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COMPARISON OF DIFFERENT DEEP LEARNING OPTIMIZATIONS IN RIVER FLOW PREDICTION

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Asst. Prof. Dr. Hüseyin Çağan KILINÇ

By

Cem CEYLAN

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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.

Cem CEYLAN

ABSTRACT

COMPARISON OF DIFFERENT DEEP LEARNING OPTIMIZATIONS IN RIVER FLOW PREDICTION

Ceylan, Cem

M.Sc. Civil Engineering

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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 flows 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, flow measurements made obtained 2002-2011 at a selected FMS in the Euphrates River Basin, the largest basin in our country, are analyzed. In this analysis, Artificial Neural Networks and Deep Learning enhancers are used. Also in this analysis, 4 different scenario models were used and R^2= 0.9923 in Adam optimizer and Logcosh loss function for the most statistically significant scenario. The statistical success of the model will provide much more accurate and easy estimation of the new input parameters that will occur on this basin, and will also shed light on other studies in this area.

Keywords: ANN, Deep learning, River Stream, Flow Measurement Station

ÖZET

NEHİR AKIM TAHMİNİNDE FARKLI DERİN ÖĞRENME İYİLEŞTİRİCİLERİNİN KARŞILAŞTIRILMASI

Ceylan, Cem

Yüksek Lisans, İnşaat Mühendisliği Bölümü

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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, ülkemizdeki en geniş havza olan Fırat Nehri Havzasında seçilen bir Akım Gözlem İstasyonunda (AGİ), 2002-2011 yılları arasında yapılan akım ölçümleri analiz edilmektedir. Bu analizde, Yapay Zekâ tekniklerinden Yapay Sinir Ağları ve Derin Öğrenme iyileştiricileri kullanılmaktadır. Yine bu analizde 4 farklı senaryo modeli kullanılmış olup istatistiksel açıdan en anlamlı senaryo olan Adam iyileştiricisi için Logcosh kayıp fonksiyonunda R^2=0,9923 değeri elde edilmiştir. Modelin istatistiksel başarısı bu havza üzerinde oluşacak yeni girdi parametrelerini çok daha doğru ve kolay tahmin edilmesini sağlayacak ve ayrıca bu alanda yapılacak diğer çalışmalara da ışık tutacaktır.

Anahtar kelimeler: ANN, Derin Öğrenme, Nehir Akımı, Akım Gözlem İstasyonu

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SYMBOLS AND ABBREVIATIONS

AF	: Atrial Fibrillation
AI	**:** Artificial Intelligance
ANN	**:** Artificial Neural Network
API	: Application Programming Interface
BN	: Bayesian Network
CNN	**:** Convolutional Neural Network
CVD	: Cardio Vascular Disease
COVID-19	: Coronavirus Disease
DL	**:** Deep Learning
DLNN	**:** Deep Learning Neural Network
DNN	: Deep Nervous Networks
DSI	**:** General Directorate of State Water Affairs
DTL	: Deep Transfer Learning
DBN	: Deep Belief Networks
DDL	: Distributed Deep Learning
DRL	: Deep Reinforcement Learning
FMS	**:** Flow Measurement Station
FUC	: The Field Under the Curve
GEP	**:** Genetic Programming
GRA	: Gray Relational Analysis
GRANN	**:** General Regression Artificial Neural Network
GRU	**:** Gated Repetitive Unit
HM	: Heavyweight Metal
IWT	: Water Transfer Between Basins
km	**:** kilometer
km²	**:** kilometer square
LSTM	**:** Long-Short Term Memory
m	**:** meter
m³	**:** cubic meter

MAD : Mean Absolute Deviation
MAE : Mean Absolute Error
MAPE : Mean Absolute Percentage Error
MEAN : Actual-Predicted
ML : Machine Learning
mm : milimeter
MSE : Mean Squared Error
NAG : Nesterov Accelerated Gradient
PBM : Physically Based Models
PDE : Partial Differential Equation
PDLA : Python Deep Learning Aplication
PT : Portfolio Theory
RBF ANN : Radial Basic Functional Artificial Neural Network
RBM : Restricted Boltzmann Machines
RL : Reinforcement Learning
RMSE : Root Mean Square Error
RNN : Recurrent Neural Network
SIMP : Punitive Solid Isotropic Material
SMA : State Meteorological Affairs
STD : Standart Deviation
THM : Trihalomethane

CHAPTER 1
INTRODUCTION

1.1 General Overview

It has been known for centuries that water is a source of life for human life. Due to the low amount of water to be consumed in the world, it is important to ensure the sustainability of water in order to reach future generations. Day by day, it faces many negativity that will jeopardize its sustainability. These dangers include global warming, drought, unplanned and unconscious consumption of water. The continued existence of water is one of the factors that enables the continuity of human life. It is not possible to artificially create these water sources, which play a major role in the continuity of life. Therefore, predicting water resources allows planned, efficient and economical use of water from all perspectives in the future. Otherwise, the problem of mis-management of water resources arises. This mis-management can also reduce the quality of life to the highest levels by endangering the continuity of the living life of water resources. It is stated that water management mistakes, implemented water policies and the increase in water demand as the population increases in various sectors, global climate change is the cause of water problems (Aküzüm et al., 2010).

Water resources management continues throughout the period from rainwater collected in river basins to the transfer of these rainwater to consumers. With the accuracy of estimates made in flow measurement stations in the management of river basins, the evaluation of land soil is of great importance. Throughout the whole process, the main goal should be to protect these river basins from unconscious use, to plan, to try to make them sustainable. Thus, in order to achieve the main objectives, many forecasting models can be created today and planning of water resources management can be done strategically. In order to eliminate the future water crisis, some people emphasize that water research should be started and scientific projects related to this issue should be produced and supported (Istanbulluoğlu et al., 2006).

Artificial neural network (ANN) and Deep Learning (DL) models from Artificial Intelligence (AI) techniques are these prediction methods. All these forecast conclusions provide appropriate planning for both the producer and the user for the production of water resources to living beings, irrigation, hydroelectric power generations and the transfer of water to future generations. The flow in the streams is determined by the measurement stations that the relevant institutions have established at certain points of the stream. However, it is difficult to operate these stations in cases such as the failure to obtain data for various reasons and failure of stations (Terzi and Köse, 2012). While the regulations and applications in streams and rivers are being projected, it is of great importance to make reliable flow estimates. Traditional flow estimation process may be insufficient to make effective predictions due to the non-linear structure of the system. Alternative forecasting process are needed for this (Yurdusev, 2008). Accurate flow estimation is an important component in terms of water volume and quality. In recent years, AI technology has proven to be a computer science department that can model various hydrological processes. On the other hand, it is a high level AI branch composed of multiple layers of neurons representing the DL process. DL can handle large scale data and is good in different fields. DL is used today in various fields and predictions such as model identification, medical prediction and speech recognition. Unlike traditional learning algorithms, DL can overcome dependence on manually designed features (Boulemtafes et al., 2020).

In the area of machine learning (ML), ANN are often used to solve many problems. However, in the so-called "AI Hibenation", works in this field have arrive to a standst place mainly necessary to hardware constraints and other problems. ANN, which became a favorite area again in the early 2000s, has transitioned from fordable meshs to deep meshs with GPU improvements. This approach has been successfully used in a broad range of ways, from image processing, natural speech processing, medicinal implementations to action recognition (Şeker et al., 2017).

DL has made great progress in the area of ML by eliminating the problems that employees have been dealing with for many years. Because deep networks, unlike conventional ML and image processing techniques, perform learning on crude data. When processing crude data, it wins the necessary information with actings that it has created in different layers. DL first came to attention in 2012 with its achievement in the large-scale visual identification (ImageNet) contest for object classification. While the foundations of DLare based on the past, the first of the most important reasons why it has been popular especially in recent years is that there is enough data for education and secondly there is hardware infrastructure to work with this data (Inik and Ulker, 2017).

In this research, the estimation of river flow was completed using existing data measured at the FMS to create a DLmodel with ANN and AI technology. DLoptimizer was used to evaluate the performance analysis and multi-year daily flow value of 1 station in the Euphrates Basin, one of Turkey's 25 basins. The best forecast model is determined by comparing actual data with the forecast model.

CHAPTER 2

LITERATURE REVIEW

Water is an indispensable source of life for human life. Water is known to be the most important tool in maintaining human life for centuries. In fact, it is worth remembering the fact that the human body has about 70% water. Therefore, it is impossible to think of a life without water. For the world, the loss of water can be explained as the cannot be a life anymore. Because water; it is a resource that cannot be artificially produced, created, imitated. These limited water resources are important for the life of living things. Therefore, water and water resources are very important. Although Turkey seems rich in water resources, it remains well below the world average in terms of the amount of water consumption per capita (Tombul, 2014).

The rapid increase of the world population, urbanization, industrialization and environmental pollution brought about by unconscious excessive use of medicines and fertilizers in agricultural areas have disrupted the quality of water resources. The supply, treatment and distribution of the needed drinking and drinking water has therefore become very difficult and costly. For this reason, searches have been made for the protection, planning and management of water resources. The aim of modern integrated water resources usage planning and management is to allow for a systematic approach (Gündoğdu and Kocataş, 2006).

One of the most important places where water resources are found are river basins. Basin-scale integrated water resources management plans are primarily evaluated in terms of climatic, hydrometeorological, topographic, water resources and ecosystem balances of the project site. In this context, it is important to create data bases and to define the dynamic relationships in the relevant basin and sub-basins within the scope of both historical data and the changes anticipated to occur in the future. Following this, it is necessary to determine the temporal and spatial change in surface and groundwater resources using hydrological and hydrogeological analysis or modeling approaches, and subsequently, the integrated water resources budget at the basin scale should be formed within the framework of a sustainable approach (Tunçok and

Bozkurt, 2015). Water Transfer Between Basins (IWT) is a complicated decision-making handle that often be attached to on agents ranging from hydro-meteorological conditions to socio-economic prints. Hydrological modeling is especially difficult below these conditions and requires right quantitative knowledge that may not every time be available (Essenfelder and Giupponi, 2020). Despite the enormous variety in modeling necessitys for handy hydrological applications, the need continues to improve more trustworthy and clever professional systems used for real-time forecast intents. The difficulty in meeting the standards of an professional system is principally due to the effect and behavior of hydrological processes conclusioning from natural undulations on the physical scale and the variance that occurs in the basic model input data sets. River flow estimation is a mandatory task for water resource management and direction, water request evaluations, irrigation and agriculture, early admonitory of floods, and hydroelectric generations (Yaseen et al., 2019).

In areas with water resources, there are many dangers that cause water depletion. One of them is floods that occur. Floods cause significant damage every year around the world. Accurate prediction of floods can significantly reduce damage of life and property. However, necessary to the complication during flood creation, the correctness of conventional flood prediction models suffers from performance reduction with increasing time necessary (Lv et al., 2020). Estimating water level is an highly important task as it allows to reduce the effects of floods, reduce and avert disasters. Physically based models generally give good conclusions, but they require expensive computation time and a variety of hydro-geomorphological data to improve the estimation system. Alternatively, data-driven prediction models are generally faster and easier to build (Nguyen, 2020). New generation smart rainwater systems promise to reduce the need for new structures by improving the existing infrastructure with real-time controls. Intelligent rainwater systems dynamically react to individual storms by controlling distributed assets such as valves, gates, and guns (Mullapudi et al., 2020).

One of the process of supplying water is water resources located under ground. The rapid depletion of these groundwater and the deterioration of groundwater quality in many parts of the world due to natural causes have caused serious concerns for the world. This inevitable depletion is attributed to widespread groundwater extraction for agriculture, industrial and domestic use, while various natural and anthropogenic pollution is a primary contributor to groundwater quality deterioration. Therefore, a smart, efficient and regional-scale framework is required for sustainable groundwater management based on informed modeling approaches and reseable data. In recent years, data-based predictions such as AI methods are used quite frequently in the field of hydrology. Therefore, it can be effectively used to model the amount of groundwater and the distribution of large contaminants in groundwater. Using appropriate modeling techniques, combining information and data on dependent and other independent variables can lead to a better understanding of the primary triggers that change groundwater dynamics and the factors affecting the distribution of pollutants in groundwater today and in the future. Given more recent data availability, these process can produce more accurate estimates and be useful in better management of groundwater resources (Malakar et al., 2020).

AI is a field of computer science that mimics the structures and working principles of the human brain. ML belongs to the field of AI and seeks to improve models from exposure to training datum. DL is other subset of AI where models exemplify geometric transmutations on many diverse layers. This technic has shown enormous potential in fields such as computer vision, talk recognition, and natural language processing (Lavecchia, 2019). With the rapid development of AI and DL technics, it is crucial to provide the security and sturdiness of deployed algorithms. Lately, the vulnerability of DL algorisms to competing examples has been widely recognized (Ren et al., 2020). AI in recent years; Theory and research on decision making in directio and organization studies have regained importance. In particular, last advances in DL boost their analytical capabilities by promising benefits for decision-making within organizations, such as helping employees with computing. This helps to transition to more creative and useful jobs. For decision-making in organizations, an accessible training data of DL and implementation of DL algorithms is presented. A review of a European e-commerce firm and films was conducted with two case studyes based on image recognition and emotion analysis tasks carried out on datasets from Zalando. As a result, recommendations have also been made for managers dealing with these challenges with the commitments and challenges of the DL (Shrestha et al., 2020).

ML, a sub-branch of artificial intelligence, has played a valuable role in environmental remote sensing (UA) research throughout history. Due to rapid advances in ML around the world, with proportionately increasing data, new process have emerged that can help the earths environmental monitoring. In the last decade, DL improved from the conventional nervous network (NN) has outperformed a state-of-the-art ML models. Significant progress has been observed in growing a DL methodology for various place science implementations. Consequently, the focus is on the use of traditional NN and DL process to advance the peripheral remote sensing process (Yuan et al., 2020). ML and Web technologies fields have witnessed significant developments in recent years. This has led to an uninterrupted and rapid growth in the exchange of views and experiences regarding services or products over the Internet in different fields. Therefore, a busy online data flow is available for analytical studies (Nassif et al., 2020).

DL, mentioned above, has been adapted in many fields of AI such as talk recognition, image recognition, natural language processing, robot navigation systems and self-driving cars. This area also helps in analyzing the spread of dangerous diseases as in pandemic cases with many social behavior and other environmental factors, modeling state diseases such as obesity, and monitoring public health. There are several categories of tools that help DLengineers work faster and more efficiently. There are many classes of tools that enable DLengineers to do their job faster and more effectively. Some of the tools include TensorFlow, Caffe, Torch and the like. DL models utilize a variety of advanced algorithms. Excellent knowledge of advanced DL techniques, types, and applications can help users pursue this for a variety of purposes (Nisaha et al., 2020). DL has be the principal focal point of researchs in the area of AI. DL primarily involves automatic property subtraction using deep nervous networks (DNNs) that can assort pathological and radiological images. Convolutional nervous network (CNNs) can also be practial to pathological display analysis, such as detecting tumours and measuring cellular properties. First, it designate the blackbox problem of shoaly NNs, the notion of regulation subtraction, the renewed assault of the blackbox problem in DNN architectures and the paradigm shift concerning DL's clearness using rule subtraction. Next it review DL's limitations in pathology in terms of histopathology and cytopathology. As a conclusion, it provide new combined information to derive qualitatively interpretable regulations for pathological and radiological images (Hayashi, 2020). DL techniques, computer vision, native language processing, big data administration, etc. has achieved significant conclusions in their fields (Kallioras and Lagaros, 2020). AI in the form of DL technic has uniquely spread in the consumer space comparisoned to former public aim technologies. DL is usually extended by infusion so adding to pre-existing technologies that are anyway in use. DL-infusion provides fast and broad simplification. For example, when a DL system is applied to YouTube, it seems to reach almost a third of the world's population. It is argued that flow innovation diffusion and adoption theories have limited relevance for DL-infusion because it is a process driven by businesses rather than individuals. The social and ethical consequences are also discussed. Regarding this, larger tech companies appear to benefit relatively more from DL-infusion because they already have a large number of users. This suggests that the value taken from the DL will follow the Matthew Effect accumulated advantage online: many pre-existing users, providing better DL-focused features, attracting even more users, etc. provides a large number of behavioral data. The strengthening process may limit the ability of new companies to compete (Engström and Strimling, 2020).

DL is an ever major tool for large-scale data analyticals and DL workloads are also extensive in today's production clusters due to the growing number of DL focused services. To tackle ever-growing training data sets, it's extensive to do Distributed Deep Learning (DDL) training to use various machines in equidistant. Training DL models in equidistant can cause important bandwidth contention in divided clusters. As a conclusion, the netting is a well-known constriction for dispensed education. Efficient network planning is necessary to maximize the performance of DL training. DL training is feedback-driven exploration, requiring multiple retraining of DLmodels that differ in their configurations. Knowledge at the matutinal stage of all retraining can ease the direct search for high quality models. Therefore, reducing the matutinal stage time may expedite the discovery of DL education (Zhou et al., 2020).

The last increase in DL research over the past decade has successfully solved many hard problems. The area of quantitative analysis is gradually adapting new processs to its problems. However, due to problems such as the unstable nature of financial datum, major difficulties have to be overcome before the DL can be exactly used (Tsantekidis et al., 2020). DL models have proven very powerful in solving many challenging problems, particularly those concerned to computer vision, text and speech. However, the design of such models is difficult due to the large search area and computational complexity to explore. In studies, it is to reduce the human effort required by using a system that allows specific model making, alternative production and evaluation to automatically explore large design areas (Gottapu and Dagli, 2019).

In these periods when AI was at the center of our lives, predictions and improvements were made in different areas. By using artificial intelligence, positive contributions have been made in many areas. These developments are given below.

Singha et al. (2020), groundwater heavyweight metal (HM) pollution is a serious problem threat human and animal health as well as drinking water safety. Therefore, it is important to assess groundwater HM pollution to avoid accompanying dangerous ecological effects. In the study; 226 groundwater samples were collected and analyzed from Arang, India's state of Chhattisgarh. Groundwater in the work field is contaminated with high concentrations of Cd, Fe and Pb necessary to natural and anthropogenic pollution. Two private layers with 26 and 19 neurons in the premier and second latent layers, respectively, were optimized with the rectified linear unit activation function. The conclusions were also validated using ANN-based models for the predictive performance of all pollution indices. Therefore, it is recommended to use groundwater HM pollution using PMI as the best indexing approximate in the flow study field. It can be concluded that the proffered DL model could be a suitable approach in the area ofcomputationally chemistry by addressing overfitting problems. Accurate prediction of groundwater level is a key element in the proper planning and direction of utilitys from aquifers in the basin. Conceptive model, Bayesian Network (BN) and ANN models were used to estimate the monthly groundwater level in Birjand Aquifer in the Southern Khorasan region of Iran. In this context, 13 observation piezometers and total monthly vaporization, on average temperature, aquifer charge and discharge over a 12-year period and water table for the previous months were used as input variables to estimate the groundwater level in the coming months. The conclusions of the several models elicited that Bayesian network models are superior to ANN and mathematical models. The Bayesian network, ANN and mathematical models advanced for 13 piezometers have an average determination coefficient of 0.9, 0.76 and 0.72 respectively. The conclusions of this work show that BNs are effective vehicles for predicting groundwater level (Moghaddam et al., 2019).

Identifying areas with landslip danger is an important step in assessing landslip hazard and reducing landslide-related losses. In the study, two new DLalgorithms, recurrent neural network (RNN) and convolutional neural network (CNN) were applied for national scale landslip susceptibility mapping of Iran. A data set consisting of 4069 historical landsliplocation and 11 conditioning factors was prepared and divided into two sides as training and test dataset. RNN and CNN algorithms were developed to create landslip susceptibility maps of Iran using the training dataset. The field under the curve (FUC) was used for the quantitative estimation of the landslip sensitivity maps using the test data set. Better performance in both training and testing phases was ensured by the RNN algorithm (FUC = 0.88) from the CNN algorithm (AUC = 0.85). It was concluded that 6% and 14% of Iran's estate field is very high and highly susceptible to future landslips in Chaharmahal and Bahhtiari Province respectively. Approximately 31% of Iranian cities are located in regions with high landslip sensitivity. The conclusions of this study will be helpful for the improving of landslip dangers reduction strategies (Ngo et al., 2020). Van Dao et al. (2020), describe the growth and validation of a spatially open DL nervous network model for the estimate of landslip sensitivity. Based on 217 landslip events from the Muong Lay area (Vietnam), a geospatial database was created, for which a suite of nine landslip conditioning factors was eproduced. Various performance measures showed that the DL model performed well in terms of good fit with both the training dataset. The efficiency of the model was compared with quadratic discriminant analysis, Fisher's linear discriminant analysis and multilayer perceptron neural network. The information this provided from the study will be valuable for the further development of landslip prediction models and for a clear spatial assessment of landslip-prone fields around the world. A comparative analysis using Wilcoxon signed-rank tests put forth a important development in landslip estimate using the spatially open DL model compared to other models.

The emergence of DL prepares to significantly change the delivery of healthcare services in the near future. The DL has not only deeply affected the healthcare industry, but also global businesses. In healthcare, the potential is huge due to the need to automate processes and develop error-free paradigms. Therefore, it is imperative that radiologists know about DL and learn how it differs from other AI approaches. The next generation of radiology will see an important role of DL and possibly lay the foundation for augmented radiology (AR). Better clinical evaluation with AR will help to improve the quality of life and make life-saving decisions while helping to reduce healthcare costs (Saba et al., 2019). Even though the first uses of AI in medicine date back to the 1980s, it was just at the early of the recent millennium that care in this industry exploded worldwide. Therefore, it are witness an exponential increase in health-related know with the conclusion that conventional analysis techniques are not suitable for satisfactory government of this large amount of data. AI implementations, on the another hand, are inherently sensitive to dealing with this data increase, as they every time work more good as the quantity of training data increments. A exhaustive and in-depth study of DL processologies and implementations in the medical field is recommended. How, where and why DL models are applied in medicine are disputed and analyzed. Finally, flow challenges and future research directions are outlined and analyzed (Piccialli et al., 2020).

Hong et al. (2020), many models have been improved in preceding studies to predict the formation of disinfection by-products in drinking water. In their study, they proposed a radial basic functional ANN(RBF ANN), RBF ANN hybrid process, and gray relational analysis (GRA) to estimate trihalomethane (THM) levels in real distribution systems. THM levels and 8 water quality parameters, dissolved natural carbon, bromide, residual free chlorine, nitrite and ammonia were used to educate and validate the proposed model. The study shows that GRA can be an efficient technics to simplify the creation of robust RBF ANN models with fewer agents. Soil damp plays a critical role as a key ingredient of global water resources by regulative the exchange of mass and energy among the land surface and the atmosphere. Quantifying these change processes requires accurate characterization and simulation of soil water movement. Physically based models (PBMs) and ML process (MLPs) can be used in soil moisture simulation. However, their performance in soil water simulation has just been crosschecked in a limited number. In addition, almost all of them can be carried out in area work with fixed soil, initial condition and limit condition (Li and al., 2020).

It recommend a long-term cyclical hydrology forecasting model in China with the help of Long Short Term Memory developed pursuant to Reciprocal Information (RI) analysis into practical hydrological data of the Xixian Basin in 2011-2018. First, by translating the original data, classifying and analyzing RI, hydrological features such as rainfall, reservoir water level and flow are extracted as time series propertys of the long short term memory cyclic (LSTMC) prediction model. Next, the structure of the LSTMC model is trained and determined by modeling the precipitation process to reflect the long term variation of flood flow. Finally, the actual flood data is used to validate the output of our model. Compared to some traditional and MLflood prediction schemes, it can be shown that our model can accurately integrate the long and short lead-time hydrology prediction task (Lv et al., 2020). Essenfelder and Giupponi (2020), propose a methodology to simulate IWT flow contributions in the absence of observational data with a combined ML hydrological modeling approach. This methodology uses a hydrological model to simulate the precipitation-flow process of a watershed while a ML algorithm is used to simulate the decision-making process of IWTs. The process are demonstrated by simulating the hydrological balance of the Dese-Zero River Basin (DZRB). This basin is an artificially modified basin located in Northeast Italy. Based on the conclusion of this forecast model, this methodology shows that the studied basin can successfully simulate the complex water flow dynamics and can be a useful tool to support complicated scenario analysis under conditions of IWT data scarcity.

Como (Italy) lake water flow is estimated using different ML algorithms for accurate flow prediction. The study estimate is made for different days, one-three days of arrra varying.It is evaluated using three statistical measures: Average Absolute Error (OMH), Average Root Squared Error (RMSE), and Nash-Sutcliffe Efficiency Coefficient.Pursuant to forecast conclusions, it shows that the Neural Network performs better for flow prediction with MAE and RMSE (Pini et al., 2020).

In order to prioritize management and administrative measures to combat desertification caused by wind erosion in a dry fields, it is essential to predict wind erosion events and determine the relevant powerful factors. The study 50s to assess the feasibleness of nine ML models. The averages for predicting the seasonal dust storm index are made in the a dry regions of Iran, taking into account the range of 2000–2018 according to DSI data. The conclusions indicated that the average process of receiving outperformed other individual ML models in predicting DSI changes in all seasons. Overall, our conclusions show that combining independent ML models with the average process helps us improve a more right approach to predicting the timer changes of powder events in adgical territorys (Ebrahimi et al., 2020).

Next generation sequencing (NGS) process are at the center of much of biologic and medicinal investigative. Their basic significance has composed an ever-increasing demand for processing and analysis process of the data sets manufactured, and addressing questions such as variable search and metagenomics. ML techniques can frequently be preferred for such dutys. In special, DL process using multi-layer artificial nervous networks (ANNs) for supervised, semi-supervised and unsupervised learning have attracted considerable attention for such implementations. Here, it highlight significant network architectures, implementation fields and DL makings in the NGS context (Schmidt and Hildebrandt, 2020). AI is becoming a staminal notion in physic, leading to the rapid emergence of major vehicles for medicinal diagnosis. As a very important ML vehicle in the area of computer vision, DL is widely used in medicinal imaging. Also, as noticed in the medicinal literature, DL is widely used in medicinal research. However, the handy implementation of DL in clinical diagnostic is relatively little and is a new field that may have some difficulties. How tomake medicinal image analysis effectively is an significant problem in the area of illness diagnostic and anymore diagnostic process need to be advanced. At this state, the DL can be seen as a blackbox that requires information about its inner workings and thus presents some important technical challenges that require anymore methodological development. Then, with appropriate diagnoses, pre-operative computerized simulation planning can be maked to use suitable surgical intervention technology (Wong et al., 2020). Wong et al. (2020), presents important questions about the diagnosis of cardio vascular disease (CVD) using strong and poorly understood technology. Debates the problems posed by the paradigm shift of AI Provides possible solutions to possible problems in CVD diagnosis against DL, and predicts the future of relevant machine intelligence applications. The issues discussed are divided into modular aspects of DL regarding CVD image grading, division and invention. An appropriate perspective on the management of these problems is the key to a prosperous technological application of DL in modern medicinal knowledge. Ebrahimi et al. (2020), present a exhaustive review work on last DL process applied to the ECG signal for classification aims. In his studies; It deals with various DL methods such as Convolutional Nervous Network (CNN), Recurrent Nervous Network (RNN), Long Short Term Memory (LSTM), Deep Belief Network (DBN) and Gated Repetitive Unit (GRU). Of the 75 studies reported in 2017-2018, CNN is predominantly observed as a appropriate technique for feature issue and is view in 52% of these studies. DL process have performed very well in the accurate grading, of Atrial Fibrillation (AF) (100%), Supraventricular Ectopic Beats (SVEB). In the field of health, the whole world has faced with COVID-19 disease and has to grapple with the disease. The modern age uses AI and DL techniques, including Data Science, to a large extent. Spreading, diagnosis of disease, drug-vaccine discovery, treatment, patient care, etc. AI techniques can be used to find solutions to epidemics similar to COVID-19. However, DL requires powerful computing resources in addition to large data sets. Therefore, Deep Transfer Learning (DTL) will be powerful as it hears from one duty and can work on other duty. Also IoT, Drone, Webcam, Intelligent Medical Equipment, Robot etc. Edge Devices (ED) are much beneficial in a pandemic case. However, they are equipped with low computing resources, so implementing DLs is also a bit difficult. Therefore DTL will be powerful there too. My work scientifically examines the potential and challenges of these problems. He disclosed relevant technical backgrounds and inspections of relevant cutting edge technology (Sufian et al., 2020).

Kallioras and Lagaros (2020), developed the DL Scale process, which is based on the combination of topology optimization and topology optimization process to minimize the computational loads. One of the oldest process of topology optimization is Punitive Solid Isotropic Material (SIMP). While the quality of SIMP's conclusions is exceptionally tall, it is noteworthy that it is a computationally serious process in thin discrete networks. Deep Belief Networks (DBNs) are probabilistic generating models formulated by sequentially connecting the Restricted Boltzmann Machines (RBM). In his work, a new methodology is suggested in which a DBN is recursively used with SIMP to greatly reduce the computational overhead of finely discrete networks in topology optimization through model upgrade. This is reached by training DBN to find latent patterns and correlations among the initial intensities of finite elements produced by SIMP and the final intensity per element proposed by SIMP.

The smart grid (SG) is a recent invention in the electrical services industry (EUI) over the past decade. With all passing day, some recent forward technologies are emerging that are forcing public utility engineers to contemplate about its application to make the electricity grid clever. AI technics such as ML, ANN, DL, reinforcement learning (RL), and deep reinforcement learning (DRL) are samples of technology. All these technologies are available in the search for solutions to the problems mentioned above. However, the most popular AI method DL is used in various research areas. DL offers options to handle crude data without the need for anything. The study presents the taxonomy of DL algorisms that can be practical to several problems in EUI. The aim of the study is to provide the research engineer with a comprehensive insight into the applications of DL process for power systems studies and the future research scope (Mishra et al., 2020).

A comprehensive review of DL studies regarding financial time series forecasting has been provided. Studies have been categorized not only pursuant to the intended application areas such as indices, commodity and forex forecasting, but also pursuant to DL models such as Deep Belief Networks (DBNs), Convolutional Neural Networks (CNNs) and Long-Short Term Memory (LSTM). In addition, it was tried to predict the future of the field by emphasizing the possible disruptions and opportunities that could be beneficial to interested researchers (Sezer et al., 2020).

Lima et al. (2020), propose the application of DL, one of the emerging themes in the area of AI, as a sun predictor. To prove its capability, he technically compared other consolidated solar prediction strategies such as the Multilayer Sensor, Radial Base Function and Support Vector Regression. Additionally, the integration of AI process into a new adaptive topology based on Portfolio Theory (PT) is proposed to improve solar forecasts. After testing with data from Spain and Brazil, the conclusions show that the Mean Absolute Percent Error (MAPE) for estimates using DL is 6.89% and the proposed integration (called PrevPT) is 5.36% with respect to data from Spain. For data from Brazil, the MAPE for estimates using DL is 6.08% and for PrevPT 4.52%. In both cases, DL and PrevPT conclusions are better than other techniques used.

Li et al. (2020) aims to automatically classify complicated and transitive landforms by explaining a DL algorithm. The Loess Plateau in China, which consists of transitional and complicated landforms, was chosen as the work field for data education. Two sample fields in the Loess Plateau with transitional and complicated loess crest and ridge land forms were used to verify the land shape types classified using the recommended DL process. The recommended DL approach can reach the ultimate land form classification correctness of 87% in the transition field with the data combination of DEMs and images. The classified loess land forms represent the several stages of land form improving in this field. Finally, the suggested DL process can be spread to another land form fields to classify complicated and transitional landforms.

CHAPTER 3

MATERIAL&METHOD

3.1 Study Area

The daily flow values of the flow measurement station (FMS) in the Euphrates Basin, which is the largest of the 25 basin in Turkey, were examined. Performance analysis has been improved and evaluated using in-depth learning optimizers for this basin (Figure 3.1).

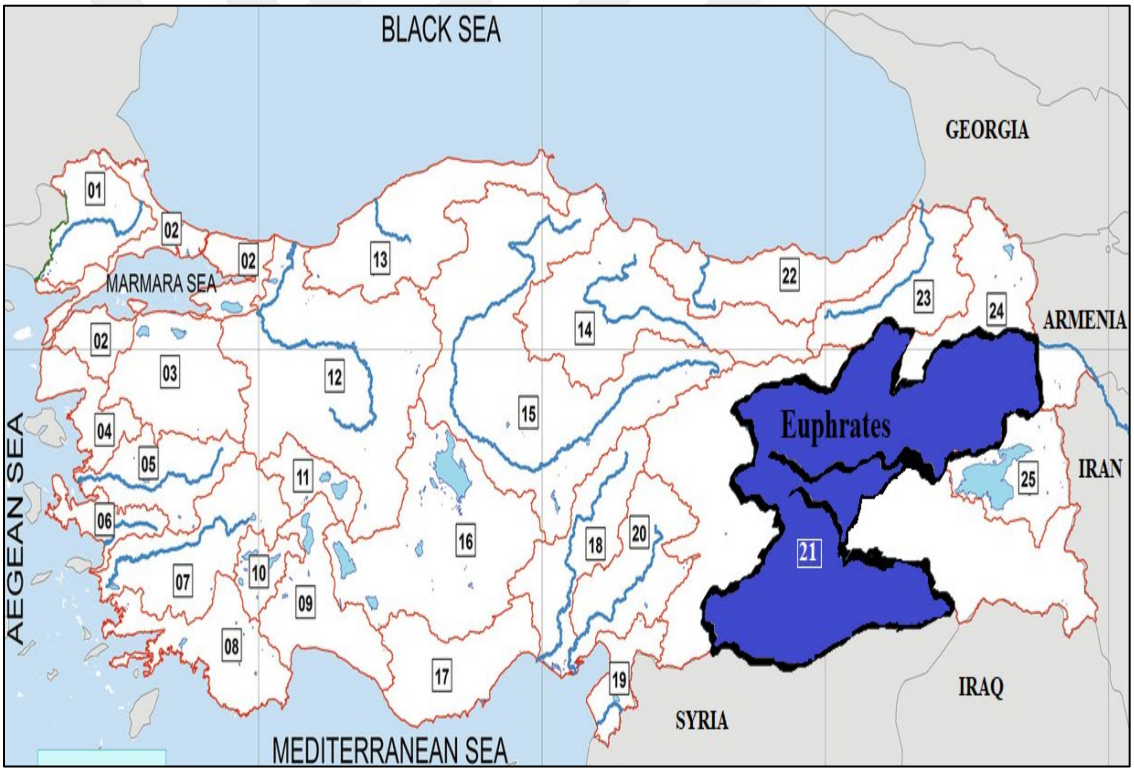

Figure 3.1 Location of the study area in Turkey map

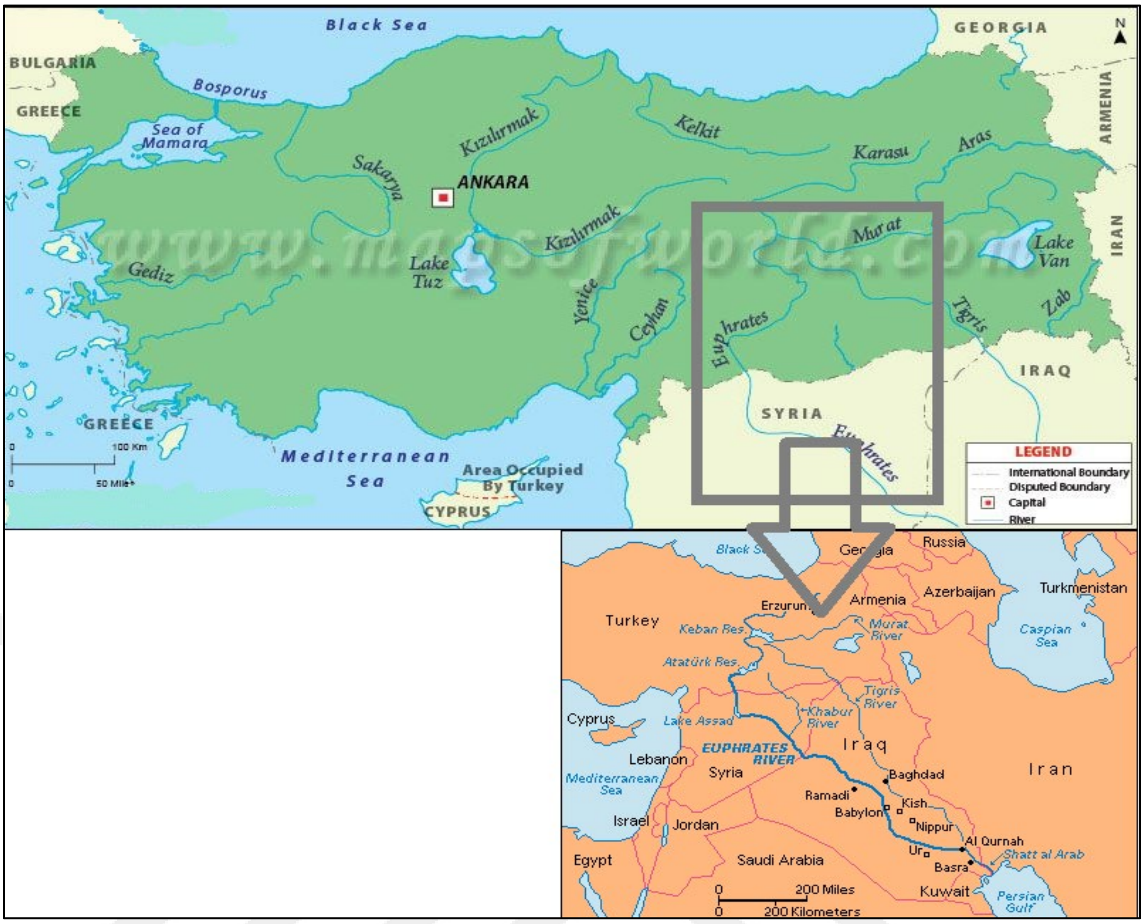

Figure 3.2 Euphrates river basin and its drainage network

Euphrates basin was selected as the field of study. Located in the eastern part of Turkey, this basin has an area of 127304 km² and is the largest wetland in the country. The Murat River, which boils from Ağrı Diyadin, and the Karasu River, which boils in Erzurum Dumludağ, are important rivers that provide water to the Euphrates River. Peri, Çatı and Munzur streams can be counted as other streams. The Euphrates River crosses the Turkish provinces of Erzincan, Tunceli, Elazig, Malatya, Diyarbakir, Adiyaman, Gaziantep and Sanliurfa to Syria and then iraq. It joins the Tigris river in an area called Sattul-Arab to flow together into the Persian Gulf. The Euphrates basin is divided into three sub-basins called the Upper Euphrates, the Middle Euphrates and the Lower Euphrates. The basin has an average annual rainfall of 540.1 mm and a capacity of 720,000 km² of water collection, equivalent to 17% of the total volume in Turkey. The average height of the basin is 1010 m. Precipitation turns into snowfall in winter, depending on the height of the basin. Since it is time-consuming for the snow to turn into flow, the flow of streams in the winter season shows that its rate decreases.

Euphrates Basin has been chosen as the study area (Figure 3.2). The Euphrates River flows along the borders of Erzincan, Tunceli, Elazığ, Malatya, Diyarbakır, Adıyaman, Gaziantep and Şanlıurfa provinces, first through the Tigris River, then through Syria and then through Iraq to the Persian Gulf, which is called Sedul-Arab. Euphrates is a transboundary river. The average annual water volume of the Euphrates Basin is 32 billion cubic meters. 90% of it from Turkey, 10% comes from Syria. Born in the Erzurum and Ağrı regions of Eastern Anatolia, the Murat River and the Karasu River entered the Keban Dam and merged with the Tigris River, 955 km away, creating the Euphrates. It is 559 kilometers over Syria, 815 kilometers over Iraq, and 2,330 kilometers in total. In total catchment area of 440,000 km^2 and is located within a fraction of 40% over Turkey. The Euphrates River Basin is divided into three independent sub-basins: Upper Euphrates River, Middle Euphrates River and Lower Euphrates River (Şorman, 2019).

Euphrates basin, one of the largest and most productive basins in Turkey. Rainfall in the basin is generally in the form of snow in winter. Due to the melting of snowfalls in the spring, the highest flow rate was found. There are 5 dams and / or HEPPs on the Euphrates River. These dams; Keban Dam (Elazığ), Karakaya Dam (Malatya-Elazığ), Atatürk Dam (Adıyaman-Şanlıurfa), Birecik Dam (Birecik) and Karkamış Dam (Kargamış) Dam. These dams, hydroelectric power plants of 6396 MW of electricity through Turkey's manufacturing and electricity production can meet the 8.127's% 27 699% of total electricity consumption. It is aimed to plow 1.1 million hectares of land in the Euphrates Basin and produce 20 kW.h of energy. In addition, if all planned projects are implemented, a total of 1.1 billion m^3 of water will be provided each year to meet the drinking, utility and industrial water needs of settlements. In these planned projects, the irrigation water demand is between 6,590 m^3 / ha and 10,120 m^3 / ha (Tiryaki, 1994).

3.2 Artificial Intelligence

AI is a set of software and hardware systems used to cover a wide variety of sub-domains dedicated to creating algorithms to perform tasks that mimic human intelligence (Mutasa et al., 2020). Since the notion of AI emerged in 1956, it has led to technological noveltys in many areas and has entirely changed conventional models. The application of AI in various areas is basically explained from four aspects. These;

ML, intelligent robot, image recognition technology and expert systems. With the development of globalization in recent years, various research institutions around the world have conducted a series of research on this subject. Therefore, AI has reached important breakthroughs and will show broad improvingprospects in the forthcoming (Liu et al., 2020). AI tools have attracted care from the literature and commercial organizations, especially with the developments in ML techniques in the last decade. However, considering the huge potential of AI technologies to solve problems, there are problems with strategically using AI to create business value and lack of knowledge. AI techniques have gained momentum over the past two decades, particularly for disruption modeling and evaluation of water distribution networks. However, a exhaustive critical comment of water infrastructure modeling through AI and ML techniques is lacking in the literature. This purposes to fill the gap in the body of info and address the limitations stated above (Dawood et al., 2020).

ANNs, one of the AI applications, imitate the working structure of the human brain and become new information information processing technology with learning algorithms different from these data. The superior properties of the brain have led scientists to teach and are being investigated to derive a mathematical model from the neurophysical structure of the brain. In order to accurately model all the behaviors of the brain, various artificial cell and network models are produced with the correct double thought of its components. The functionality formed in this network can be improved by changing the variables in the neurons representing each cell. When training input-output data is used for the result, the error between the outputs produced using the ANN method and the actual data outputs is tried to be minimized. When this error is minimized, the ANN training process is completed (Kara, 2019).

3.3 Deep Learning

DL is a set of algorithms in machine learning that try to model high-level abstractions in data with multiple nonlinear transformations. It mimics activity in many layers of neurons in the brain's cortex, and ANN is a state-of-the-art set of values. It is a new breakthrough in ML. In DL, there is a structure based on learning or presenting multiple levels of traits. Top-level properties are derived from low-level properties by creating a hierarchical representation.This representation learns the multiple levels of representation that correspond to different levels of abstraction. DL is basically based on learning from the representation of data (Tribe, 1992).

One of the main reasons behind the success of DL can be attributed to its strong representational power with multiple layers of hidden variables. However, complex models are often covered by overfitting issues when limited training data is available. It is known to be particularly useful in transferring information and parameter sharing between classes. However, this process can be performed by modeling large data sets and sample training examples of DLmodels.It can be understood that a simple neural network has only one hidden layer, a deep neural network has multiple hidden layers (Chen and Srihari, 2020).

Many unprocessed processes are used for deep learning, decoder and information. Its cascading layer takes the output from the previous layer as input. Algorithms can be supervised or unsupervised. With the advent of deep learning, image analysis, sound analysis, robotics, autonomous vehicles, gene analysis, cancer diagnostics and virtual reality, etc. It is being used in many areas. In such a very common application, the major reason is the high accuracy it achieves in solving problems. In fact, some problems such as voice recognition and image identification exceed human performance (İnik and Ülker, 2017).

Supervised Learning

Supervised ML is a model that makes evidence-based predictions within uncertainty. A supervised learning algorithm trains a known set of input data and a model to take known responses to the data and then create reasonable estimates for responding to new data. If the known data for the output attempted to estimate is present, it can use supervised learning. Supervised learning algorithms are divided into classification and regression algorithms. In the case of classification algorithms, their purpose is to select a value from a predetermined set for each instance (Ahi and Soğukpınar, 2020).

Unsupervised Learning

Unsupervised learning is a ML technique that does not require a control model. Instead, the model should be allowed to work on its own to discover information. Compared to supervised learning, unsupervised learning algorithms can perform more complex compute tasks. Unsupervised methods can help find attributes that can be used for classification (Ahi and Soğukpınar, 2020).

DL is a neural network system with many hidden layers. Automatic attribute determination is created by specifying the attributes of the input data that can be used as a pointer to accurately determine the input data. In fact, all stages are affected by the output data characteristics of the previous stage. There are 7 main applications implemented in DL. These; Automatic Speech Recognition (ASR), Image Recognition, Natural Language Processing, Suggestion Systems, Deep Learning Frameworks, Tensor Flow, Python Deep Learning Application (Hordri et al.2016).

3.3.1 Deep Learning Bookcase

The ML library mentioned is actually a library for programming the system. There's more than one system in the library. They're like, "I' TensorFlow (Python), Caffe (Python), Theano (Python), Python DLapplication (Python), Torch (C++), Deeplearning4j (Java), Covnetjs (Java), Mxnet (Python), PyLearn2 (Python), DLToolbox-Matlab, Accord, NET (C#), Sci-Kit Learn (Python), Accord. All these processes make the functioning of the system different from each other. One of its common features is that it is one of the most widely used software for deep learning.

3.4 Python Deep Learning Aplication

Python Deep Learning Aplication (PDLA) is a DL library for Python that provides a convenient way to define and train all kinds of DL models. It is a high-level neural networks API written in Python that can run on PDLA, Tensorflow, Theano and CNTK. Thanks to its many functional functions, PDLA allows you to easily create a DLmodel and train it. Also, human-machine interaction is an important issue of design for smart systems such as PDLA. Since direct control of the robotic arm takes a high cognitive load by the user, special attention is paid to the robotic subsystem to be given a certain degree of autonomy, while physically disabled persons may have difficulty using a joystick or push buttons skillfully. A color vision sensor and a force / torque sensor are mounted to the end effector of the robotic arm of the PDLA to detect the environment. To test the system, four basic tasks have been described as picking a glass on the table, picking up a pencil on the floor, moving an object to the user's face, and using a button on the wall. Here, structures such as pre-processing and feature extraction are ignored and these operations are performed automatically within the neural network. In the deep convolutional neural network, feature extraction is determined within the network and the properties of the structure to be determined within the layers are determined. There is an interconnected hierarchical structure between the lower layer and the upper layer. There is no special phase for feature extraction. In its structure within layers, distinctive features of the object-event are determined (Hinton and Salakhutdivot, 2006).

3.4.1 Python Deep Learning Aplication Models

Python Deep Learning Application (PDLA) is an API designed for humans, not machines. PDLA follows best practices to reduce cognitive load. It offers consistent and simple APIs, minimizes the number of user actions required for common use cases, and provides clearly actionable error messages. It also has extensive documentation and developer guides. There are general stages in creating the PDLA model. These stages are; Defining training data, defining the model and layers, defining hyper parameters such as Epoch (Number of Rotations), Loss Function and optimizer, and feeding the model with training data. There are 2 different ways to create Python Deep Learning Application models. These; It is designated as sequential and functional sequential API. The sequential model is very simple, but limited to single-input, single-output layer stacks. Functional API support model architectures are fully featured APIs that are easy to use. The functional API allows the creation of much more flexible models as they can easily define models where only the layers are connected to more layers than the previous and next layers.

The Python DL App has been widely adopted in industry and research outside TensorFlow since mid-2018 and is stronger than other DL frameworks. Python DL applications are also accepted by researchers from major scientific organizations such as CERN and NASA.

3.4.1.1 Physiological API

The Python Deep Learning Application (PDLA) Physiological API is a way to create a more flexible model than the API. Physiological API can handle models with nonlinear topologies, shared layers, and even multiple inputs or outputs. It can call the layer instance and return the tensor. It can then use it to define the input tensor and the output tensor. This type of model can be compared to the sequential model of the

Python deep learning implementation. Models can be easily reused using the Physiology API.

3.4.1.2 Methods of Sequential

For databases and digital files, the importance of choosing a program that can organize files correctly affects how much data can be produced and how efficient it is on the user's site. A good plan for the file can lead to good results. Sequential file organization will be stored in specific files in a particular order based on the file type, data or type of individual files collected on the computer. This sequence is processed in an orderly and planned manner, making the system more detailed. Sequential file organization, control is transparent. It helps to select the system according to the needs and to convert it into different forms by optimizing it according to the preferred system. The simplest sequential file organization is known to have files sorted sequentially. First file first paste, next second file, etc. This simple straightforward method allows files without destroying the array. The least complexity of the organizational method comes when it takes a long time to find information, starting with the first file and looking at it. The system lists the bus or purpose in alphabetical order in a predefined order. When the user wants to create a file, the existing system must add the new file directory correctly or reprogram it to create it as the entire file number. When designing a sequential file system, file add-change plans and when searching for data should be convenient. In archive-type systems, it is easier for searches, although it grows steadily as the user adds new files. It makes sense to use an alphabetic or another index that allows users to find a particular fast. There are two parameters for consecutive file editing methods. These; speed and storage space. When the user saves the sequences, there is no space in the file to shrink one later. The system must either store additional information elsewhere or have the knowledge to free up space and re-save all files. Both of these methods take a lot of time. Sequential file systems solve this problem by allocating extra emptiness for its create load file.

3.5 Set Optimizers

3.5.1. Adam

Adam is an adaptive learning speed optimization algorithm specially designed to train deep neural networks. It is simple to implement and requires very little memory. Its name is derived from the adaptive moment prediction, and this is because Adam uses predictions of the first and second gradient moments to adapt the learning rate for each weight of the neural network. Algorithms use the power of adaptive learning rates methods to find individual learning rates for each parameter. 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 (Kingma, 2014).

$$w_{t+1} = w_t - \frac{a}{\sqrt{S_t + \in}} . \hat{V}_t$$

$$\hat{V}_t = \frac{V_t}{1 - \beta_1{}^t}$$

$$\hat{S}_t = \frac{S_t}{1 - \beta_2{}^t}$$

$$S_t = \beta_1 S_t + (1 - \beta_1) \frac{\partial L}{\partial w_t}$$

$$S_t = \beta_2 S_t + (1 - \beta_2) \left[\frac{\partial L}{\partial w_t}\right]^2$$

S and V are preferred as 0, a=0.001, β_1=0.9, β_2=0.999 and $\in 10^{-8}$ for starters. The flow gradient ($\frac{\partial L}{\partial w_t}$) is multiplied by the learning coefficient (a) and its flow weight (w_t) is determined (Seyyarer et al., 2020).

3.5.2. AdaGrad

AdaGrad is a stochastic optimization method that adapts the learning rate to the parameters. It performs smaller updates for parameters associated with frequently occurring features, and larger updates for parameters associated with infrequently occurring features. Adaptive gradient methods such as AdaGrad and its variants update the stepsize in stochastic gradient descent on the fly according to the gradients received along the way; such methods have gained widespread use in large-scale optimization for their ability to converge robustly, without the need to fine-tune parameters such as the stepsize schedule. Yet, the theoretical guarantees to date for AdaGrad are for online and convex optimization (Ward et al., 2019).

$$w_{t+1} = w_t - \frac{a}{\sqrt{S_t + \epsilon}} \cdot \frac{\partial L}{\partial w_t}$$

$$S_t = S_{t-1} + \left[\frac{\partial L}{\partial w_t}\right]^2$$

Here S is initially taken as 0, ε is usually taken as a very small number (10^{-7}) to save the operation from the error of splitting it to zero. The flow gradient ($\frac{\partial L}{\partial w_t}$) is multiplied by the learning coefficient (a) and its flow weight (w_t) is determined (Seyyarer et al., 2020).

3.5.3. RMSprop

RMSprop is an unpublished optimization algorithm designed for neural network. RMSprop lies in the realm of adaptive learning rate methods, which have been growing in popularity in recent years, but also getting some criticism. Adaptive gradient methods that rely on scaling gradients down by the square root of exponential moving averages of past squared gradients, RMSProp have found wide application in optimizing the nonconvex problems that arise in DL(Bengio and CA, 2015).

$$w_{t+1} = w_t - \frac{a}{\sqrt{S_t + \epsilon}} \cdot \frac{\partial L}{\partial w_t}$$

$$S_t = \beta S_{t-1} + (1 - \beta)\left[\frac{\partial L}{\partial w_t}\right]^2$$

S is originally preferred as 0, a=0.001, β=0.9, and ε 10^{-6}. The flow gradient ($\frac{\partial L}{\partial w_t}$) is multiplied by the learning coefficient (a) and its flow weight (w_t) is determined (Seyyarer et al., 2020).

3.6. Loss Functions

3.6.1 Huber

The Huber loss is a robust loss function used for a wide range of regression tasks. To use Huber loss, a parameter that controls transitions from a second-degree function to an absolute value function must be selected. Since the Huber function has the ability to linearly penalise inputs with large mismatch deviations and square small errors, new, robust, regulated support vector machines are available for data regression based on Huber loss functions (Meyer, 2019).

3.6.2 Logcosh

Another loss function which attempts to combine best of both worlds is the Logcosh loss function. Logcosh is the logarithm of the hyperbolic cosine of the prediction error. For small and large, Logcosh is approximately equal. This means that "logcosh" works mostly like mean square error, but won't be too affected by the occasional wildly wrong guesswork.

3.7. Assessment Methods

According to many scientific areas, the use of qualitative or quantitative methods has become a topic of discussion in certain schools of thought, while preferring one method in each discipline, trying to despise another school. The qualitative method insists that the purpose of quantitative method is to underestimate absolutely insurmountable factors and even hide the accuracy of the social events studied to ignore or ignore them. Quantitative methods can be used with spherant qualitative frameworks, but qualitative methods can be used to understand the meaning of numbers produced by quantitative methods. Classification techniques are applied to many scientific studies in various disciplines. There are several ways to evaluate classification algorithms. The analyzes and importance of the measurements must be interpreted correctly to evaluate different learning algorithms. Most of these measures are scalar and some of them are graphic methods (Tharwat, 2020).

3.7.1 MAD (Mean Absolute Deviation)

Mean Absolute Deviation (MAD) provides measurements of the expected deviation of a random variable from its mean value. 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 tendency survey. The absolute values of the distinction among the data points and their central tendencies can be summation and disunited by the number of points in the data set.

3.7.2 MAPE (Mean Absolute Percentage Error)

Average absolute percent error (MAPE) is a statistical measure of how accurate an estimation system is. MAPE is widely used because it is easy to interpret and explain. For example; A MAPE value of 11.5% comes as the average difference between the predicted value and the actual value is 11.5%. Another feature of MAPE is that the lower the value, the better the estimate. MAPE is often used as a loss function for regression problems and in model evaluation because of its very intuitive interpretation in terms of relative error. Using MAPE as a loss function for regression analysis is applicable from both a practical and theoretical point of view.

3.7.3 MEAN (Actual / Predicted)

It is a "Mean" number divided by the sum of all data points in the data set divided by the total data point. 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 estimated results in a single time frame will be compared. A summary of the forecast error is derived from the sum of these time points. Typically, the negative value of the result is used to define the value of the wrong result.

3.7.4 STANDART DEVIATION

Standard deviation is a measure used to summarize the spread of data values in probability theory and statistics. Find out how much of the data is close to the average with standard deviation. If the standard deviation is small, it means that the data are scattered close to the mean, and vice versa, if the standard deviation is large, the data are scattered far from the mean. If all values are the same, the standard deviation result is obtained as zero. Deployment becomes more common as Standard deviation grows (Ozbek et al., 2007).

3.7.5 CORRELATION

Correlation analysis is an analysis technique that measures the strength of the linear (Pearson correlation) or monotone (Spearman correlation) relationship between two continuous 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 a measure of the strength of the relationship between 2 variables. Variables can have a high correlation, but also have low agreement (Schober and Vetter, 2020).

3.8 Data

The data used in this study was FMS taken from Hydraulic State Works (DSİ) which are the most accurate data in the Euphrates river and they are located at the same basin area. This station is D21A212 (Handeresi Balayan Village). The daily discharge data taken into account for this study covered the period of 2002-2011 for D21A212 (Figure 3.2).

CHAPTER 4

RESULT & DISCUSSIONS

4.1 General

In this section of the study, according to the estimated results of the ML model, the data obtained from the study called "Estimates of river flows are made with data from existing measuring stations" called D21A212 and the results obtained from DL are compared. The learning model of Adam, AdaGrad and RMSprop was used as optimizers. The results of the test and training data were compared with the Huber and Logcosh loss functions. This data, which is divided into two parts as a training and test data set, is 70% and 30% respectively. Graphical comparisons were based on training and test data (Figure 4.1). As the amount of data used for training increases, the performance of classical ML algorithms in dealing with big data has not been sufficient. ML algorithms have increased the size of data that can be reached with both fast operation and rapid improvement. It has become important that the performance value of the result reached is better than reaching the fast result. DLsystems, on the other hand, can achieve efficient results by using this big data effectively (Figure 4.2).

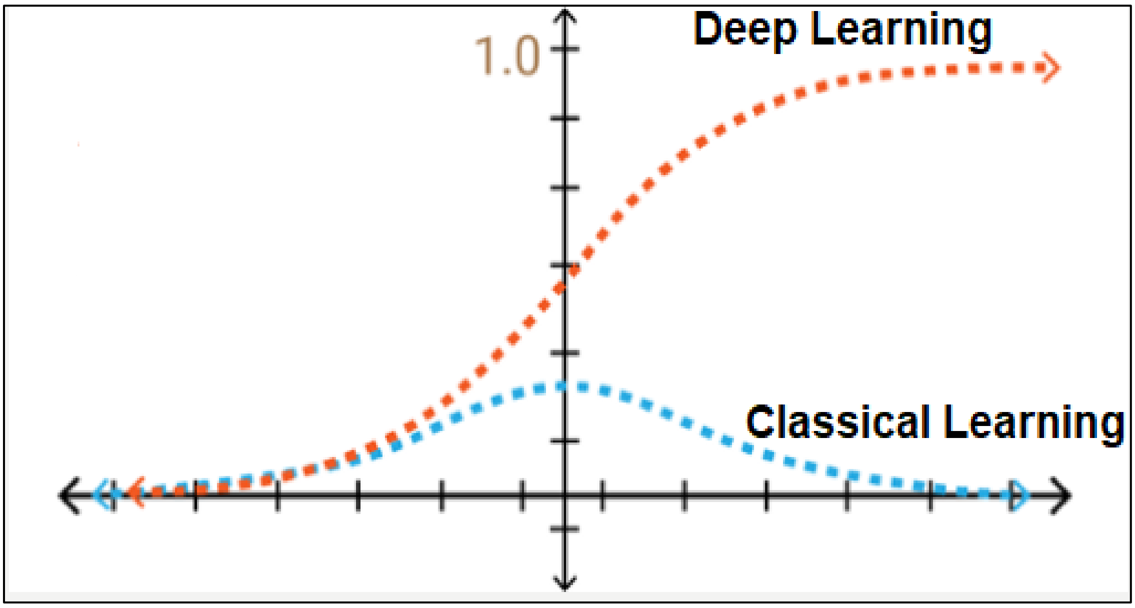

Figure 4.1 Comparison Made for Deep and Classical Learning

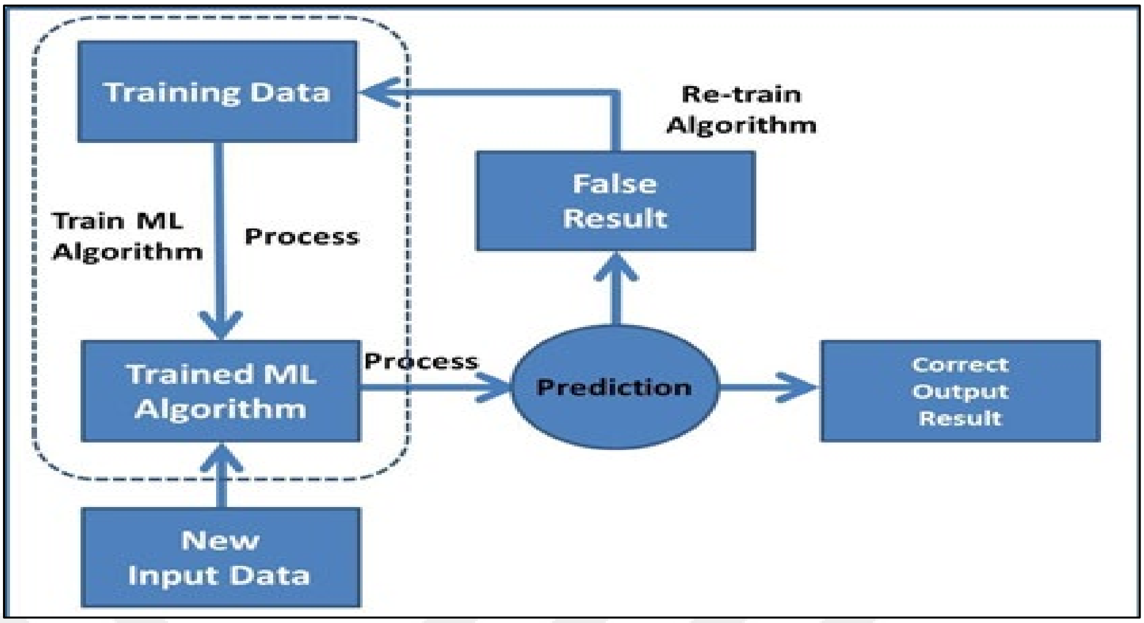

Figure 4.2 Flowchart of the ML model applied

4.2 Comparison of Adam Optimizer and Huber loss both testing and training outputs with Actual results

Using Adam Optimizer and Huber as loss functions, the training and test accuracy results of the model are shown in Table 4.1. According to the data in the table, Results Test dataset is 0,9952 and the Training dataset is 0,9904. MEAN Test dataset 0,7532 and Training dataset average 0,8375. The Test dataset for MAPE is 125,7225 and the Training dataset is 28,2394. The Adam Optimizer and Huber loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Huber function of the Test data is a more successful loss in the DLmodel.

Table 4.1 Statistical evaluations of Huber loss for Adam

Statistics	Train	Test
MAD	0,1239	0,1100
MSE	0,0611	0,0201
RMSE	0,2472	0,1418
MAE	0,2823	0,0844
MAPE	28,2394	125,7225
MEAN (actual/predicted)	0,8375	0,7532
Standart Deviation	0,4276	0,3450
Correlation	0,9904	0,9952
R^2	0,9810	0,9625

As shown in the chart in Figure 4.3, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 4,020 and Predicted forecast value of 1.56 for training data set en inputs is the point where '352' shows the highest deviation.

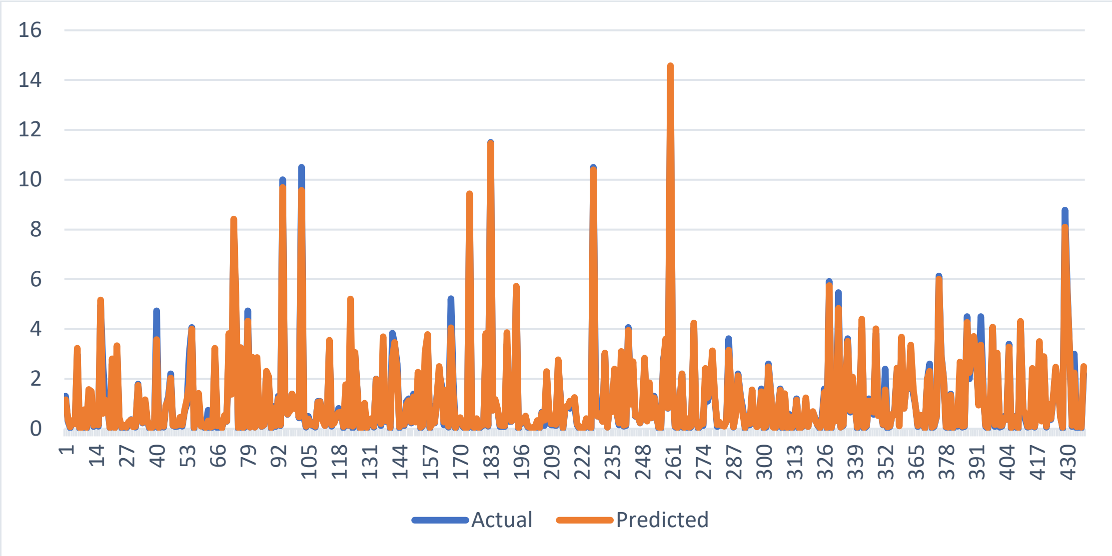

Figure 4.3 Training correctness in crosscheck for Adam Optimizer and Huber loss

DLresults for the Adam optimizer and Huber loss function in the dataset are shown in Figure 4.4. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,981, which belongs to Predicted 14,57 point with Actual 14 point, and the DL model gives more realistic results.

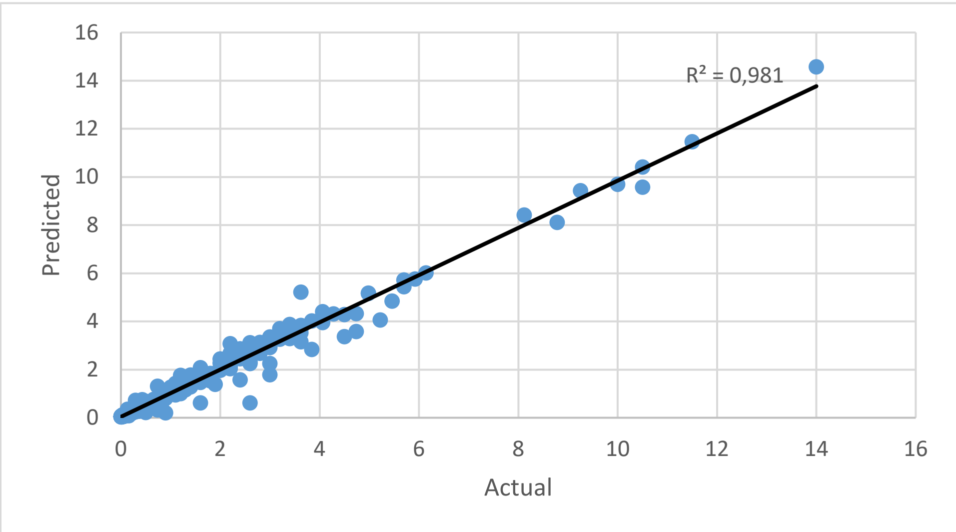

Figure 4.4 Huber loss for Comparing and Training Adam Optimizer Actual and Projected Results

When Adam optimizer and Huber are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.5). According to the chart, it can be said that the row with the highest difference between Actual estimate value 7,02 and Predicted forecast value of 6,69 for training data set en inputs is the point where '27' shows the highest deviation.

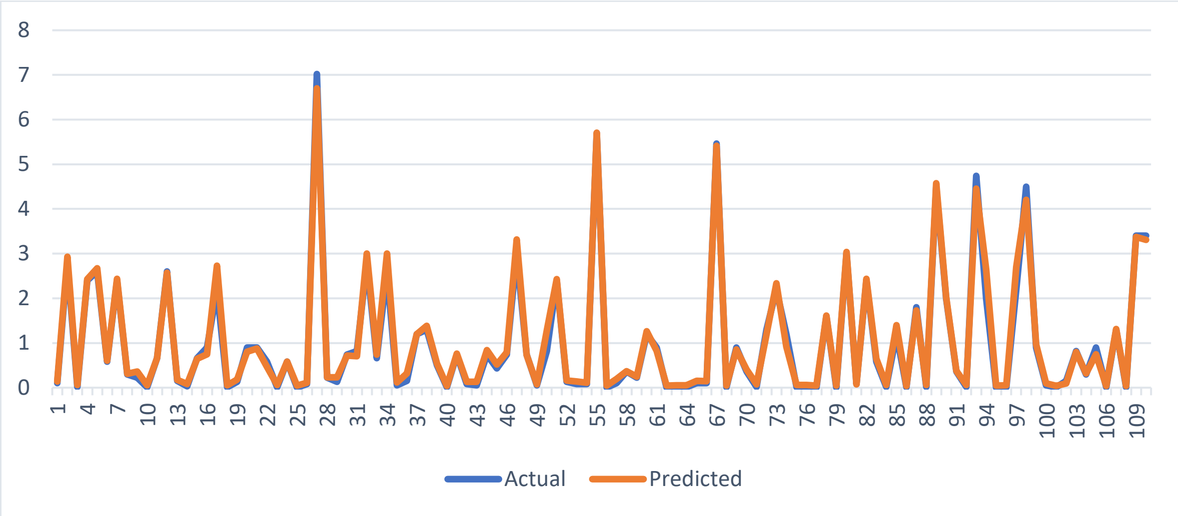

Figure 4.5 Actual and Predicted Results for Adam Optimizer and Huber loss for testing

The estimated results of the data set from the test and model were compared in Figure 4.6. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7.02 and Predicted 6.69 point is expressed as 0.9904 and the DL model gives more realistic results.

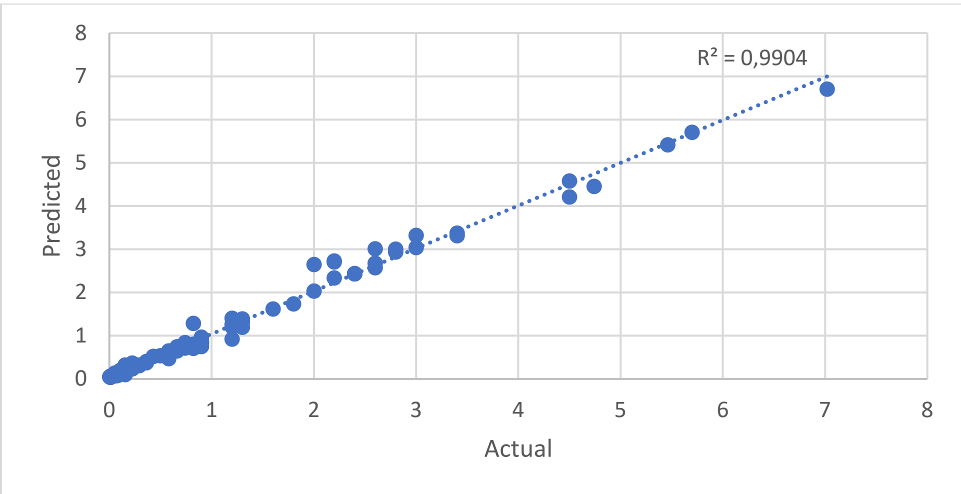

Figure 4.6 Comparing Adam Optimizer and Huber loss with Test Results and Predicted Results

4.3 Comparison of Adam Optimizer and Logcosh loss both testing and training outputs with Actual results

Using Adam Optimizer and Logcosh as loss functions, the training and test accuracy results of the model are shown in Table 4.2. According to the data in the table, Correlations Test dataset is 0,9961 and the Training dataset is 0,9908. MEAN Test dataset 1,1125 and Training dataset average 0,8466. The Test dataset for MAPE is 83,8453 and the Training dataset is 90,5492. The Adam Optimizer and Logcosh loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Logcosh function of the Test data is a more successful loss in the DL model.

Table 4.2 Statistical evaluations of Logcosh loss for Adam

Statistics	Train	Test
MAD	0,1313	0,0741
MSE	0,0654	0,0190
RMSE	0,2557	0,1378
MAE	0,9054	0,0731
MAPE	90,5482	83,8453
MEAN(actual/predicted)	0,8466	1,1125
Standart Deviation	2,6125	2,2803
Correlation	0,9908	0,9961
R^2	0,9817	0,9923

As shown in the chart in Figure 4.7, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 3,87 and Predicted forecast value of 1.47 for training data set en inputs is the point where '352' shows the highest deviation.

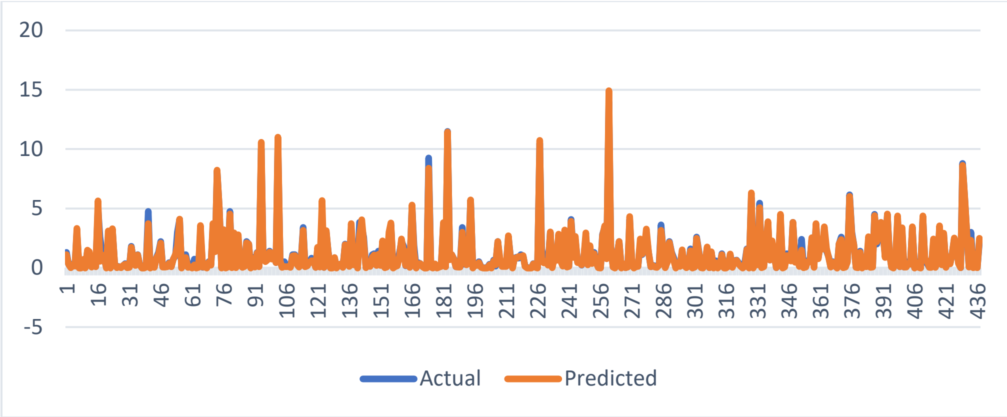

Figure 4.7 Crosscheck training correctness for Adam Optimizer and Logcosh loss

DL results for the Adam optimizer and Logcosh loss function in the dataset are shown in Figure 4.8. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,9817, which belongs to Predicted 14,92 point with Actual 14 point, and the DL model gives more realistic results.

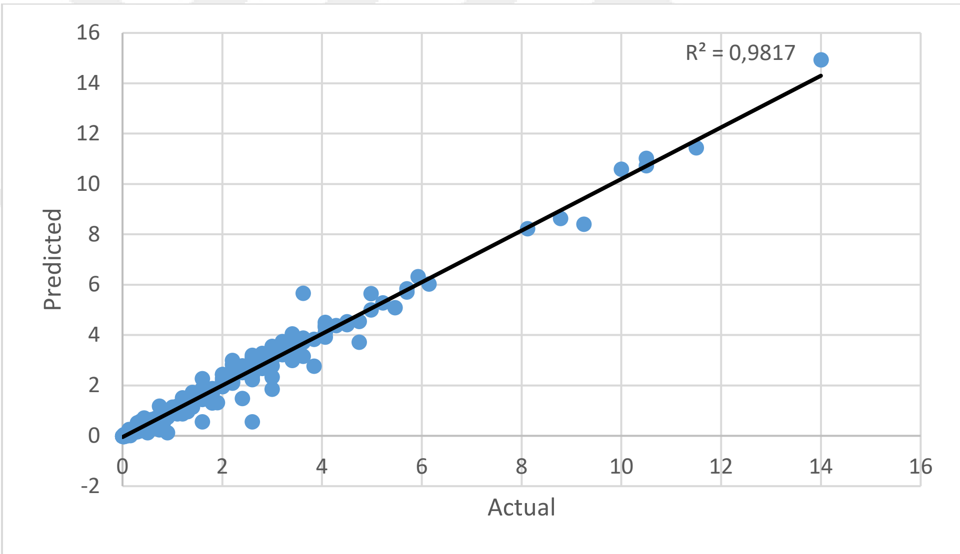

Figure 4.8 Crosscheck of Training Results and Predicted Results of Adam Optimizer and Logcosh loss

When Adam optimizer and Logcosh are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.9). According to the chart, it can be said that the row with the highest difference between Actual estimate value 2,6 and Predicted forecast value of 2,24 for training data set en inputs is the point where '12' shows the highest deviation.

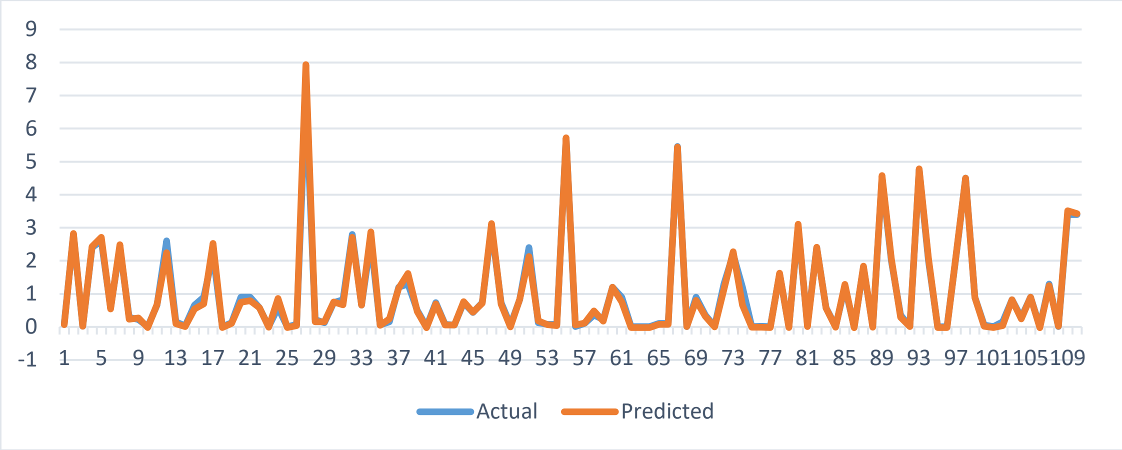

Figure 4.9 Crosscheck test correctness for Adam Optimizer and Logcosh loss

The estimated results of the data set from the test and model were compared in Figure 4.10. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7.02 and Predicted 7,93 point is expressed as 0.9923 and the DL model gives more realistic results.

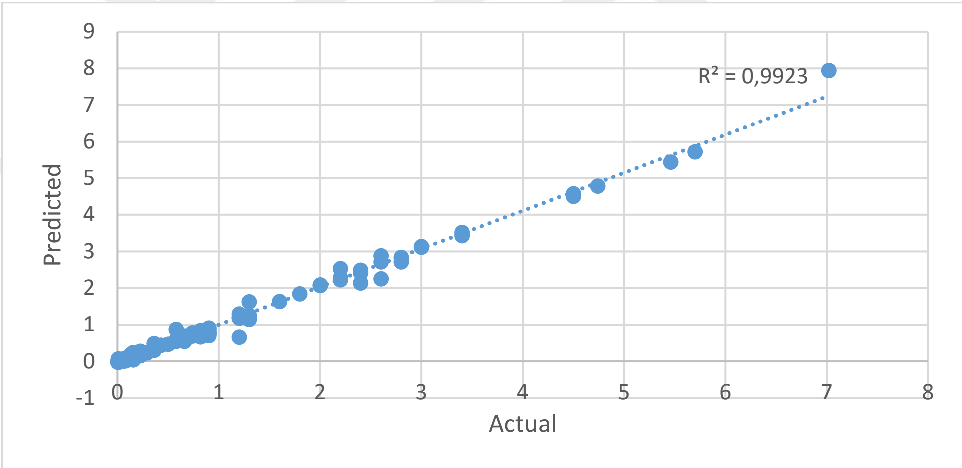

Figure 4.10 Crosscheck of Actual Results and Predicted Results of Adam Optimizer and Logcosh loss for testing

4.4 Comparison of RMSprop Optimizer and Huber loss both testing and training outputs with Actual results

Using RMSprop Optimizer and Huber as loss functions, the training and test accuracy results of the model are shown in Table 4.3. According to the data in the table, Correlations Test dataset is 0,9943 and the Training dataset is 0,9917. MEAN Test dataset 0,6445 and Training dataset average 0,6713. The Test dataset for MAPE is 489,3237 and the Training dataset is 38,4059. The RMSprop Optimizer and Huber loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Huber function of the Test data is a more successful loss in the DL model.

Table 4.3 Statistical evaluations of Huber loss for RMSprop

Statistics	Train	Test
MAD	0,1782	0,0902
MSE	0,0617	0,0382
RMSE	0,2484	0,1955
MAE	0,3840	0,1507
MAPE	38,4059	489,3237
MEAN(actual/predicted)	0,6713	0,6445
Standart Deviation	0,3889	0,4291
Correlation	0,9917	0,9943
R^2	0,9835	0,9888

As shown in the chart in Figure 4.11, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 4,26 and Predicted forecast value of 1.52 for training data set en inputs is the point where '352' shows the highest deviation.

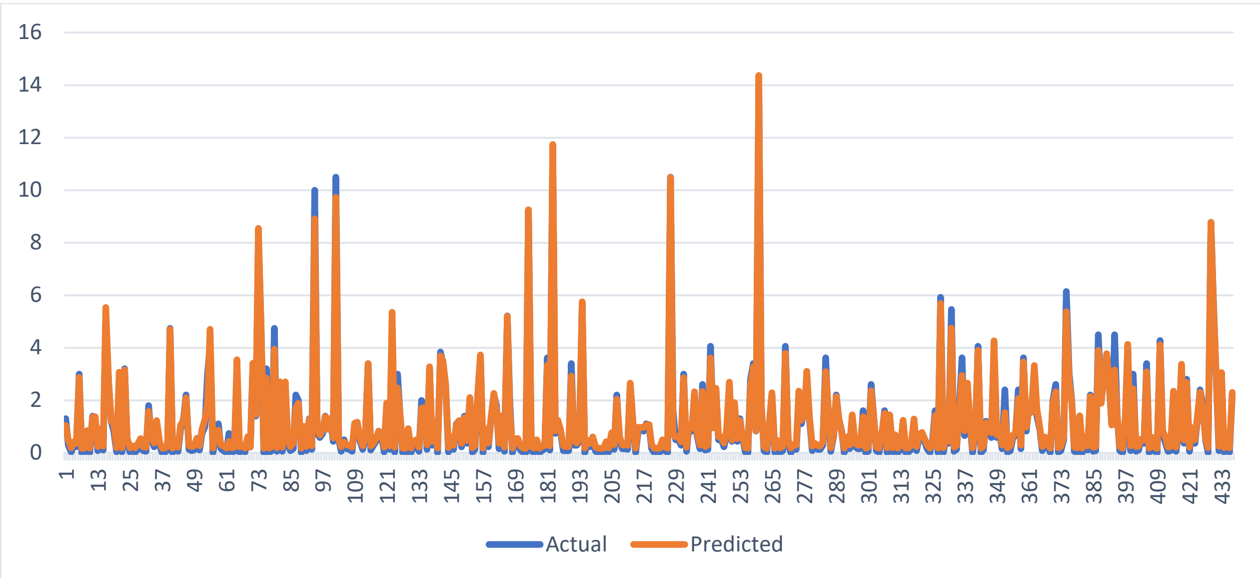

Figure 4.11 Crosscheck of training correctness for RMSprop Optimizer and Huber loss

DL results for the RMSprop optimizer and Huber loss function in the dataset are shown in Figure 4.12. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,9835, which belongs to Predicted 14,36 point with Actual 14 point, and the DL model gives more realistic results.

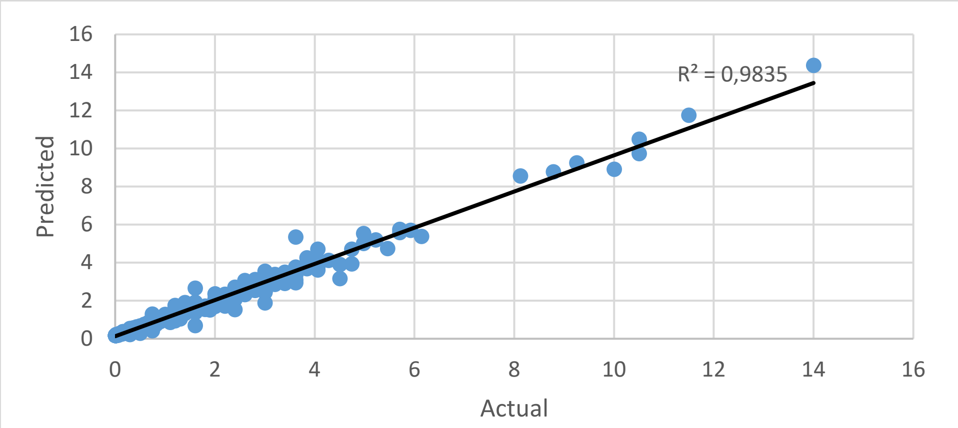

Figure 4.12 Crosscheck of Actual Results and Predicted Results of RMSprop Optimizer and Huber loss for training

When RMSprop optimizer and Huber are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.13). According to the chart, it can be said that the row with the highest difference between Actual estimate value 2,46 and Predicted forecast value of 2,35 for training data set en inputs is the point where '5' shows the highest deviation.

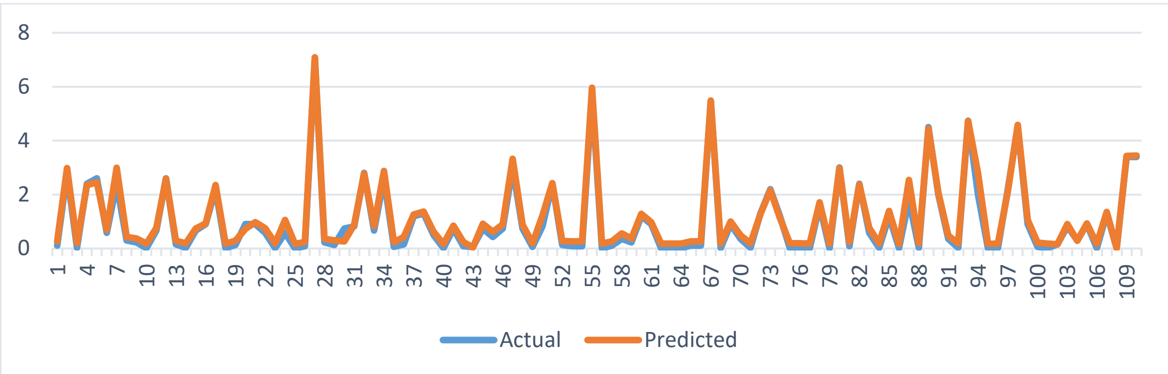

Figure 4.13 Crosscheck of testing correctness for RMSprop Optimizer and Huber loss

The estimated results of the data set from the test and model were compared in Figure 4.14. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7,02 and Predicted 7,08 point is expressed as 0,9888 and the DL model gives more realistic results.

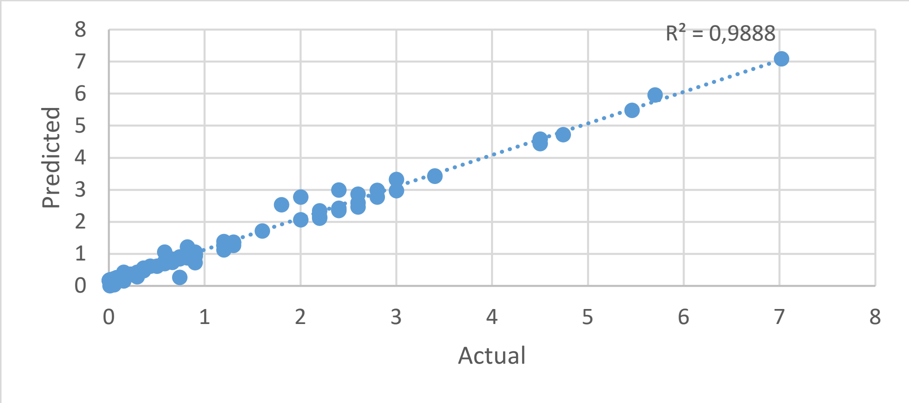

Figure 4.14 Crosscheck of Actual Results and Predicted Results of RMSprop Optimizer and Huber loss for testing

4.5 Comparison of RMSprop Optimizer and Logcosh loss both testing and training outputs with Actual results

Using RMSprop Optimizer and Logcosh as loss functions, the training and test accuracy results of the model are shown in Table 4.4. According to the data in the table, Correlations Test dataset is 0,9958 and the Training dataset is 0,9903. MEAN Test dataset 0,9758 and Training dataset average 1,0749. The Test dataset for MAPE is 30,4629 and the Training dataset is 47,8640. The RMSprop Optimizer and Logcosh loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Logcosh function of the Test data is a more successful loss in the DL model.

Table 4.4 Statistical evaluations of Logcosh loss for RMSprop

Statistics	Train	Test
MAD	0,1072	0,0795
MSE	0,0624	0,0205
RMSE	0,2498	0,1435
MAE	0,4786	0,0714
MAPE	47,8640	30,4629

MEAN(actual/predicted)	1,0749	0,9758
Standart Deviation	1,3159	1,0564
Correlation	0,9903	0,9958
R^2	0,9808	0,9917

As shown in the chart in Figure 4.15, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 4,28 and Predicted forecast value of 2,44 for training data set en inputs is the point where '410' shows the highest deviation.

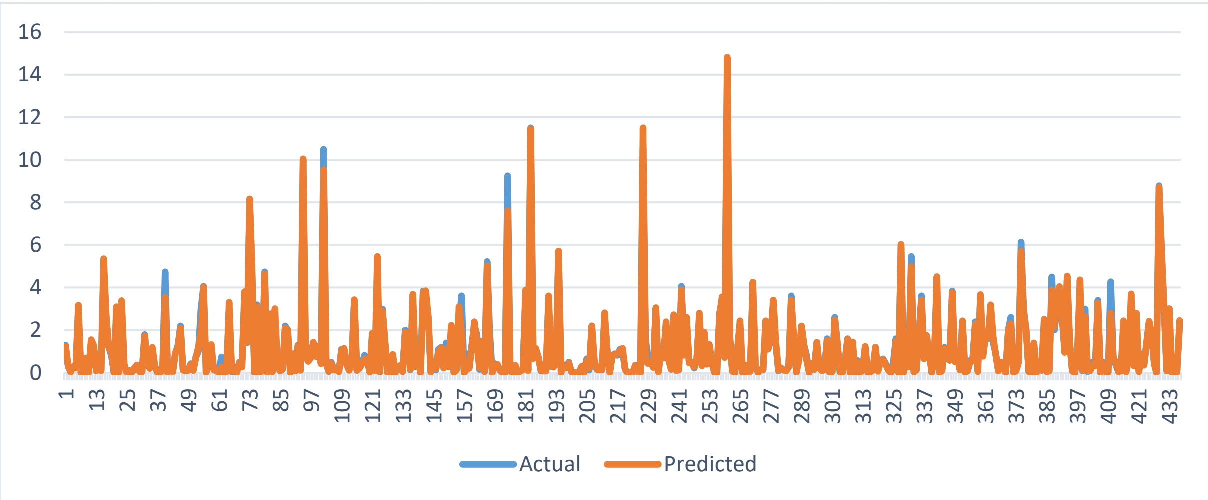

Figure 4.15 Crosscheck training correctness for RMSprop Optimizer and Logcosh loss

DL results for the RMSprop optimizer and Logcosh loss function in the dataset are shown in Figure 4.16. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,9808, which belongs to Predicted 14,82 point with Actual 14 point, and the DL model gives more realistic results.

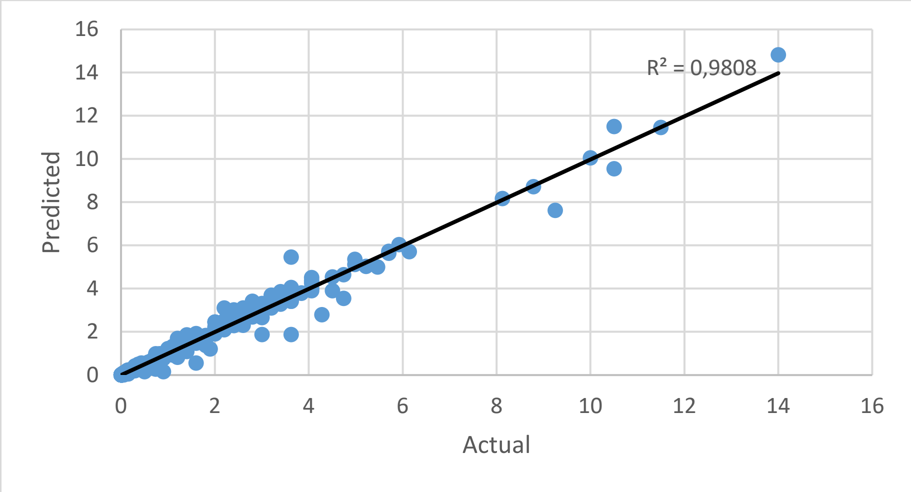

Figure 4.16 Crosscheck of Training Results and Predicted Results of RMSprop Optimizer and Logcosh loss

When RMSprop optimizer and Logcosh are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.17). According to the chart, it can be said that the row with the highest difference between Actual estimate value 0,9 and Predicted forecast value of 0,77 for training data set en inputs is the point where '105' shows the highest deviation.

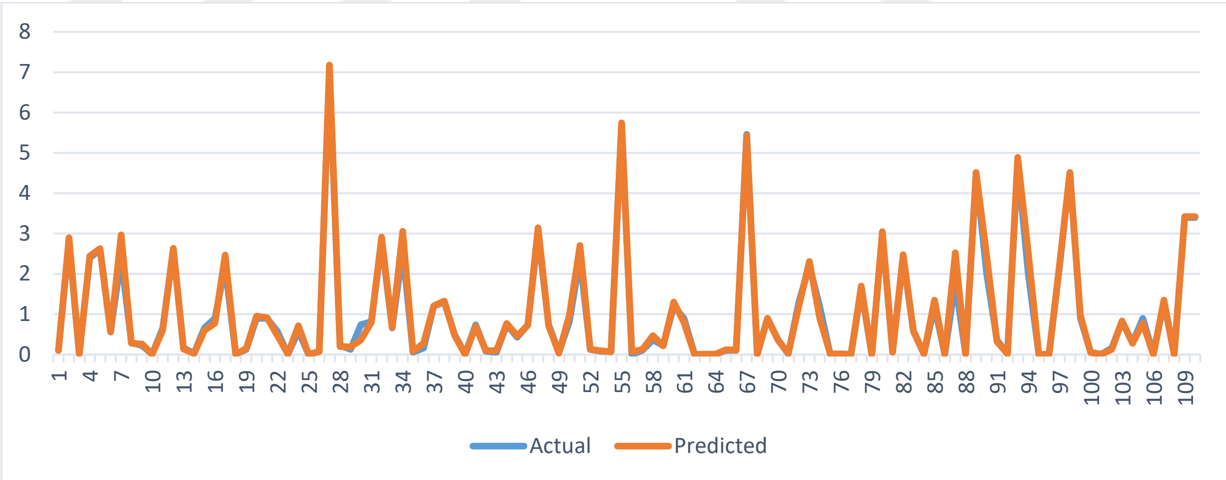

Figure 4.17 Crosscheck test correctness for RMSprop Optimizer and Logcosh loss

The estimated results of the data set from the test and model were compared in Figure 4.18. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7,02 and Predicted 7,17 point is expressed as 0,9917 and the DL model gives more realistic results.

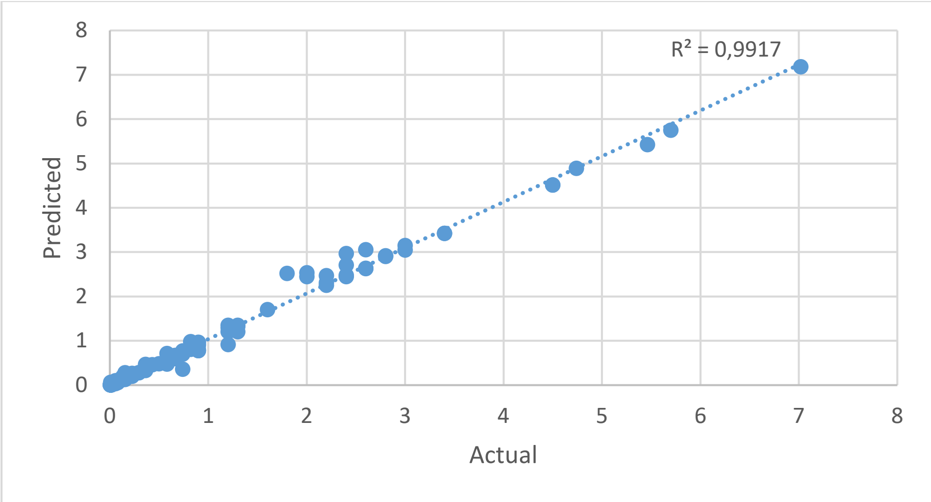

Figure 4.18 Crosscheck of Actual Results and Predicted Results of RMSprop Optimizer and Logcosh loss for testing

4.6 Comparison of AdaGrad Optimizer and Huber loss both testing and training outputs with Actual results

Using AdaGrad Optimizer and Huber as loss functions, the training and test accuracy results of the model are shown in Table 4.5. According to the data in the table, Correlations Test dataset is 0,9956 and the Training dataset is 0,9863. MEAN Test dataset 0,7375 and Training dataset average 0,8221. The Test dataset for MAPE is 148,7643 and the Training dataset is 28,3074. The AdaGrad Optimizer and Huber loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Huber function of the Test data is a more successful loss in the DL model.

Table 4.5 Statistical evaluations of Huber loss for AdaGrad

Statistics	Train	Test
MAD	0,1347	0,1402
MSE	0,0888	0,0264
RMSE	0,2980	0,1627
MAE	0,2830	0,0885
MAPE	28,3074	148,7643
MEAN(actual/predicted)	0,8221	0,7375

Standart Deviation	0,4449	0,3299
Correlation	0,9863	0,9956
R^2	0,9729	0,9912

As shown in the chart in Figure 4.19, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 10,5 and Predicted forecast value of 8,66 for training data set en inputs is the point where '227' shows the highest deviation.

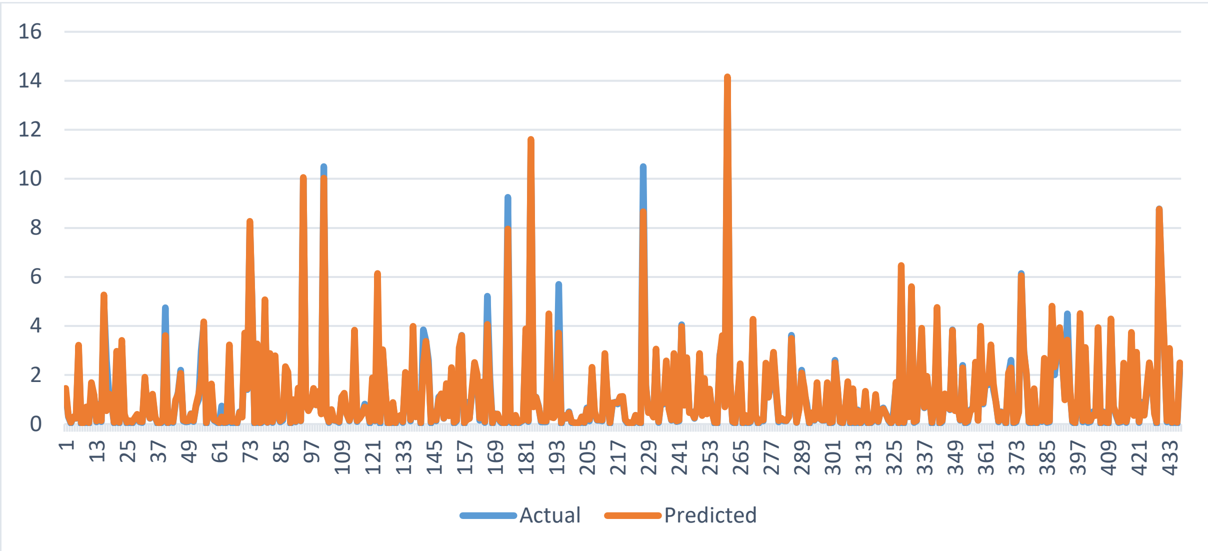

Figure 4.19 Crosscheck training correctness for AdaGrad Optimizer and Huber loss

DL results for the AdaGrad optimizer and Huber loss function in the dataset are shown in Figure 4.20. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,9729, which belongs to Predicted 14,16 point with Actual 14 point, and the DL model gives more realistic results.

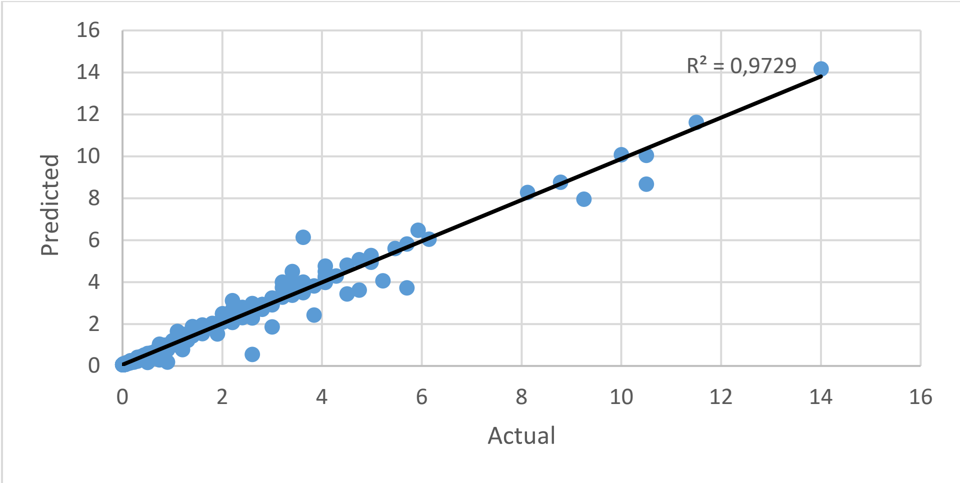

Figure 4.20 Crosscheck of Actual Results and Predicted Results of AdaGrad Optimizer and Huber loss for training

When AdaGrad optimizer and Huber are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.21). According to the chart, it can be said that the row with the highest difference between Actual estimate value 2,4 and Predicted forecast value of 2,2 for training data set en inputs is the point where '51' shows the highest deviation.

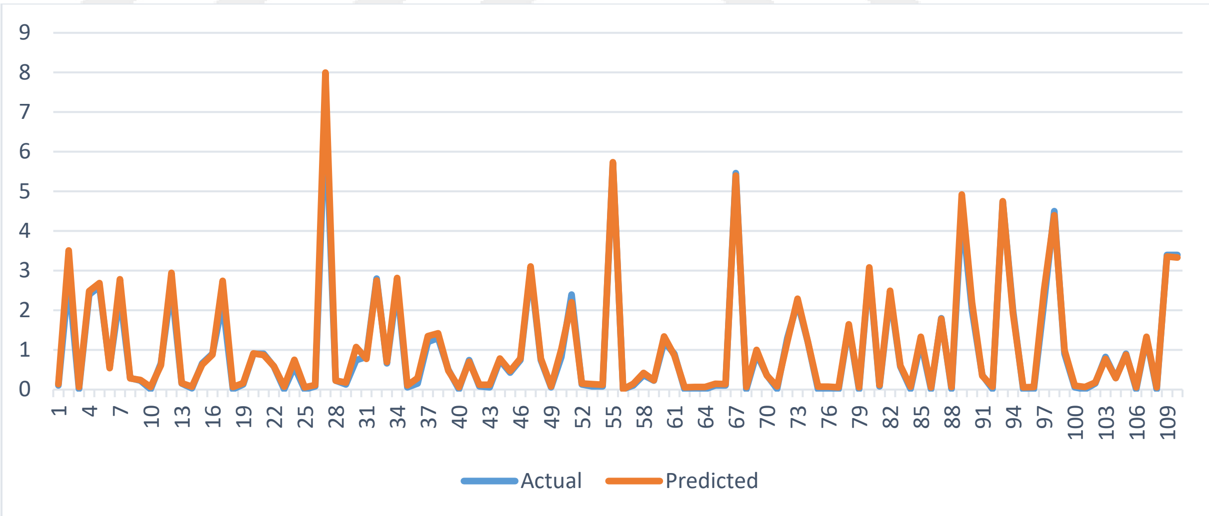

Figure 4.21 Actual datas and predicted Results for AdaGrad Optimizer and Huber Loss for testing

The estimated results of the data set from the test and model were compared in Figure 4.22. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7,02 and Predicted 7,99 point is expressed as 0,9912 and the DL model gives more realistic results.

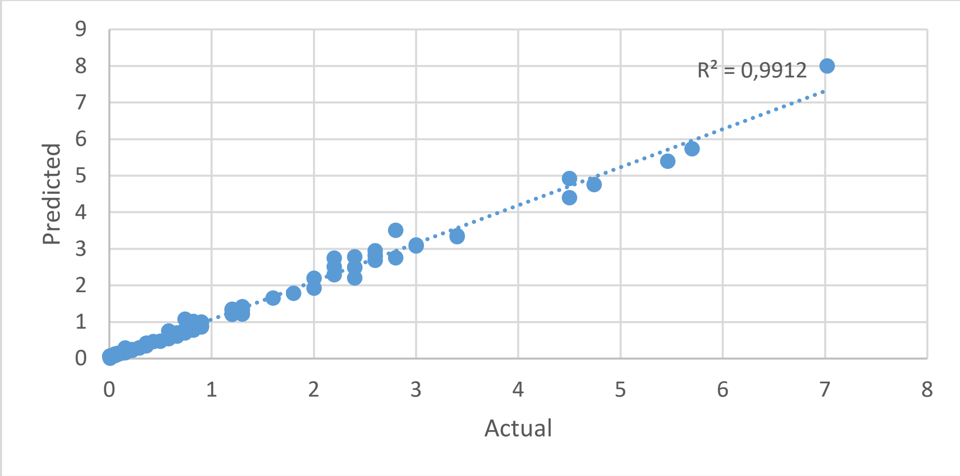

Figure 4.22 Crosscheck of Test Results and Predicted Results of AdaGrad Optimizer and Huber loss

4.7 Comparison of AdaGrad Optimizer and Logcosh loss both testing and training outputs with Actual results

Using AdaGrad Optimizer and Logcosh as loss functions, the training and test accuracy results of the model are shown in Table 4.6. According to the data in the table, Correlations Test dataset is 0,9959 and the Training dataset is 0,9910. MEAN Test dataset 0,7890 and Training dataset average 0,8692. The Test dataset for MAPE is 70,3331 and the Training dataset is 22,3849. The AdaGrad Optimizer and Logcosh loss function seems to provide the most accurate optimization for MSE, MAD, MAE, MAPE, MEAN and Correlation. The result is that the Logcosh function of the Test data is a more successful loss in the DL model.

Table 4.6 Statistical evaluations of Logcosh loss for AdaGrad

Statistics	Train	Test
MAD	0,1090	0,1329
MSE	0,0606	0,0237
RMSE	0,2462	0,1541
MAE	0,2238	0,0871
MAPE	22,3849	70,3331
MEAN(actual/predicted)	0,8692	0,7890
Standart Deviation	0,3984	0,2775
Correlation	0,9910	0,9959

R^2	0,9821	0,9918

As shown in the chart in Figure 4.23, the ratio comparison of predicted and actual values of the model for the training data set is shown. According to the chart, it can be said that the row with the highest difference between Actual estimate value 2,44 and Predicted forecast value of 1,26 for training data set en inputs is the point where '352' shows the highest deviation.

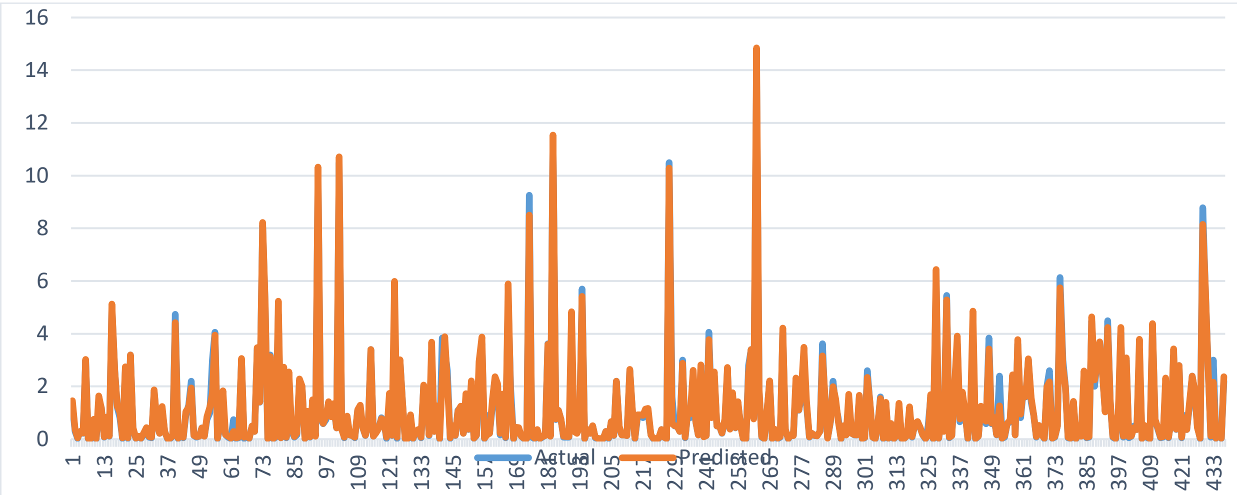

Figure 4.23 Crosscheck training correctness for AdaGrad Optimizer and Logcosh loss

DL results for the AdaGrad optimizer and Logcosh loss function in the dataset are shown in Figure 4.24. When the closeness to the correct result is examined, it is seen that the values closest to the truth are expressed as R^2 value 0,9821, which belongs to Predicted 14,84 point with Actual 14 point, and the DL model gives more realistic results.

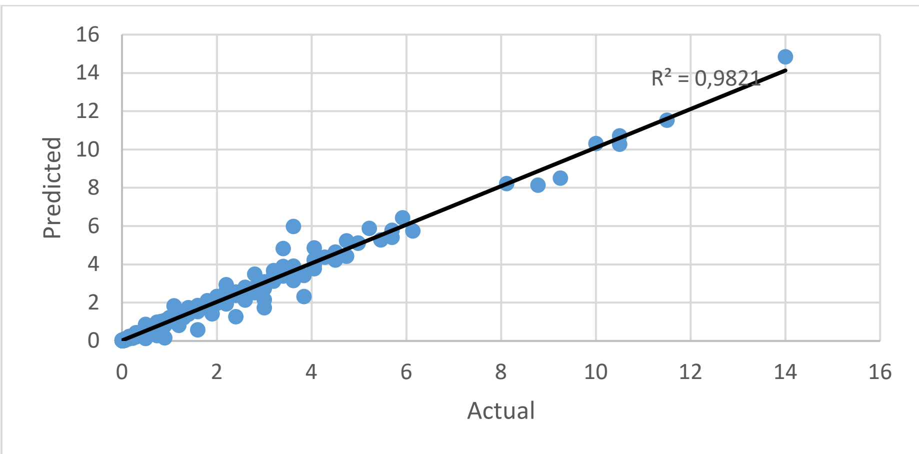

Figure 4.24 Crosscheck of Training Results and Predicted Results of AdaGrad Optimizer and Logcosh loss

When AdaGrad optimizer and Logcash are used as loss functions, the model compared the training and model results with a test accuracy graph (Figure 4.25). According to the chart, it can be said that the row with the highest difference between Actual estimate value 4,5 and Predicted forecast value of 4,33 for training data set en inputs is the point where '98' shows the highest deviation.

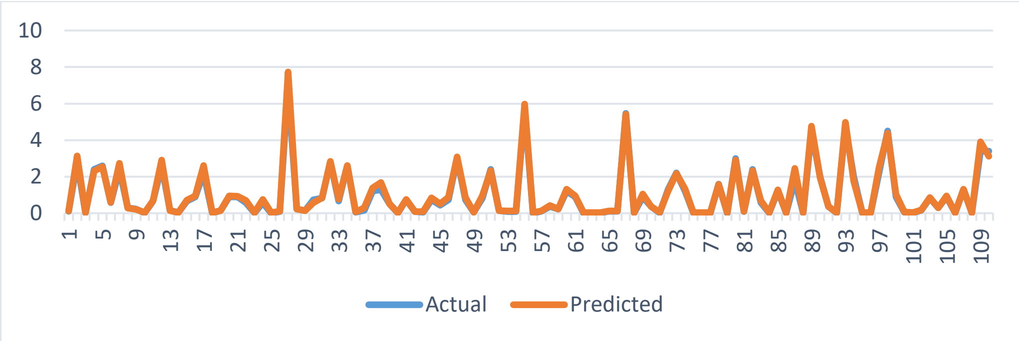

Figure 4.25 Crosscheck test correctness for AdaGrad Optimizer and Logcosh loss

The estimated results of the data set from the test and model were compared in Figure 4.26. When the approximation to the correct result is examined, it is seen that the R^2 value of the Actual 7,02 and Predicted 7,72 point is expressed as 0.9918 and the DL model gives more realistic results.

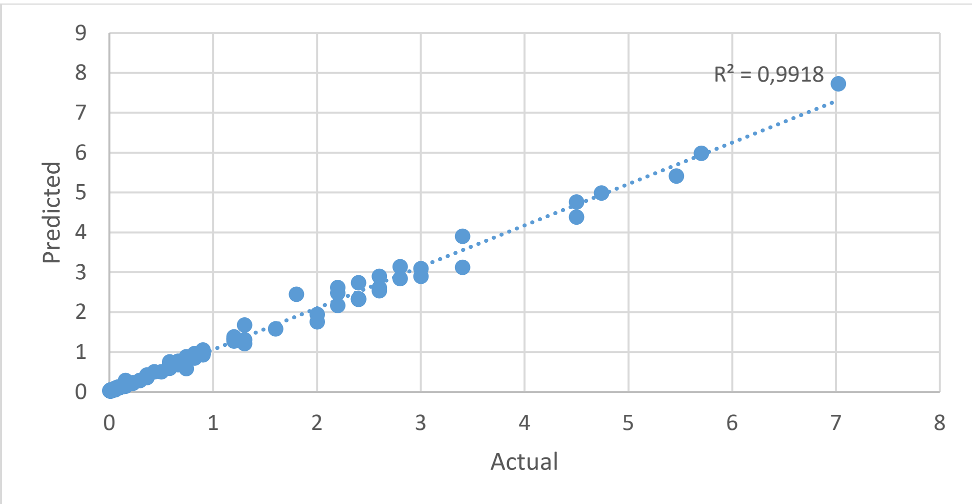

Figure 4.26 Crosscheck of Test Results and Predicted Results of AdaGrad Optimizer and Logcosh loss

4.8 Crosscheck of All Optimizer's and all losses in Statistical Results

According to data in Table 4.7 and Figure 4.27, the most accurate Result for MAD, MAE, and MAPE is from the DL model that uses Adam optimizers crosschecked to all optimizer Huber and Logcosh losses. According to these results, it can be called that the Logcosh loss is more accomplished for the test in the DL model.

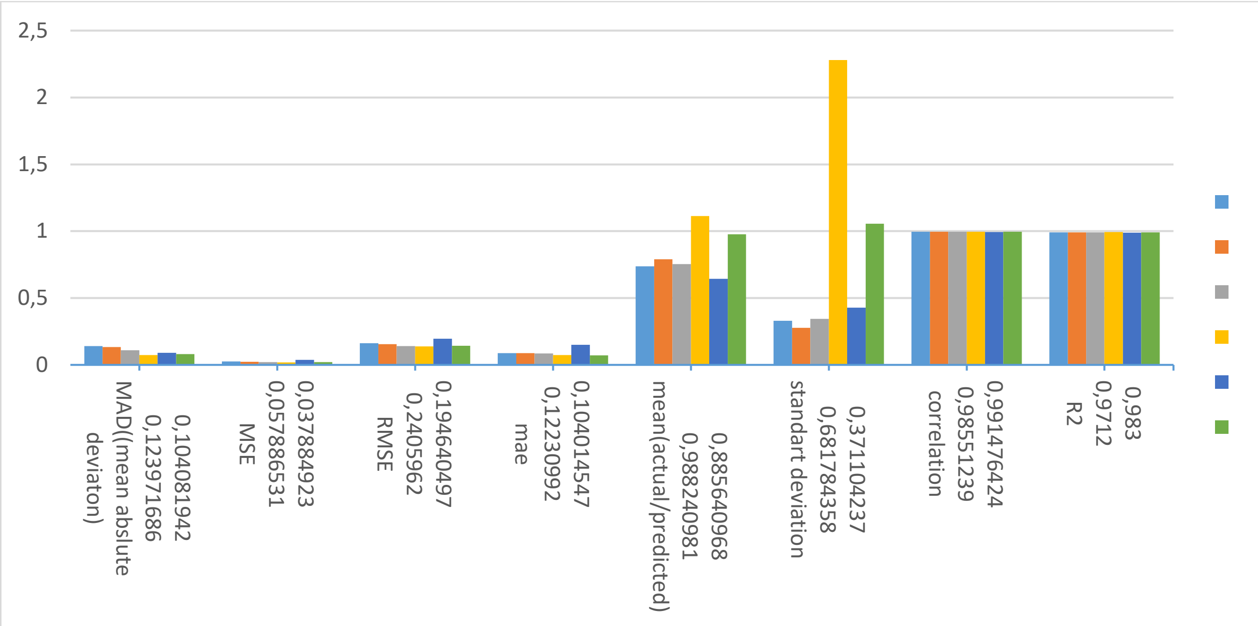

Figure 4.27 Crosscheck of statistical results for all optimizers

Table 4.7 Crosscheck of all optimizer results for Statistical Evaluation

Statistics	**AdaGrad**		**Adam**		**RMSprop**	
	Huber	Logcosh	Huber	Logcosh	Huber	Logcosh
MAD	0,1402	0,1329	0,1100	0,0741	0,0902	0,0795
MSE	0,0264	0,0237	0,0201	0,0190	0,0382	0,0205
RMSE	0,1627	0,1541	0,1418	0,1378	0,1955	0,1435
MAE	0,0885	0,0871	0,0844	0,0731	0,1507	0,0714
MAPE	148,7640	70,3331	125,722	83,8453	489,3238	30,4629
MEANactual/prediction	0,7375	0,7890	0,7532	1,1125	0,6445	0,9758
Standart Deviation	0,3299	0,2775	0,3450	2,2803	0,4291	1,0564
Correlation	0,9956	0,9959	0,9952	0,9961	0,9943	0,9958
R^2	0,9912	0,9918	0,9904	0,9923	0,9888	0,9917

CHAPTER 5

CONCLUSIONS

DL models have been created along the Euphrates River, one of the most important water resources in southern Turkey, that can be used to estimate today's value. When analyzing the performance of the model, the closeness between the actual value and the estimated value was checked. The model seeed in the research was created using the Python DL application library Python DL application library. The model used in the research includes 1 input layer, 4 hidden layers and 1 output layer. The Python library utils Adam, AdaGrad, and RMSprop optimizers. Huber and Logcosh loss functions are used for these optimizers. 70% of the data for 4 conversion scenarios are used for training and 30% for testing. In the method used in model evaluation, correlation, determination coefficient (R^2), mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), average absolute deviation (MAD) and standard deviation literatureis used as the evaluation method.

Data covering the village of Handeresi Balayan between 2002 and 2011 comes from the daily measurement values of the DSI FMS obtained from station D21A212. These flow values are divided into 4 time shifts used in the data set. The 5th day forecast used a data set of 4 time shift schemes, and the flow value began until the day before the previous 4 days. The evaluation results obtained by comparing DL results with actual results are listed in Table 4.7. The recording program is one of the most important charts for comparing the actual value with the predicted values. According to 4 conversion scenarios, training and test results are shown in Figure 4.27. The more linear the actual and predicted values displayed in this chart type, the closer the values are. The closest result according to the chart in the graph is the educational result of the scene with the highest correlation value.

The most successful results in terms of regression coefficients (R^2) in the station were obtained from the 'Logcosh' loss function model for the Adam optimizer, whose flow measuring station and basin river flow prediction were determined. The R^2 value of the training and test results obtained from 4 quick scenario models for the lost value of Adam optimizer 'Logcosh' belonging to Handeresi Balayan FMS was found to be 0,9923. As a result of the application, the Standard Deviation coefficient from the analysis techniques of these optimizer algorithms was 2,2803 and the RMSE coefficient was 0,1378. When we look at these charts, it is understood that the results are quite successful. This result obtained with the Adam Optimizer and Logcosh loss function was obtained by using the data as 70% training and 30% test with 4 days shift. The fact that it has achieved a statistically much higher estimation success than the traditional teaching is a guide in the design phase of the engineering structures to be created in different basins and a new input parameter to be added to the existing measurements in the Euphrates Basin used in the study can be predicted without the need for conventional measurement methods. Testing different optimizers and loss functions with different input parameters will increase the reliability of the studies and the possibility of giving meaningful results.

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