Its Applications, 28-29 August, 2017, Surabaya- Indonesia
doi: 10.1109/ISITIA.2017.8124093

[32] Fauziyah M., Adhisuwignjo S., Rifai M. and Dewatama D. Based Fuzzy Logic Temperature Control for a Coffee Roaster Machine. 3rd Annual Applied Science and Engineering Conference (AASEC 2018), 18 April, 2018, Bandung-Indonesia, (IOP Conf. Series: Materials Science and Engineering Vol.434, 2018)
doi: 10.1088/1757-899X/434/1/012202

[33] Samodro B., Mahesworo B., Suparyanto T., Atmaja D. B. S., and Pardamean B. Maintaining the Quality and Aroma of Coffee with Fuzzy Logic Coffee Roasting Machine. The 3rd International Conference on ECO

Engineering Development, 13-14 November, 2019, Solo-Indonesia, (IOP Conf. Series: Earth and Environmental Science Vol. 426, 2020)
doi: 10.1088/1755-1315/426/1/012148

[34] Rutayisire J., Markon S. and Raymond N. IoT Based Coffee Quality Monitoring and Processing System in Rwanda. Proceedings of the IEEE International Conference on Applied System Innovation IEEE-ICASI, 13-17 May, 2017, Sapporo-Japan
doi: 10.1109/ICASI.2017.7988106

[35] Terano M., Kimura A., Ozawa J., Nishikawa Y., Takenaka T., and Oura F. Lifestyle Analysis With IoT Data Acquired From Coffee Roaster For Service Development. IEEE International Conference on Consumer Electronics (ICCE), 11-13 January, 2019, Las Vegas-USA
doi: 10.1109/ICCE.2019.8661953

[36] Rodriguez J. P., Montoya-Munoz A. I., Rodriguez-Pabon C., Hoyos J., and Corrales J. C. IoT-Agro: A Smart Farming System to Colombian Coffee Farms. Computers and Electronics in Agriculture. 2021, vol 190, page 42-50.
doi: 10.1016/j.compag.2021.106442

[37] Sujiwa A., and Santoso I. Automatic Coffee Maker Machine Based on Internet of Things (IoT). Journal of Applied Electrical & Science Technology – University of PGRI Adi Buana Surabaya, Vol. 04, No. 01, 2022
doi: 10.36456/best.vol4.no01.5343

[38] Imammuddin A. M., Wirayoga S., and Susilo, S. H. Application of Fuzzy Logic for Roasting Maturity Level Determination Systems and IOT-Based Coffee Grinding Machines. International Conference on Electrical and Information Technology (IEIT), 14-15 September, 2023, Malang-Indonesia.
doi: 10.1109/IEIT59852.2023.10335535

[39] Syamsiana I. N., Wahyudi M. A., Syamsuri T. U., Nafisah N., and Sumari A. D. W. Implementasi Sistem Monitoring Alat Pengering Biji Kopi Berbasis IoT (Internet of Things). Elposys Jurnal Sistem Kelistrikan. 2024, vol 11, page 62-67.
doi: 10.33795/elposys.v11i1.4964

[40] Minoli C. A., Carmona P. C., Mesa M., Gil J. D. V., and Velasquez J. P. IoT-Based Technology for the Coffee Drying Process Data Analysis of Small Farmers. Revista Facultad de Ingeniería. 2024, vol 33, page 1-12.
doi: 10.19053/uptc.01211129.v33.n69.2024.17404

[41] Sagita D., Mardjan S. S., Purwandoko P. B., and Widodo S. Low-Cost IoT-Based Multichannel Spectral Acquisition Systems for Roasted Coffee Beans Evaluation: Case Study of Roasting Degree Classification Using

Machine Learning. Journal of Food Composition and Analysis. 2024, vol 133, page 78-82.
doi: 10.1016/j.jfca.2024.106478

[42] Faridah F., Parikesit G. O. F., and Ferdiansjah F. Coffee Bean Grade Determination Based on Image Parameter. TELKOMNIKA, December 2011, Volume 9, No.3, page 547-554.
doi: 10.12928/telkomnika.v9i3.747

[43] Turi B., Abebe G. and Goro G. Classification of Ethiopian Coffee Beans Using Imaging Techniques. Article in East African Journal of Sciences · January 2013, Volume 7, No.1, page 1-10.
doi: 10.20372/eajs.v7i1.145

[44] Nasution T. H., and Andayani U. Recognition of Roasted Coffee Bean Levels using Image Processing and Neural Network. 1st Annual Applied Science and Engineering Conference, IOP Conf. Series: Material and Science Engineering, 16-18 November, 2017, Bandung-Indonesia, (Material and Science Engineering Vol. 180, 2017)
doi: 10.1088/1757-899X/180/1/012059

[45] Arboleda E. R., Fajardo C. A., and Medina R. P. Classification of Coffee Bean Species Using Image Processing, Artificial Neural Network and K Nearest Neighbors. IEEE International Conference on Innovative Research and Development ICIRD, 11-12 May, 2018, Bangkok-Thailand
doi: 10.1109/ICIRD.2018.8376326

[46] Akbar M. N. S., Rachmawati E., and Sthevanie F. Visual Feature and Machine Learning Approach for Arabica Green Coffee Beans Grade Determination. 6th International Conference on Communication and Information Processing, November 27–29, 2020, Tokyo-Japan
doi: 10.1145/3442555.3442571

[47] Okamura M., Soga M., Yamada Y., Kobata K., and Kaneda D. Development and Evaluation of Roasting Degree Prediction Model of Coffee Beans by Machine Learning. 25th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems, 8-10 September, 2021, Szczecin-Poland, (Procedia Computer Science 192, Vol 192, 2021)
doi: 10.1016/j.procs.2021.09.238

[48] Simbro G. C., Vera I. H., Ruiz E., and Fragoso K. G. Automatic Tariff Classification System using Deep Learning, International Journal of Advanced Computer Science and Applications. January 2022, Vol. 13, No. 7, page 904-911.
doi: 10.14569/IJACSA.2022.01307105

[49] Arduino:
https://search.arduino.cc/search?tab=&q=arduino+mkr+wifi+1010

[50] Thermocouple: https://www.omega.com/enus/resources/thermocouple-hub

[51] K Type Thermocouple: https://www.filotronix.com/thermal/167-k-type-thermocouple.html

[52] DHT11: https://components101.com/sensors/dht11-temperature-sensor

[53] https://www.espboards.dev/sensors/dht11/

[54] Cooling Fan: https://www.hepsiburada.com/tidar-92x92x25-hsl-220v-ac-fan-pm-HBC00005Q8K49

[55] Single Channel Relay Module: https://circuitdigest.com/microcontroller-projects/interface-single-channel-relay-module-with-arduino

[56] Single Channel Relay Module: https://www.addicore.com/products/1-channel-relay-module-active-low-control

[57] Heat Gun: https://www.bosch-professional.com/tr/tr/products/ghg-20-60-06012A6400

[58] Arduino Cloud: https://docs.arduino.cc/arduino-cloud/guides/overview/

[59] Arduino IDE: https://docs.arduino.cc/software/ide-v1/tutorials/arduino-ide-v1-basics/

[60] Arduino IDE: https://docs.arduino.cc/software/ide-v2/tutorials/getting-started-ide-v2/

[61] Lavalier Microphone: https://store.godox.eu/en/microphones/5587-godox-lms-12-ax-omni-directional-lavalier-microphone-12m-6952344220757.html

[62] Dynamic Microphone: https://www.zuhalmuzik.com/behringer-sl-85s-dinamik-mikrofon-166625

[63] Phone Microphone: https://www.n11.com/urun/xiaomi-redmi-note-9-pro-128-gb-6-gb-ram-xiaomi-turkiye-garantili-1377366?magaza=ms-tekno&renk=yesil

[64] Colab: https://colab.research.google.com/#scrollTo=5fCEDCU_qrC0

[65] Python: https://www.python.org/doc/essays/blurb/

[66] Wabang K., Nurhayati O. D., and Farikhin F. Application of The Naive Bayes Classifier Algorithm to Classify Community Complaints. Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi). 2022, vol 6 page 872 – 876
doi: 10.29207/resti.v6i5.4498