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COMPARISON OF SAVRAN AND AKDERE FLOW MEASUREMENT STATION DATA USING DEEP LEARNING METHODS

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Ali Osman ZENGİN

ABSTRACT

COMPARISON OF SAVRAN AND AKDERE FLOW MEASUREMENT STATION DATA USING DEEP LEARNING METHODS

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Water is the most important source of life in human life for centuries. Due to the growing population, the need for water on earth is increasing day by day. In contrast to this increase, water resources; global warming, drought, climate changes, unplanned consumption is desiphering and losing sustainability. The forward forecast of river currents is of great importance in order to ensure sustainability. If the predictions are made correctly; major improvements can be made in the future management, operation, storage and correct use of water. The input-output account of the waters that have recently rened in rivers is predicted by forward-looking artificial intelligence techniques. The long-term estimates provide suitable planning for both the producer and the user for the production of water resources for living beings, irrigation, hydroelectric power generation and the transfer of water to future generations. In this study, the estimation of river currents is done by creating artificial neural network (ANN) and Deep Learning model from Artificial Intelligence (AI) techniques using numerical current data measured in flow measurement stations (FMS). Performance analyses were examined and evaluated using deep learning optimizers for many years of daily flow values of 2 different rasts in the Euphrates Basin, one of the 25 basins in Turkey. The best forecast model is determined by comparing actual data and forecast models. The highest correlation for Akdere and Göksu was determined at MAE values using ADAM and ADAMAX optimizers.

Keywords: ANN, Deep learning, River Stream, Flow measurement station

ÖZET

SAVRAN VE AKDERE AKIM İSTASYON VERİLERİNİN DERİN ÖĞRENME YÖNTEMLERİ KULLANILARAK KARŞILAŞTIRILMASI

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Yüzyıllardan beri insan hayatının en önemli yaşam kaynağı, sudur. Artan nüfus sebebi ile yeryüzünde suya olan ihtiyaç gün geçtikçe artmaktadır. Bu artışın aksine su kaynakları; küresel ısınma, kuraklık, iklim değişiklikleri, plansız tüketim sebebi ile azalarak sürdürülebilirliğini kaybetmektedir. Sürdürülebilirliğin sağlanması için nehir akımlarının ileriye dönük tahmini büyük önem kazanmaktadır. Tahminler doğru yapılır ise; suyun ileriye dönük yönetimi, işletilmesi, depolanması ve doğru kullanılması açısında büyük gelişmeler kaydedilebilmektedir. Son zamanlarda nehirlerde biriken suların girdi-çıktı hesabı ileriye dönük yapay zekâ teknikleri ile tahmin edilmektedir. Yapılan tahminlerin uzun süreli olması su kaynaklarının canlılar, sulama, hidroelektrik enerji üretimi ve suyun gelecek nesillere aktarılması için hem üreticiye hem de kullanıcıya uygun planlama imkânı sağlamaktadır. Bu çalışmada nehir akımlarının tahmini, akım ölçüm istasyonlarında (AGİ) ölçülen sayısal akım verileri kullanılarak Yapay Zekâ tekniklerinden Yapay Sinir Ağı (ANN) ve Derin Öğrenme modeli oluşturularak yapılmaktadır. Türkiye'de bulunan 25 havzadan biri olan Fırat Havzası'nda belirlenen 2 farklı rasatın uzun yıllar günlük debi değerleri derin öğrenme iyileştiricileri kullanılarak performans analizleri incelenmiş ve değerlendirilmiştir. En iyi tahmin modeli, gerçek veriler ve tahmin modelleri karşılaştırılarak belirlenmektedir. Akdere ve Göksu için en yüksek korelasyon, ADAM ve ADAMAX iyileştiricileri kullanılarak MAE değerlerinde görülmüştür.

Anahtar kelimeler: ANN, Derin Öğrenme, Nehir Akımı, Akım gözlem istasyonu

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SYMBOLS AND ABBREVIATIONS

AI **:** Artificial Intelligance
ANFIS **:** Adaptive Network Fuzzy Inference System
ANN **:** Artificial Neural Network
CNN **:** Convolutional Neural Network
DL **:** Deep Learning
DLNN **:** Deep Learning Neural Network
DSI : General Directorate of State Water Affairs
FCN : Full Convolutional Network
FFFANN : Feed Forward Feedback Artificial Neural Network
FMS : Flow Measurement Station
GEP : Genetic Programming
GRANN : General Regression Artificial Neural Network
GRU : Gated Repetitive Unit
km : kilometer
km^2 : kilometer square
KNN : K-Nearest Neighbor
LSTM : Long-Short Term Memory
m : meter
m^3 : cubic meter
MAD : Mean Absolute Deviation
MAE : Mean Absolute Error
MAPE : Mean Absolute Percentage Error
MBUP : Multivariable Bayes Uncertainty Processor
MEAN : Actual-Predicted
MLANN : Multi-layer Artificial Neural Network
MLR : Multi Linear Regression
mm : milimeter
MSE : Mean Squared Error
NAG : Nesterov Accelerated Gradient
NLP : Natural Language Processing
PDE : Partial Differential Equation
RMSE : Root Mean Square Error
RTANN : Radial Based Artificial Neural Network

SMA : State Meteorological Affairs

STD : Standart Deviation

ε-SVM : Support-Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 General Overview

Water is a source of life that is vital for humans and brings life almost to a halt in case of lack. It faces many negativities that will jeopardize its sustainability day by day. Global warming, drought, unplanned and incorrect consumption of water are among the main dangers. Sustainability of water resources leads the life. For this reason, predicting water resources enables water to be used in every future in a planned, efficient and economical way. Otherwise, the problem of unconscious management of water resources arises. Unconscious and mismanaged water resources can create a danger for the continuity of living and bring the quality of life to the lowest levels. Water resources management extends to the rainwater collected in river basins and the transfer of these rainwater to consumers. In the management of river basins, evaluation of land soil is of great importance along with accurate estimation of current measurement stations. The main goal should be to protect, plan and sustain river basins. In this context, planning of water resources management can be done strategically by creating many prediction models. ANN and deep learning models, one of the artificial intelligence techniques, are among these prediction methods. Estimates can provide suitable planning opportunity for both the producer and the user for water resources, living things, irrigation, hydroelectric power generation and transfer of water to future generations.

Accurate estimation of flow is an necessary component for both water amount and amount direction. In last years, Artificial Intelligence (AI) techniques have been evidented as a computer science branch to model a vast variety of hydrological handle. A number of research studies are conducted to find a more fruitful approach in terms of correctness and acticality (Mehr et al., 2013).

Deep learning is an develope branch of artificial intelligence consisting of a large number of layers of neurons that symbolize the learning handle. Deep learning can get over with large-scale data and excel in several fields. Accordingly, surveyors pay more notice to investigating deep learning for intrusion detection (Aldweesh et al., 2020). Deep learning is one of the developed touches to machine learning and has been gaining more and more note in last years. Today, it is used in several fields and practices such as version identification, medical estimation and talk identification. Unlike conventional learning algorithms, deep learning can skip dependence on hand-designed features. The deep learning experience is developed especially by taking advantage of strong infrastructures such as clouds and by take up seriously cooperative learning for model education (Boulemtafes et al., 2020). With the rapid growth of deep learning algorithms, many high-correctness models were developed and implemented in the real world space. Deep learning is parallel and suitable for distributed computing, which can significantly increase system efficiency. A kind of distributed computing system is proposed for deep learning. The design concept of cache pre-transmission aims to use reinforcement learning to train a pre-forward policy to increase the cache hit rate. Due to the characteristics of reinforcement learning, this policy can be adapted and applied to different computer environments. Finally, this system has been demonstrated experimentally (Cheng et al., 2020).

Since the 60s, statistical process that have been increasingly sophisticated, Machine Learning and newly Deep Learning have been used to presage protein constructive knowledge at various levels of detail. In this review, he in a nutshell introduces the problem of prediction of protein structure and the basic factors of Deep Learning, and then discusses the evolution of predictiveism. This commentary summarizes the flow role of Deep Learning techniques in larger pipelines to foretell protein structures and try to predict what challenges and opportunities may later arise (Le et al., 2020). This deep learning, a branch of machine learning, shows promising conclusions in previous studies for the detection of security breaches. In addition, intelligence tecqnies devices produce large volumes, variety and real data. Thus, when big data technologies are included, higher performance and better data processing can be achieved (Amanullah et al., 2020).

In this study, estimations of river flows are made with the data obtained from current measurement stations. Prediction is realized by making use of artificial intelligence methods ANN and deep learning models. As a conclusion of the crosscheck, the best prediction model can be determined and can be a guide in similar studies.

The estimation of river flows is done by creating Artificial Neural Network (ANN) and Deep Learning model from Artificial Intelligence (AI) techniques using numerical current data measured in current flow measurement stations (FMS). Performance analyses were examined and evaluated using deep learning optimizers for many years of daily flow values of 2 different rasts in the Euphrates Basin, one of the 25 basins in Turkey. The best forecasting model is determined by comparing actual data and forecast models. A crosscheck of the conclusions of deep learning modeling and soft computational techniques is also discussed in this article. The conclusions obtained are statistical methods of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Actual-Predicted (MEAN), Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Deviation (MAD) and Standart Deviation (STD) respectively. The aim of this study is to compare the optimizer results based on the evaluation criteria in the estimation of hydrological data using deep learning methodology. The proposed deep learning model is clearly given and made available in practical applications.

CHAPTER 2

LITERATURE REVIEW

2.1 General

Water has been a natural resource of great importance for all civilizations for centuries, and all the great civilizations are gathering by the water. With the advancement of technology, the methods and rates of utilization of water resources increase, the development of water resources for many areas such as drinking water, irrigation water, energy production play an important role in the economic development of countries (Akkaya et al., 2006). Increasing water requirement with the world population day by day makes it necessary to use the available water resources in the most economical way. Therefore, the need for water resources engineering and the science of hydrology that will form a basis for this is inevitable. Hydrology; It is a basic and applied science that examines the cycle, distribution, physical and chemical properties of water on earth, underground and in the atmosphere. It is also of great importance in the design and operation of water structures. While a water structure is being designed, hydrological studies are carried out first, hydraulic studies are started, and finally the building is dimensioned. In this way, the water cycle is formed. The water in the world moves in a hydrological cycle with the help of solar energy. The creatures living on earth meet the water they need for many activities from this hydrological cycle and return the water back to the same cycle after use. Sufficient amount and quality of water needed by living things must be supplied from this hydrological cycle in order to maintain vital activities in an ecological balance. Planning for the conservation, development and sustainable use of our country's water resources needs to be done at the basin level (Yüksek, 2004). In the following years, meeting the increasing water demand increases the importance of water management. Problems encountered in water management; physical infrastructure insufficiency, water quality deterioration, water pollution, insufficiency of water transmission-distribution systems and management problems (Çakmak et al., 2006). Although it is known that nothing artificial can be found to replace water in the future, more attention than ever helps to use resources wisely with new strategies (Mengü and Akkuzu, 2008).

2.2 Deep Learning

Deep learning lets computational models consisting of plural working layers to learn representations of data with plural levels of abstraction. These methods have significantly improved the latest technology in many other areas, such as speech identification, visual object identification, object detection and medicament exploration and genomics. Recently, deep learning has admitted a lot of note due to its good conclusions. It is to reach even conclusions that are not possible to reach a solution in previous studies (LeCun et al., 2015).

Deep Learning discover the complicated structure in large datasets by using the re propagation algorithm to specify how a machine must change the internal parameters used to calculate the presentment on all layer from the presentment in the former layer. Networks have made inventions in the processing of images, videos, speeches and sounds, while repetitive networks have shed light on sequentive data such as text and conversation (LeCun et al., 2015).

In last years, deep learning models have been widely used in remote sensing images. Deep learning is done in remote sensing images as well as in all areas to be able to classify performance better than present touches and to detect property inssiables on its own. Further studies are being carried out on hyperspectral images, especially in remote sensing. The most prominent reason for this is that it can carry a large number of data propertys. A large number of data properties means that there are many attributes for that image (Toğaçar et al., 2018).

Deep Learning is tempting to learn from large amounts of untagged/unchecked data, making it attractive to remove meaningful representations and patterns from big data. Deep learning methods represent complex relationships between data, allowing more useful conclusions to be produced than standard methods (Hasan et al., 2017).

2.3 Overview Studies

Zhou (2020), the point revealed a new methodology for predicting possible water quality based on estimates. Multivariable Bayes Uncertainty Processor (MBUP) is being used to model the intercourse among point estimates made by deep learning ANN and the corresponding observed water quality based on the potential. The methodology was tested using hourly water quality series on the island of Shanghai City in China. Here, predictive deploys encountered in multi-stage water quality estimates have been effectively reduced to small intervals. The conclusions show that the deep learning plus post-processing approach appropriately reveals the complex dependency structure between the model's output and the observed water quality, thus predicting model reliability.

AI is of great importance in identifying these strategies. Artificial Intelligence (AI) is a simulation of human intelligence processes carried out by machines and especially computer systems. In a broader definition, AI is a computer science field that handles the creation of intelligent machines that work and react like humans.

AI tools have attracted interest from the literature and commercial organizations over the past decade, especially with advances in machine learning techniques. The big factor in his interest is the solutions he brings to the problems (Borges et al., 2020).

With the development of AI over the years, machine learning, which is a sub-part, emerges. Machine learning and Artificial Intelligence are frequently judged jointly. In some cases, it can be used in place of each other. While all machine learning resolutions are Artificial Intelligence, the absence of machine learning for all AI solutions is an important distinction. Today, machine learning works everywhere. Machine learning algorithms come into play to provide an fruitful, seamless and secure experience when we interact with banks, shop online, or use social media. Machine learning and the technology within this framework are rapidly evolving, and the features we have discovered are just the tip of the iceberg. Machine learning, like artificial intelligence, has not eded significantly in many years. It became popular with data mining in the 1990’s and began to develop deep learning in the early 2000s.

Current improvings in machine learning, especially deep learning, prove to be effective in identifying and quantifying patterns in medical images. The crucial point of these progress is the capability of deep learning touches to obtain hierarchical feature representation immediately from images, which eliminates the need for handcrafted propertys. Deep learning is rapidly transforming into cutting-edge technology for medical image processing and conclusions in performance improvements in various clinical implementations. The basics of deep learning methods are discussed with an survey of successful applications that include image segmentation for different medical applications. Some research topics are highlighted and highlighted that there is a need for further improvement in the future (Haque and Neubert, 2020). The performance of deep learning models recently developed for image classification is higher than that of radiologists. It is aimed to determine whether the high performance of deep learning in mammograms can be transferred to external data with a different distribution of data. Performance discrepancies are observed between data sets and models. For this reason, it can be seen that the high performance of deep learning models in a data set cannot be easily transferred to invisible external data sets, these models need more evaluation and validation before being applied in clinical practice (Wang et al., 2020). By combining image local features and machine learning method designed manually by researchers, various image recognition tasks are carried out in the image recognition area before 2010. However, after entering 2010, many image recognition methods using deep learning are proposed. Image recognition methods that use deep learning are far superior to the methods used prior to the emergence of deep learning in general object recognition competitions. Therefore, how deep learning is applied to the image recognition area and the latest trends of deep learning based autonomous driving are explained (Fujiyoshi et al., 2019). Due to the enormous success of deep learning image classification, object detection techniques using deep learning have been actively studied in recent years. Extensive research on the latest developments in visual object detection with deep learning is presented. Most of the recent studies in the literature are reviewed, and existing object detection frameworks are systematically analyzed (Wu et al., 2020).

A deep learning model is being developed to estimate whether individual spread investors are profiting from future transactions. Traditional machine learning requires data that represents the feature-goal relationship and is often based on costly development, maintenance and revision of handicraft features. As a conclusion, it is difficult to model highly variable heterogeneous models such as trader behavior. Deep learning promises a cure. Automatically learning hierarchically distributed representations of data (eg risk-taking behavior) reveals productive features that set the goal (for example, merchant's profitability), avoids manual feature engineering and is more robust to change (eg dynamic market conditions). The conclusions of using a deep network for operational risk prediction confirm the ability of deep learning to learn features, provide guidance in designing an appropriate network architecture, and demonstrate the superiority of deep learning through machine learning and rule-based criteria (Kim et al., 2020).

It introduces the Deep Learning Neural Network (DLNN) model to landslide susceptibility assessments and compares predictive performance with cutting-edge machine learning models. The Frequency Rate method is used to estimate the relationship between the landslide related variables and the presence of landslides. Although DLNN is rarely used in landslide susceptibility assessments, it emphasizes that the use of the deep learning approach can be considered a satisfactory alternative approach for landslide susceptibility mapping (Bui et al., 2020). Proposes and evaluates a new approach to flash flood sensitivity mapping based on the Deep Learning Neural Network (DLNN) algorithm with a case study in a high-frequency tropical storm region in the northwestern mountainous region of Vietnam. The conclusions can be concluded that the proposed hybridization of the Geographic Information System and deep learning can be a promising tool to assist government officials and involve the parties in flash flood mitigation and land use planning (Bui et al., 2020). Modeling the spatial distribution of mobile organisms under rapidly changing environmental conditions is a challenging effort to take whenever the effects of changes are evaluated in dynamic scenarios. Habitat suitability is modeled for Lake sturgeon (Acipenser fulvescens) and White perch (Morone americana). It emphasizes that using tidal and hydraulic models, along with acoustic telemetry and machine learning, can be used to estimate the spatial distribution of mobile organisms, even in highly variable ecosystems, such as estuaries, using Deep Feed Feed Artificial Neural Networks (Guénard et al., 2020).

Natural language processing (NLP), the transformation of free text into structured data, and the latest innovations in Deep learning technology provide improved NLP performance. It is aimed to investigate the basics of deep learning NL+P and to examine its research on radiology. Research and use of in-depth learning NLP in radiology is increasing. Getting acquainted with this technology can help radiologists prepare for changes in their field (Sorin et al. 2020). In many applications, estimates are based on numerical solvers for partial differential equations (PDEs). Although the use of deep learning techniques has been proposed, actual applications are restricted due to the training data being obtained using conventional PDE solvers. Thus, the use of deep learning techniques is limited to the areas where the PDE solvent is applicable (Hähnel et al., 2020).

River flow estimation is important to provide basic information in the face of various problems related to the design and operation of river systems. While conceptual or physical models are important in understanding hydrological processes, there are many practical situations where the main concern is to make accurate predictions at certain locations. In this case, it is preferable to apply a simple "black box" model to define a direct mapping between inputs and outputs without considering the internal structure of the physical process in detail. ANN is the most successful machine learning technique with flexible mathematical structure that can define complex nonlinear relationships between input and output data (Dibike and Solomatine, 2001).

Terzi and Köse (2012), in the flow estimation of Göksu River, ANN models are developed by using the current values of the stations no.1714, 1, 2, 3, 4 and 5 days ago and the current values of the stations no 1719 and 1720 as input. It is observed that the developed model's coefficient of clarity and average absolute error value gives better conclusions compared to other models.

Yurdusev et al., (2008), estimation of monthly flows in the closed basin of Akarçay river from rain and flow observations using the ANN method, models are designed in 4 different categories depending on the parameters such as the location of the precipitation observation stations present in the basin and the observation interval. The conclusions obtained are compared with the conclusions of multivariate regression analysis and it is revealed that ANN can be successfully applied to the flow prediction problem from the flow and precipitation observations and produces safe estimates.

Gemici et al., (2013), in 5 different stations selected on the side branches of the Kızılırmak River, the stream cross section is divided into slices under 22 different flow conditions and its flow rate is determined by speed-area method. The determined base slope, base roughness coefficient, cross section slice width, water level passing through the slice and river cross section width values are used as input data. With this data used, the flow rate through each slice is estimated with multi-layer artificial neural networks (MLANN), radial-based artificial neural networks (RTANN) and adaptive network-based fuzzy inference system (ANFIS) models. It was observed that ANN and fuzzy logic models were very successful in determining the flow rate, and the model performances were close to each other. The best performance was obtained from the ANFIS model.

The flow rate of the Lower Sakarya River gives the highest determination coefficient (R2) of the four-day time shift using flow data obtained from Doğançay Current Observation Station using Feed Forward Back Propagated Neural Networks from ANN models. This study on the Sakarya river is thought to help future energy planning and flood studies (Kızılaslan et al., 2013).

An ANN model is developed and applied to the daily flows of the Coruh River in the Coruh basin. The ANN model, which needs current values 1 and 2 days ago as input, has been trained using the current data of 1643 days between 03.10.1991-01.04.1996; Using the 1643 daily flow data between 02.04.1996-30.09.2000, the internal dependent stochastic AR (2) model structure is compared with ANN. The ANN model created successfully represents the daily flows of the Coruh River; Thus, it is thought that the developed model structure can be used successfully in the estimation of daily flows of other river basins (Okkan and Mollamahmutoğlu, 2010).

Gündüz (2011), daily flow data in 1968-2006 period is used for ANN and wavelet transformation models developed to estimate river flow in Fırat-Dicle basin. Findings obtained with ANN and wavelet transform models are compared with multiple linear regression models. To test the suitability of the conclusions obtained from the models; Conclusions are analyzed according to the square root mean square error (SMSE), average absolute error (AAE) and the coefficient of salience (R2) statistics. Crosscheck conclusions show that Artificial Intelligence techniques can be used successfully in river flow prediction. 6 models are created by using various combinations of Köprüçay daily flow values as input. It is observed that the Köprüçay currents estimated by the forward feed backward propagation ANN method give better conclusions when compared with the conclusions of the linear regression (LR) model (Demirpençe, 2005). An ANN model is being developed using current measurement data from Ipsala, Plovdiv, Svilengrad and Kirişhane flow observation stations on the Meriç River between 2005-2011 (Kökçam et al., 2018).

Artificial Intelligence Methods such as ANN, Genetic Algorithm and Fuzzy Logic are widely used in modeling the precipitation-flow relationship. The relationship between the monthly average flow data of the 2157 current observation station in the Central Euphrates Basin and the monthly total precipitation data of the rainfall observation station numbered 17204, among the ANN methods, Feed Forward Feedback Neural Network (FFFANN), Generalized Regression Artificial Neural Network (GRANN) and Radial Based It is researched with Artificial Neural Network (RTANN) and then these conclusions are compared with the more classical method, Multiple Linear Regression (MLR) method. It is determined that the current values estimated by the RTANN method converge better to the observed current values compared to the values estimated by the other ANN methods used (Gümüş et al., 2013).

Current values of the current observation station of Söğütlühan (1535), Yamula (1501) and Bulakbaşı (1539) on the Kızılırmak River from the General Directorate of State Meteorological Affairs (SMA) Kayseri, Sivas and Zara three different models are developed to estimate the current values of Söğütlühan station by taking the precipitation values of the stations. When the developed models are compared, it is seen that all models give appropriate conclusions and the best conclusion is obtained only when current values are used (Önal, 2009). While the ANN models were developed by evaluating the daily flow values obtained from Karahacılı (1714), Kırkkavak (1719) and Hamam (1720) current observation stations in the Göksu River and evaluating the performance of these models, average absolute error values are used. When the performance of the models is evaluated, it is seen that the ANN method can be used in the flow estimation (Terzi and Köse, 2012).

Okkan and Mollamahmutoğlu (2010), the ANN model prepared for the modeling of the daily flows of Yiğitler Stream in the Gediz basin is compared with the multiple linear regression model, and the model performances are tested with the measured daily current values of the Yiğitler Stream. As a conclusion of the analysis, ANN algorithm performance is found to be more successful than the regression model. Although a pixel mapping unit with a spatial resolution of 300 m was used on a total area of 50641 km^2 covering the borders of Karaman, Mersin, Adana, Osmaniye and

Hatay in the Eastern Mediterranean region, using the ANN method. With the obtained data, it is thought that it will make an important contribution in determining the relationship between landslides and environmental variables controlling landslide incidents on a regional scale and in reducing the losses caused by landslides (Tekin et al., 2015).

Sensitivity evaluation of shear type landslides in Ermenek stream basin is obtained by mapping 354 landslides with a total area of 183 km2 in the study area and its correctness is obtained by comparing the sensitivity classes with the existing landslides. It is observed that 74% of the existing landslides are found in the high and very sensitive classes corresponding to 30% of the study area and it is seen that the sensitivity map obtained has a high predictive capacity (Tekin and Çan, 2015).

In order to find the best classification model in deep neural networks, 20 different models are created using combinations of optimization method (Sgd, Adagrad, Rmsprop, Adam and Nadam), activation function (Tanh and ReLU) and neuron numbers. Although the selection criteria of optimization algorithms are not clear in deep learning studies, the algorithms show different performances depending on the nature of the problem and the parameters. Therefore, in case of creating different combinations of optimization algorithms, activation functions and neuron numbers while modeling in deep learning studies, more suitable architecture can be obtained for the data set (Ser and West, 2019).

In order to develop hydrological models that can represent different geological climate systems in China, Support-Support Vector Machine (ε-SVM) and ANN are applied in three different basins for simulation and prediction flow. The Evolutionary Strategy (ES) optimization method is used to optimize ANN and SVM sensitive parameters. As a conclusion of comparing the relative performance of the two models, it is seen that both models perform well for moist and semi-moist systems (Bafitlhile and Li, 2019). Implementing Artificial Intelligence techniques for river flow prediction can improve water resources and flood prevention management. Particle flock optimization (PSO) hybridization is used to develop the support vector machine (SVM) based model and estimate short-term daily river flow in the Upper Berta Basin in Cameron Highland, Malaysia. Four SVM-based models are proposed, SVM1, SVM2, SVM-PSO1 and SVM-PSO2, to estimate 1 to 7 days before river flow. SVM-PSO1 and SVM-PSO2 hybrid models appear to provide higher performance compared to SVM1 and SVM2. Hybrid models are also more effective in predicting river flow in the study area 1 to 7 days before (Zaini et al., 2018)

Cevik et al., (2009) proposed the application of soft computational techniques to estimate the strength of aluminum alloy columns excavated by heat treat, which did not succeed as a conclusion of bending sprains. It is presented as soft computational techniques used in neural networks (NN) and genetic programming (GEP) studies. Experimental data used to train software calculation models are obtained from the data in the literature. Compared with the GEP and NN submitted for the proposal with the existing models and the codes (EC9 and ISO) proposed by Rasmussen. The conclusions of GEP and NN models are more accurate than previously given codes.

Üner (2019) investigated whether better knowledge can be extracted from an experimental approach with an approach aimed at Deep Learning. Experiments are carried out with 6 different Machine Learning methods using gene expression from the LINCS L1000, SMILES sequence representation in atomic structure of drug molecules. Using its chemical structures and gene expression properties, the multilayer sensor (MLP)-based model outperforms state-of-the-art research on the prediction of the possibility of side effects, reaching 88% microAUC and 79% macro-AUC. Even if the features are eliminated by different deep learning models, it is observed that the chemical structure has a stronger predictive ability than the appearance of gene expression. And finally, the in-house neural network-based model using SMILES drug sequences per tk provides a good degree of regulation of 82% macro-AUC and 88% micro-AUC, which outperform these models that use gene-expressive chemical structure properties.

Yetiş (2019) used 2D floor designs and appearance projects produced from the very beginning as a data set. This data obtained is divided different Evolutionary Networks to generate relevant architectural information. Because Deep Learning shows promising success in finding solutions to problems. Semantically separated projects are converted into 3D models using Digital Geometry Processing methods at the next stage. Semantic separation conclusions in the 2D model and two case studies in the 3D model were evaluated to represent the correctness of the process and compared separately with each of the different measurement methods. Using the most advanced methods, this study proposes an automated process for reconstructing 3D models and can make them available even to a non-technical person.

Paker (2019) draws attention to the widespread use of Deep Learning in bioinformatics and computational biology, with the increasing number of data on biological information in recent years. The main problem discussed in his thesis is related to bioinformatics. Therefore, in this study, it is discussed whether the given microRNA and the mRNA molecule are linked to each other. The study developed a web interface to identify miRNA regions both efficiently and quickly and provide interface to the end user. By looking at different data sets and configurations, they were compared. Compared to 6 classical machine learning methods, LSTM model gives better conclusions according to some evaluation criteria.

Tanimu (2019) examined the cracks that may occur in structures such as roads that may cause major problems in the future. While investigate the cracks, the fixation methods are examined in two ways as destructive and non-destructive. This study analyzes cracks that have formed materials with ground radar analysis, due to its advantage over other methods. A laboratory environment has been created in order to conduct studies. Ground radar and temperature image measurements of fractures of different shapes and materials and various blocks were made. After the applied visual and temperature analysis, GPR raw data wavelet transform and entropy methods were preferred for new analyzes. The considered Wavelet-CNN crack detection method demonstrates that it detects cracks much better than raw data or b-scan signals directly.

Çakır (2019) analyzes the effect of controlled and uncontrolled Deep Learning algorithms in detecting zero-day attacks. The performances of the obtained algorithms were compared by performing analyzes on different DL models. According to the test conclusions, it is more successful with 95.3% correctness score and 97% f1 score in determining the attacks of uncontrolled DL methods. Apart from the training and test datasets created in the same environment, test sets created in different environments than the training set were used in order to try DL methods. Built-in tests show that DL methods can detect some, if not all, attacks in clusters created in different areas, and can detect low false positive rates.

Özgenel (2018) explains the term data design that emerged to describe the process of problem solving from beginning to end with appropriate deep learning algorithms with a wide range of applications, including problems in design. In parallel with this, the research contributes to the literature not only with the introduction of data design and framing, but also with the suggestion of crack detection special evaluation criteria for both image classification and segmentation applications. A new method using quadtrees and deep learning algorithms is proposed. Finally, data design and related conclusions are discussed in depth. Case dependency is shown regarding the effects of the decisions taken during implementation on both the process and the conclusions.

Tienin (2019), using the deep learning (DL) technique to compare traditional image processing methods. At the initial stage, a two-class classification study was carried out. Its purpose in the study is to distinguish between images that are clouds and not. The function of eviitation Nervous System and TendermaxWithLoss is used for forecast and grading. During the training process, 92% correctness was reached by fine-tuning the model. Among the second process, cloud images detection and segmentation were carried out using image processing techniques. Among the third phase, Full Convolutional Networks (FCN) and U-NET DL processs were used for division. During the training phase, the Dice coefficient was found to be 87% as U-NET and 45% as lost. FCN system, stokastic incline, drop, Adam's momentum and Nesterov momentum techniques have been practical to several training methods. According to all conclusions, the best achievement was achieved with Adam's momentum technique with 63.12%.

Sorkun (2018) focalize on forecasting models by working on a statistical timing series in her studies. This study aims at the suitability of deep learning and timing series estimation methods on solar radiance data. Solar radiation time series forecast was made with curative Nervous System variation Long Short Term Memory (LSTM) and Gated Repetitive Unit (GRU) models. It gave very good conclusions in estimating the radiation data of the values obtained by optimizing the parameters. The LSTM and GRU versions appear to be appropriate and competitive for predicting time series above the 1-hour horizon in solar radiance data.

Anwer (2017) describes a clinical support system based on deep learning for the diagnosis of breast cancer in medicine. Study aims to investigate whether DL approaches yield successful conclusions in the field of medicine. Wisconsin Breast Cancer datas in the UCI Machine learning warehouse are used to test the deep learning capability of several techniques. Medical decision making with machine learning approaches and experiments also shows a promising direction.

Kutlu (2019), Artificial Intelligence algorisms is one of the most searched and advanced, exercises of recent times. Study, a control programme that appraises image data coming from unmanned atmospheric vehicles and makes diverse inferences has been created. The training time was tried to be shortened by using the method of redeveloping the last layers of ANN models, which were previously developed with the data set. With this study, the success coefficient has been tried to be increased. As a conclusion of the 2 pre-trained models used in the study and the training of these models, the values of 25.39 and 27.87 mAP were reached as a conclusion of the training of 190 thousand steps.

The suggestion system produced by Kantepe (2019) was designed using the AutoEncoder deep learning method. This generated recommendation system was implemented using the Python language on the TensorFlow platform. The MovieLens 1M dataset, which consists of movie ratings ranging from 1 to 5 and collected by GroupLens researchers from MovieLens website users, was used. This work has been written in four chapters. Gradient Descent conclusions obtained by using RmsProp, Momentum and Adam algorithms are shown in pictures and charts. In the third part, the findings are appraiseed and as a conclusion, it is indicate that Adam is the best algorism with 1.363 points of test error. It has been observed that the more data a training set has, the more prosperous the suggestion system is.

Özyurt (2019) is conducting research to eliminate the manual originality step of images by researching the deep learning technique. In the study carried out, by using the perceptual hash function, which does not cause any distortion in the image structure, data is obtained visibly directly from the raw images. Some parameters such as BER, MSE, PSNR are taken into account in order to evaluate the progression of this proposed perceptual hash function. These parameters are compared with each other. The conclusions obtained by applying this process to the liver and Caltech-101 view database were evaluated by thinking ANN, Support Vector Machines (SVM), K-Nearest Neighbor (KNN). This suggested technique not only advances classification performance but also provisions positive effects on overworking problem.

Büber and Şahingöz (2017) perform image processing and recognition of numerical characters using deep learning. Handwritten images to be used for the application are used for training and testing, respectively, 50,000 and 10,000 data from the MNIST data set from 250 different individuals. Before using the deep learning method, the effects of hyperparameters on algorithm performance should first be determined. As a conclusion, it was stated that the success rate of digital hyperparameters determined to be used in the test phase is 94.75%.

Razavi and Yalçın (2017) aimed to determine the herb sort from the data collected from clever farming stopping place. The study suggested a machine learning process that can automatically remove attributes from two-dimensional herb data. 4800 images of 16 facility classes in the TARBIL data set are used in the construction of the CNN architecture. To determine that the CNN-based approach by using 3 different deep learning methods has approximately 97.47% correctness, by studying 16 types of plants, and the grading correctness is preferable than other process.

Shahbazi et al. (2014) investigates the flexible buckling of intelligent slight column building integrated with the surface piezoelectric layer using artificial intelligence techniques. Intelligent lightweight columns have finite element modeling using ANSYS® software. In the next stage, the eigenvalue buckling analysis is used to calculate the initial buckling load of the structure. Afterwards, parametric studies were conducted for the length changes, width and thickness of the elastic core and piezoelectric outer layers, and the relevant buckling load data sets for Artificial Intelligence were collected. As a conclusion, software based methods including ANN, fuzzy inference system (FIS) and adaptive neuro fuzzy inference system (ANFIS) are applied. Crosscheck of the conclusions reveals that the ANFIS model provides high correctness in predicting buckling load in smart light columns, and even better estimates than other methods. Using the feed forward algorithm from the ANN model, it has been revealed that there are accurate and reliable conclusions.

Ghetiya and Patel (2014) discuss a systematical approach to optimizing frictional welding process parameters for aluminum alloy. In the study, it was attempted to join AA8014 aluminum alloy with FSW (Friction stir welding) using conventional milling machine. Friction stir welding was performed on AA8014 plate, which is 4 mm thick. ANN is developed based on error back propagation (BP) for estimation of tensile strength in FSW. ANN was then trained with experimental data. As a conclusion, it is seen that the ANN conclusions are in good agreement with the experimental data. As can be seen, this neural network can be thought of as another way to calculate tensile strength for certain process parameters.

Yuan and Bao (2018) evaluate guided wave (GW) -CNN based fatigue fracture determination method. Different simulation options for creating different sultion frequencies GW attributes extracted from GW marks are used as input data to a trained CNN for the diagnosis of fatigue fracture. According to the conclusions obtained, the recommended method was found to be promising.

Ly et al. (2019) develop different Artificial Intelligence (AI) methods, namely simulated annealing (SA) and biogeography-based optimization (BBO), two ANFIS optimized with the adaptive neuro-fuzzy inference system (ANFIS) and meta-heuristic methods. Excellent conclusions were obtained using the BBO optimization technique. Those who used the SA technique were not much different. Finally, sensitivity analysis was performed and it was concluded that the most important defects affecting the column buckling capacity were the initial in-plane loading eccentricity at the upper and lower ends of the columns. Improved methodology and AI models can pave the way for an improved approach to predicting the damage of compressed columns.

Durmuş et al. (2006), 6351 kinds of aluminum alloy temperatures, load shear rate, abrasive grain diameter, etc. ANN has been used to improve the effects of aging conditions. These conclusions obtained by operating the experimental conclusions in the ANN program were compared with the experimental values. It is seen that the experimental conclusions coincide with the ANN conclusions.

Hassan et al-2009) examines the potential for the power to use the feedback nerve network to predict the physical properties and hardness of composite-synthesized aluminum-copper/silicaium carbide composites. The actions seen on a metal matrix of 4% Al-4% Metal matrix of silicon carbür addition as copper and reinforcing particles as an alloy element were examined. The top-level absolute relative error percentage for estimated values should not exceed 5.99%. Accordingly, it is seen that by using ANN output data, satisfactory conclusions can be predicted outside of measurement and therefore the duration and cost of testing can be reduced.

Akdağ (2017), hardware improvements in GPUs and CUDA, which enables general purpose programming of GPUs, have undergon drastic changes in some areas that require a high degree of data parallelism, such as image processing. Thanks to advances in gpu and deep learning, significant achievements have been achieved in interpreting camera images in real time, without the need for human factor. The data set was created with pictures with an weapon object in it to perform the application. DetectNet and YOLO deep neural network models are trained using this data set created. In terms of test conclusions and operating performance on the Jetson TX1 card, a CUDA-powered embedded system, the DetectNet model has been found to be more successful than the YOLO model.

Ashaj (2020), an improved power management system, handles many key aspects of electrical management, such as reducing power consumption to lower possible limits, controlling ambient temperature, and turn some devices on and off depending on human activity. In the study, a camera compatible with a minicomplement as a Raspberry Pi is used to record images or real-time streaming video to detect human presence and activity. Deep learning based on the structure of verifying Neural Networks has been used as an effective approach to properly classifying objects. The Python computer program language has been used because it has a large bookcase function and is compatible with the programming of the embedded system in real time. According to the conclusions, it was confirmed that the system can manage electricity consumption intelligently and accurately. In addition, the recognition algorithm quickly achieves good conclusions in separating other objects in human form, with detection correctness of 97.9% and convergence time reaching 0.9 seconds.

Dokuz (2020), aims to propose mini-stack sample selection strategies for deep learning-based voice recognition systems. Deep learning-based voice recognition systems, along with the popularity and achievements of deep learning architectures, have become much more common and the most modern system in the field of voice recognition. Resyeration Neural Networks (RNN) and Long Short Term Memory are highly common and successfully used architectures for RNN voice recognition applications. The proposed strategies use meta features such as gender and accent properties found in audio datasets. Experimental conclusions have shown that recommended strategies are useful for improving the performance of deep learning-based voice recognition systems.

CHAPTER 3

MATERIAL&METHOD

3.1 Study Area

The daily flow values of 2 different flow measurement stations in the Fırat Basin, one of the 25 basins in Turkey, were examined and evaluated for performance analyses using deep learning optimizers (Figure 3.1 and Figure 3.2).

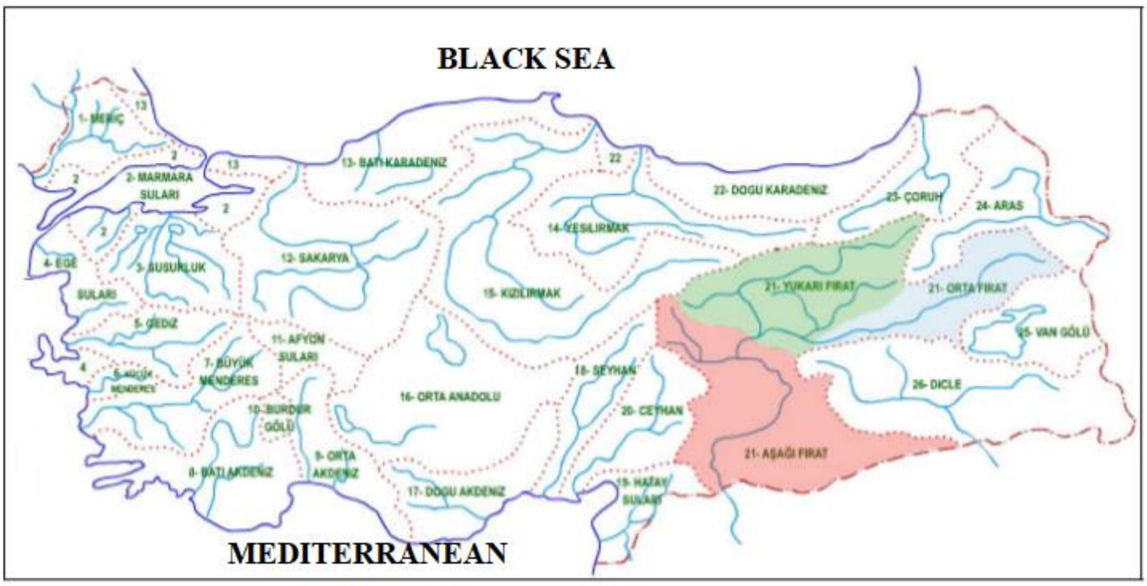

Figure 3.1 Location of the study area in Turkey map

Figure 3.2 Euphrates river basin and its drainage network

Euphrates basin was chosen as the study area. This basin is located in the eastern part of Turkey with a 127304 km^2 area –making it the biggest wetland area in the country. River Murat and River Karasu are important rivers supplying Euphrates River with water. Peri, Cati and Munzur creeks can be mentioned as other rivers. Euphrates River flows through Erzincan, Tunceli, Elazig, Malatya, Diyarbakir, Adiyaman, Gaziantep and Sanliurfa provinces in Turkey and later on reaches Syria, then Iraq. It joins with river Tigris at the area called Sattul-Arab to flow together into the Persian Gulf. Euphrates basin is divided into threesub-basins called Upper Euphrates, Middle Euphrates and Lower Euphrates. The basin has 540,1 mm average annual precipitation turns into flow. This value is 17% of the total volume with in Turkey. Average altitude of the basin is 1010 m. Precipitation turn into snowfall during winter times, with respect to the altitude of the basin. As snow takes sometime to turn into flow, stream flow during winter season shows decline in its rate. On the contrary, spring and summer show an increase in stream flow rate –leading to overall increases in water potential of the region.

Euphrates is a stream that crosses borders with this aspect. The Euphrates basin has an average annual water volume of approximately 32 billion m^3. 90% of this amount is from Turkey and the remaining 10% is from Syria, and Iraq has no contribution to the Euphrates' water potential (Bilen, 1996). The Euphrates has water shortage between 70% and 80% of the water volume by irrigation, evaporation and leakage to the ground until it is combined with the Tigris (Kolars et al., 1991). Murat and Karasu rivers, which are born in the mountains of Erzurum and Agri region in eastern Anatolia, form the Euphrates river by ingingly near Keban dam, and from this point until it joins with the Tigris river, 955 km pass through Turkey, 559 km through Syria and 815 km through Iraq, reaching a total length of 2330 km (Bilen, 1996). The Euphrates river has a total pool area of about 444000 km^2, including 155000 km^2 in Turkey, 84360 km^2 in Syria and 204240 km^2 in Iraq (Kibaroglu, 1998). Tohma river, which is located near Malatya until it reached the Syrian border to the Euphrates river stream, Kahta river on the border of Adiyaman province, Kahta river and Göksu branch on the border of Adiyaman province, Hacihıdır and Hacıkamil creeks in Karacadag direction in Urfa province, and Karasu and Nizip rivers at Gaziantep provincial border contribute (Toklu, 1999). The Euphrates basin is divided into three separate sub-basins: Upper Euphrates, Middle Euphrates and Lower Euphrates (Figure 3.1). It has an average annual rainfall of 540.1 mm, of which 31.61 km^3 flows. This amounted to 17% of the 186 billion m3 of water flowing through Turkey (EEI, 2000). The average annual current of the Euphrates river is 26.6 billion m^3 near Atatürk dam, 30 billion m^3 near Birecik and 31.6 billion m3 in Karkamış according to observations covering 1937-1993 (Toklu, 1999).

Rainfall in the Euphrates basin during the winter season is usually seen in the form of snow. For this reason, the highest flows in basin streams are observed in spring season. Due to the lack of immediate flow of snow, stagnation is observed in the rivers during the winter, while in spring and summer the flow in the streams increases with the melting of the snow and the water potential in the region increases. There are 7 main projects in Turkey that are made up of 57 projects of different scales within the

Euphrates basin. While some of these projects are in operation, the rest are in the construction and project stages. Turkey recently plans to consume 16.32 billion m3 of water from the Euphrates river and its subsidiary (Ergener, 2002). The Euphrates basin is a high plateau with an area of 444000 km^2. The average height of the basin is 1010 m. The topographic structure and hydrological conditions of the Euphrates basin make the region advantageous in terms of hydroelectric power generation. Considering that 47% of the hydroelectric power produced in 2005 is produced only from Keban, Karakaya and Atatürk dams, the location and importance of the Euphrates basin within Turkey's hydroelectric production potential is revealed (USIAD, 2010).

3.2 Artificial Intelligence (AI)

The idea of creating smart machines, especially smart systems that can learn and predict, was put forward in the 1980s. Artificial intelligence, which has become a part of our daily life with the development of technology; expert systems have become structures that can learn, reason, make use of past information, plan, offer suggestions and communicate with fuzzy logic, genetic algorithms and artificial neural networks. While artificial intelligence systems are used for different purposes in many disciplines, the methods developed during this widespread use continue to contribute to the development of other fields (Arslan, 2020). Artificial intelligence has the capabilities to analyze complex medical data. The ability of artificial intelligence methods to reveal meaningful relationships within a data set is used in many clinical scenarios to predict diagnosis, treatment and outcome. The main artificial intelligence methods that are widely used today; expert systems are fuzzy logic, genetic algorithms and artificial neural networks (Demirhan et al., 2010). As we live in an advanced era in the digital field today, it is necessary to make the right forecast in order to study and research the subject matter further and finally be prepared for future changes in the industries. In practice, artificially created entities are addressed while simulating human-like functions such as intelligence, learning and problem solving features (Özmen, 2019). Also, Artificial Intelligence is an area of electronic brain science that creates intelligent machines. Research on Artificial Intelligence has become more and more specialized technically day by day. The main problems of Artificial Intelligence include computer programming for certain features such as knowledge, sensitivity, ability, program solving, manipulating objects and moving objects (Okyay, 2018).

ANN is an application technique that uses the functions of the human brain and contains dozens of cells capable of mimicking function connections between cells. The functionality (Figure 3.3) in this network can be improved by changing the variables in the neurons representing each cell. When the conclusioning training input-output data is used, the error between the outputs generated using the ANN method and the actual data outputs is tried to be minimized. When this error is minimized, ANN training is completed (Kara, 2019). ANNs or connectivity systems are indefinitely inspired computer systems using biological neural networks. In recognizing the images in the system, they can analyze the system entries in a healthy way and define them as desired. By way of example, they can learn to identify photos with cats. Using the conclusions to identify cats in images can be given by using "cat" or "no cat" according to the desired conclusion in these entered data. They do this without any information about cats. This is because they can create automatic restrictive properties from the instances they handle. ANN is based on a collection of dependented units said artificial neurons that freely model neurons in the brain in a biological system. Addition, all neuron has its own unique connectivity function. With all connection, neurons can transmit a signal to other neurons, this as synapses in a biological brain. The neuron receiving the signal can then handle it, understand it and show the neurons attached to it. This shows a network of communications between neurons. In ANN applications, the signal given in a connection is an actual number, and the information output from each neuron is calculated by a nonlinear function of the sum of their input. This calculation is also calculated in different ways. Informed neurons and so-called connectivity edges have a typically tuned then as learning progresses. Weight can both increase and reduce the power of the signal connected.

Neurons are highly differentiated cells and are normally involved in the G0 phase of the cell cycle (Koç, 2013). Neurons should be a limit at which each signal is sent only if the sum of transmitted signals exceeds this limit. Usually neurons are collected as layers and processed from the edges into the system. It can perform different changes in different layers, inputs. There may be some such transformations. Signals move from the input layer to the output layer as expected. This is how the system is completed. The main purpose of ANN is to solve problems in a systematic way, as if they had lived and designed naturally in the human brain. ANNs; Computer vision, hearing, speech, processing, machine translation, social network filtering for people, etc. used in various tasks. Over time, ANN began to provide services that would make human life easier.

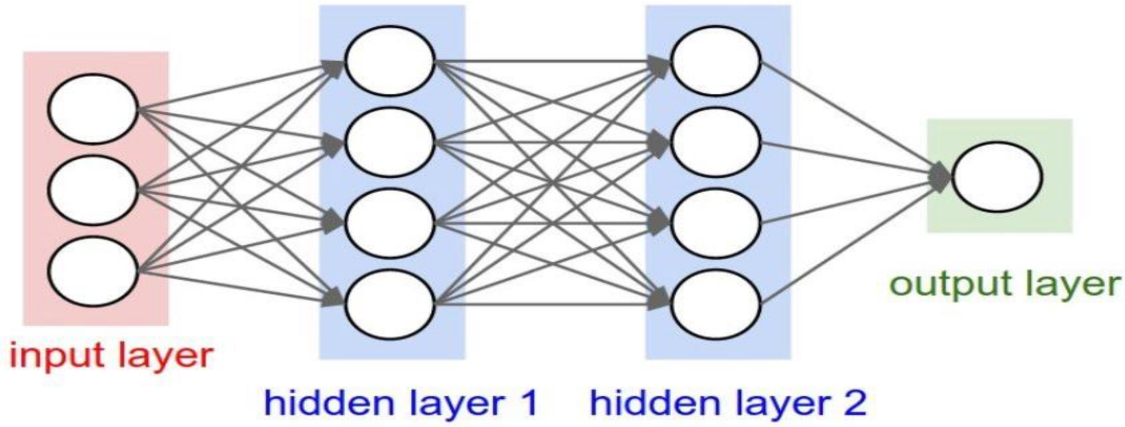

Figure 3.3 The appearance of ANN

Another data mining method used in predictions and classifications is ANN. These neural networks are signal engraving regimes that try to mimic the biological neural regime, by presenting a mathematical model of many neuronal components dependent to a network (Haykin & Lippmann, 1994). Neurals are establish in input-output and hidden layers, if whichever. If a neuron appears important, the weights incorporated with that neuron also modify. This means that the neuron will be more effective than other neurons at the same level. ANN learns by adjusting the weights between neurons (Mumbuçoğlu, 2019).

3.3 Deep Learning

The history of Deep Learning goes back to 1943, when Walter Pitts and Warren McCulloch imitated the human brain and developed a computer model based on neural networks. They used a combination of mathematics and an algorithm they called "threshold logic" to imitate the thinking process (Kamachy, 2019).

Deep learning allows computational models consisting of multiple processing layers to learn representations of data with multiple levels of abstraction.These methods have significantly improved the latest technology in many other areas, such as speech recognition, visual object recognition, object detection, drug discovery and genomics. Deep learning explores the complex structure in large datasets by using the re propagation algorithm to specify how a machine must change the internal parameters used to calculate the representation on each layer from the representation in the previous layer. Deep-eve networks have made breakthroughs in the processing of images, videos, speeches and sounds, while repetitive networks have shed light on sequentive data such as text and speech (LeCun et al., 2015). Deep learning has serious potential to change and improve many things in our lives, and research is supported in every way by making significant investments (Keleş, 2018).

Deep Learning is tempting to learn from large amounts of untagged/unchecked data, making it attractive to remove meaningful representations and patterns from big data. Deep learning methods represent complex relationships between data, allowing more useful conclusions to be produced than standard methods (Hasan et al., 2017). In recent years, deep learning models have been widely used in remote sensing images. Deep learning is done in remote sensing images as well as in all areas to be able to classify performance better than existing approaches and to detect property inssiables on its own. Further studies are being carried out on hyperspectral images, especially in remote sensing. The most important reason for this is that it can carry a large number of data features. A large number of data properties means that there are many attributes for that image (Toğaçar et al., 2018).

By its nature, deep learning is a more complex form of ANN. Traditional neural networks are in the structure of an advanced-feeding neural network. All input neuron has a confidential stratum to which it is attached. In this way, every neuron in the secret stratum is dependent to a neuron in the output stratum. Typically, a only linear output neuron is used to forebode an output. All contacts within the network are urged from input to output layer. Deep neural networks can be created by adding more hidden layers, where each neuron is attached to each neuron in the next stratum. Deep learning provisions a very powerful framework in the supervised learning handle. It is easy to match the input-output vector with human help. However, the process can be carried out through modeled large data sets and sample training examples through the deep learning model. Most understandably, simple neural networks have only one hidden layer, while deep neural networks have multiple hidden layers (Figure 3.4) (Paker, 2019).

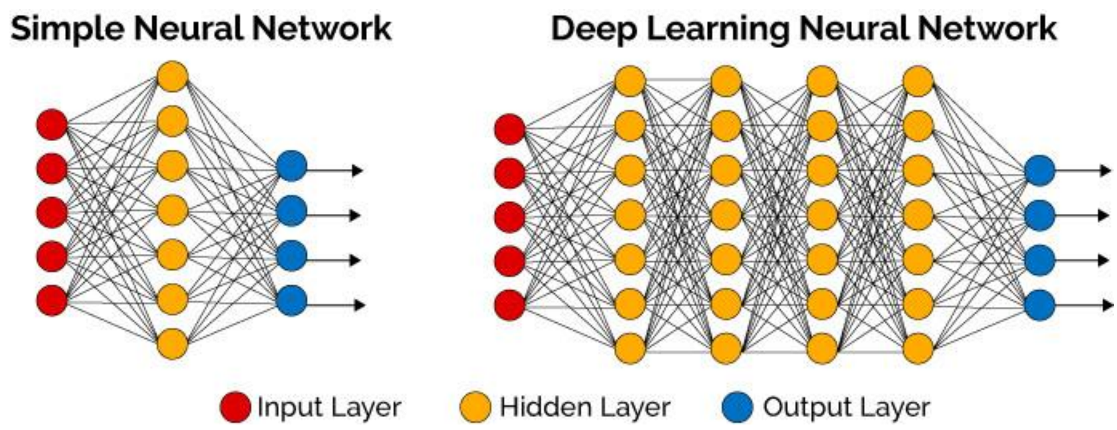

Figure 3.4 The appearance of the difference between a simple neural network and a deep learning neural network

The most general description of DL is that it is a Nervous System with multiple confidential layers. Automatic property determination is created by determining the property of input data that can be used as a pointer to accurately determine input data. In fact, all stage is affected by the output data properties of the former stage. That's a breakthrough in his ability to see with a computer. In contrast, for shallow networks, feature extraction required a large amount of manual design and image processing experience. In addition, conversions from images of input data to vectors have lost interesting information.

There are 7 main applications that are mainly practiced in DL (Hordri et. al, 2016):

- Automatic Speech Recognition (ASR)
- Image Recognition
- Natural Language Processing
- Recommendation Systems
- Deep Learning Frameworks
- Tensor Flow
- Python Deep Learning Aplication

In addition, Deep Learning is in the ANN group, which is a broader and more useful machine learning method. Therefore, a correct learning is created by working with deep learning, ANN. However, learning may not every time be on the right track. Learning can be supervision in several ways. It can be semi-controlled or uncontrolled.

Deep Learning is a machine learning system. It lets us to train the dataset to predict the output later input data of a given or desired information. In this way, it ensures that appropriate rating and conclusions are reached as soon as possible after the necessary data are entered. The more data input capacity is increased, the preferable Artificial Intelligence propertys will emerge as output. Because as the classifications are entered, it will be easier to reach the desired data. However, as data grows, things get more complex. As the complexity increases, there will be some unwanted shifts from Artificial Intelligence to machine learning. As you get more complicated, there will be relays from machine learning to deep learning. In this way, the user will see how useful learning is. In machine learning, the experiences of human beings from the past to the present have been introduced to the machine through parameters. Because with the data, parameters and experience entered into the technology, the conclusions will increase in direct proportion. After entering information such as shape, color, size and stem of pear, apple, orange, etc., the conclusion will be reached easily. Deep learning can learn all this differently on its own. For example; creates his own rules by showing only apple, orange and pear to the deep learning system. Revealing differences such as color and shape are my main distinguishing features. Thus, it can perform its activities by creating its own discriminatory abilities without the need for basic human skills.

3.3.1 Deep Learning Bookcase

The mentioned machine learning bookcase is actually a bookcase of program the systems. There is more than one system in the library. These are respectively; TensorFlow (Python), Caffe (Python), Theano (Python), Python Deep Learning Aplication (Python), Torch (C ++), Deeplearning4j (Java), Covnetjs (Java), Mxnet (Python), PyLearn2 (Python), Deep Learning Tool Box-Matlab, Accord, NET (C #), Sci-Kit Learn (Python). All these program the systems are operated differently from each other. One of their common features is that it is one of the most used software for deep learning.

3.4 Python Deep Learning Aplication (Keras)

Python Deep Learning Aplication is a python library for deep learning. Besides this bookcase it also works with Theano or Tensorflow libraries which can be helpful for deep learning usage. It works on GPU or CPU libraries and helps the work come to a conclusion. Because it is a high-level bookcase, the user can develop applications more easily than Theano or Tensorflow. For this reason, it is widely used. This bookcase can be used by many developers around the world.

There are two main API structures in Python Deep Learning Aplication. The models to be installed can be designed by combination one of these two several main structures and successive models should be designed in stratums. It is designed as a functional structure. It allows to design more pliant and improved models. Since the input stratum data will be used in the model call structure, the input size of the data must be specified. The other layers do not need to be specified as they receive data from the previous stratum. The output size determined to get the conclusions of the output layer is usually the output size of the stratum before the last activation layer.

In addition, KARES refers to a rehabilitation robotic system with 6 degrees of freedom robotic arm mounted on a motorized wheelchair to assist the disabled and elderly people in their independent livelihood. Human machine interaction is very important in this system. While direct control of the robot arm takes a high cognitive load on the user side, physically disabled persons may have difficulty using joysticks or push buttons for precise movements. Therefore, a certain degree of autonomy of the robotic system is needed. Color vision and force / torque sensors are mounted on the end effector of KARES 'robotic arm to detect the environment. Four basic tasks are tested: grabbing a glass from a table, picking up a pen from the floor, moving an object to the user's face, and actuating a switch on the wall. These tasks are performed autonomously in a semi-structured environment (Song et al., 1998).

3.4.1 Python Deep Learning Aplication Models

There are 2 different ways available to compose Python Deep Learning Aplication models that defined as sequential and functional sequential API. Models offer users to compose multiple stratum models for many problems they encounter. The functional API allows the creation of much more flexible models, as easily define models where only the stratums are connected to the stratum more than the previous and next stratums. Python Deep Learning Aplication is an API designed for humans, not machines. Python Deep Learning Aplication examines best practices for alleviating cognitive load. As a Python Deep Learning Aplication user, users are allowed to try more ideas than user competition while being more productive. This helps the user to win machine learning competitions. Python Deep Learning Aplication integrates with lower-level deep learning languages, allowing the user to practice anything the user might have created in the base language. Specifically, as Python Deep Learning Aplication, the Python Deep Learning Aplication API seamlessly integrates with user Tensor Flow workflows (Figure 3.5).

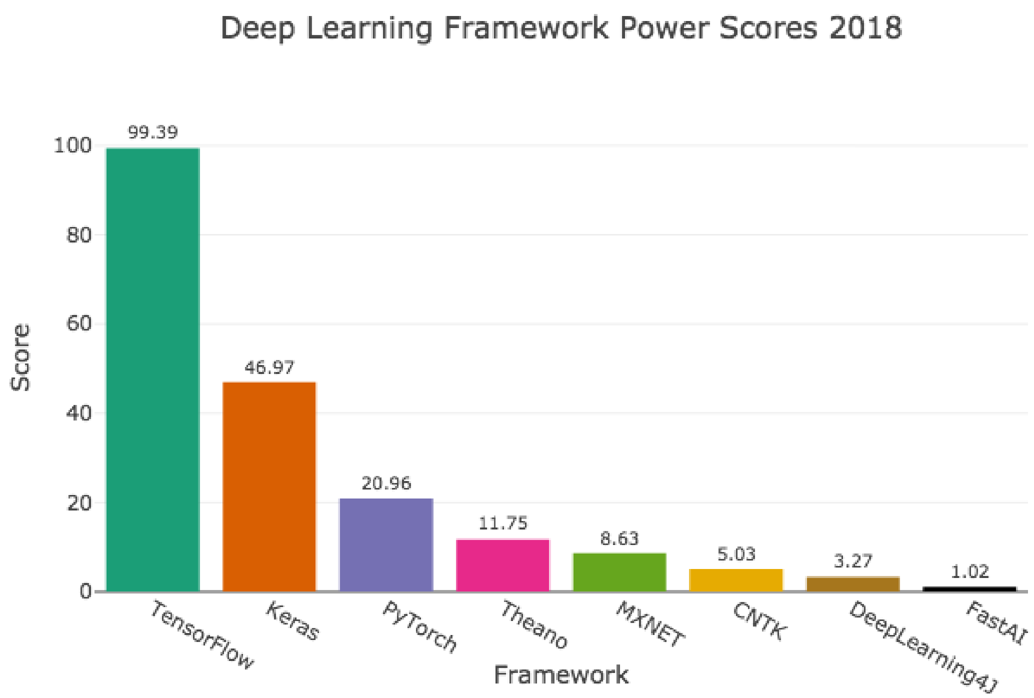

Figure 3.5 Ranking of deep learning frameworks

Python Deep Learning Aplication has been adopted more strongly than any other deep learning frameworks outside of TensorFlow in industry and research, with over 250,000 users since mid-2018. Users are already interacting with features created with Python Deep Learning Aplication. Netflix, Uber, Yelp, Instacart, Zocdoc, Square etc. used in areas. It enjoys enormous popularity among initiatives that make deep learning the center of their work. It was of great importance that Python Deep Learning Aplication was also accepted by researchers at large scientific organizations such as CERN and NASA.

3.4.1.1 Physiological API

The Python Deep Learning Aplication physiological API is a way to define models with uncertainty, such as multiple output models, directed acyclic graphs. A layer instance can be called and returns a tensor. It can then be used to describe the input tensors and output tensors. Such a model can be compared to Python Deep Learning Aplication Sequential models. It is easy to reuse models with the physiological API. It should be noted that only by reusing the architecture of the model, a model can be called, and the user can reuse its weights.

3.4.1.2 Methods of Sequential

For database records and digital files, the importance of choosing the system that will systematically organize the files correctly affects how much data can be made and how useful and efficient the user system is. The better the files are planned, the better. Sequential file organization means that data, information or files collected on computers are stored in a specific file in a specific order according to the data or file type. This sequence is processed in a regular and planned manner, making the system more useful. The sequential file organization is transparent to the user. It helps to choose the system according to the needs and to install the most suitable files for the preferred system, to obtain effective data and to transform them into different forms. The simplest sequential file organization is the one that saves files sequentially as they are created by the user. The first file is saved first, the next is the second file, etc. While this method is simple, it also allows the user to delete files without destroying the array. The least complexity of the organizational method means that it takes a long time to find information, as a search starts from the first file and looks at each file. The system lists the files or data in a predefined order in alphabetical order. When the user wants to create a file, the current system must add the new file in the correct directory order or re-schedule the entire file list to create it regularly. It also takes longer to create new files and place them in the index. However, finding information takes less time. Because the user knows where to look in this indexed system. When designing a sequential file system, the user needs to look at how often the user plans to add or change files along with how often they need to search for data. In archive-type systems, searches are increasingly rare, although the user is constantly growing as the user adds new files. Although the call center database is relatively stable, it is constantly exposed to calls. It is logical to use an alphabetical or other index that allows users to find specific records quickly. There are two critical parameters for sequential file editing methods. These; speed and storage space. When the user stores the files sequentially, there is no room to enlarge a file later. The system must either store additional information elsewhere or have the ability to free up space and re-save all files. Both methods take a lot of time. Sequential file systems solve this problem by allocating extra space for each file when the system creates it. This avoids lag, but uses much more space. When setting up the system, the user must decide whether the time saved or the space used is more valuable and use the corresponding method to organize the files.

3.5 Optimizers

3.5.1 Adam

Adam is an algorithm for first-order gradient-based optimization of stochastic target functions based on adaptive estimates of low-order moments. It is simple to implement, computationally efficient and requires very little memory. It is invariant by rescaling the gradients diagonally and is well suited for large problems in terms of data and / or parameters. The method is also suitable for unstable targets and problems with very noisy and / or sparse gradients. Hyper parameters have intuitive interpretation and typically require little adjustment. Some links with the related algorithms that Adam inspired were discussed. Furthermore, by analyzing the theoretical convergence properties of the algorithm and under the online convex optimization framework, a regret limit can be achieved to the convergence ratio comparable to the best known conclusions. Empiric conclusions indicate that Adam works well in practice and is more positive than another stochastic optimization process. Finally, there is AdaMax, an Adam version based on the infinity norm (Kingma, 2014).

Adam has two main components; one component of momentum and another component of adaptive learning rate. However, it can be shown that the regular momentum is conceptually and empirically lower than a similar algorithm known as Nesterov's accelerated gradient (NAG). Preliminary evidence is presented showing how Adam's momentum component can be modified to take advantage of the NAG's insights, and then making that substitution improves the convergence speed, the quality of the learned models (Dozat, 2016)

Reddi et al., stokastic optimization methods, which have been successfully used in training deep networks such as RMSProp, Adam, Adadelta, Nadam, have been imposed on using gradient updates scaled with superanne squares. For example, if you want to use in many types of applications, learning with large output aerospaces has been empirically observed that these algorithms do not come close to an optimal conclusion and solution. One of the reasons for similar errors is the superethal moving average used in algorithms. Here is a distinct example of a simple convex optimization setting where Adam cannot merge with the optimal solution and the user's Adam algorithm can see exactly the analysis problems that have been made before. As a conclusion of the analysis, it shows that convergence problems can be corrected by equipping such algorithms with the long-term memory of past gradients, and the Adam algorithm can not only correct convergence problems, but also suggest new variants that mostly conclusion in better experimental performance.

3.6. Assessment Methods

The use of qualitative or quantitative methods, according to many areas of science, has become a topic of discussion with certain schools of thought, trying to despise the other while preferring one method in each discipline. Qualitative methods maintain that quantitative methods are aimed at devaluing factors that are in no way immeassible, or even hiding the reality of social events studied for ignoring or neglecting them. Quantitative methods can be used with a sphering qualitative framework, but qualitative methods can be used to understand the meaning of numbers produced by quantitative methods.

Unfortunately, even this practice leads to a controversy between the two research topics while exploring the complementarity of quantitative and qualitative research methods. Some researchers claim that combining these two different approaches in one research method is beneficial and the social world will become more complete. They believe that epistemologies that aim to support any approach that can be evaluated are too different to be reconciled even in a research project (Gadd, 2006).

3.6.1 MAD (Mean Absolute Deviation)

It is the average of the absolute deviations of the data at a given information point or simply the "mean absolute deviation" (MAD) in the data set. In global form, the central point can be the conclusion of a randomly selected data point associated with the data set given by the median, mode, mean, or any central trend measure. The absolute values of the difference between the data points and their central tendencies can be summed and divided by the number of points in the data set.

The MAD model is actually used to solve large portfolio optimization models, including an internationally diversified investment model, a long-term asset and liability management model, and a mortgage-backed securities portfolio optimization model. Recently, the MAD model has been shown to have many advantageous theoretical properties (Konno and Koshizuka, 2005).

3.6.2 MAPE (Mean Absolute Percentage Error)

MAPE, where the actual value is not zero but is quite small, will often get extremely high values. The precision of this scale makes MAPE insignificant as a measure of error when using it for low volume data. MAPE is the most commonly used summary measure to assess the correctness of population estimates. Although MAPE has many desirable criteria, it argues that, from both normative and relative perspectives, the common practice of using it only to evaluate population estimates should be changed. It is normally considered that MAPE does not meet the validity criterion because it exaggerates the error found in a population estimate as a summary measure (Tayman et al., 1999).

3.6.3 MEAN (Actual / Predicted)

For statistics, a forecast error is the difference between the actual value of a time series and the predicted or predicted value. With the prediction error derived from the same data scale, crosschecks between prediction errors of different series can only be made on the same serial scale.

In simple cases, the conclusions of an estimate in a single time frame are compared. A summary of the estimation errors is generated from the sum of such time points. As a rule, the value of the error conclusion is defined using the minus value of the guess.

In other cases, the estimate may consist of estimated values during the delivery time. In this case, the estimate error assessment may need to consider more general ways to evaluate the match between the time profiles of the estimate and the conclusion. If the main application of the estimate is to predict when certain thresholds will be exceeded, one possible way to evaluate the estimate is to use the scheduling error. When there is interest in the maximum value reached, the evaluation of estimates can be done using any difference. To summarize the forecast error through a group of units, it could be a calendar prediction error or a cross-sectional forecast error (Graphe and others, 2010).

3.6.4 Standart deviation

Standard deviation is a measure used in probability theory and statistical science to summarize the propagation of data values, such as an anacuma, a sample, a probability distribution, or a random variable. In other words, it is a measure that shows how high each data in a study group is compared to the average and how common the distribution is in another frequency. If defined in another way; The indication that the trait studied in a given population (or particularly relevant values or measurements) is distributed over a range (narrow or) within a range is the variance and the Standard deflection, which is its derivative. The low conclusion of the Standard deflection indicates that the data set tends to be closer to the mean. A high Standard deflection conclusion means that the values are spread over a wider range. Accordingly, there is a distance and proximity to the intended or targeted conclusions. The margin of error reported for an investigation is calculated by the average standard error method. In the scientific field, some researchers report the standard deviity of experimentally obtained data. The conclusions are generally considered statistically significant to deviate more from an empty expectation than an empty one. Random errors or changes to metrics are distinguished from possible conclusions in this way.

3.6.5 Correlation

Correlation analysis is an analysis technique used to examine the relationships between two sets of variables, each with at least two variables. In analysis, one variable set can be defined as a descriptive or argument set, and the other can be defined as a dependent variable set. However, variable sets do not have to be defined in this way. In the broadest sense correlation is any statistical association, though it commonly refers to the degree to which a pair of variables are linearly related (Keskin et al., 2004)

Correlations, predictions that can be misused in practice can point to a beneficial relationship. For example; It can be given that an electric utility can generate less power on a warm day due to the correlation between electricity demand and weather. In this example there is a cause-effect relationship. E.g; weather conditions cause people to use more electricity for heating and cooling. According to all these conclusions, the existence of a correlation is not sufficient to understand the existence of a causal relationship.

3.7 Data

The data used in this study was flow measurement stations taken from General Directorate of State Water Affairs (DSI) which are the most accurate data in the Euphrates river and they are located at the same basin area. The stations are D21A183 (Akdere Çayı Aşağıçöplü Köyü), D21A186 (Göksu Savran) respectively. The daily discharge data taken into account for this study covered the period of 2011-2018 for D21A183, 1984-2004 for D21A186 (Figure 3.2).

CHAPTER 4

RESULT & DISCUSSIONS

4.1 General

What to do in this section is based on the estimated conclusions of the machine learning model and the data from the work called ‘Estimations of river flows are made with the data obtained from current measurement stations’ called D21A183 and D21A186 are compared with the conclusions obtained from deep learning and its applications. The sequential model of Adam, Adamax's learning method was used curatively. Test and training data conclusions are compared with MAE and MSE losses. The data set is divided into training and test data data. As a conclusion; The training set is 70% and the test set is 30%. In this study, each tests and each trains of two different data sets were compared graphically separately. In this chapter all related figures are indicated at the vertical columns as the flow rate and the horizontal columns indicated as the data number.

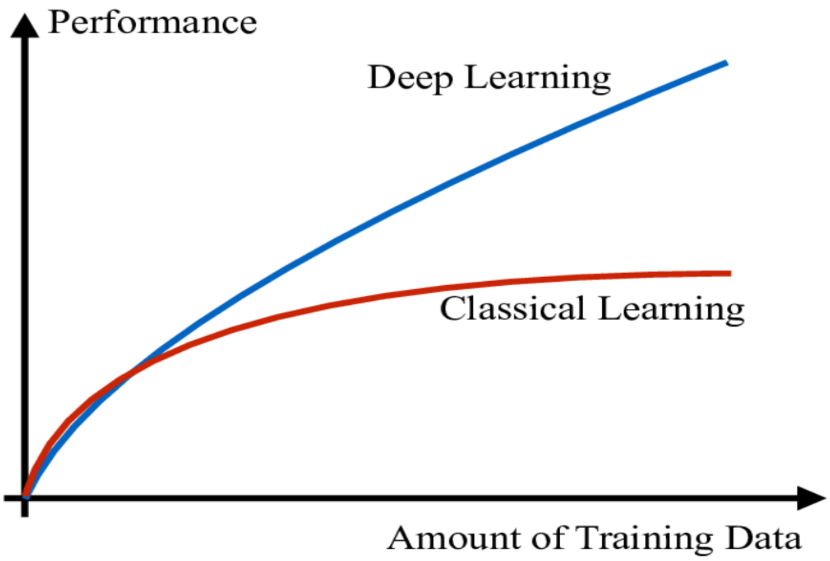

Figure 4.1 Comparison of Deep Learning and Classical Learning

The flowchart of the implementation of deep learning model used in the thesis and is indicate down Figure 4.2.

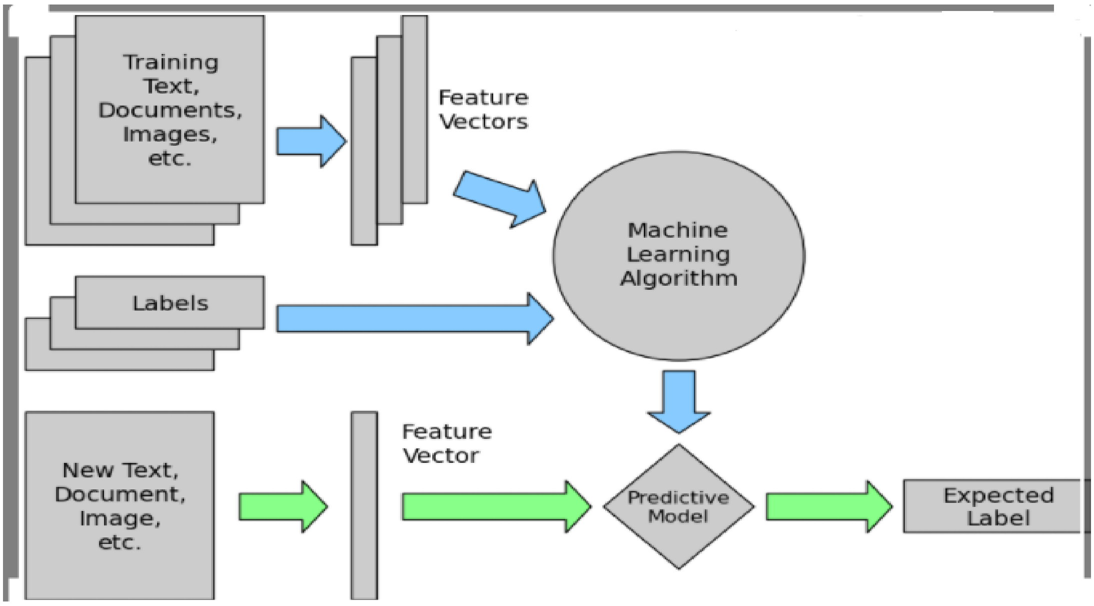

Figure 4.2 Flow chart of applied model

4.2 Crosscheck of Adamax Optimizer's and MAE loss for testing and training Conclusions and Actual Conclusions for Akdere

When using Adamax as optimizer and MAE as loss, the training and test correctness of the model are shown in Table 4.1. According to the table, the Test dataset correlation is 0,994 and the Training dataset is 0,990. Test dataset average is 1,035 and the training dataset average is 1,015. Test dataset of MAPE is 18,324 and the MAPE of the training dataset is 15,697. Adamax Optimizer and MAE loss are seen as providing the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The conclusion is that test data is more successful loss in the deep learning model of the MAE function.

Table 4.1 Statistical evaluations of MAE loss for Adamax

Statistics	Train	Test
MAD	0,104614	0,137982
MSE	0,106870	0,126831
RMSE	0,326910	0,356134
MAE	0,156971	0,183245
MAPE	15,69714	18,324535
MEAN(actual/predicted)	1,015204	1,035630
Standart Deviation	0,345707	0,550444
Correlation	0,990168	0,994584

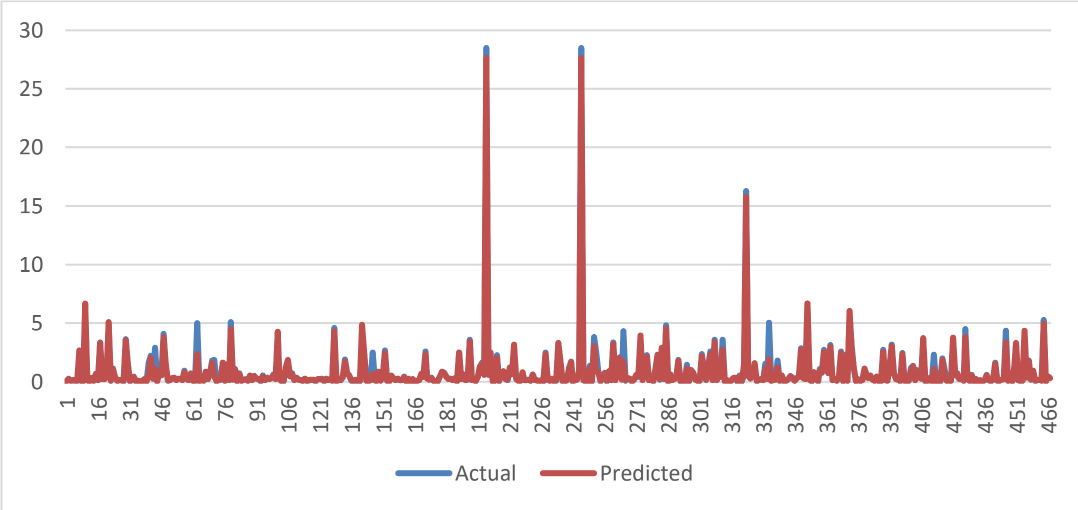

Figure 4.3 Training correctness in crosscheck for Adamax Optimizer and MAE loss

As shown in the chart in Figure 4.3, the conclusions of the training and model were compare in terms of rate. It can be said that there is a range of 307-460 as the range with the highest deviations according to the graph.

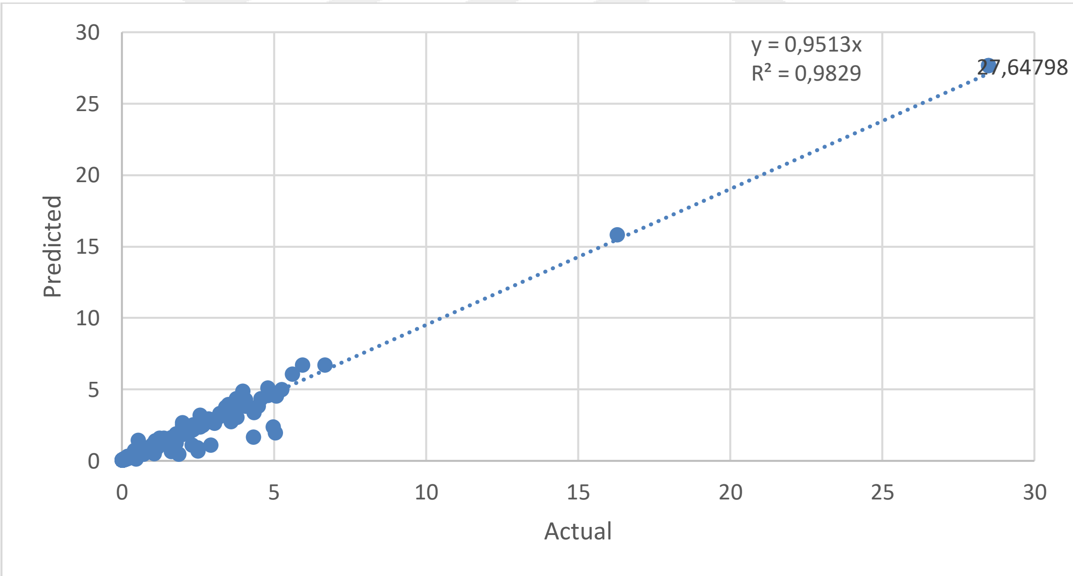

Figure 4.4 MAE loss for Comparing and Training Adamax Optimizer's Actual and Projected Conclusions

Deep learning conclusions for Adamax and MAE in the dataset are examples in Figure 4.4. When the nearness to the right conclusion is investigated, it is seen that the highest point is expressed as 28.5 and the deep learning model gives more realist conclusions.

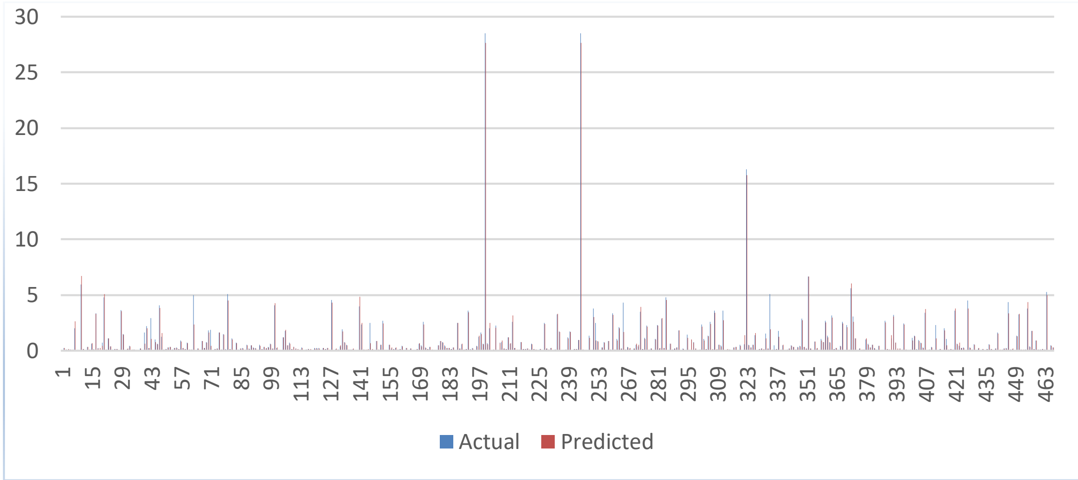

Figure 4.5 Actual Predicted Conclusions for Training of Adamax Optimizer MAE Loss

The conclusions in all line are crosschecked with the actual and predicted software calculation techniques. MAEs of the conclusions maked from the deep learning model are crosschecked in (Figure 4.5). It is seen that the dots with the least errors belong to the DL conclusionss.

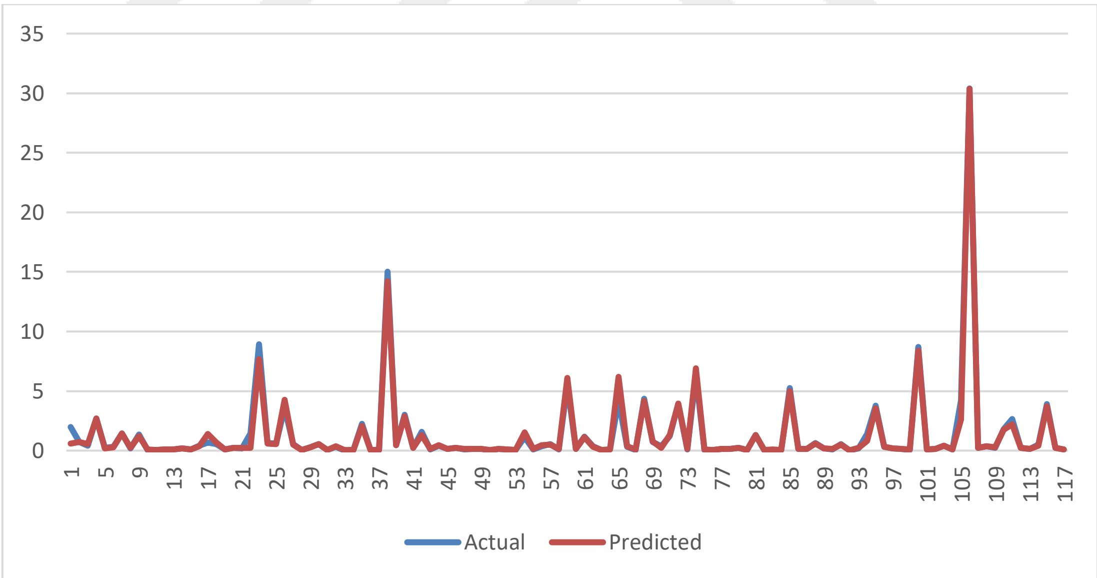

Figure 4.6 Actual and Predicted Conclusions for Adamax Optimizer and MAE loss for testing

When Adamax is used as a optimizer and MAE as a loss, the correctness of the model according to the test (Figure 4.6) is also seen. The chart compares training and model conclusions. According to this chart, there are not many high deviations.

The test conclusions of the data set and the forecast conclusions from the model are compared in Figure 4.7. It is seen that the highest point to the correct conclusion is 30.4 and the deep learning model gives more realistic conclusions.

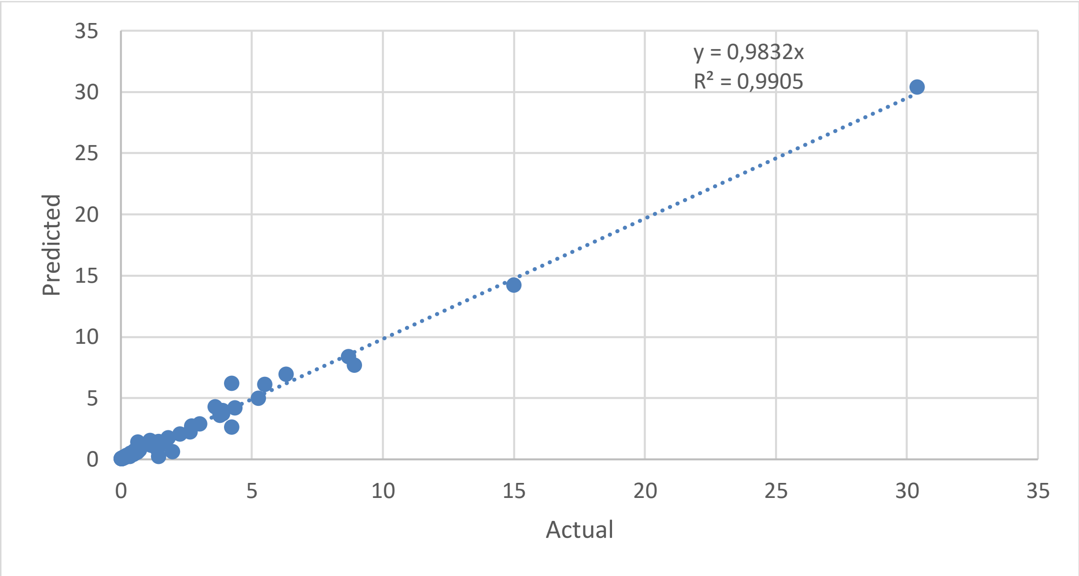

Figure 4.7 Comparing Adamax Optimizer and MAE loss with Test Conclusions and Predicted Conclusions

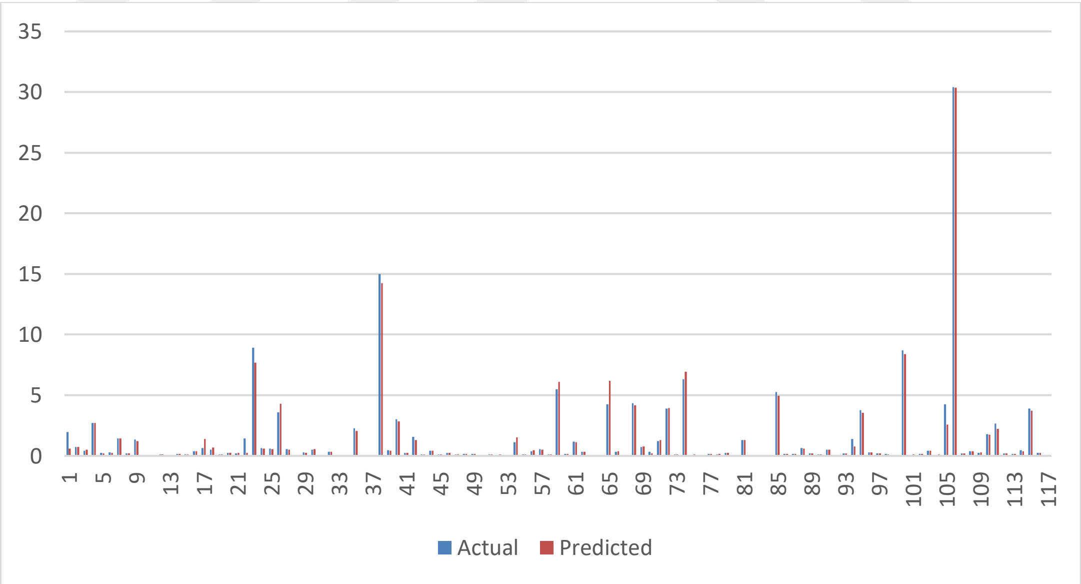

Figure 4.8 Actual datas and predicted conclusions for Adamax Optimizer MAE Loss for testing

The test conclusions in the data set and the forecast conclusions from the model are compared in Figure 4.8. It is seen that the point where the error rate is the least belongs to the DL conclusions.

4.3 Crosscheck of Adamax Optimizer's and MSE loss for testing and training Conclusions and Actual Conclusions for Akdere

When Adamax is used as an optimizer and MSE as a loss, the model's training and test results are indicated in Table 4.2. As a conclusion; the correlation of test dataset is 0.987 and the Training Dataset is 0.984, the average Test Dataset is 0.917, and the training dataset averages 0.892, the Test Dataset MAPE is 24,301, and the MAPE of the training dataset is 20,792. Test correlation is more accomplished for optimizer analyzing in the deep learning model of the loss function.

Table 4.2 Statistical Conclusions of Adamax Optimizer and MSE loss

Statistics	Train	Test
MAD	0,138035	0,214169
MSE	0,165303	0,282030
RMSE	0,406574	0,531065
MAE	0,207926	0,243009
MAPE	20,792630	24,300934
MEAN(actual/predicted)	0,892999	0,917398
Standart Deviation	0,341493	0,501119
Correlation	0,984111	0,987941

In the chart in Figure 4.9, training conclusion and model conclusions are crosschecked in terms of value. Pursuant this chart, it can be said that the range with the top deflections is between 273-460.

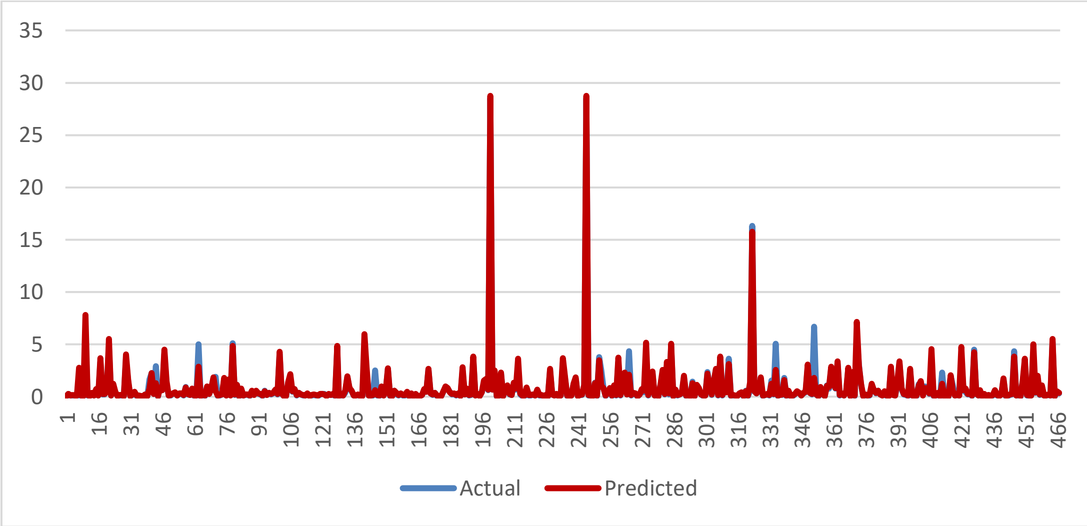

Figure 4.9 Crosscheck training correctness for Adamax Optimizer and MSE loss

The conclusions of all line are crosscheck with actual and predicted, which are the soft computing techniques, and the MSEs of the conclusions wined from the deep learning model are crosscheck in (Figure 4.10). It is sighted that the dots where the errors are least belong to the deep learning conclusions.

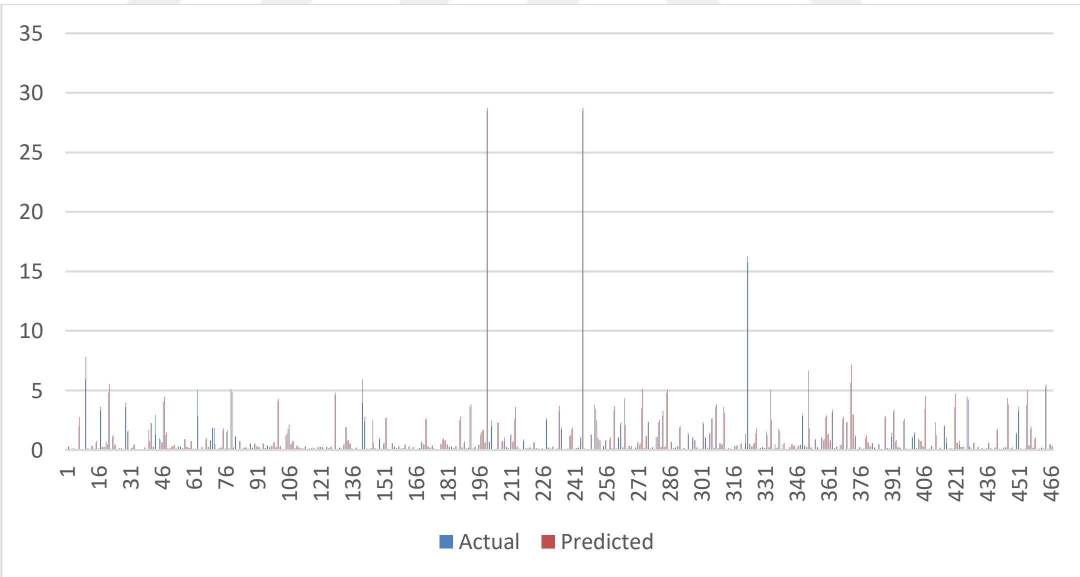

Figure 4.10 Actual conclusions and predicted conclusions for Adamax Optimizer MSE Loss for training

In the dataset is an sample for the deep learning conclusions for Adamax & MSE (Figure 4.11). When the nearness to the correct conclusion is investigated, it is sighted that highest point is stated as 28.5 and DL model gives more realistic conclusions.

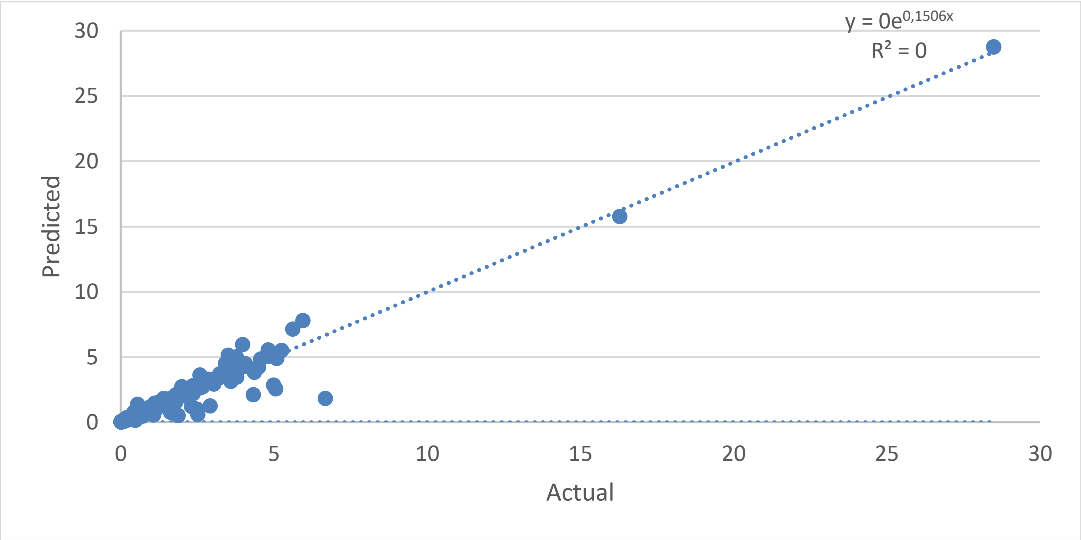

Figure 4.11 Crosscheck of Training Conclusions and Predicted Conclusions of Adamax Optimizer and MSE loss

Test correctness of the model when Adamax is used as an optimizer and MSE is used as loss (Figure 4.12) also seen. In the graph, testing conclusions and model conclusions are crosscheck in terms of rate. According to this chart, there are not many high deflection.

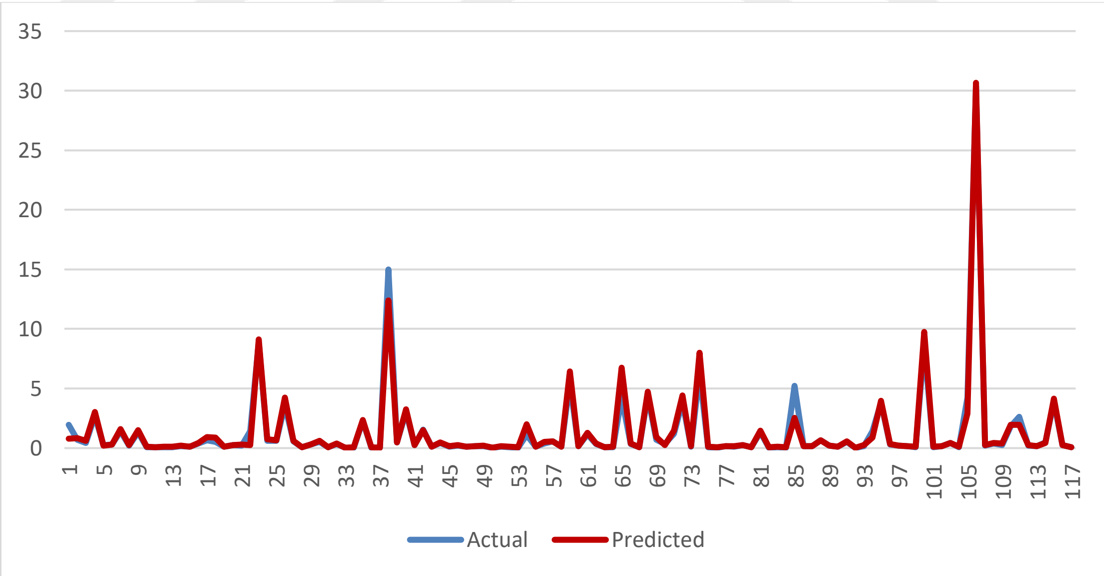

Figure 4.12 Crosscheck test correctness for Adamax Optimizer and MSE loss

The crosscheck of the test conclusions of all dataset with the forecast conclusions from the model is showned in Figure 4.13. When the nearness to the right conclusion is investigated, it is observed that highest point is stated as 30.4 and deep learning model gives more realistic conclusions.

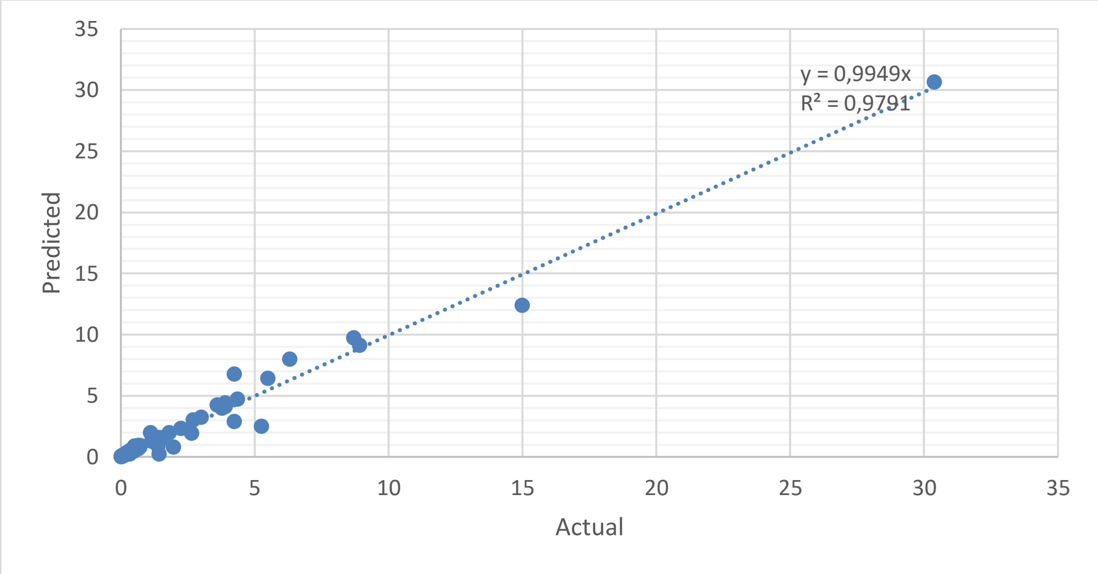

Figure 4.13 Crosscheck of Actual Conclusions and Predicted Conclusions of Adamax Optimizer and MSE loss for testing

The crosscheck of the test conclusions in the dataset with the forecast conclusions from the model is mentioned at Figure 4.14. It is observed that the points where the faults are least belong to the deep learning conclusions.

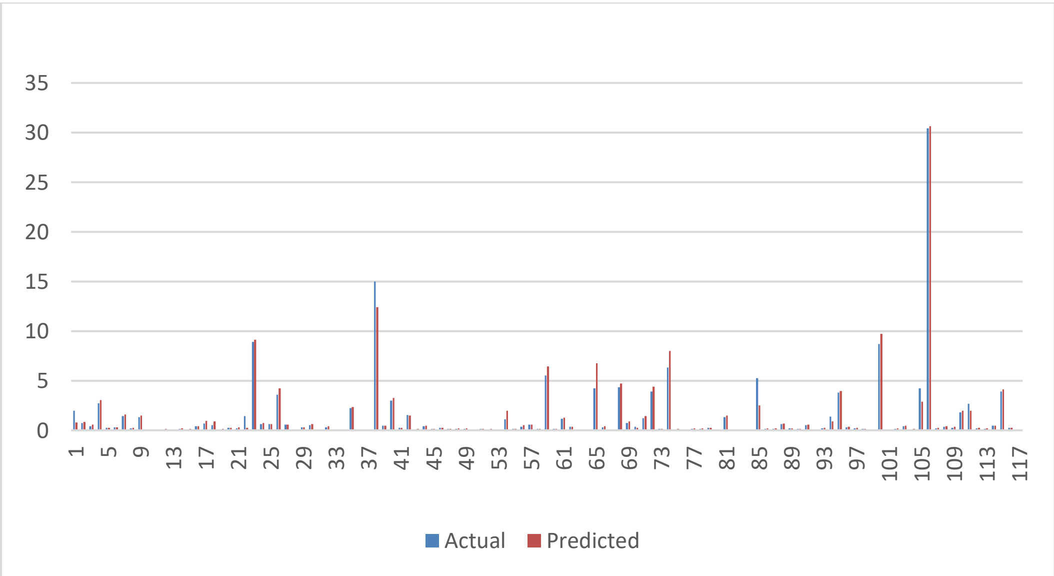

Figure 4.14 Actual conclusions and predicted conclusions for Adamax Optimizer MSE Loss for testing

4.4 Crosscheck of Adam Optimizer's and MAE loss for testing and training Conclusions and Actual Conclusions for Akdere

When ADAM is used as an optimizer, the model's training and test correctness are shown in Table 4.3. As a conclusion; the test dataset of correlation is 0,994 and the Train Dataset is 0,993 the average Test Dataset is 1,10 and the training dataset average is 1,076, the Test Dataset MAPE is 16,987 and the MAPE of the training dataset is 13,121. MAE is more successful for testing as an optimizer in the deep learning model of the loss function.

Table 4.3 Statistical Conclusions of Adam Optimizer

Statistics	Train	Test
MAD	0,093133	0,134152
MSE	0,076730	0,124868
RMSE	0,277002	0,353367
MAE	0,131213	0,169879
MAPE	13,121290	16,987900
MEAN(actual/predicted)	1,076315	1,100508
Standart Deviation	0,308443	0,556797
Correlation	0,993335	0,994630

In the chart in Figure 4.15, training conclusions and model conclusions are crosscheck in terms of value. Pursant to this chart, it can be said that the row with the highest deflection is between 358-460.

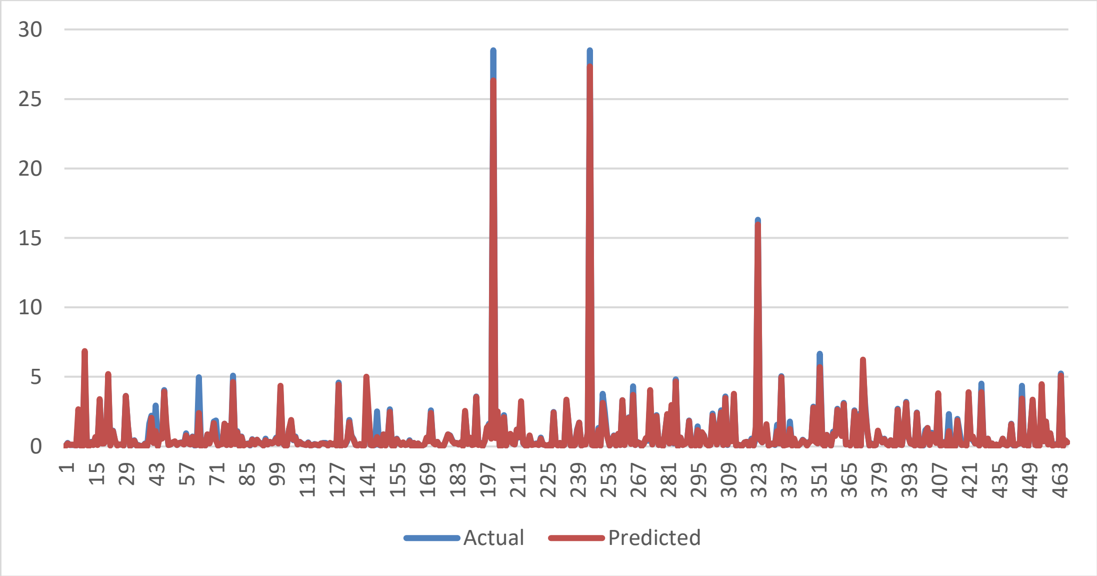

Figure 4.15 Crosscheck of training correctness for Adam Optimizer and MAE loss

The conclusions of all line are crosschecked with actual and predicted, which are the soft computing techniques, Adam and the MAEs of the conclusions wined from the deep learning model are crosschecked in (Figure 4.16). It is observed that the points where the errors are least belong to the deep learning conclusions.

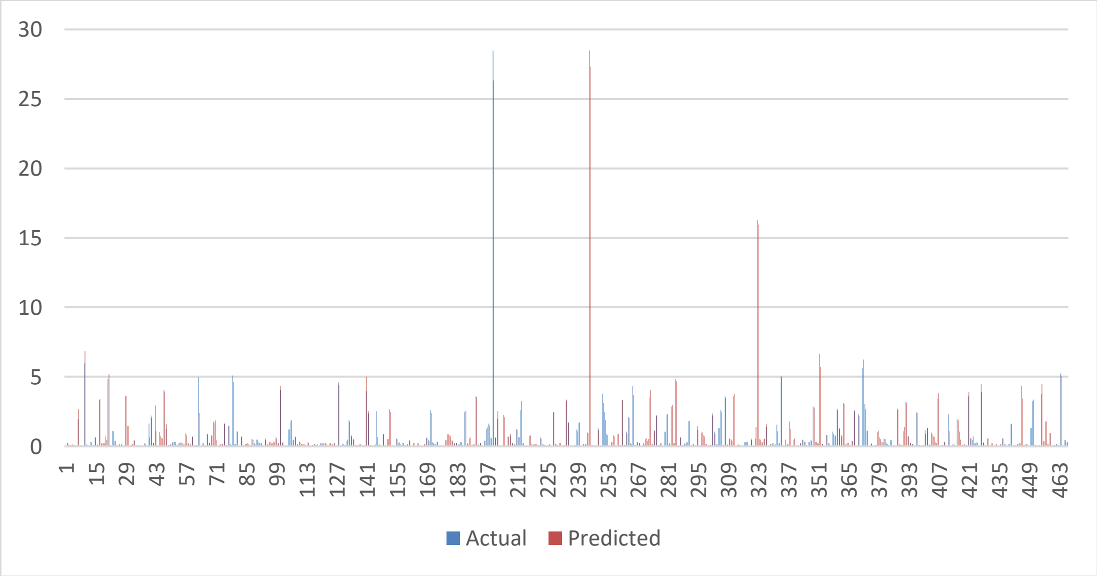

Figure 4.16 Actual datas and predicted conclusions for Adam Optimizer and MAE loss for training

In the dataset is an sample for the deep learning conclusions for Adam & MAE (Figure 4.17). When the nearness to the right conclusion is examined, it is observed that highest point is stated as 28.5 and deep learning model gives more realistic conclusions.

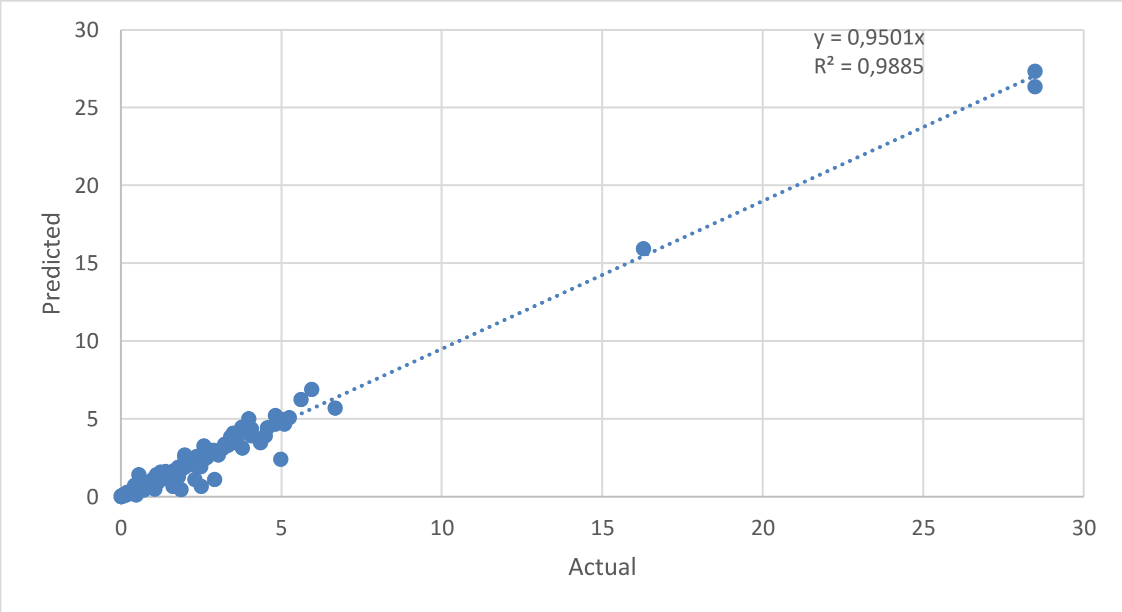

Figure 4.17 Crosscheck of Actual Conclusions and Predicted Conclusions of Adam Optimizer and MAE loss for training

Test correctness of the model when Adam is used as an optimizer and MAE is used as loss (Figure 4.18) also seen. In the chart, training conclusions and model conclusions are crosscheck in terms of value. According to this chart, there are not many high deviations.

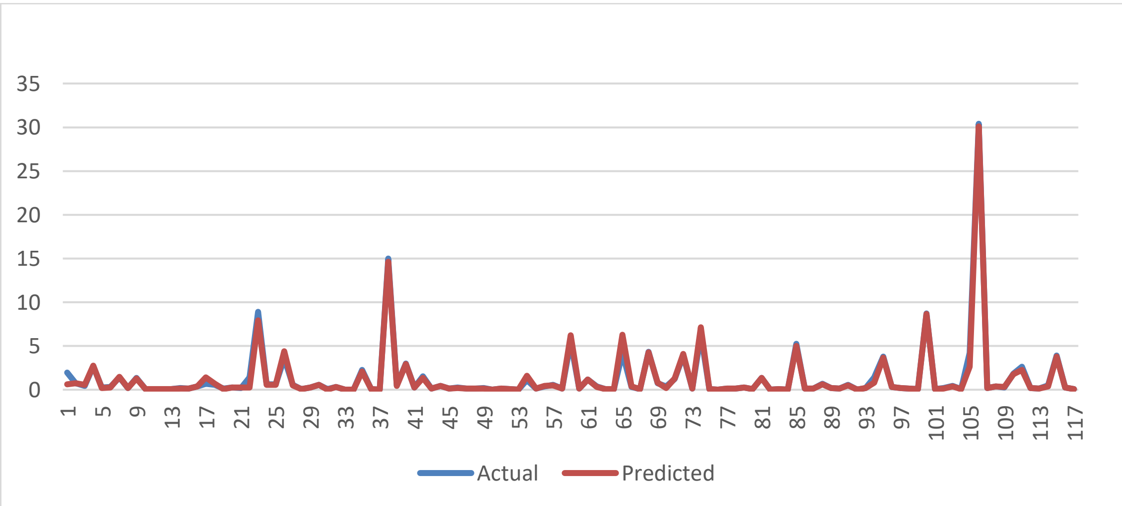

Figure 4.18 Crosscheck of testing correctness for Adam Optimizer and MAE loss

The crosscheck of the test conclusions in the dataset with the forecast conclusions from the model is mentioned at Figure 4.19. It is observed that the points where the faults are least belong to the deep learning conclusions.

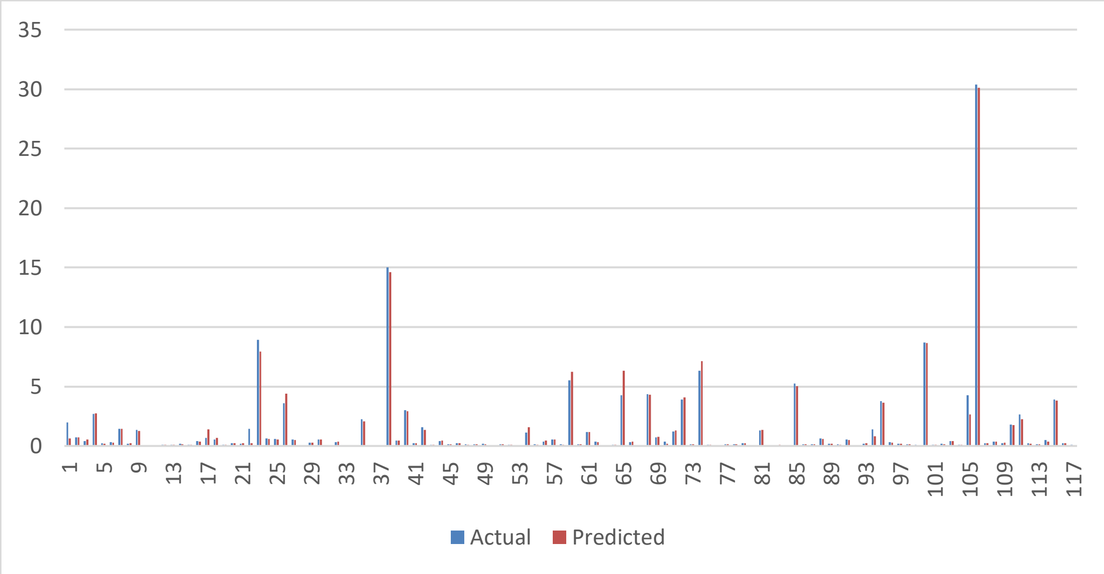

Figure 4.19 Actual datas and predicted conclusions for Adam Optimizer and MAE loss for testing

The crosscheck of the test conclusions of each dataset with the estimation conclusions from the model is showned in Figure 4.20. When the nearness to the correct conclusion is examined, it is observed that highest point is stated as 30.4 and deep learning model gives more realistic conclusions.

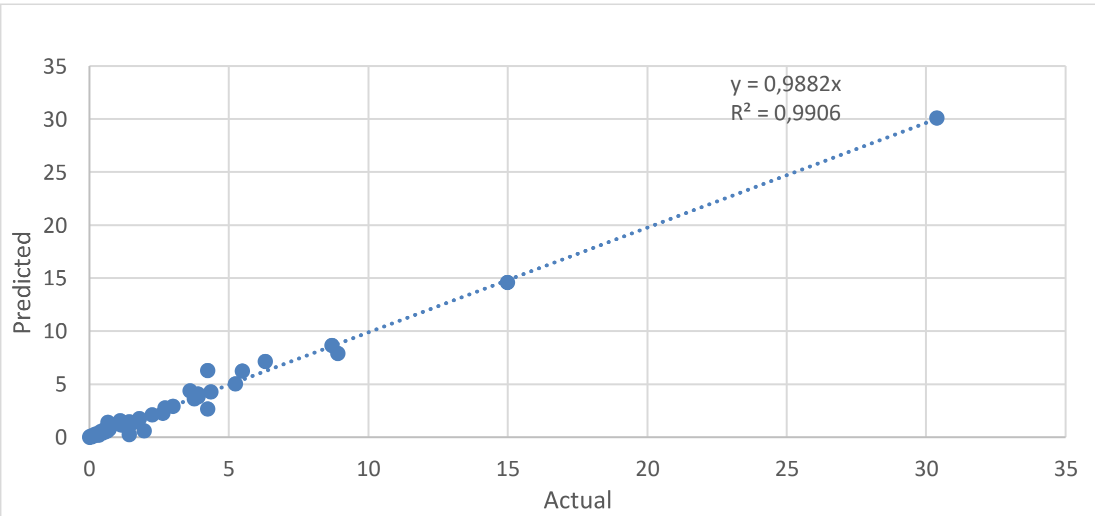

Figure 4.20 Crosscheck of Actual Conclusions and Predicted Conclusions of Adam Optimizer and MAE loss for testing

4.5 Crosscheck of Adam Optimizer’s and MSE loss for testing and training Conclusions and Actual Conclusions for Akdere

The model's train and test correctness are indicated in Table 4.4. Test dataset correlation is 0.993 and Train dataset correlation is 0.989. Mean of Test dataset 0.913 and MEAN of train dataset is 0.891. MAPE of Test Dataset 22.857 and MAPE of train dataset is 20.033. For MSE, MAD, MAE, MAPE, MEAN and Correlation the best conclusions are view in Adam Optimizer and MAE Loss. Within this, Test data is more successful for optimizer in deep learning model.

Table 4.4 Statistical Conclusions of Adam Optimizer

Statistics	Train	Test
MAD	0,127528	0,164533
MSE	0,112732	0,159106
RMSE	0,335757	0,398880
MAE	0,200332	0,228568
MAPE	20,033220	22,856840
MEAN(actual/predicted)	0,891921	0,912371
Standart Deviation	0,316181	0,481517
Correlation	0,989179	0,993660

In the chart in Figure 4.21, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, it can be said that the range with the highest deviation is 256 and 460.

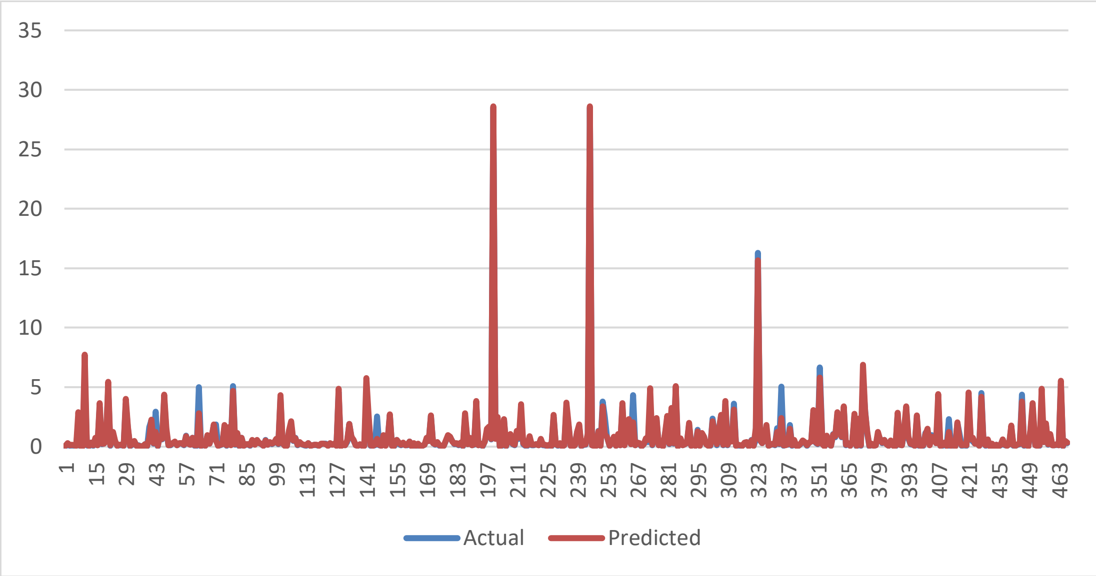

Figure 4.21 Crosscheck training correctness for Adam Optimizer and MSE loss

The conclusions of all line are compared with actual and predicted, which are the soft computing techniques, Adam and the MSEs of the conclusions wined from the deep learning model are crosschecked in (Figure 4.22). It is observed that the points where the faults are least belong to the deep learning conclusions.

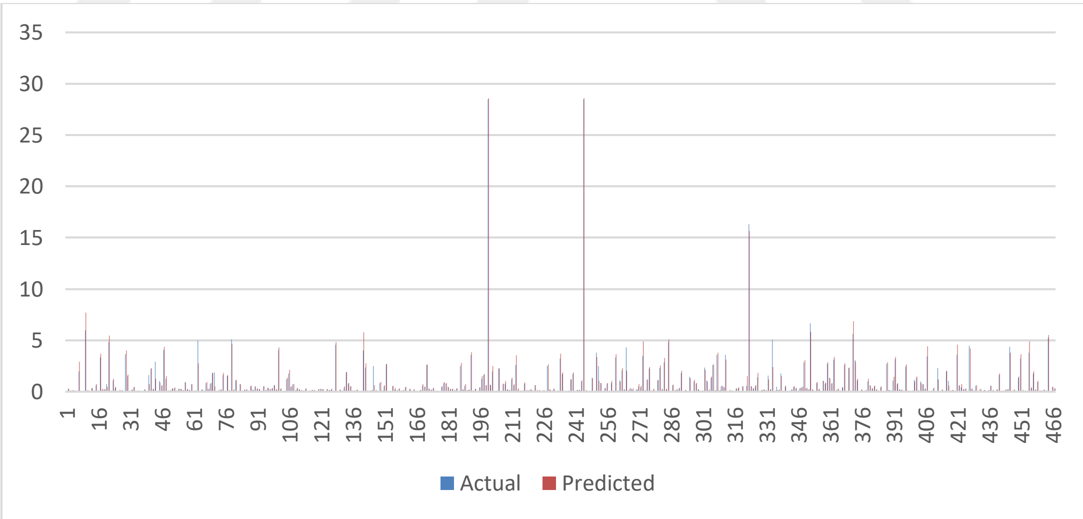

Figure 4.22 Actual conclusions and predicted conclusions for Adam Optimizer MSE Loss for training

In the dataset is an sample for the deep learning conclusions for Adam & MSE (Figure 4.23). When the nearness to the right conclusion is investigated, it is observed that highest dot is stated as 28.61 and deep learning model gives more realistic conclusions.

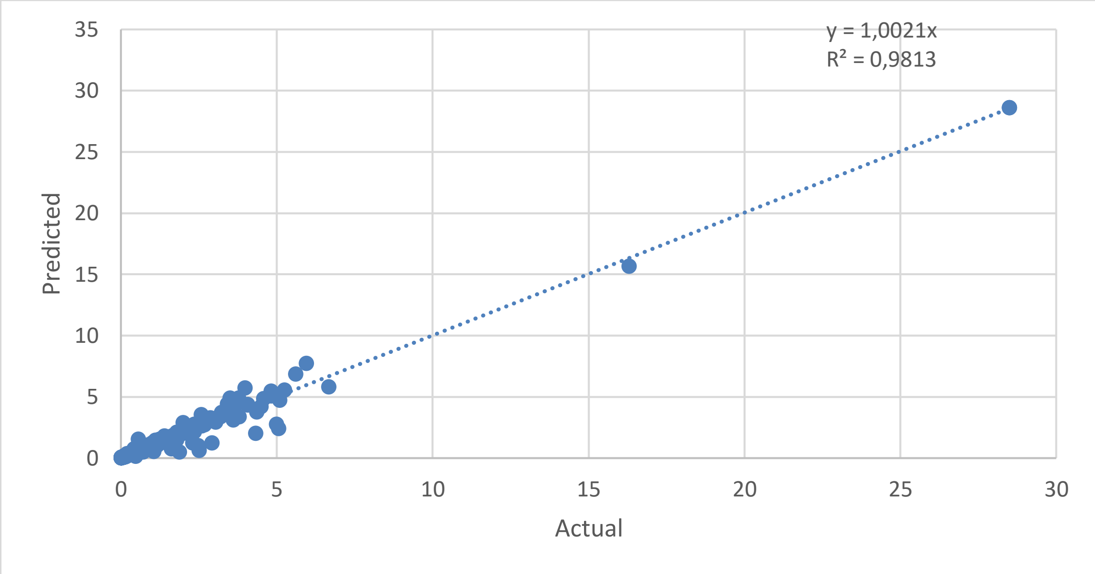

Figure 4.23 Crosscheck of Training Conclusions and Predicted Conclusions of Adam Optimizer and MSE loss

Test correctness of the model when Adam is used as an optimizer and MSE is used as loss (Figure 4.24) also sight. In the chart, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, there are not many high deviations.

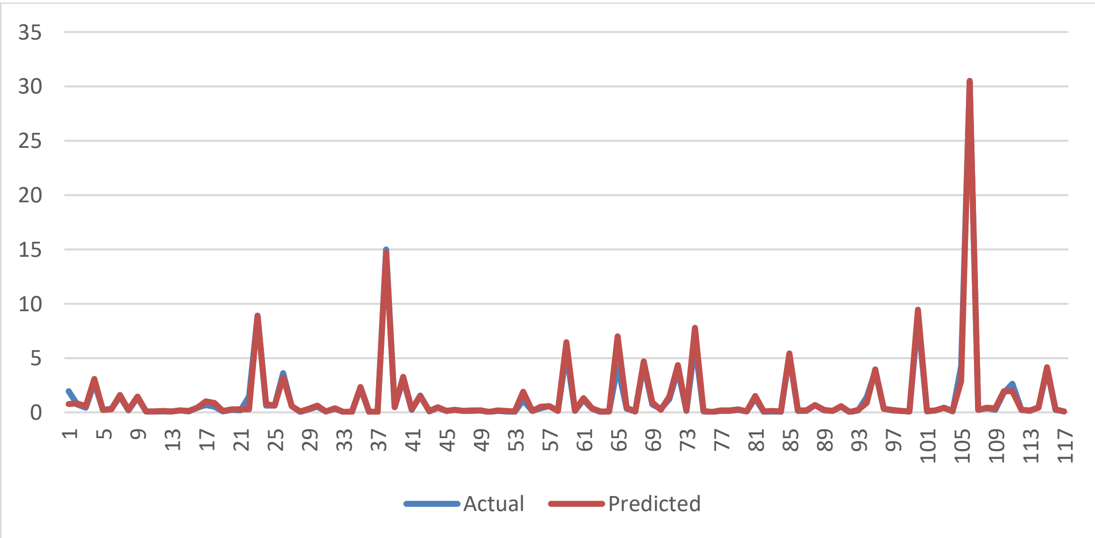

Figure 4.24 Crosscheck test correctness for Adam Optimizer and MSE loss

The crosscheck of the test conclusions in the dataset with the forecast conclusions from the model is mentioned at Figure 4.25. It is observed that the dots where the faults are least belong to the deep learning conclusions.

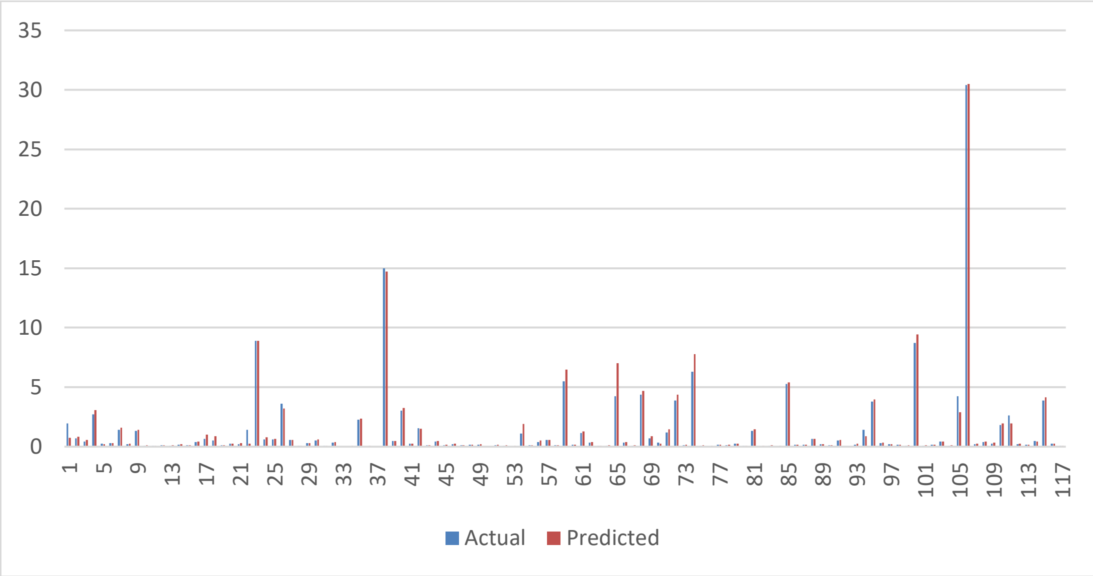

Figure 4.25 Actual conclusions and predicted conclusions for Adam Optimizer MSE Loss for testing

The crosscheck of the test conclusions of all dataset with the forecast conclusions from the model is indicateed in Figure 4.26. When the nearness to the right conclusion is investigated, it is observed that highest point is stated as 30.51 and deep learning model gives more realist conclusions.

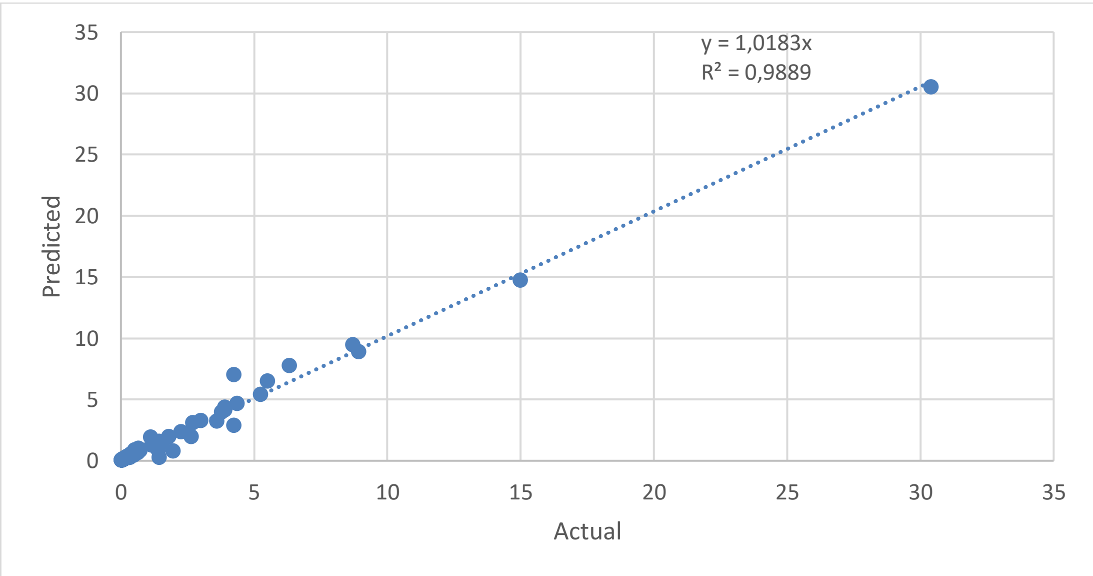

Figure 4.26 Crosscheck of Actual Conclusions and Predicted Conclusions of Adam Optimizer and MSE loss for testing

4.6 Crosscheck of Adamax Optimizer's and MAE loss for testing and training Conclusions and Actual Conclusions for Göksu Savran

The model's train and test correctness are indicate in Table 4.5. Test dataset correlation is 0.990 and Train Dataset correlation is 0.981. Mean of Test dataset is 1.006 and MEAN of train dataset is 1.010. MAPE of Test dataset is 4.74 and MAPE of Train dataset is 6.06. For MSE, MAD, MAE, MAPE, MEAN and Correlation, the conclusions are seen in Adamax Optimizer. In this status, MAE loss function is more prosperous for optimizer Test in deep learning model.

Table 4.5 Statistical Conclusions of Adamax Optimizer

Statistics	Train	Test
MAD	0,830171	0,622395
MSE	5,727104	2,189509
RMSE	2,393137	1,479699
MAE	0,060608	0,047468
MAPE	6,060798	4,746841
MEAN(actual/predicted)	1,010507	1,006424
Standart Deviation	0,197736	0,133838
Correlation	0,981205	0,990967

In the chart in Figure 4.27, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, it can be said that the range with the highest deviation is between 247-1149.

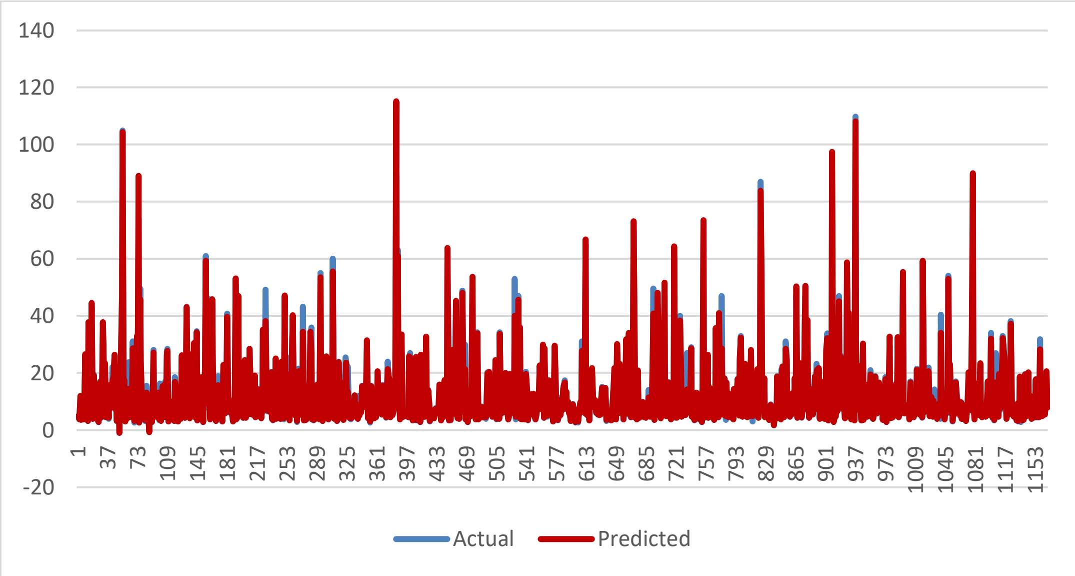

Figure 4.27 Crosscheck training correctness for Adamax Optimizer and MAE loss

The conclusions of all line are crosschecked with actual and predicted, which are the smooth computing techniques, and the MAEs of the conclusions wined from the DL model are crosschecked in (Figure 4.28). It is observed that the dots where the faults are least belong to the deep learning conclusions.

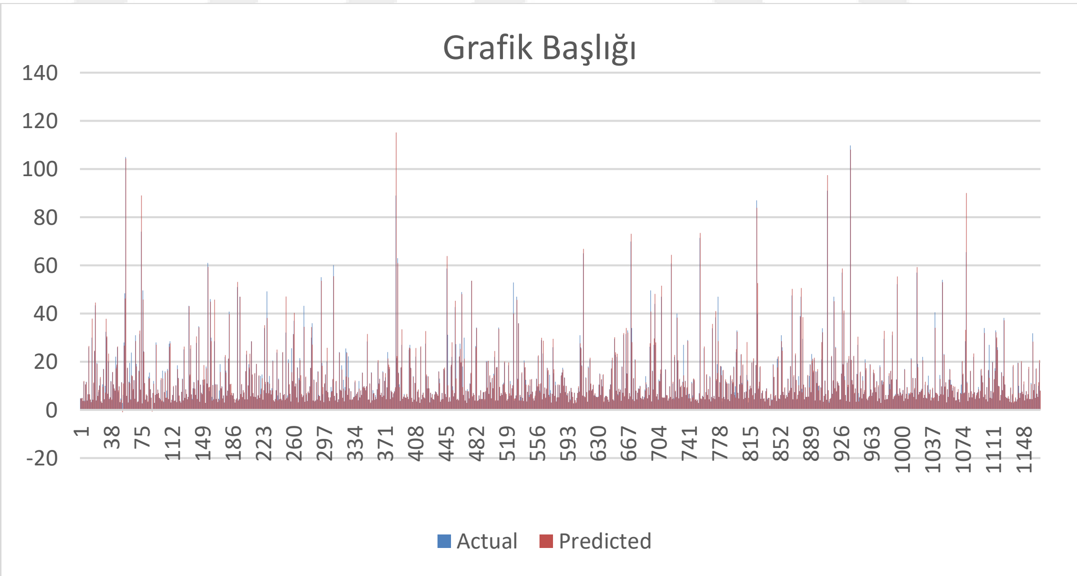

Figure 4.28 Actual conclusions and predicted conclusions for Adamax Optimizer MAE Loss for training

In the datumset is an sample for the deep learning conclusions for Adamax & MAE (Figure 4.29). When the nearness to the right conclusion is investigated, it is observed that highest dot is stated as 109.8 and deep learning model gives more realist conclusions.

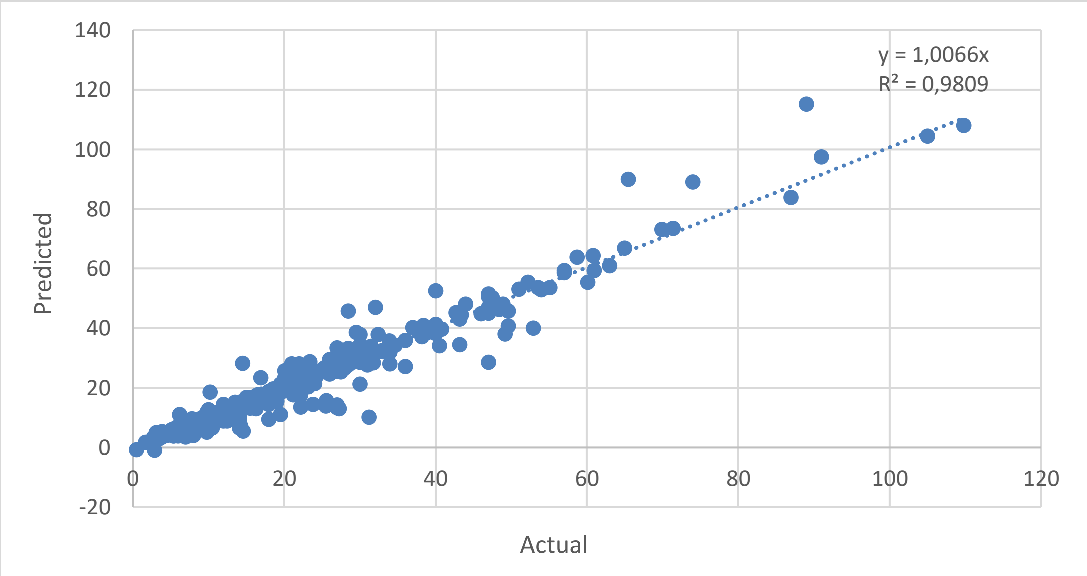

Figure 4.29 Crosscheck of Actual Conclusions and Predicted Conclusions of Adamax Optimizer and MAE loss for training

Test correctness of the model when Adamax is used as an optimizer and MAE is used as loss (Figure 4.30) also seen. In the graph, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, there are not many high deviations.

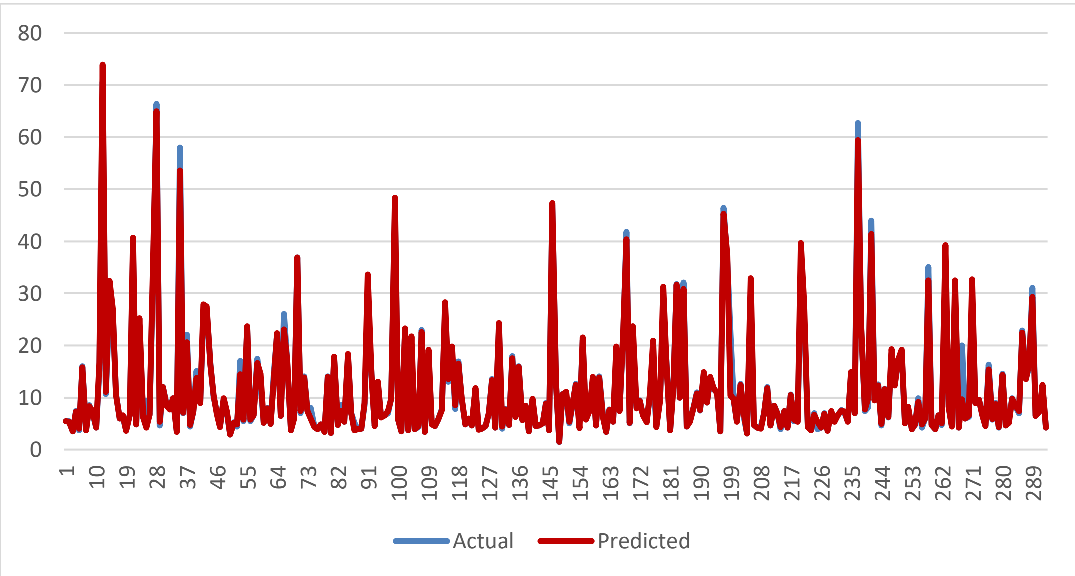

Figure 4.30 Actual datas and predicted conclusions for Adamax Optimizer MAE Loss for testing

The crosscheck of the test conclusions in the datumset with the forecast conclusions from the model is mentioned at Figure 4.31. It is sighted that the points where the errors are least belong to the deep learning conclusions.

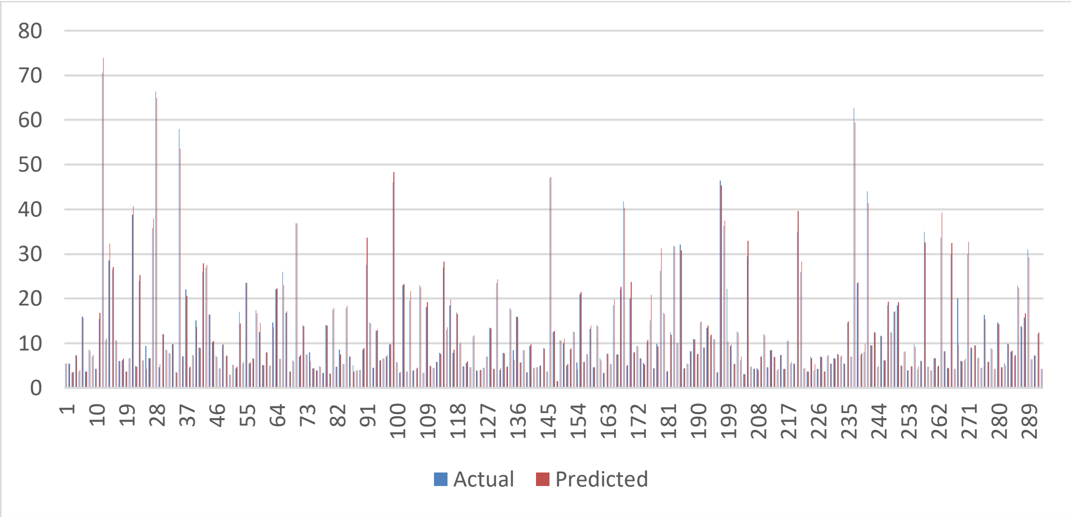

Figure 4.31 Actual datas and predicted conclusions for Adamax Optimizer MAE Loss for testing

The crosscheck of the test conclusions of all dataset with the forecast conclusions from the model is showned in Figure 4.32. When the nearness to the right conclusion is investigated, it is sighted that highest point is stated as 70.6 and deep learning model gives more realistic conclusions.

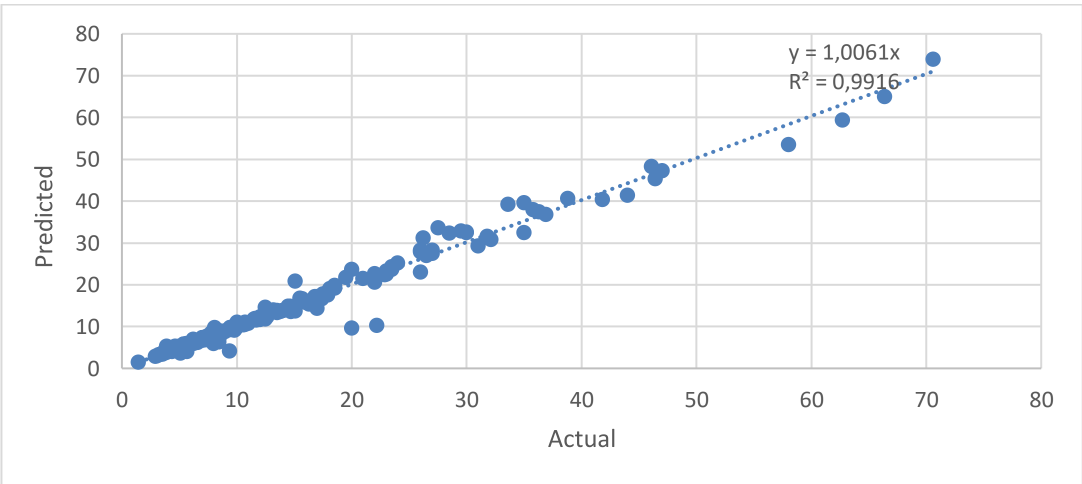

Figure 4.32 Crosscheck of Test Conclusions and Predicted Conclusions of Adamax Optimizer and MAE loss

4.7 Crosscheck of Adamax Optimizer's and MSE loss for testing and training Conclusions and Actual Conclusions for Göksu Savran

The model's train and test correctness, are shown in Table 4.6. Test dataset correlation is 0.988 and Train dataset correlation is 0.984. MEAN of Test dataset is 0.964 and MEAN of train dataset is 0.965. MAPE of Test dataset is 7.250 and MAPE of train dataset is 9.014. For MSE, MAD, MAE, MAPE, MEAN and Correlation, the conclusions are seen in Adamax Optimizer and MAE Loss. Test Correlation is more effective for Optimizer seen in Table 4.6.

Table 4.6 Statistical Conclusions of Adamax Optimizer

Statistics	Train	Test
MAD	0,912761	0,782848
MSE	4,589886	2,646744
RMSE	2,142402	1,626882
MAE	0,090145	0,072502
MAPE	9,014511	7,250185
MEAN(actual/predicted)	0,965368	0,964288
Standart Deviation	0,331668	0,111089
Correlation	0,984087	0,988986

In the chart in Figure 4.33, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, it can be said that the range with the highest deflections is between 235-1132.

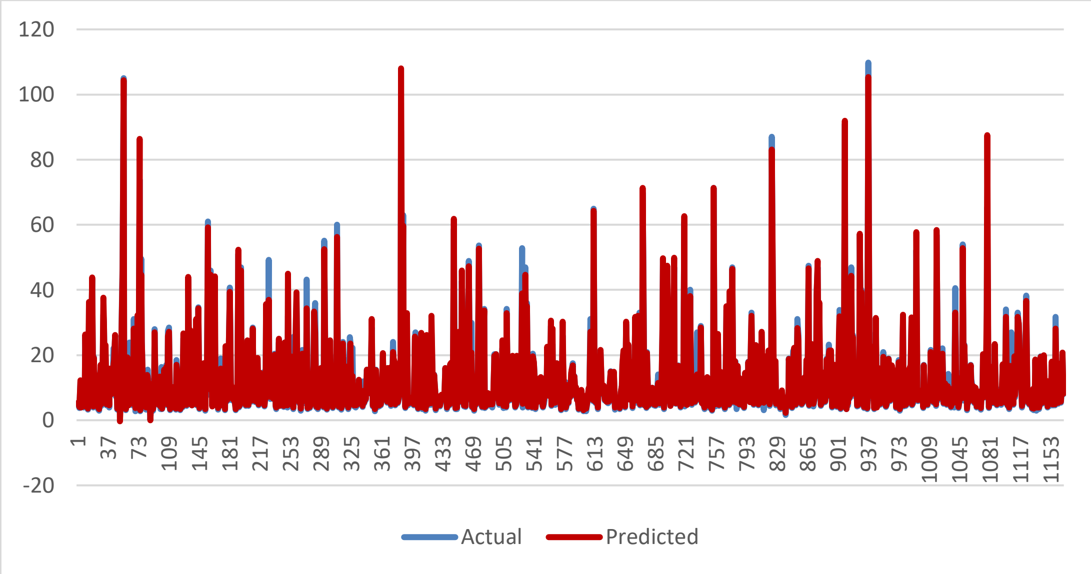

Figure 4.33 Crosscheck training correctness for Adamax Optimizer and MSE loss

The conclusions of all line are crosschecked with actual and predicted, which are the smooth calculating techniques, and the MSEs of the conclusions wined from the deep learning model are crosschecked in (Figure 4.34). It is sighted that the dots where the errors are least belong to the deep learning conclusions.

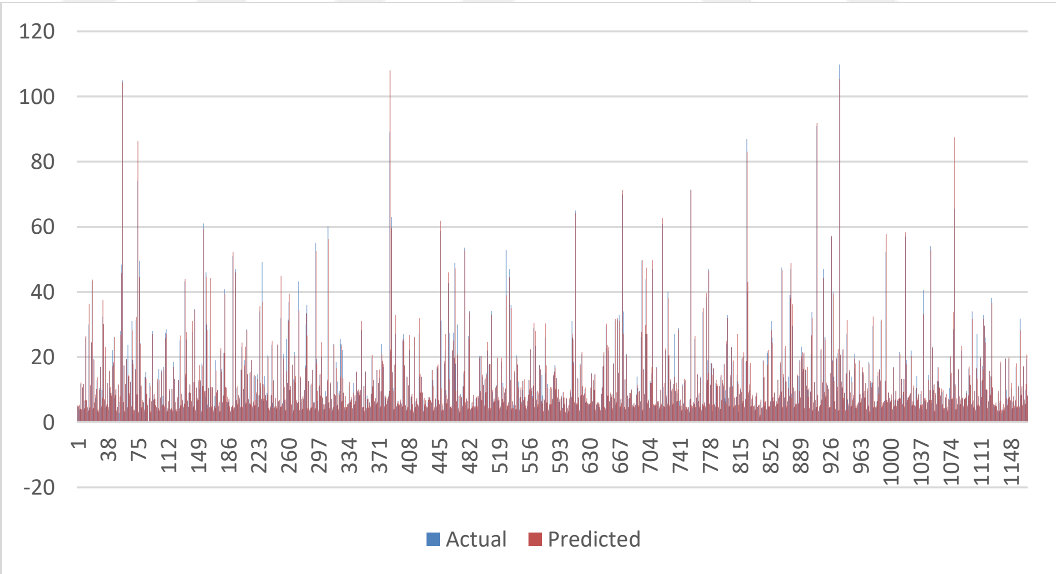

Figure 4.34 Actual conclusions and predicted conclusions for Adamax Optimizer MSE Loss for training

In the datumset is an sample for the deep learning conclusions for Adamax & MSE (Figure 4.35). When the nearness to the right conclusion is investigated, it is sighted that highest point is stated as 109.8 and deep learning model gives more realistic conclusions.

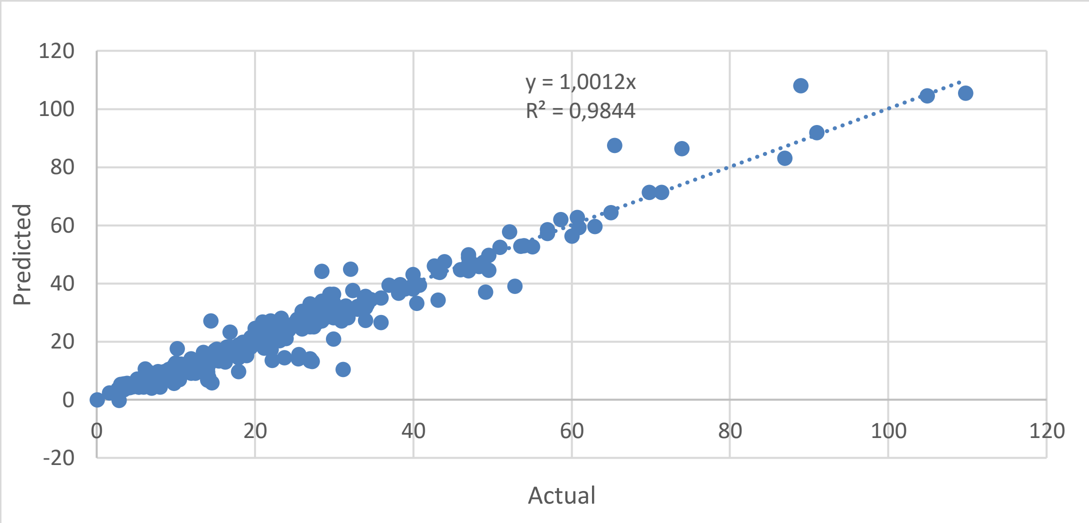

Figure 4.35 Crosscheck of Training Conclusions and Predicted Conclusions of Adamax Optimizer and MSE loss

Test correctness of the model when Adamax is used as an optimizer and MSE is used as loss (Figure 4.36) also seen. In the chart, training conclusions and model conclusions are crosschecked in terms of value. According to this chart, there are not many high deviations.

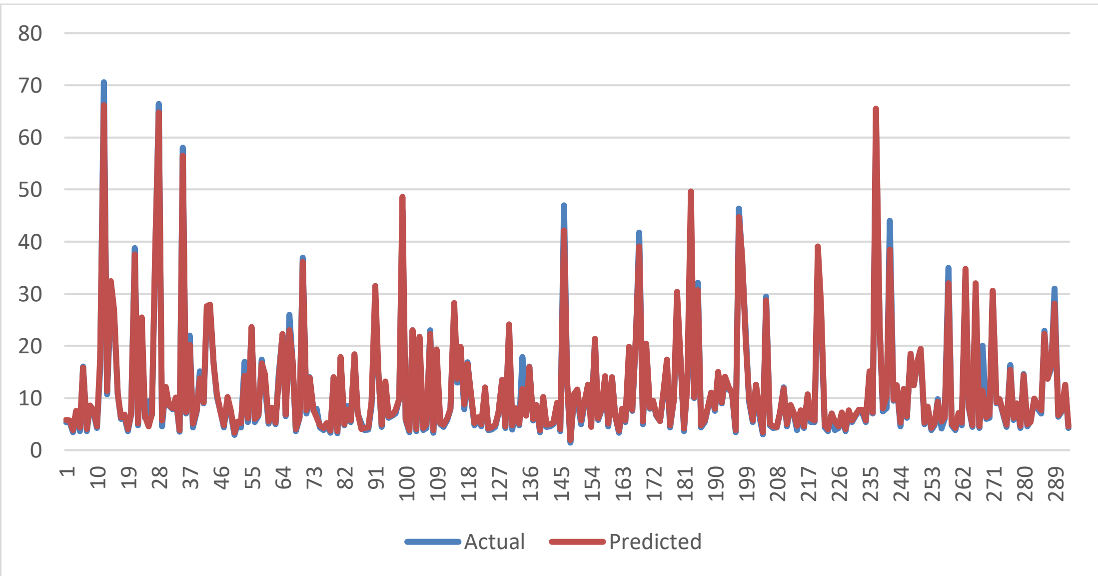

Figure 4.36 Crosscheck test correctness for Adamax Optimizer and MSE loss

The crosscheck of the test conclusions in the datumset with the forecast conclusions from the model is mentioned at Figure 4.37. It is sighted that the dots where the errors are least belong to the deep learning conclusions.

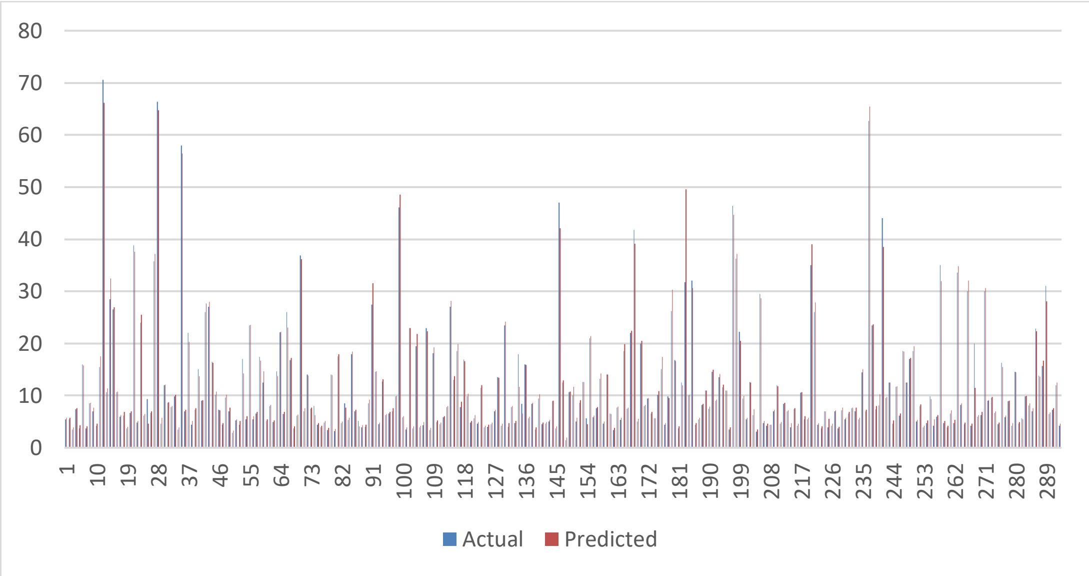

Figure 4.37 Actual conclusions and predicted conclusions for Adamax Optimizer MSE Loss for testing

The crosscheck of the test conclusions of each datumset with the forecast conclusions from the model is showned in Figure 4.38. When the nearness to the right conclusion is investigated, it is sighted that highest point is stated as 70.6 and deep learning model gives more realistic conclusions.

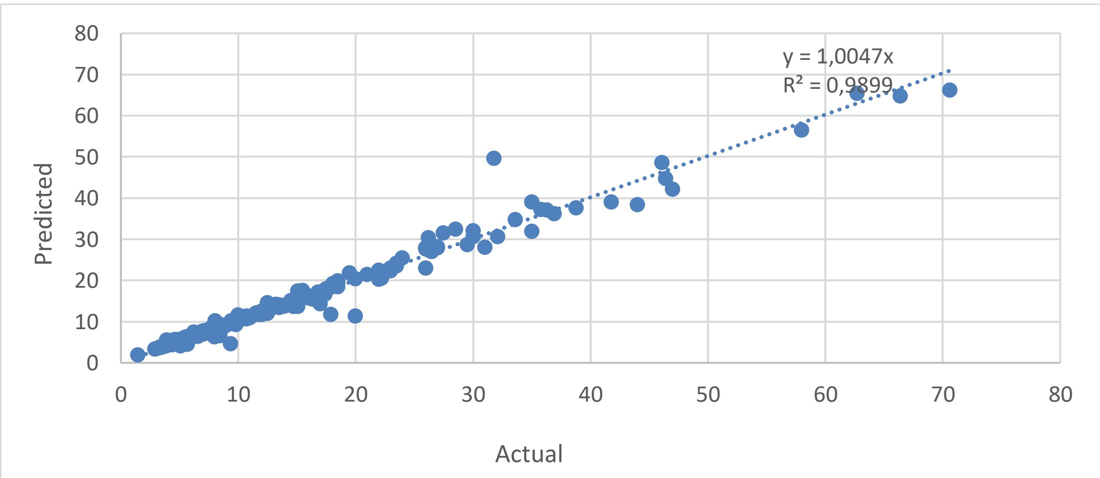

Figure 4.38 Crosscheck of Test Conclusions and Predicted Conclusions of Adamax Optimizer and MSE loss

4.8 Crosscheck of Adam Optimizer's and MAE loss for testing and training Conclusions and Actual Conclusions for Göksu Savran

The model's train and test correctness are indicate in Table 4.7. Test correlation is 0.944 and Train dataset correlation is 0.960. MEAN of Test Dataset 1.024 and MEAN of Train dataset is 1.021. Mape of Test Dataset 7.192 and mape of train datumset is 7.110. For MSE, MAD, MAE, MAPE, MEAN and Correlation, the best conclusions are seen in All Optimizer and MAE Loss. The Train dataset is more prosperous for MAE loss function and optimizer in deep learning model.

Table 4.7 Statistical Conclusions of Adam Optizimer for MAE loss

Statistics	Train	Test
MAD	1,031372	1,106446
MSE	11,256180	13,144080
RMSE	3,355023	3,625476
MAE	0,071103	0,071919
MAPE	7,110321	7,191915
MEAN(actual/predicted)	1,021154	1,024794
Standart Deviation	0,192813	0,191738
Correlation	0,960930	0,944940

In the chart in Figure 4.39, training conclusions and model conclusions are crosschecked in terms of value. According to this chart, it can be said that the range with the highest deviations is between 42-1149.

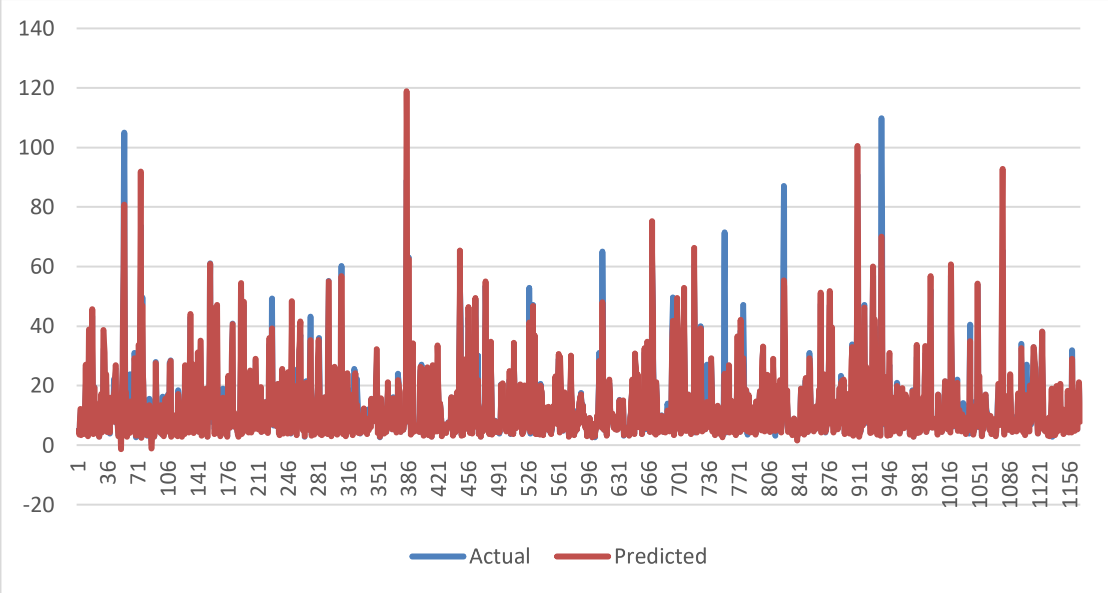

Figure 4.39 Crosscheck of training correctness for Adam Optimizer and MAE loss

The conclusions of all line are crosschecked with actual and predicted, which are the soft computing techniques, Adam and the MAEs of the conclusions wined from the deep learning model are crosschecked in (Figure 4.40). It is sighted that the points where the errors are least belong to the deep learning conclusions.

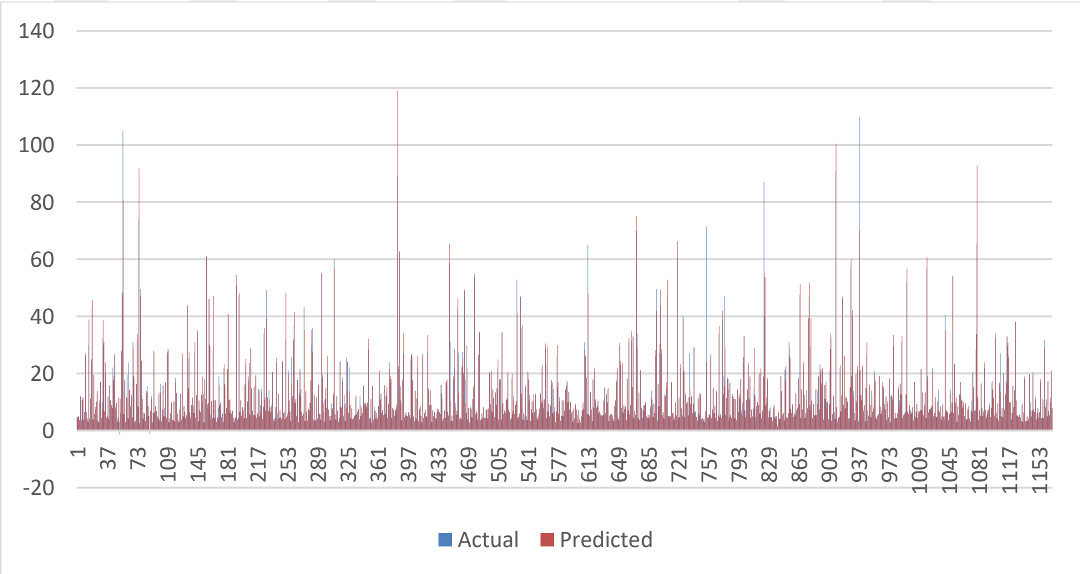

Figure 4.40 Actual datas and predicted conclusions for Adam Optimizer and MAE loss for training

In the datumset is an instance for the machine learning conclusions for Adam & MAE (Figure 4.41). When the intimacy to the right conclusion is investigated, it is sighted that highest point is stated as 109.8 and machine learning model gives more realistic conclusions.

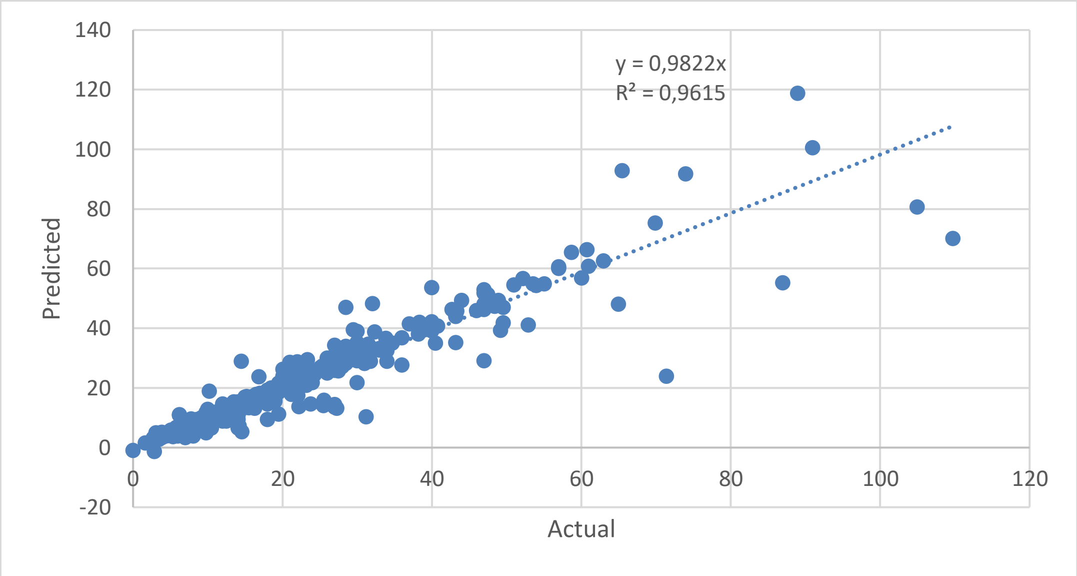

Figure 4.41 Crosscheck of Actual Conclusions and Predicted Conclusions of Adam Optimizer and MAE loss for training

Test correctness of the model when Adam is used as an optimizer and MAE is used as loss (Figure 4.42) also seen. In the chart, training conclusions and model conclusions are crosschecked in terms of value. Pursuant to this chart, there are not many high deviations.

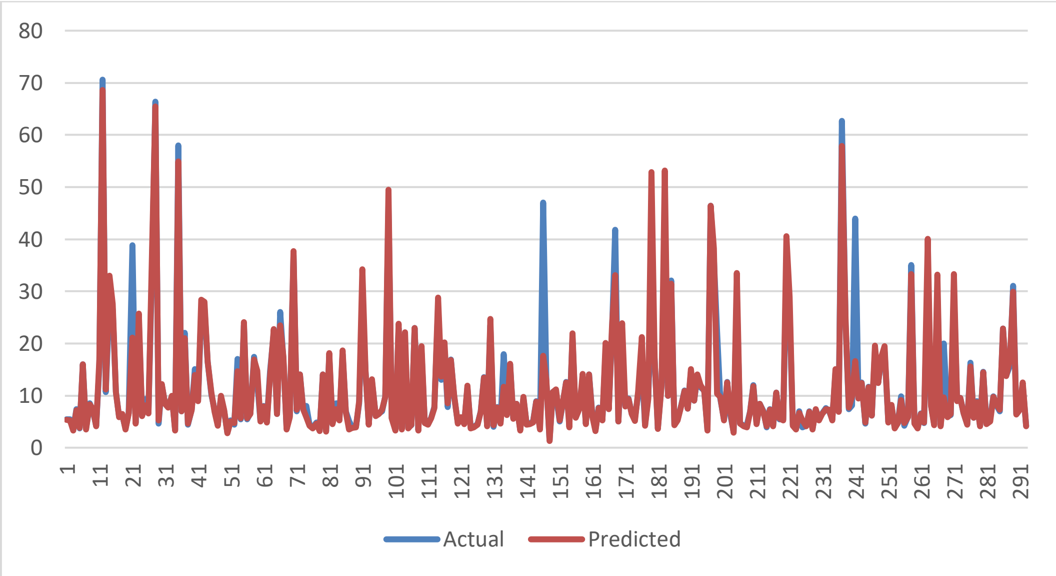

Figure 4.42 Crosscheck of testing correctness for Adam Optimizer and MAE loss

The collation of the test conclusions in the datumset with the estimate conclusions from the model is mentioned at Figure 4.43. It is sighted that the dots where the errors are least belong to the machine learning conclusions.

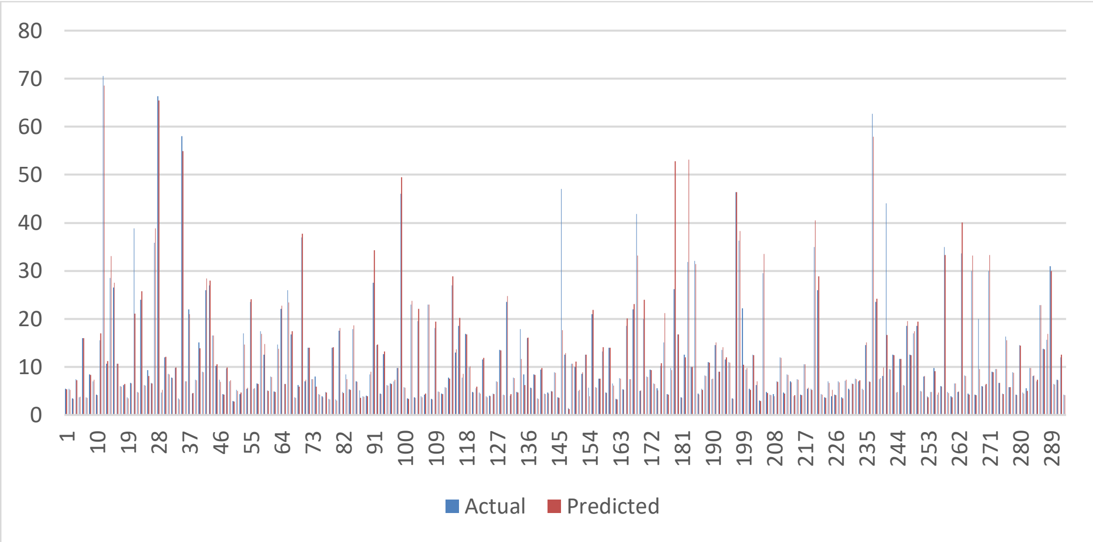

Figure 4.43 Actual datas and predicted conclusions for Adam Optimizer and MAE loss for testing

Crosscheck of each data set of data used with test conclusions and forecast conclusions from the model is shown in Figure 4.44. It is seen that the highest conclusion in achieving the right conclusion is 70.6 and the deep learning model gives very close conclusions to reality.

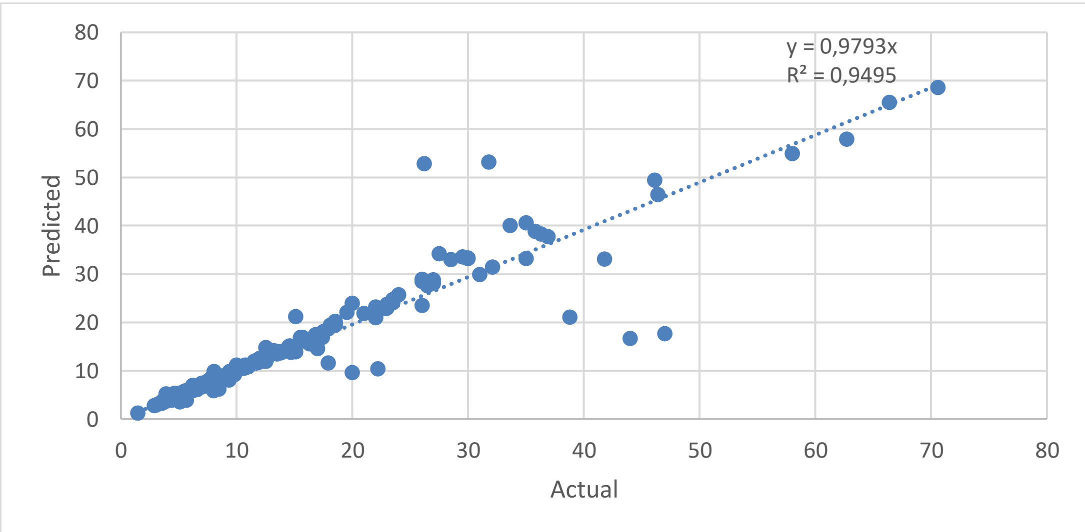

Figure 4.44 Crosscheck of Actual Conclusions and Predicted Conclusions of Adam Optimizer and MAE loss for testing

4.9 Crosscheck of Adam Optimizer's and MSE loss for testing and training Conclusions and Actual Conclusions for Göksu Savran

The Training and Test data correctness of the created model shown in Table 4.8. Test dataset correlation is 0.976 and Train Dataset correlation is 0.961. MEAN of Test Dataset is 0.980 and MEAN of Train dataset is 0.919. MAPE of Test dataset is 8.015 and MAPE of Train dataset is 17.243. The Test dataset is more prosperous for MAE loss function and optimizer in deep learning model.

Table 4.8 Statistical Conclusions of Adam Optimizer's for MSE loss

Statistics	Train	Test
MAD	1,189014	0,968410
MSE	11,947850	5,581397
RMSE	3,456567	2,362498
MAE	0,172435	0,080152
MAPE	17,243490	8,015159
MEAN(actual/predicted)	0,919395	0,980196
Standart Deviation	2,734253	0,131406
Correlation	0,961174	0,976469

The training and model conclusions seen in the chart in Figure 4.45 were crosscheck in terms of value. When looking at the values in the chart, it can be said that the range with the highest deviations is between 67-1156.

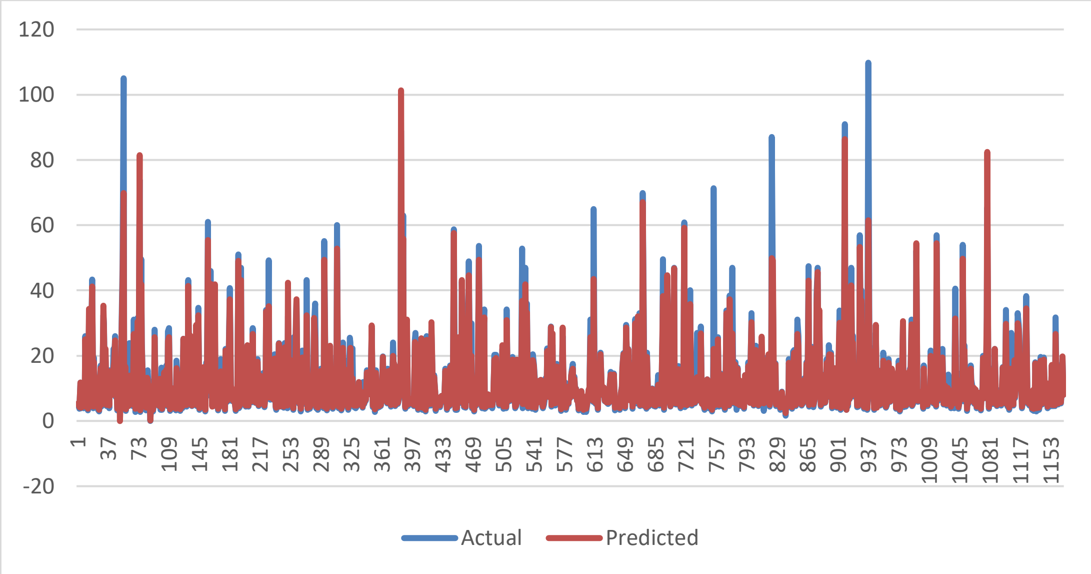

Figure 4.45 Crosscheck training correctness for Adam Optimizer and MSE loss

The conclusions of each row are crosschecked with software calculation techniques based on actual and forecast conclusions. And the conclusions from the machine learning model are crosschecked in Figure 4.46. It is seen that the level with the least error rate belongs to the deep learning technique.

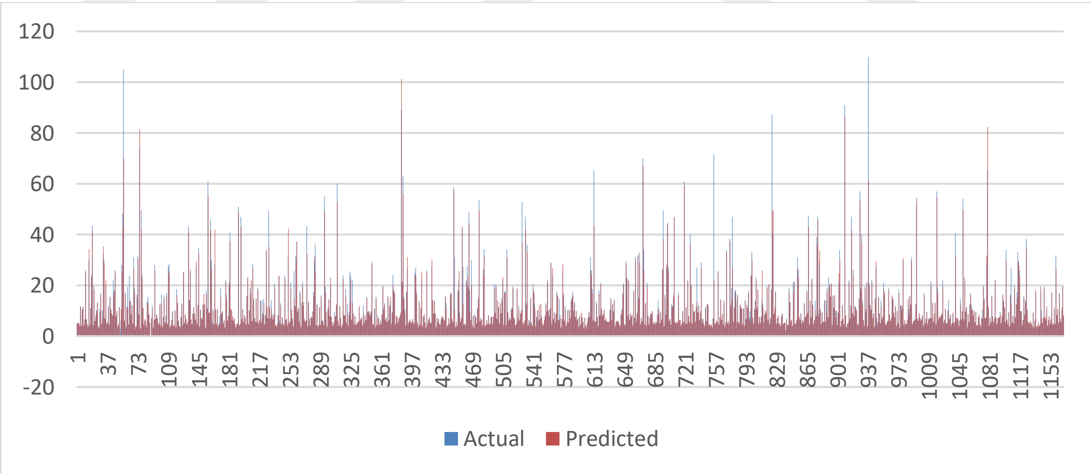

Figure 4.46 Actual conclusions and predicted conclusions for Adam Optimizer&MSE Loss for training

The data set provides the conclusions of a machine learning sample for Adam & MSE (Figure 4.47). When the correctness of the conclusionis investigate, it is seen that the best point is stated as 109.8 and the deep learning model gives more realistic conclusions.

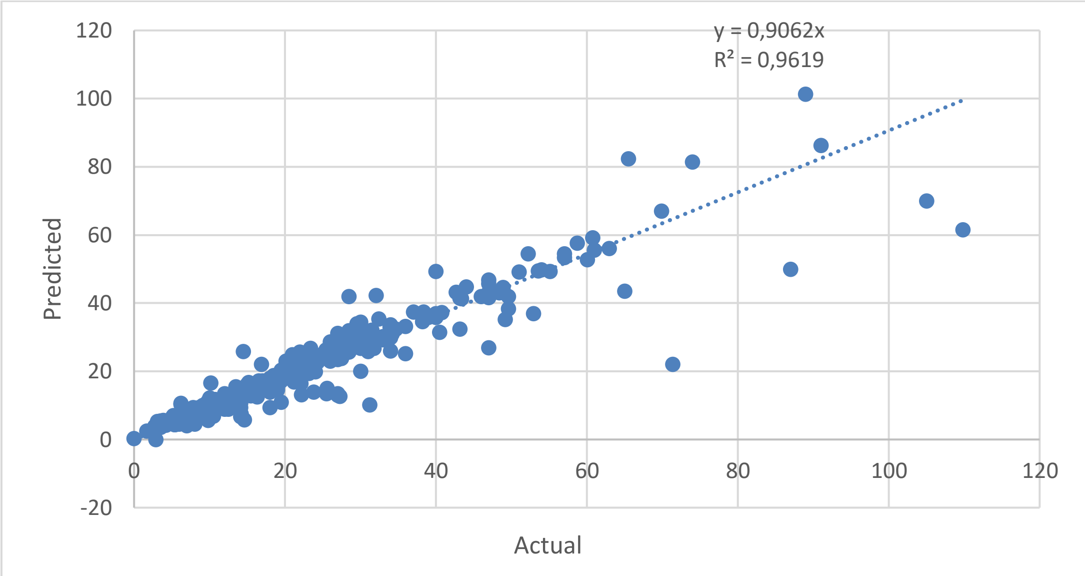

Figure 4.47 Crosscheck of Adam Optimizer with Training Conclusions and Predicted Conclusions of MSE Loss

The test correctness of the model is also observed when the man is used as a tester Adam and MSE is used as a loss (Figure 4.48). In this chart, the conclusions of the training and model are crosschecked in terms of value. According to this chart, there are not too many high deviations.

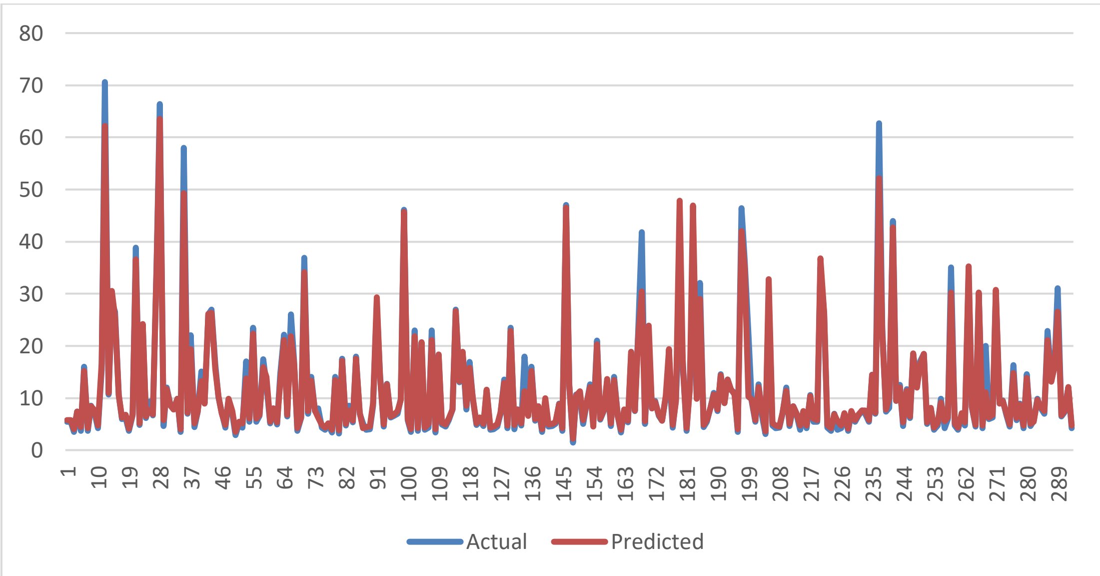

Figure 4.48 Crosscheck of Adam Optimizer and test correctness for MSE loss

Using the data in the data set, the test conclusions and the forecast conclusions obtained from the model are crosschecked in Figure 4.49. The points where the error rate is at the lowest level can be seen in the deep learning technique.

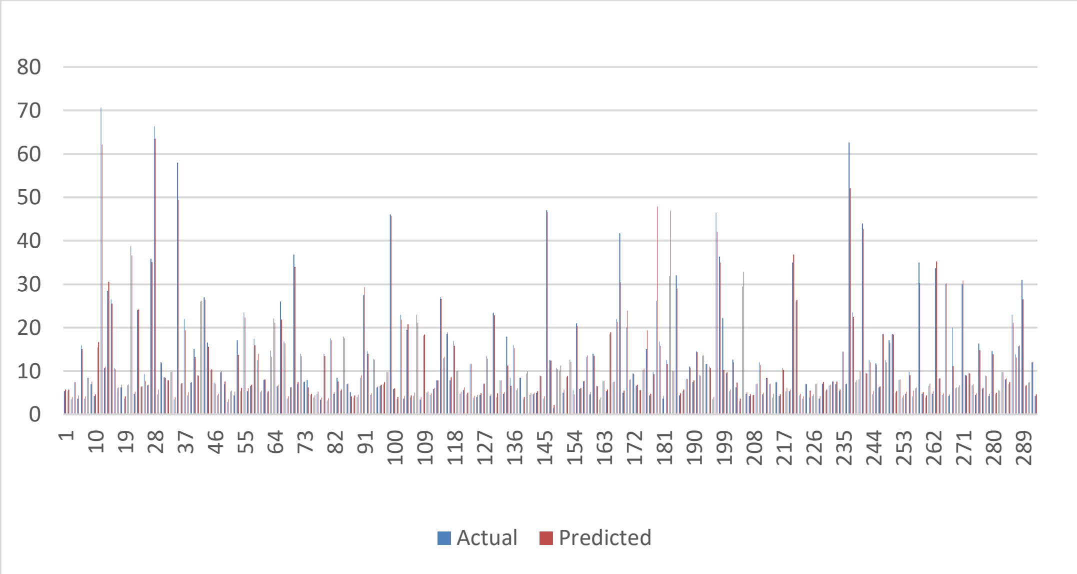

Figure 4.49 Real and predictive conclusions for Adam Optimizer and MSE Loss for testing

The collation of the dataset test conclusions and the forecast conclusions obtained from the model is shown in Figure 4.50. When the proximity to the right conclusion is investigate, it is seen that the highest point is stated as 70.6 and the deep learning model gives more realistic conclusions.

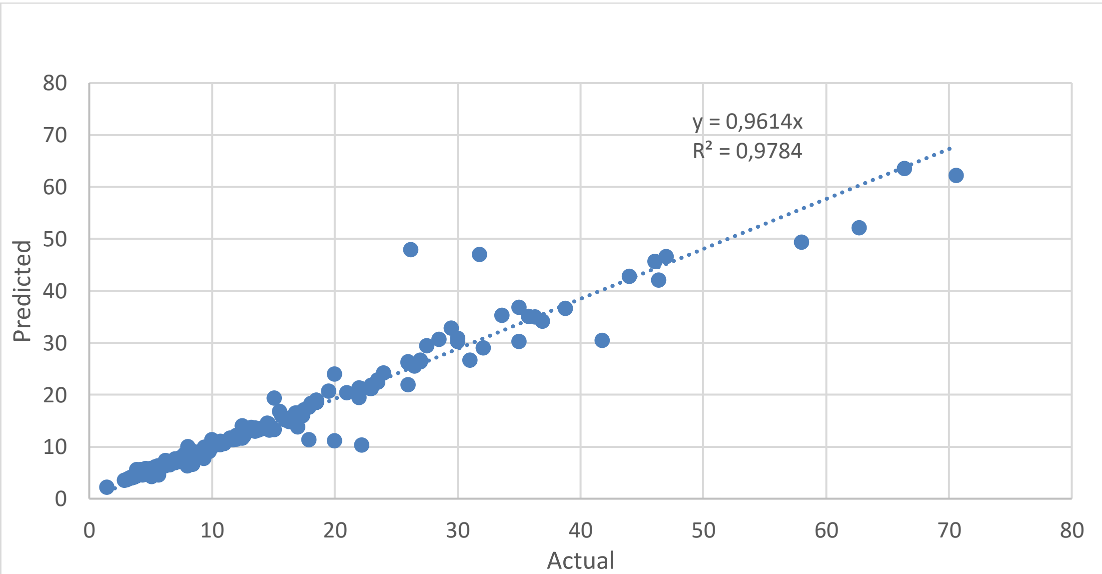

Figure 4.50 Crosscheck of Adam Optimizer's Actual and Predicted Conclusions and MSE loss for testing

4.10 Crosscheck of All Optimizer's and all losses in Statistical Conclusions for Akdere and Göksu Savran

According to data in Table 4.9 and Table 4.10, the most accurate conclusion for MAD, MAE, and MAPE is from the deep learning model that uses Adamax optimizers crosschecked to all optimizer MAE and MSE losses. According to these conclusions, it can be called that the MAE loss is more accomplished for the test in the deep learning model.

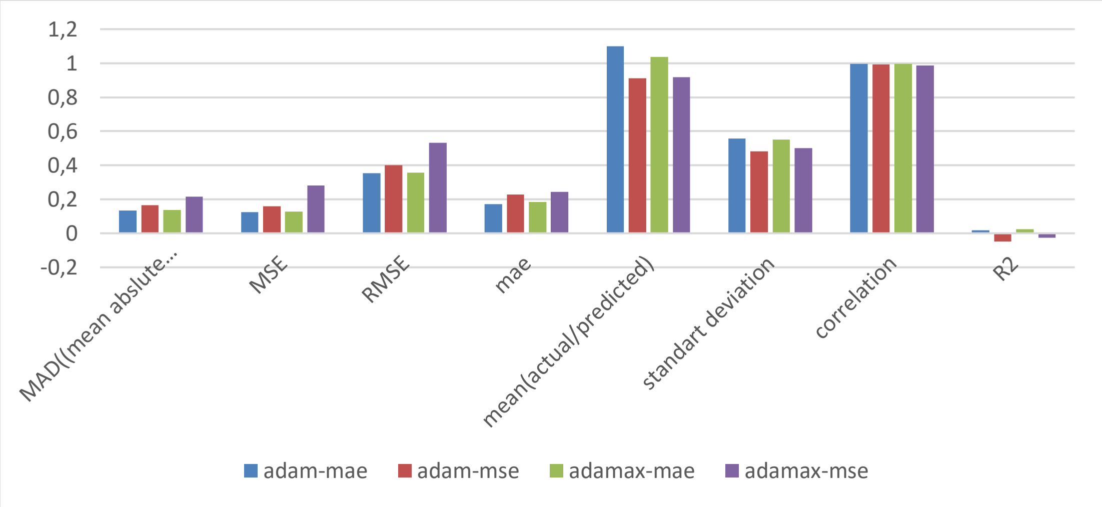

Figure 4.51 Crosscheck of statistical conclusions for Akdere station

Table 4.9 Crosscheck of All Remedial Conclusions for Statistical Evaluation for Akdere Station

AKDERE				
Statistics	Adamax-MAE	Adamax-MSE	Adam-MAE	Adam-MSE
MAD	0,137982	0,214168	0,134152	0,164533
MSE	0,126831	0,282030	0,124868	0,159106
RMSE	0,356134	0,531065	0,353367	0,398880
MAE	0,183245	0,243009	0,169879	0,228568
MEAN(actual/predicted)	1,035630	0,917398	1,100508	0,912371
Standart Deviation	0,550444	0,501119	0,556797	0,481517
Correlation	0,994584	0,987941	0,994630	0,993660

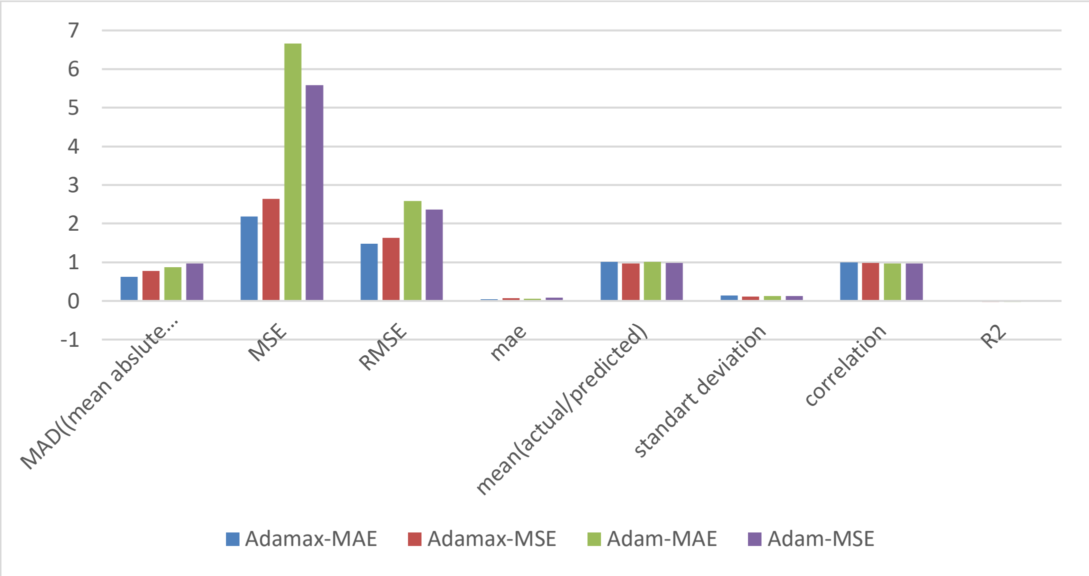

Figure 4.52 Crosscheck of statistical conclusions for Göksu station

Table 4.10 Crosscheck of All Remeidal Conclusions In Statistical Evaluations for Göksu station

GÖKSU				
Statistics	Adamax-MAE	Adamax-MSE	Adam-MAE	Adam-MSE
MAD	0,622395	0,782848	1,106446	0,968410
MSE	2,189509	2,646744	13,144080	5,581397
RMSE	1,479699	1,626882	3,625476	2,362498
MAE	0,047468	0,072502	0,071919	0,080152
MEAN(actual/predicted)	1,006424	0,964288	1,024794	0,980196
Standart Deviation	0,133838	0,111089	0,191738	0,131406
Correlation	0,990967	0,988986	0,944940	0,976469

CHAPTER 5

CONCLUSIONS

The data set used in this study taken from the daily measurements of DSI flow measurement station from Akdere, the village of Aşağıçöplü No D21A183 (2011-2018) on the Göksu River, and Göksu Savran No D21A186 (1984-2004). These flow values were divided into 4 time-shifted scenarios, and 2 separate data sets were used. The data set of 4 time-shifted scenarios, the flow values starting from 4 days before to one day before were used as input in the 5th day forecast. In the study, the Sequential Model was created by using Python Deep Learning Aplication Bookcase, which is a deep learning bookcase. The model used in the study consists of 1 input layer, 4 hidden layers and 1 output layer. The Epoch (Iteration) number is 1024 for the 4-shift scenario. Iteration function is defined as 'Adam' loss function, and 'MSE'. 70% of the data belonging to 4 shifting scenarios used for training and 30% for testing. In this study, in the south of Turkey and one of the major water sources of a deep learning model to predict current values of the Euphrates River branch were formed. While analyzing the performance of the model, the proximity between the real values and the estimated values was examined. Correlation, Determination coefficient (R^2), Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD), Standard deflection, among the methods used for the evaluation of models in the literature, were used as evaluation methods. The evaluation conclusions obtained by comparing the deep learning conclusions with the real conclusions were shown in Table 4.9 and Table 4.10. Regression chart, which is one of the most important charts comparing the real values with the estimated values, were shown in Figure 4.51 and Figure 4.52 separately according to the training and test conclusions for the 4-shift scenario. The more linear the actual and predicted values shown in this type of chart, the closer the values are. According to the charts in the figures, the conclusions with the closest to real values are the training conclusions of the scenario with the highest correlation value. Correlation values of the training and test conclusions obtained from the model for the 4-shifting scenario were found as 0.9946 for Akdere-Adam MAE and 0.9909 for Göksu Savran-Adamax MAE. One-to-one conclusions were obtained in places that seem like a single line. Looking at these charts, it is understood that the conclusions are quite successful. In order to obtain the best conclusions from the model, different healing functions, loss functions and iteration numbers have been tried while compiling the model. The model was run many times by creating hidden layers with different numbers and properties. As a conclusion of these studies, the conclusions of the four-shift scenarios were compared separately and the conclusions of the experiment of the best conclusions were used in the study. In order to examine the realism of the conclusions, the model using this information was run repeatedly and it was observed that similar conclusions were obtained in each run.

Considering all the conclusions, it was observed that the success of the 4 translational scenarios and the deep learning model was very good. The use of this scenario and the Deep Learning model in future studies will guide the forecast of current values. In this study, an forecast was made based on single current values and successful conclusions were obtained. When the input parameters are increased, it will be useful to use them in future studies with different scenarios. In addition, with these estimated flow values, an important data was obtained in terms of designing and feasibility of a potential dam that is planned to be built on different rivers.

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