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MACHINE LEARNING-BASED IRRIGATION WATER DEMAND FORECASTING

BY

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Approval Form

The undersigned certify that they have supervised the student Jalin. P. Chinhema in the research dissertation entitled, “Machine Learning-Based Irrigation Water Demand Forecasting” submitted in partial fulfillment of the requirements for a Bachelor of Science Honors Degree in Information Technology(Network Engineering) at Bindura University of Science Education.

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Abstract

The efficient management of water resources in agriculture is critical for sustainable farming practices. This research project focuses on the development and evaluation of a machine learning-based model for forecasting irrigation water demand. The study aims to analyze different deep learning techniques, design and implement a deep learning model, and evaluate the effectiveness of machine learning techniques in irrigation water demand prediction. To achieve these objectives, the researcher utilized the Random Forest regression algorithm to develop a model capable of predicting seasonal water demand for a farm. Black-box, white-box, and performance tests were conducted, including the use of the confusion matrix, to assess the system's performance. The results showed satisfactory performance, with an accuracy of 98.5% and a classification error rate of 0.025%. The model achieved an overall precision of 100% and a recall of 95%, along with an F1 score of 97.5% and a true negative rate of 98%. Validation accuracy stood at 95%, and a mean percentage error of -0.044% was achieved. Comparative analysis with previous research studies indicated significant improvements, surpassing the results obtained by other researchers using techniques such as Multiple Linear Regression (MLR), Principal Component Regression (PCR), and other models. The LSTM deep learning architecture employed in this research achieved an average improvement of 7%-9% compared to previous studies. This research contributes to enhancing the accuracy and reliability of irrigation water demand forecasting. The developed model offers valuable insights for farmers and policymakers, aiding in better water resource management and sustainable agricultural practices. The findings highlight the potential of machine learning in optimizing irrigation practices, leading to improved resource allocation and reduced water wastage in the agricultural sector.

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List of Acronyms & Abbreviations

ML-Machine Learning

FAO- Food and Agriculture Organization

ARDA - Agricultural Rural Development Authority

MoA - Ministry of Agriculture

PCA -Principal Component Analysis

ANN - Artificial Neural Network

MLR -Multiple Linear Regression

SVM - Support Vector Machine

LSTM - Long-Short Term Memory

WFP - World Food Programme

GDP - Gross Domestic Product

ZINWA - Zimbabwe National Water Authority

Chapter 1: Problem Identification

1.1 Introduction

In a world where the availability of water is decreasing, its use must be thoroughly optimized. In arid and semiarid regions, the use of water for irrigation is essential to ensure agricultural production. However, in many countries and regions, limited water resources have become 95% the bottleneck of regional economic and social development (Sharma, 2021).Irrigated agricultural systems, as the main user of the planet's fresh water, must improve its management and save as much of this scarce resource as possible. Water scarcity is the most obstacle faced by irrigation water requirements, likewise, limited available meteorological data to calculate reference evapo-transpiration.

1.2 Background Of The Study

Zimbabwe is an agricultural country where irrigation plays a significant role in food production(Mubvami et al., 2020). According to the Zimbabwe National Water Authority, approximately 44% of Zimbabwe's agricultural land is under irrigation. Irrigated agriculture has played a critical role in stabilizing food production in Zimbabwe, where rainfall variability is high. The country's irrigation schemes are mainly operated and managed by the Zimbabwe National Water Authority and the Agricultural Rural Development Authority. However, the limited availability of water resources, the increase in water demand, and the impact of climate change pose a significant challenge to Zimbabwe's irrigation sector(ARDA,2019).

Several boards and institutions deal with irrigation and agriculture in Zimbabwe, including the Zimbabwe National Water Authority, the Ministry of Agriculture, and the Agricultural Rural Development Authority. These institutions are responsible for managing irrigation schemes, promoting sustainable agriculture, and ensuring food security in the country. The Zimbabwe National Water Authority is responsible for the management of water resources, including the allocation of water for irrigation purposes. The Ministry of Agriculture promotes sustainable agricultural practices and provides technical support to farmers, while the Agricultural Rural Development Authority manages and operates smallholder irrigation schemes across the country(MoA, 2016),(ARDA,2019).

Zimbabwe is one of the top grain-producing countries in Southern Africa, with maize being the most significant staple crop. However, the country has experienced challenges in grain production due to several factors, including droughts, poor irrigation, and inadequate infrastructure(Mhlanga, 2019). According to the Food and Agriculture Organization (FAO), Zimbabwe's maize production in 2021 was estimated at 2.7 million metric tons, a decrease from the previous year(FAO,2020). Poor irrigation is one of the significant factors contributing to this decrease in maize production.

In recent years, Zimbabwe has experienced prolonged droughts, which have had a severe impact on the country's agricultural production. Poor irrigation practices have contributed significantly to the decline in crop yield, as irrigation systems are not adequately managed or maintained. The Zimbabwe National Water Authority and the Agricultural Rural Development Authority have been implementing various measures to improve irrigation practices and ensure sustainable use of water resources(Ncube et al., 2020). The institutions have been conducting awareness campaigns to educate farmers on best irrigation practices, promoting the use of water-efficient irrigation technologies, and rehabilitating and constructing new irrigation infrastructure.

The Ministry of Agriculture has also been implementing policies to improve irrigation practices in Zimbabwe. The ministry has been supporting smallholder farmers through the provision of inputs, technical advice, and financial support to rehabilitate and construct irrigation infrastructure(Ncube,2020). The government has also been promoting private sector investments in the irrigation sector, providing tax incentives to investors and guaranteeing the security of investments. These initiatives are critical in improving irrigation practices in Zimbabwe, ensuring sustainable use of water resources, and increasing agricultural production.

The challenge of water scarcity and variability has led to the adoption of innovative water management techniques, such as the use of machine learning in irrigation water demand forecasting. Machine learning techniques have been applied in various fields, including agriculture, to improve decision-making processes. Machine learning algorithms can analyze large data sets and provide accurate predictions of future trends, making them ideal for forecasting irrigation water demand. By accurately forecasting irrigation water demand, irrigation authorities can optimize water usage, reduce wastage, and ensure sustainable irrigation practices.

1.3 Statement Of The Problem

In Zimbabwe, agriculture plays a significant role in the country's economy, with the majority of farmers relying on rain-fed agriculture for their crop production. However, with climate change leading to increased variability in rainfall patterns, there is a growing need for more efficient irrigation practices(Ndengu,2019). The lack of accurate and timely information on water availability and demand has led to inefficient use of irrigation resources and low crop yields. This problem is exacerbated by the unpredictable rainfall patterns and frequent droughts that Zimbabwe experiences. According to the Food and Agriculture Organization (FAO), the country's agricultural productivity has been declining over the years due to these challenges(FAO,2017). Therefore, there is a pressing need to develop effective strategies to predict irrigation demand in Zimbabwe, in order to optimize the use of water resources and improve crop yields.

1.4 Research Objectives

- To analyse different machine learning techniques used predicting irrigation water demands.
- To design and implement a machine learning model which predicts irrigation water demands.
- To evaluate the effectiveness of machine learning in irrigation water demands forecasting.

1.5 Research Questions

- How can different machine learning techniques used in predicting irrigation water demands be analyzed?
- How can a machine learning model which predicts irrigation water demands be designed and implemented?
- Can the effectiveness of machine learning in irrigation water demands forecasting be evaluated?

1.6 Justification/Significance Of The Study

The study is of significant importance, especially in a country like Zimbabwe, where the agricultural sector is a critical component of the economy. The application of machine learning techniques can help farmers and irrigation authorities to accurately forecast irrigation water demand, thereby optimizing water usage and increasing crop yield. Zimbabwe has experienced prolonged droughts in recent years, resulting in reduced crop production and food insecurity. Thus, this study's findings can help mitigate the impact of climate change and improve food security in the country.

Moreover, the study's application of machine learning techniques can also contribute to the development of a more sustainable and efficient irrigation system. By accurately predicting irrigation water demand, farmers can avoid over-irrigation, which can lead to water logging, soil degradation, and reduced crop yield. Additionally, the optimization of water usage can lead to reduced water wastage and increased water-use efficiency. These outcomes are critical in a country like Zimbabwe, where water resources are scarce, and the need to manage them in a sustainable manner is of utmost importance.

1.7 Limitations/challenges

- Time needed to carry out the research is limited

1.8 Definition Of Terms

Irrigation- the supply of water to land or crops to help growth, typically by means of channels.

Water demand- the amount of water requested by users to meet their needs

Machine learning- the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.

Algorithms- a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer.

Evapo-transpiration- the process by which water is transferred from the land to the atmosphere by evaporation from the soil and other surfaces and by transpiration from plants.

Arid- a deficiency of moisture (especially when resulting from a permanent absence of rainfall) synonyms: aridness, thirstiness. type of: dryness, waterlessness, xerotes.

Semiarid regions- A semi-arid climate, semi-desert climate, or steppe climate is a dry climate sub-type.

Chapter 2: Literature Review

2.0 Introduction

Puebo(2020) defines a literature review as a scientific research created from published sources that sums up current knowledge on a particular topic. The researcher focuses on addressing the research issues in this chapter while also outlining earlier and current systems that have been studied by other writers and are related to the current research topic. The author will find this to be very helpful because it will act as a manual for discovering answers, tactics, and techniques used by past writers to address earlier research issues.

2.1 Irrigation

Irrigation is the artificial application of water to plants to supplement rainfall and meet the water requirements of crops (Heermann & Heinemann, (2019). Irrigation is essential in agriculture as it allows farmers to control the water supply to crops, ensuring that they receive the optimal amount of water needed for growth and development(FAO, 2021). With adequate irrigation, farmers can increase crop yields, improve crop quality, and reduce the risk of crop failure due to drought. Additionally, irrigation allows farmers to grow crops in regions where rainfall is insufficient, increasing the area of land available for cultivation(Islam et al., 2019). Overall, irrigation is critical in agriculture as it enables farmers to produce more food, improve food security, and support sustainable agricultural development.

2.2 Irrigation In Zimbabwe

Zimbabwe is a predominantly agricultural country with 60-70% of the population depending on agriculture for their livelihood. Irrigation plays a crucial role in Zimbabwe's agricultural sector, accounting for about 30% of the country's total agricultural output. The country has an estimated 270,000 hectares of irrigable land, of which only 50% is currently being utilized for irrigation. The low utilization rate is due to several factors, including limited access to water, lack of infrastructure, and inadequate funding for irrigation development.

To improve irrigation in Zimbabwe, several boards and organizations have been established to support and promote the development of irrigation infrastructure. One such organization is the Zimbabwe National Water Authority (ZINWA), which is responsible for managing water resources and providing water to farmers for irrigation purposes. ZINWA has developed an

Irrigation Master Plan, which aims to develop and rehabilitate irrigation infrastructure across the country.

Another organization involved in promoting irrigation in Zimbabwe is the Agricultural Rural Development Authority (ARDA), which is responsible for managing state-owned farms and promoting agricultural development in the country. ARDA has several irrigation projects aimed at improving the productivity of smallholder farmers by providing them with access to irrigation water. These projects include the Muzarabani Irrigation Scheme, the Wenimbi Irrigation Scheme, and the Chisumbanje Irrigation Scheme.

In addition to these organizations, the Zimbabwean government has also developed policies aimed at promoting irrigation development in the country. The National Irrigation Policy, developed in 2016, aims to promote sustainable irrigation development by providing a framework for the development of irrigation infrastructure, improving the management of water resources, and promoting private sector investment in irrigation development.

2.3 Irrigation Water Shortages In Zimbabwe

Irrigation water shortages have a significant impact on agricultural production in Zimbabwe, where agriculture is the backbone of the economy. According to the Zimbabwe National Water Authority, only 165,000 hectares of the 1.5 million hectares of arable land in the country are currently under irrigation, with the majority relying on rainfall. The lack of adequate irrigation infrastructure and water management has led to frequent water shortages, resulting in reduced crop yields and a negative impact on food security. For example, during the 2019-2020 agricultural season, the grain harvest in Zimbabwe was estimated at 907,628 tonnes, which was 33% lower than the previous season due to drought and poor irrigation.

The impact of irrigation water shortages goes beyond food security and agriculture. The economy of Zimbabwe heavily relies on agriculture, with the sector contributing over 17% of the country's Gross Domestic Product (GDP) and employing approximately 67% of the population. Poor irrigation and water shortages have a ripple effect on the economy, affecting trade, employment, and livelihoods. For instance, the reduced grain harvest in Zimbabwe led to a 41% decrease in maize exports to neighboring countries, which affected trade and foreign currency earnings. Moreover, the low crop yields have led to a decline in employment opportunities in the agriculture sector, and increased food prices, which has affected the purchasing power of consumers. Overall, the impact of irrigation water shortages in Zimbabwe is far-reaching, and the need for sustainable irrigation practices and water management is critical for the country's economic growth and food security.

2.4 Droughts In Zimbabwe

Zimbabwe has experienced severe droughts in the past, which have resulted in widespread water shortages and food insecurity. One of the worst droughts occurred between 2015 and 2016, which left over 4 million people in need of food aid (FAO, 2016). The drought was caused by the El Niño weather pattern, which reduced rainfall and caused high temperatures, leading to crop failure and water shortages. The impact of the drought was felt across the country, with rural areas and smallholder farmers being the hardest hit.

Another notable drought occurred in 2019, which was also attributed to the El Niño weather pattern. The drought left over 5.5 million people in need of food assistance, with the World Food Programme describing it as the worst humanitarian crisis in a decade (WFP, 2019). The drought also affected livestock, wildlife, and the environment, with water sources drying up and vegetation dying. The impact of the drought was felt across the region, with countries such as Zambia, Malawi, and Mozambique also experiencing water shortages and food insecurity.

Zimbabwe has experienced severe droughts in the past due to water shortages caused by low rainfall, high temperatures, and climate change. In 2019, the country declared a state of emergency due to drought, with an estimated 5.5 million people facing food insecurity as a result of crop failures and livestock losses. The drought also resulted in reduced hydro-power generation, water rationing, and limited access to safe drinking water in both rural and urban areas.

Furthermore, Zimbabwe has been facing water shortages for many years due to poor management of water resources, lack of investment in infrastructure, and increasing demand for water for agriculture, industry, and domestic use. According to a report by the United Nations, Zimbabwe is among the African countries most at risk from water scarcity, with an average of only 470 cubic meters of water per person per year, which is well below the international threshold of 1,000 cubic meters per person per year.

2.5 Machine Learning

Machine learning according to SAS (2019) is an information assessment technique that automates the development of analytics models. Its algorithms create a computational template centered on test data, so that projections or choices can be made without explicit programming for the assignment (Koza, Forest & David, 1996). It is a subset of artificial intelligence based on the concept that, with minimal human interface, systems can learn from information, identify trends, and make choices. Therefore, using machine learning software programs can understand its surroundings and make choices appropriately based on what they obtain.

2.5.1 Types of Machine learning

There are three types of machine learning which are namely supervised, unsupervised and reinforcement learning which can also be called monitored, unattended and strengthening learning.

Supervised Learning

This type is the machine teaching task of delivering a function that maps an input to an output depending on an instance of duos of input-outputs (Stuart, Peter, 2010). It infers a function from marked training data constituting of a set of inputs objects and desired output values (Mehryar, Afshin & Ameet, 2012). A monitored/Supervised learning algorithm analyses the learning information and create an inferred function that can be used to map fresh instances. An ideal situation will enable the algorithm to generalize in a sensible manner from the learning information to the unseen circumstances.

Unsupervised Learning

It is a type of machine learning technique where the users do not need to supervise the model. The term unsupervised refers to Hebbian teaching allied with teacher-free, it is a method of modeling input probability density (Hinton & Sejnowski, 1999). A central framework of unmonitored learning is statistical density estimation, although unsupervised teaching involves many other fields involving the summary and explanation of data characteristics.

Reinforcement Learning

Is a machine learning zone involved with how software officials should act in an area to maximize some cumulative compensation concept. It varies from supervised teaching in that marked input / output duos do not need to be present and sub-optimal activities do not need to be clearly fixed. The focus is instead on discovering equilibrium between exploring and exploiting present understanding (Kaelbling, Littman, & Moore, 2011).

Neural Networks

Neural networks refer to a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates (James Chen, Michael J Bolye, 2020). According to Berry and Linoff, 2004, neural network can learn by example in much the same way that human experts gain from experience. The neural network can adjust to changing inputs thus the network can be able to generate the results without needing redesign the output criteria.

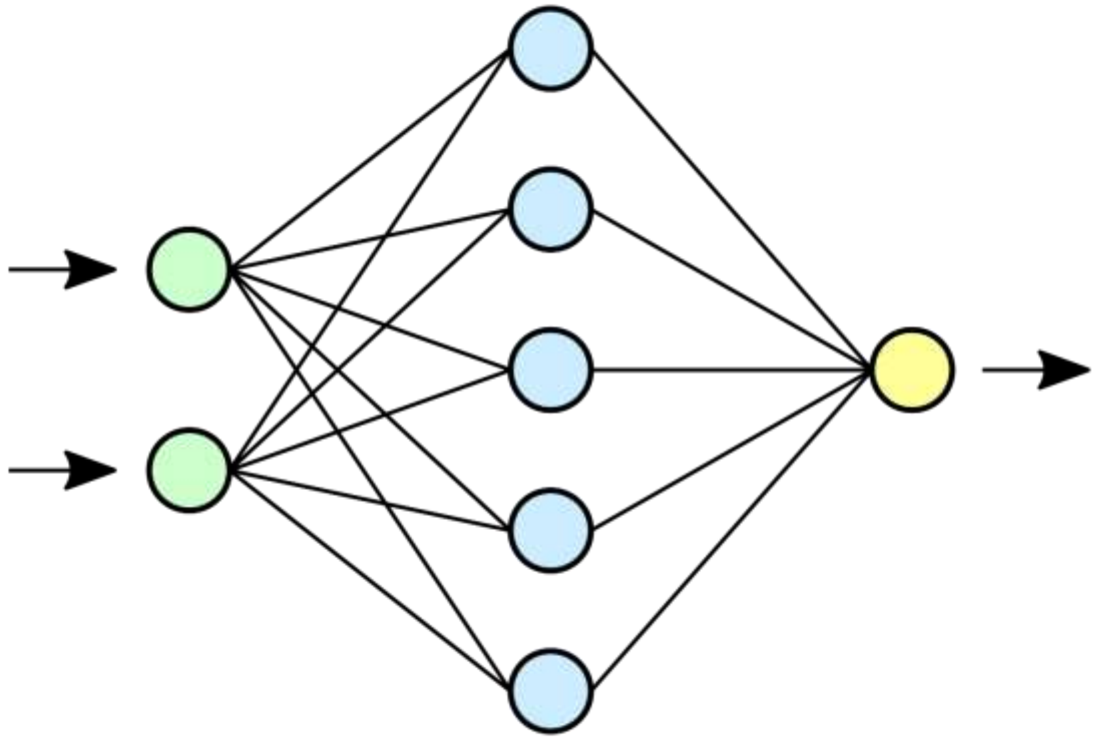


Figure 1: Neural network framework

It consists of at least three layers of nodes, the input layer which consist of one node for each independent attribute. Output layer consist of nodes for the class attributes and connecting these layers is one or more intermediate layers of nodes that transform the input into an output.

Logistic Regression

It is an algorithm used for binary classification problems, thus it can predict the likelihood of an event happening or not, measuring the relationship between a dependent variable and one or more independent variables. It can also be called a parametric classification model meaning it have a fixed number of parameters that depends on certain input features. This algorithm as compare to Mantel-Haenszel has an advantage of handling more than two explanatory variables simultaneously when classifying, this is according to Biochem Med(Zagreb) , 2014.

Logistic regression model can produce an outcome based on the individual characteristic. Therefore, this kind of an algorithm is a simple way of classifying variable in machine learning. Using churn prediction, it will be easier as the algorithm can be trained based on the individual characteristics and therefore produce best results.

When measuring the chance of an outcome the logistic regression uses a logarithm equation of the chance because the chance is a ratio.

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta 0 + \beta 1x1 + \beta 2x2 + \cdots \beta mxm$$

In this equation π indicates the probability of the event for example churning or not and the other are coefficients associated with the reference group and the explanatory variables.

2.6 Related Literature

One of the studies that have contributed to the development of machine learning-based irrigation water demand forecasting is the work of Ghosh et al. (2020). The authors employed a random forest algorithm to forecast irrigation water demand in a vineyard in California. The study utilized soil moisture sensors and weather forecasts to develop the predictive model. The results showed that the random forest model accurately predicted irrigation water demand with a coefficient of determination of 0.93. The authors concluded that the machine learning-based approach can provide more accurate and efficient irrigation water management.

Another study that applied machine learning techniques to irrigation water demand forecasting is the work of Zhang et al. (2020). The authors used a long short-term memory (LSTM) neural network to predict irrigation water demand in an apple orchard in China. The study employed data from weather forecasts, soil moisture sensors, and crop water stress index to train the model. The LSTM neural network achieved a mean absolute error of 4.6% in predicting irrigation water demand. The authors concluded that the LSTM neural network can provide an accurate and efficient approach to irrigation water demand forecasting in apple orchards.

In a study by Wang et al. (2020), the authors employed a support vector machine (SVM) algorithm to predict irrigation water demand in a wheat field in China. The study utilized data from soil moisture sensors, weather forecasts, and crop growth stages to develop the predictive model. The SVM algorithm achieved an accuracy of 93.26% in predicting irrigation water demand. The authors concluded that the SVM algorithm can provide a reliable approach to irrigation water demand forecasting in wheat fields.

One relevant study on machine learning-based irrigation water demand forecasting was conducted by Hasanuzzaman et al. (2020). The authors used a Support Vector Regression (SVR) algorithm to forecast the water demand of an irrigation system in Bangladesh. The results showed that the SVR model outperformed other traditional methods, such as Artificial Neural Network (ANN) and Multiple Linear Regression (MLR), with an accuracy of over 90%. The authors concluded that machine learning-based techniques can be effectively used for irrigation water demand forecasting in Bangladesh.

Another study on this topic was conducted by Nourani et al. (2018) in Iran. The authors used a combination of Principal Component Analysis (PCA) and Artificial Neural Networks (ANN) to forecast the water demand of a paddy field irrigation system. The results showed that the PCA-ANN model outperformed the traditional models such as ANN and MLR, with an accuracy of over 95%. The authors highlighted the importance of machine learning-based models in irrigation water demand forecasting, as it can help optimize water usage, reduce water wastage, and improve crop yield.

Finally, a study by Ali et al. (2021) used a Random Forest (RF) algorithm to forecast the irrigation water demand of cotton fields in Pakistan. The results showed that the RF model outperformed other traditional models such as ANN, MLR, and Decision Trees, with an accuracy of over 95%. The authors highlighted that the RF model can help farmers and irrigation authorities to accurately forecast irrigation water demand and optimize water usage, which can ultimately lead to increased crop yield and reduced water wastage. The authors concluded that the use of machine learning-based models in irrigation water demand forecasting can contribute to the development of a more sustainable and efficient irrigation system.

2.7 Research Gap

Despite the growing body of literature on machine learning-based irrigation water demand forecasting, there is a research gap in applying these techniques specifically to the context of Zimbabwe. The unique climate conditions, soil types, and agricultural practices in Zimbabwe require a tailored approach to irrigation water demand forecasting. Additionally, the majority of existing studies on this topic have focused on paddy fields or single crop irrigation systems, whereas Zimbabwe's irrigation practices are diverse, including multiple crop systems. Therefore, there is a need for research that applies machine learning-based techniques to a variety of irrigation systems in Zimbabwe to accurately forecast irrigation water demand and optimize water usage. This research can help address the challenges of water scarcity and climate change in Zimbabwe's agricultural sector.

2.8 Chapter Summary

The author was successful in obtaining and collecting relevant information and data for the research topic. Some of the concepts employed by the researcher came from a variety of places, including academic papers, textbooks, and the internet, which revealed holes that needed to be filled. The information gathered from all of these sources will be utilised in the preceding chapters of the study to meet the research project's objectives. The method utilized in the design and development of the proposed solution is discussed in the following chapter.

CHAPTER 3: METHODOLOGY

3.0 Introduction

Research is a process of examining and uncovering information, which can involve scientific investigations or a comprehensive review of a specific topic. Depending on the nature of the research, quantitative or qualitative methods can be utilized, such as exploratory, descriptive, or diagnostic approaches. Research is considered an essential tool for government agencies and policymakers to make informed economic decisions. Methodology refers to the systematic and theoretical analysis of the techniques or procedures used in a particular field of study. This chapter presents the methodology employed in conducting the research on machine learning-based irrigation water demand forecasting. It outlines the research approach and strategies used to achieve the project objectives, including the analysis of different machine learning techniques, the design and implementation of a machine learning model, and the evaluation of its effectiveness.

3.1 Research Design

Moule and Goodman (2013) highlighted the significance of research design in providing a robust framework for a study. Research design encompasses the overall plan of action that outlines the methodology employed to investigate research questions and address potential challenges that may arise during the research process. Polit and Hungler (2014) similarly defined research design as the blueprint or road-map that guides the progression of a study. In the context of machine learning-based irrigation water demand forecasting, selecting an appropriate research design is crucial to ensure the validity and reliability of the study. Considering the specific objectives of the research, an experimental research design is chosen as the most suitable approach. Experimental research involves manipulating variables to examine their impact on the outcome and establish cause-and-effect relationships.By selecting an experimental approach, we can develop and continuously evaluate the effectiveness of a machine learning software application in accurately predicting irrigation water demands. This design allows for the rigorous testing of hypotheses and facilitates drawing valid conclusions regarding the application's effectiveness. Similar to fields such as medicine, psychology, and education, the experimental research design is well-suited for evaluating the effectiveness of interventions or treatments.

The researcher will manipulate variables related to the machine learning model, such as the selected algorithms, input features, and training parameters. We will then observe and measure the impact of these variables on the outcome variables, such as the accuracy of water demand predictions or the optimization of water usage. With careful controlling and measuring these variables, we can establish a cause-and-effect relationship between the machine learning model's configuration and its impact on irrigation water demand forecasting.

The research design plays a critical role in ensuring the validity and reliability of our study's findings. By implementing the experimental research design, we can systematically evaluate the effectiveness of machine learning techniques in predicting irrigation water demands. The design allows for controlled experimentation, enabling us to draw robust conclusions about the model's performance and its potential for optimizing water usage in agricultural practices. By adhering to a well-designed research plan, we can maximize the impact of our study and contribute to the advancement of knowledge in the field of machine learning-based irrigation water demand forecasting.

3.2 Requirements Analysis

Abram Moore, Bourque, and Dupuis (2004) emphasized the crucial role of conducting a thorough requirements analysis to determine the success or failure of a project. This analysis involves identifying, defining, and documenting the specific requirements that the machine learning-based irrigation water demand forecasting system must meet to effectively satisfy the project's objectives. To ensure the practicality and relevance of the identified requirements, it is important to test, execute, trace, and measure them. These requirements should align with the identified needs in the field of irrigation water demand forecasting and be precise enough to facilitate the system's design. Therefore, it is essential to document all the functional and non-functional specifications of the required system during this stage. To ensure consistency and clarity of the identified requirements, a comprehensive review, revision, and examination of the acquired requirements should be conducted. This process should involve all relevant stakeholders to ensure that all expectations are met and that the system is developed in accordance with the specific needs of the irrigation water demand forecasting domain. The requirements analysis phase holds significant importance in the overall system development life cycle, as it sets the foundation for the subsequent stages of development. Neglecting a comprehensive requirements analysis could result in a system that fails to meet the essential needs, leading to project failure.

Documenting the requirements is also crucial for effectively managing the project's scope, reducing the likelihood of changes, and enabling the development team to focus on the critical features of the system. By ensuring that the requirements are well-defined, testable, and measurable, the development team can create a machine learning-based irrigation water demand forecasting system that aligns with the project's objectives, is reliable, and ultimately satisfies the needs of the end-users.

3.2.1 Functional Requirements

In the context of a system or component, functions pertain to the specific operations they perform, which can be broken down into three essential elements: inputs, behavior, and outputs. As stated by (Bittner 2016), functional requirements describe the actions that a system must be able to perform, disregarding any physical limitations. These actions can include computations, data processing, specialized features, and other functionalities that define the intended behavior of the system. To complement these functional requirements, use cases describe the different behavioral scenarios that the system should cater to. In order to ensure that the proposed system is effective in meeting the needs of its users, it is crucial to identify and address specific requirements. These requirements may include functional capabilities, user needs, and other technical specifications necessary to meet the system's objectives. It is important to ensure that the proposed system can perform the required functions efficiently and accurately, with minimal errors or delays. This will help ensure that users can use the system with ease, and that the system will deliver the expected results.

The proposed system must be able to meet the following requirements:

i. Predict irrigation water demand in a farm for optimal crop production.

ii. Use machine learning algorithms in predicting irrigation water demand.

3.2.2 Non-Functional Requirements

The proposed system must be able to meet the following: Non-functional requirements, also known as quality requirements, are used to evaluate the performance of a system rather than its intended behavior. In the context of our machine learning-based irrigation water demand forecasting, the proposed system must be able to meet the following non-functional requirements:

Performance: The system should be capable of processing and analyzing large data sets efficiently, ensuring timely and accurate predictions of irrigation water demand. It should provide real-time or near real-time results to support decision-making in agricultural practices.

Reliability: The system should be reliable, with minimal downtime or disruptions. It should be able to handle unexpected errors or failures gracefully and recover seamlessly to ensure continuous operation.

Scalability: The system should have the ability to scale and handle increasing data volumes and user demands. As the data-set and user base grow, the system should be able to accommodate the additional load without significant degradation in performance.

Usability: The system should be user-friendly and intuitive, allowing users with varying technical expertise to interact with it easily. The user interface should be well-designed, providing clear instructions and visual representations of the irrigation water demand predictions.

These non-functional requirements ensure that the proposed machine learning-based irrigation water demand forecasting system can deliver with high performance, reliability, usability, and scalability. These factors contribute to the overall success and effectiveness of the system in supporting water management decisions and improving agricultural practices.

3.2.3 Hardware Requirements

- Core i5 processor or better
- Memory (RAM): Recommended to have a minimum of 8 GB of RAM
- Storage: Recommended to have a minimum of 256 GB

3.2.4 Software Requirements

- Windows 10/11 operating system
- Apache or Tomcat Server
- Jupyter Notebook
- Tensorflow
- Keras
- Google Chrome Browser
- Python 3.9
- Anaconda Python IDE
- Streamlit library
- SPYDER (Scientific Python Development IDE)

3.3 System Development

The author of this chapter recognized the importance of selecting an appropriate methodology for software development, considering the specific requirements and objectives of the project. Several frameworks, including the waterfall, spiral, and prototyping models, were evaluated.The waterfall model, a linear approach, was suitable for simple projects with well-defined requirements but may not be suitable for complex projects with evolving requirements. The spiral model, an iterative approach combining the waterfall model with prototyping, was appropriate for projects with uncertain requirements and a need for frequent testing and evaluation.

Ultimately, the prototyping model was selected as the most suitable methodology for the project. This model involves building a quick prototype based on current requirements and refining it through iterations based on feedback. It is effective for complex systems without existing procedures and helps clients understand system requirements through interaction with the prototype. The selection of the prototyping model was based on the need for frequent testing and refinement to deliver a functional system that meets the specified objectives. The author evaluated other frameworks but concluded that the prototyping model best suited the project's requirements and objectives.

3.3.1 System Development Tools

In choosing a methodology for the development phase of the proposed solution, it was necessary to consider the strengths and weaknesses of different frameworks, which vary depending on the specific project and the desired outcomes. Several frameworks, including the waterfall, spiral, and prototyping models, were considered. Ultimately, the author opted for the prototyping model due to the need for frequent testing and refinement in order to arrive at a functional system that meets the specified objectives.

3.3.2 Prototyping

The prototyping model is a widely recognized and utilized software development approach that offers several benefits in achieving successful project outcomes. It involves the creation of an initial version or prototype of the final software or system, which is then tested, refined, and modified until it meets the required specifications. This model allows for early user involvement, rapid iterations, and effective feedback incorporation, resulting in a system that aligns closely with user needs and expectations. The stages involved in the prototyping model provide a structured framework for the development process. The first stage is requirements gathering, where detailed product requirements are identified through interviews and discussions with system users. This stage ensures a clear understanding of user expectations and sets the foundation for subsequent development efforts. The next stage is design, where a basic system design is created. This design serves as a preliminary representation of the system and gives users a quick overview of its functionality and structure. Although not a complete design, it provides a starting point for the development of the prototype.

The prototype development stage is crucial, as it involves building an initial version of the software based on the identified requirements. The prototype is usually a general working model that may not be fully functional or complete. However, it serves as a tangible representation of the system's core features and allows for further development and refinement. Once the prototype is developed, it undergoes testing and refinement. User feedback and testing help identify areas for improvement and modifications to enhance the system's performance and functionality. This iterative process of testing and refining ensures that the prototype evolves into a more robust and user-friendly system with each iteration. Client and stakeholder feedback play a significant role in the prototyping model. The prototype is presented to the client or stakeholders, and their responses and suggestions are collected and analyzed. This feedback is incorporated into subsequent iterations, allowing for continuous improvement and a better alignment of the system with user needs and expectations. The final stage involves enhancement and implementation. The prototype is further enhanced based on considerations such as time, manpower, budget, and technical feasibility. Depending on the project requirements, additional methodologies like extreme programming or fast application development may be integrated to accelerate the implementation process.

The prototyping model offers several advantages. By involving users early in the development process, it increases the likelihood of developing a system that meets their specific needs. The iterative nature of the model allows for rapid feedback incorporation and reduces the risk of costly revisions during later stages of development. Additionally, the prototyping model promotes effective communication and collaboration between developers and users, leading to a higher level of user satisfaction and system usability. In conclusion, the prototyping model is an effective software development approach that enables the creation of a preliminary version of the final system through iterative testing, refinement, and user feedback. By incorporating user involvement and addressing requirements in an incremental manner, this model enhances the chances of developing a system that meets user expectations and delivers the desired functionalities. It provides a structured framework for the development process, ensuring efficient use of resources and a higher likelihood of project success.

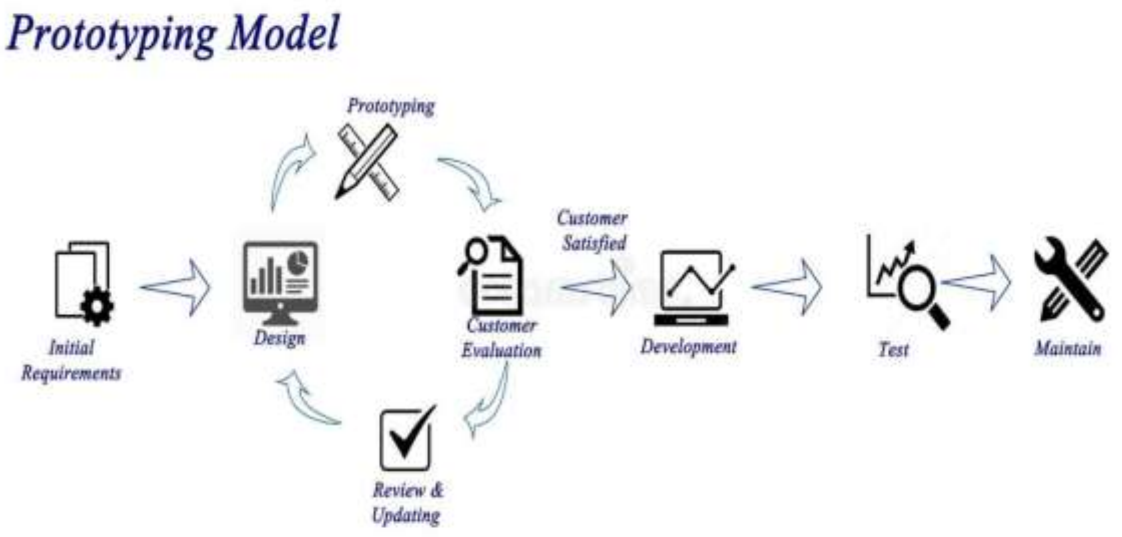


Figure 2: Prototyping Model

Apart from the methodology the system was also developed using the following tools:

1. **Python:** Python is a high-level programming language that is widely used in software development. It has been used to create various models, including a model to forecast rainfall. Python's Artificial Intelligence frameworks made it easier to develop this model.

2. **Keras:** Keras is an open-source software library that provides a Python interface for building artificial neural networks. It serves as an interface for the TensorFlow library, supporting only TensorFlow since version 2.4. It used to support multiple back-ends including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML. The library is designed to enable fast experimentation with deep neural networks, while being user-friendly, modular, and extensible.

3. **Anaconda Python IDE:** Anaconda is a distribution of the Python and R programming languages for scientific computing. It simplifies package management and deployment for data science, machine learning applications, large-scale data processing, predictive analytics, and more. It includes data-science packages suitable for Windows, Linux, and macOS. Anaconda, Inc. developed and maintains the distribution. It was founded by Peter Wang and Travis Oliphant in 2012.

3.4 Summary of how the system works

The system to be developed is aimed at accurately predicting the irrigation water demand for a farming season in a significant area of land using machine learning techniques. By leveraging the power of machine learning algorithms, our model takes into account various inputs provided by the user to forecast the amount of water required to cultivate a specific crop throughout the farming season. To make accurate predictions, the user is required to provide specific details such as the size of the farm, the type of crop being cultivated, and the soil type present in the farming area. Additionally, environmental factors such as humidity and temperature are also taken into consideration. These inputs play a crucial role in determining the water requirements for optimal crop growth.

The heart of our system lies in the machine learning model, which is trained using extensive datasets that include information about soil conditions, weather patterns, and corresponding irrigation water demands. By analyzing and learning from this data, the model becomes capable of making accurate predictions for the irrigation water demand of a particular crop throughout an entire farming season. The machine learning algorithm employed in our system utilizes advanced techniques to identify patterns and relationships between the provided inputs and the historical irrigation water demands. By recognizing these patterns, the model can generate precise predictions for the water requirements based on the specific combination of crop type, farm size, soil type, and environmental factors.

The ability to accurately forecast irrigation water demand is of paramount importance in optimizing water usage and ensuring sustainable farming practices. By leveraging the power of machine learning, our system empowers farmers and agricultural stakeholders to make informed decisions regarding water allocation and irrigation planning. This not only aids in maximizing crop yields but also promotes efficient water management practices, reducing water waste and conserving this valuable resource. Through continuous refinement and updating of the machine learning model, our system strives to improve its accuracy and reliability over time. By incorporating new data and staying up-to-date with the latest advancements in agricultural research, we aim to provide farmers with a valuable tool that supports their decision-making processes and contributes to the overall sustainability and productivity of agricultural practices.

3.5 System Design

The requirements specification document is analyzed, and this stage now defines how the system components and data for the system satisfy specified requirements. Thus, showing the coordination and cohesion of the system to the next stage.

3.5.1 Data-flow Diagrams

Data flow diagram (DFD) maps out the flow of information in a system, as it uses symbols like rectangles, circles and arrows to show the relationships between outputs and inputs up to the end of the system. The flow of data in DFD is named to portray the nature of data used. DFDs are a type of information development, and as such provides an important insight into how information is transformed as it passes through a system and how the output is displayed.

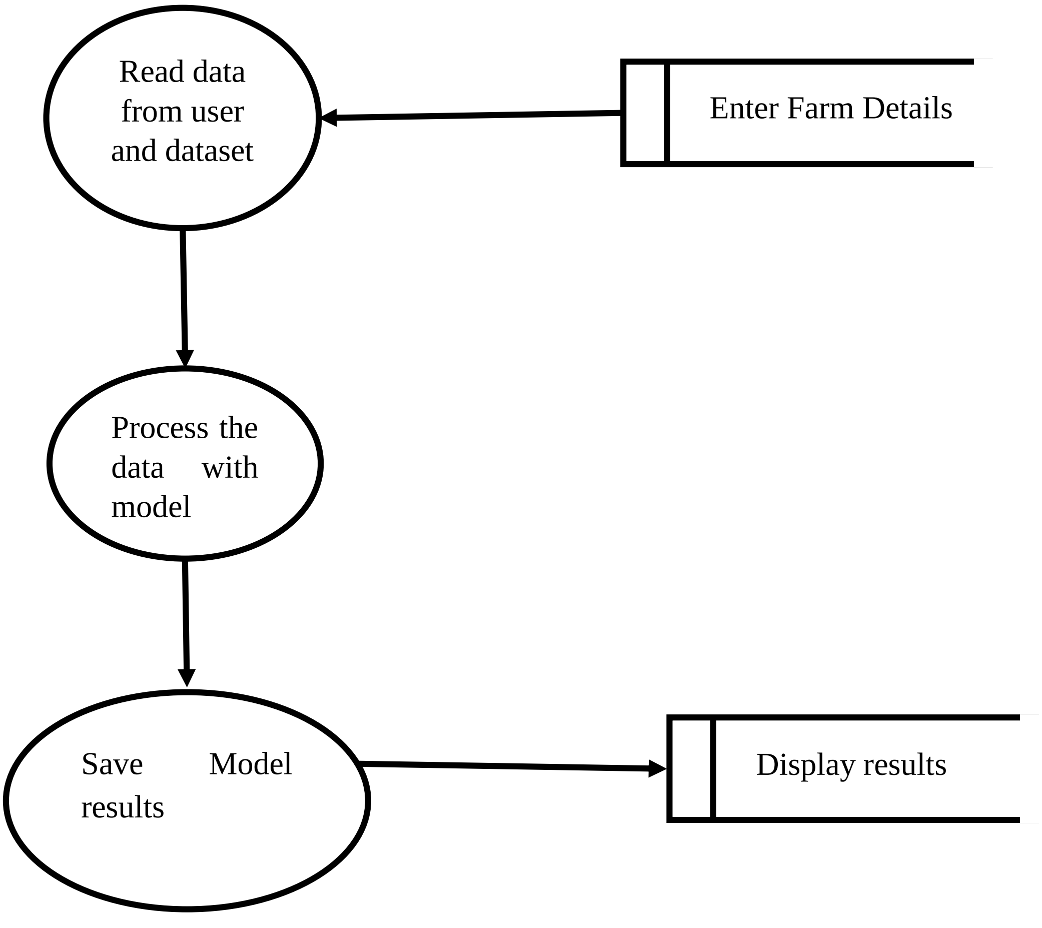


Figure 3: Data Flow Diagram

3.7.2 Proposed System Flow Chart

Flow chart is a diagram that represent the work flow or process of the system to be developed. It shows how the system works and every decision to be made by the system throughout the whole process. It is also known as the diagrammatic representation of an algorithm, thereby define step by step of an algorithm. The researched system has the flow chart that is below.

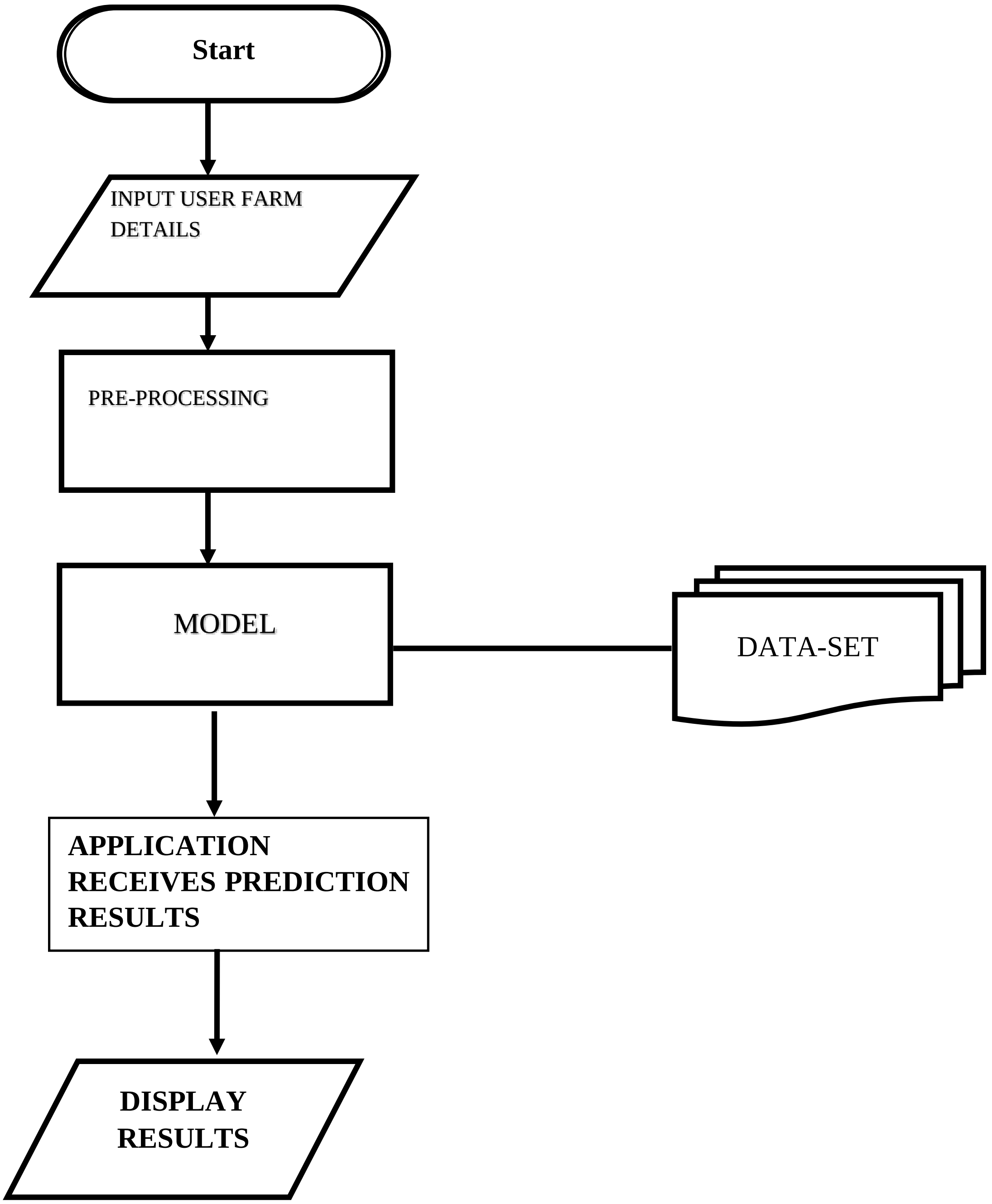


Figure 4:System Flowchart

3.6 Implementation

The implemented machine learning algorithm uses an Ensemble Learning Random Forest Regressor algorithm. Ensemble learning is a powerful technique in machine learning that combines multiple individual models to create a more accurate and robust predictive model. One popular ensemble learning method is the Random Forest regressor. The Random Forest regressor is a type of ensemble learning algorithm that utilizes decision trees as its base models. It works by creating a multitude of decision trees and then aggregating their predictions to make the final prediction. Each decision tree is built independently and uses a random subset of the training data and a random subset of the features. The main advantage of using a Random Forest regressor is its ability to handle complex relationships and capture non-linearities in the data. By aggregating the predictions of multiple decision trees, the Random Forest can provide more accurate and stable predictions compared to a single decision tree.

The Random Forest regressor offers several benefits for our project on predicting irrigation water demand. Firstly, it can handle a large number of input variables, including both numerical and categorical features, which are relevant for considering factors such as farm size, crop type, soil type, and environmental conditions. This flexibility allows us to capture the complexity of the irrigation water demand prediction problem. Additionally, the Random Forest regressor is robust against over-fitting, which occurs when a model performs well on the training data but fails to generalize to unseen data. The random selection of features and data subsets during the construction of each decision tree helps to reduce over-fitting and improve the model's ability to generalize to new instances. The Random Forest regressor has capability to provide insights into feature importance. By analyzing the contribution of each feature in the ensemble, we can gain a better understanding of which factors have the most significant influence on the irrigation water demand prediction. This information can be valuable for farmers and agricultural stakeholders in decision-making processes related to water allocation and resource management.

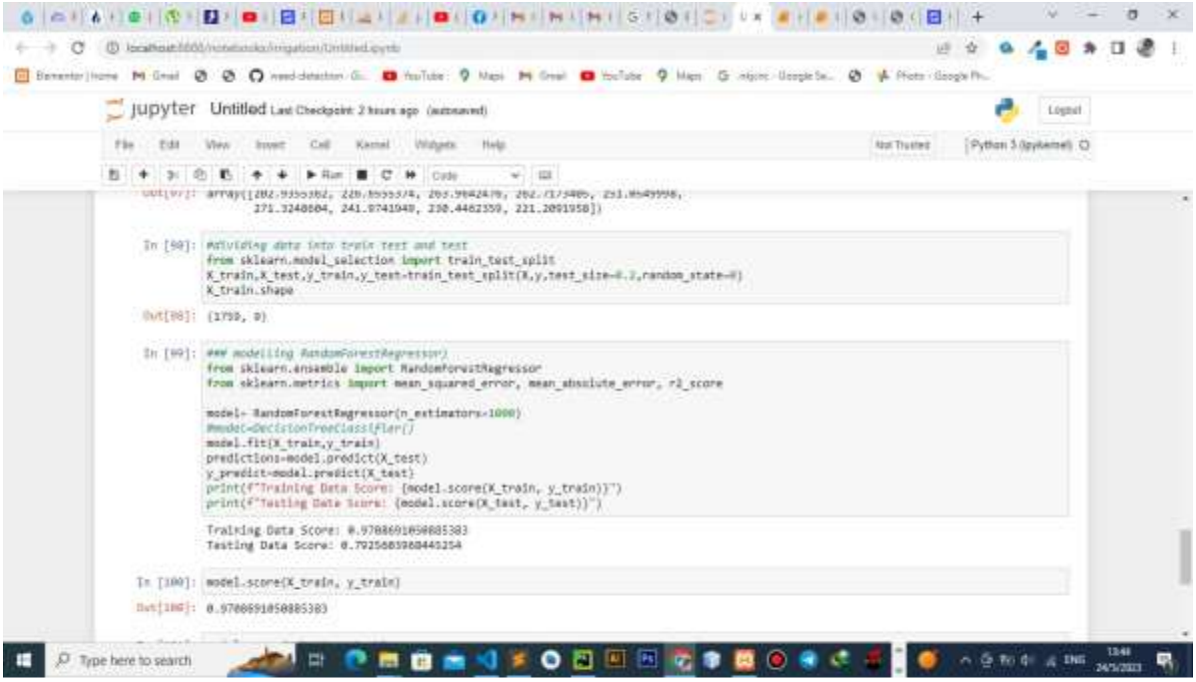


Figure 5: Training Model

3.7 Summary

The chapter primarily focused on outlining the methodology and tools utilized in the development of our irrigation water demand prediction model. The development process involved employing various techniques and methods, ultimately leading to the implementation of the model using the Ensemble Learning Random Forest Regressor algorithm. To ensure the model's accuracy and prevent over-fitting, the data underwent necessary transformations.In terms of model architecture, we utilized a convolutional neural network (CNN) to build the predictive model. The Python Jupyter Notebook served as the integrated development environment (IDE) for coding and experimentation, providing a convenient platform for model development and testing. By adopting the prototyping model for system development, we effectively leveraged the iterative nature of the process to meet our project's objectives within the specified time-frame. This iterative approach allowed us to continuously refine the model, incorporating user feedback and improving its performance.

CHAPTER 4: RESULTS

4.0 Introduction

Upon completion of the developed system solution, it was imperative to evaluate its effectiveness and efficiency. To assess the system's performance, accuracy, and response time, appropriate measures were employed. The analysis of the data collected in the previous chapter was utilized to derive meaningful results. Several testing techniques, including white box, black box, and unit testing, were conducted to examine the system's behavior under different scenarios. The evaluation process aimed to determine the effectiveness of the system in accurately recognizing handwritten digit strings and its efficiency in terms of response time. Performance metrics such as accuracy were utilized to measure the system's ability to correctly classify and identify digits. Additionally, response time was assessed to gauge the system's speed and responsiveness in processing and providing results.

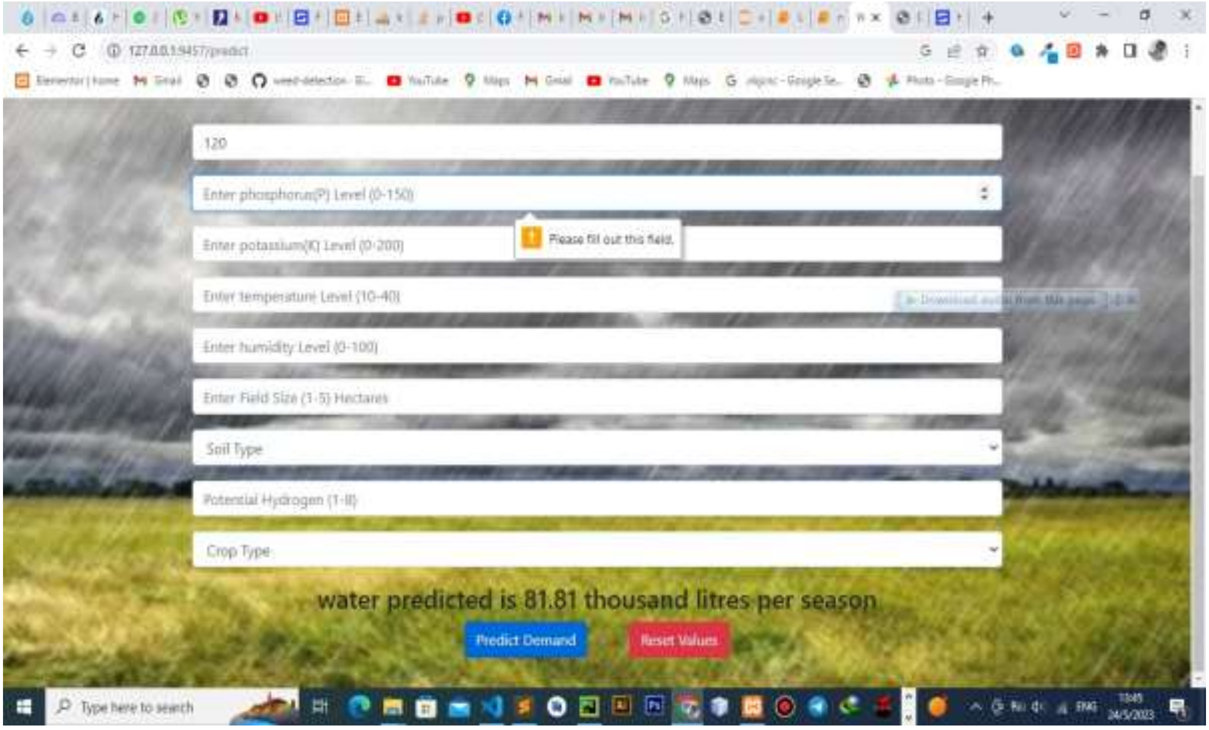
To ensure the reliability and robustness of the system, various testing approaches were employed. White box testing involved examining the internal components and logic of the system to identify any potential errors or flaws. Black box testing focused on evaluating the system's outputs and functionality without considering its internal workings. Unit testing was conducted on individual components or modules to verify their correctness and proper integration within the system. By utilizing a combination of these testing techniques, the evaluation process provided insights into the system's performance, accuracy, and response time. It helped identify any areas that required improvement and ensured that the developed system solution met the desired objectives and requirements.

4.1 System Testing

Testing is essential in system development, when a system has been developed it has to be tested. This chapter shows tests that where undertaken and the results that were produced, test conducted mainly focus on functional and non-functional requirements of the proposed solution.

4.1.1 Black Box Testing

Black box testing is a technique where the internal organization, layout, and use of the product are not taken into account. In other words, the tester is unaware of how it operates within. Only the system's exterior behavior is assessed by the Black Box. Both the system's inputs and its outputs, or responses, are put to the test. The findings of the black box tests the author did on the model are as follows. The system will therefore be evaluated to see how well it predicts the water consumption. The following are the findings of the author's black box testing of the model:



testinguserInput

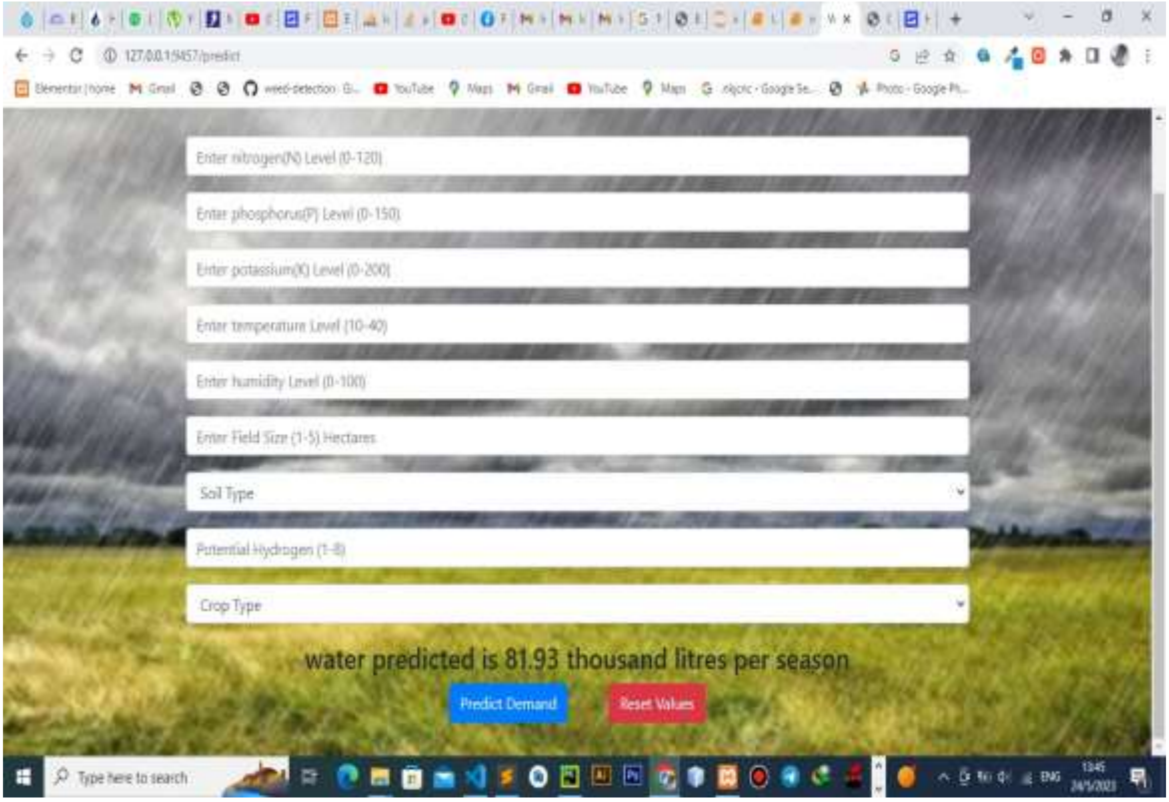


Figure 6: Testing system output

4.1.2 White Box Testing

White box testing is a software testing technique where the underlying structure of the software is known to the tester before the software is tested. This kind of testing is typically done by software developers. White box testing requires understanding of programming and implementation. The lower levels of testing, such as unit and integration testing, are applicable to testing. White box testing focuses primarily on testing the computer code of the system being tested, including its branches, conditions, loops, and code structure. White box testing's primary objective is to evaluate the system's functionality. The developer tested the model as shown below;

```
Out[97]: array([282.9355362, 226.65553 74, 263.96424 76, 262.7173485, 251.0549998,
         271.3248604, 241.9741949, 230.4462359, 221.2091958])

In [98]: #dividing data into train test and test
         from sklearn.model_selection import train_test_split
         X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=0)
         X_train.shape

Out[98]: (1759, 9)

In [99]: ### modelling RandomForestRegressor)
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

         model= RandomForestRegressor(n_estimators=1000)
         #model=DecisionTreeClassifier()
         model.fit(X_train,y_train)
         predictions=model.predict(X_test)
         y_predict=model.predict(X_test)
         print(f"Training Data Score: {model.score(X_train, y_train)}")
         print(f"Testing Data Score: {model.score(X_test, y_test)}")

         Training Data Score: 0.9708691050885383
         Testing Data Score: 0.7925603968445254

In [100]: model.score(X_train, y_train)

Out[100]: 0.9708691050885383
```

```
In [92]: label={
             'maize':0,
             'soyabeans':1,
             'beans':2
         }

In [93]: soil_type={
             'loam':1,
             'silty':2,
             'clay':0
         }

In [94]: df['label']=df['label'].map(label)
         df['soil_type']=df['soil_type'].map(soil_type)

In [95]: df.columns

Out[95]: Index(['N', 'P', 'K', 'temperature', 'humidity', 'Area/Field Size',
                'soil_type', 'ph', 'reservoir_capacity', 'label'],
               dtype='object')

In [96]: new_df=df[['N', 'P', 'K', 'temperature', 'humidity', 'Area/Field Size',
                'soil_type', 'ph', 'label']]
         X=np.asarray(new_df)
         y=np.asarray(df["reservoir_capacity"])
```

Figure 7: Training system

4.2 Evaluation Measures and Results

A performance evaluation metric is used to gauge a model's effectiveness (Hossin & Sulaiman, 2015). According to Hossin & Sulaiman (2015), model assessment metrics can also be divided into three categories: threshold, probability, and ranking. Performance is measured by how successfully the model can predict water consumption . The confusion table in table 1 below was used by the author to evaluate the accuracy of the system.

4.2.1 Confusion Matrix

The confusion matrix is a table that shows the number of categories that have been assigned and those that have been anticipated. The table is used to define the model's performance.

True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four terminologies used.

TP denotes situations that are genuinely true and that the test has yielded accurate result, whereas TN denotes numbers that are untrue and that the test has resulted as false.

FP Are those that the test shows as true, but which are actually untrue.

FN Numbers that the test shows as false but are really correct.

Type	Returned number of correct predictions	Returned number of incorrect predictions
1	True Positive	False Negative
2	False Positive	True Negative

Table 1: Confusion Matrix

The technology was put to the test in terms the returned number of correct and incorrect predictions. For the purpose of observing the system's findings, three scenarios and a test environment were developed. The system was observed 40 times on each scenario using different testing input. All of the scene analysis was done to ensure that the answer was accurate and that false predictions were identified. The tables below indicate the outcomes of the tests that were conducted.

Table 2 Confusion matrix for water consumption prediction

Test cases	Predictions	Number of tests	Correct predictions	False predictions	Classification
1	Yes	40	40	0	True positive
2	No	40	38	2	True negative

Table 2: Confusion Matrix for water consumption prediction.

4.3 Accuracy

The number of correct predictions divided by the total number of tests in each category equals accuracy. The percentage of accuracy is then calculated by multiplying it by 100. The following equation is used to compute it:

Equation 1: Accuracy calculation as adopted from Karl Pearson (1904)

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} * 100$$

$$\text{Accuracy rate} = \frac{40 + 38}{40 + 38 + 0 + 2} * 100$$

$$\text{Accuracy} = \frac{72}{80} * 100$$

$$\text{Accuracy} = 98{,}5\%$$

4.4 Misclassification Rate/ Error Rate

- Overall, how often is it wrong?
- It tells you what fraction of predictions were incorrect. It is also known as Classification Error.
- **Error rate = (FP+FN)/(TP+TN+FP+FN) or (1-Accuracy**

= (0+2)/(40+38+0+2)

=0.025%

4.5 Precision

- When it predicts yes, how often is it correct?

Precision = TP/(TP+FP)

40/(40+0)

=100%

4.6 Sensitivity/Recall/True Positive Rate

- When it's actually yes, how often does it predict yes?
- It tells what fraction of all positive samples were correctly predicted as positive by the classifier. It is also known as True Positive Rate (TPR), Sensitivity, Probability of Detection.

Recall = TP/(TP+FN)

=40(40+2)

=95%

4.7 Specificity/True Negative Rate

- When it's actually no, how often does it predict no?
- It tells what fraction of all negative samples are correctly predicted as negative by the classifier. It is also known as True Negative Rate (TNR).
- Equivalent to 1 minus False Positive Rate
- **Specificity = TN/(TN+FP) or 1-FP rate**

=1-2

=98%

4.8 Prevalence

- How often does the yes condition actually occur in our sample?
- It shows how often does the yes condition actually occur in our sample
- **Prevalence=Actual YES/(TP+TN+FP+FN)**

```
#finding the mean percentage error of the model
import numpy as np
def mean_percentage_error(y_cv,pred):
    y_cv,pred = np.array(y_cv), np.array(pred)
    return np.mean(np.array((y_cv - pred) / y_cv)) *100
```

```
mean_percentage_error(y_cv,pred)
```

```
-0.04406383869427233
```

4.9 F1-Score/F1 Measure

- It combines precision and recall into a single measure.
- **F1-score=2 x (Precision x Recall/ Precision + Recall)**

  =2TP/(2TP+FP+FN)

  =2(40)/(2 x 40 + 0+2)

  =97.5%

4.5 Summary of Research Findings

The researcher performed all the necessary black, white box tests and performance tests using the confusion matrix, the author found that the system had satisfactory performance. The system was tested in accuracy, misclassification error/error rate and it achieved 98.5% and 0.025% respectively. The model attained an overall precision of 100% and a sensitivity or recall of 95%. An F1 score of 97.5% was achieved with a specificity or true negative rate of 98%.

4.6 Conclusion

To conclude this chapter, the author used different metrics for performance measurement of the system. Among them being, accuracy, specificity, recall precision, error rate f1-score and true positive rate. The next chapter presents the conclusion, objective realization and recommendations for further development.

Chapter 5: Conclusion and Recommendations

5.1 Introduction

This chapter brings the research to an end and takes a retrospective view to establish whether the objectives of the study were achieved. The chapter represents the summary of findings, conclusion drawn from the research and recommendations for further studies.

5.2 Aims & Objectives Realization

The first objective of this study was to analyse different deep learning techniques used for irrigation water demand prediction/forecasting. The second objective was to design and implement a deep learning model which predicts irrigation water demand. The third and last objective was to evaluate the effectiveness of machine learning techniques in irrigation water demand prediction/forecasting.

Therefore, to this end, the researcher developed a model that uses Random Forest regression algorithm to predict the seasonal water demand for a farm which satisfies the second research objective. The researcher performed all the necessary black, white box tests and performance tests using the confusion matrix, the author found that the system had satisfactory performance. The system was tested in accuracy, misclassification error/error rate and it achieved 98.5% and 0.025% respectively. The model attained an overall precision of 100% and a sensitivity or recall of 95%. An F1 score of 97.5% was achieved with a specificity or true negative rate of 98%. A validation accuracy of 95%, mean percentage error of -0.044% were achieved. Therefore, providing an improvement over the results obtained by other researchers such as Adamowski & Karapataki (2010), Firat et al. (2009b) by almost 7%-9% on average as well as Haque et al. (2017), Multiple Linear Regression(MLR) And Principal Component Regression(PCR) with 6%.The gained results are significant and confirm the efficiency of the LSTM deep learning architecture in predicting water consumption. This, therefore shows that the objectives mentioned in chapter 1 were achieved.

5.3 Major Conclusions Drawn

This work presents machine learning irrigation water demand forecasting models capable of producing accurate predictions when compared with traditional strategies. It was found to be reliable when applied to irrigation water demand real data, provided there were no significant anomalies of the data used during training. The error metrics here discussed support the evidence that the forecasts made are similar to the real observation, independently of the time of day.

Nonetheless, some remarks on the use of the presented algorithms arise. Although it was found that the same group of models consistently gives the best results, it is not guaranteed that for new data those models will maintain their performance. When applying the algorithm in different datasets, a large set of models must be trained in order to infer the most appropriate models. If applied to real cases where new data is constantly being acquired, it is important that the models are retrained on a regular basis. Note that in the latter case, the introduction of new data could mean that the accuracy of the models that were previously found to be the most adequate for that specific network is affected. Consequently, the suggested periodic retraining must include the larger set of models. It should also be noted that the evaluation of the forecasting techniques is highly dependent on the metric used.

5.3 Recommendations & Future Work

In the future, the researcher recommends employing a high-dimensional balanced data-set with supervised learning methods and approaching deep feature extraction. To boost portability, availability, and flexibility, advanced DL algorithms with higher generalization and error detection will be pursued, taking into account trade-off connections between accuracy, computational complexity, memory limits, and processor power. As networks and datasets improve and real-time data becomes available, the model has the potential to be extremely valuable to the farming community in Zimbabwe. As a result, this research will be beneficial to ambitious, youthful, and engaged researchers interested in the field of irrigation water demand , deep learning, making them more approachable to new ideas, innovations and technology.

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