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An AIoT-Based Automated Farming Irrigation System for Farmers in Limpopo Province

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ARTICLE INFO

Article history:
Received 20 December 2023
Revised 27 February 2024
Accepted 11 June 2024
Available online 28 June 2024

Keywords:
Agriculture
Soil parameters
Sensors
Machine learning
Irrigation

IEEE style in citing this article:
R. Makhulu Langa and M. Nthabiseng Moeti, "An IoT-Based Automated Farming Irrigation System for Farmers in Limpopo Province," Journal of Innovation Information Technology and Application (JINITA), vol. 6, no. 1, pp. 12–27, Jun. 2024.

ABSTRACT

Limpopo, one of South Africa's nine provinces, is mostly rural, where agriculture serves as the primary occupation for around 89 percent of the total population. Agriculture relies on water, making it its most valuable asset. Through irrigation, water is supplied to crops for growth, frost control, and crop cooling. Irrigation can occur naturally, as with precipitation, or artificially, as with sprinklers. However, artificial irrigation is wasteful as it is regulated and monitored through human intervention, leading to water scarcity which is one of the obstacles that threatens the agricultural sector in the province of Limpopo. A machine learning precipitation prediction algorithm optimizes water usage. The paper also describes a system with multiple sensors that detect soil parameters, and automatically irrigate land based on soil moisture by switching the motor on/off. The objective of this paper is to develop an automated farming irrigation system that is both efficient and effective, with the intention of contributing to the resolution of the water crisis in the province of Limpopo. The proposed solution ought to be capable of decreasing labour hours, generating cost savings, ensuring consistent and efficient water usage, and gathering informed data to inform future research. Thus, farmers will have greater access to information regarding when to irrigate, how much water to use, weather alerts, and recommendations. In acquiring these, the ARIMA model was applied alongside DSRM for implementing the mobile application. The results obtained indicate that the use of AI and IoT (AIoT) in agriculture can improve operational efficiency with reduced human intervention as there is real-time data acquisition with real-time processing and predictions.

1. INTRODUCTION

Being a country with a limited supply of water, South Africa needs a comprehensive water management system to make the most of what we do have by efficiently managing our freshwater resources and wetlands. Large metropolitan populations as well as southern Africa's industrial hub are supported by the Limpopo River. In the province of Limpopo, water is crucial for agricultural production and has a big impact on food security. Water scarcity is one of the issues impacting the agricultural industry in the province of Limpopo, which influences food security. Social and economic demands have over-allocated water resources, but because of climate change, it is now even more challenging to balance supply and demand for water [1][2][3]. Some people may have access to an adequate supply of water while others are experiencing a water shortage in other parts of the world. Due to its water issues, Limpopo province in South Africa is not an exception in this regard [4][5][6].

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Limpopo province, one of the nine South African provinces, is predominantly rural consisting of approximately 89 % of the total population with the main occupation of the people being agriculture [7][8]. Agriculture represents 20 percent of the total cultivated land and contributes 40 percent of the total food produced worldwide. In South Africa, agricultural sector contributes approximately 2.3% to the Limpopo provincial GDP and the contribution of Limpopo agriculture to national agriculture is 7.6% [9]. Agriculture plays an important role in contributing to the growth of the economy, through agricultural production and job creation. It also plays a vital role in reducing poverty [10]. Irrigated agriculture is twice as productive as rain-fed land in agriculture, there-by it allows more production intensification and crop diversification.

The method of irrigation involves artificially supplying water to land to help with crop development. Many irrigation systems in South Africa are manually operated. The conventional methods include drip irrigation, terraced irrigation, ditch irrigation, and sprinkler systems. These antiquated methods are replaced with automated and semi-automatic methods. Due to the rising demand for greater agricultural production and water shortage, to name a few factors, automated irrigation systems are necessary [11]. Due to the issues listed below, farmers in and around Limpopo struggle to be successful in their farming endeavours. Most of these issues are caused by water waste in agriculture as well as a lack of understanding of crop growth and the amount of water required for its production. The challenges are separated into:

a) Amount of water needed
   - The distribution of water in rural areas is unfair and there is an inadequate supply. Water supply to the residents for other uses becomes insufficient since more water than needed is used up watering the crops.
   - During the summer, there are a great number of villages in our nation that could experience severe water shortages. Many of these settlements lack the administrative capacity to implement various water conservation strategies.

b) Lack of knowledge to predict rainfall.
   - Accurately pinpointing rainfall times is essential.
   - One of the most crucial hydrological factors influencing the economy of nations like India is rainfall. In India, monsoon forecasting is extremely significant.
   - However, due to their lack of expertise in this field, farmers are unable to forecast both the amount of rainfall and the time it will fall.

c) Lack of climate prediction information for crops
   - Climate change will impact the agriculture sector both now and, in the future, which will hinder the productivity of the agricultural resources in the area.
   - Information on climate forecasts has the potential to lessen the impact of extreme weather events. This knowledge will provide farmers the chance to put necessary strategies into action to lessen the effects of bad weather events and to boost productivity when the weather is suitable for growing a particular crop.
   - Crop climate forecasting on a monthly, annual, or seasonal basis helps farmers make better judgments about which crops to cultivate and raises each farmer's individual yield.

d) Need for automatic irrigation system for crops.
   - In the agricultural industry, using the right irrigation techniques is essential.

The field of agriculture has received significant attention from the research community, particularly focusing on the techniques and strategies applied to smart irrigation. The literature has noted over the years that water scarcity is a growing concern as it plays a vital role in successful farming. Having noted that, researchers have then applied different techniques to ensure crops get sufficient amount of water. The research community identified that the use of latest technology trends could have a positive impact on farming in general. A major contribution in this field is the use of Internet of Things (IoT) approach to enable smart farming, by utilizing different sensors in obtaining raw environmental data to manage existing sprinkler systems [46][47][48]. Newer contributions emerging in this domain are through the use of Artificial Intelligence (AI) to use plant, soil, and environment data for analysis, and decision making in the quest to use water sparingly [49][50][51]. Even so, in all the work investigated, this study still makes a novel contribution by combining the two major contributions (IoT and AI) in this field, to deliver an Artificial Intelligence of Things (AIoT) approach that introduces the element of rainfall prediction using pre-existing datasets of South African weather, which has not been seen previously in the literature. This work supplements the existing sprinkler systems that utilize soil sensors and uses the data to control the motor of the sprinklers. Currently, AI is utilized to analyze soil type from sensor data and provide suggestions on which crops are suitable for the identified soil type. Although the contributors in this domain have impactful outcomes, water may still be used inefficiently as there is no knowledge on when rainfall can be expected, which leads to over-irrigation. This paper aims to propose and contribute a technological irrigation system that can determine when to irrigate, how much water is required, and which areas to irrigate. The system will periodically determine whether the soil is dry, review the weather, and determine whether irrigation is required based on rainfall predictions. This will enable farmers to conserve every drop of water and correctly irrigate plants in accordance with their requirements.

In the next sub-section, we explore similar works that have been researched. In section two, the methods utilized are discussed in detail. Section three provides implementation details, with evaluation of the operation of the system. In section four, the results of the proposed system are discussed in-depth. Lastly, in section five, a conclusion is drawn, with suggestions for future work.

1.1 Related Work

Technology in farming is expanding and restructuring the way we normally do farming. This is due to new possible approaches and technological trends to make farming efficient. The main aim is to reduce inefficiency and costs, use minimum resources to maximize production and be able to predict future needs and change. Few solutions exist that solve this problem, and in this section, we discuss the solutions to identify differences and similarities with the work of this paper.

A remote monitoring system for smart agriculture using IoT was proposed by [12]. The system acted as a decision support model to advise farmers against pests & diseases by using image recognition on crops. The system measured soil attributes such as humidity and temperature and informs the farmer through short message service and web application which allows remote control of various operations on the farm. Similarly, the proposed paper primarily monitors humidity, temperature, and moisture to determine if there is a need to water the crops or not. However, in contrast, the proposed paper address water usage in agriculture as opposed to crop diseases.

In addressing water usage, [13] proposed a fully automated drip irrigation system that monitored and controlled water usage using Raspberry Pi paired with an android application. This system takes an image of a plant to check its growth by making use of image processing. When the plant height is short, fertilizer is spread on it, if there is no need to fertilization, it checks the temperature and soil moisture, if they are less than the set points, it opens the water motor on plants. Similarly, [14] undertook a similar approach, to automate irrigation without traditional human intervention. Both studies solely focus on crop health and water usage, which may still lead to inefficient water usage as it may rain post irrigation, leading to over-irrigation. In the proposed paper, farmers are provided with knowledge of rainfall prediction to be able to further save water.

The role of artificial intelligence in improving the agriculture sector and how to deal with huge amount of data obtained on a daily time such as soil reports, plant needs for fertilizer and the use of robots in improving crop harvesting was investigated by [15], [16] and [17]. The authors focused on the use of image-based insight generation to conduct a complete field analysis of agricultural land by combining between computer vision technology, the Internet of Things (IoT) to enable farmers by using AI to train machines based on historical weather pattern, soil quality and kind of crops to be grown, can automate irrigation then conserve water and benefit farmers in managing their water probs. However, the adoption of all these cognitive solutions is costly, and requires huge amounts of data to be adopted. In addition, the proposed study can serve as a steppingstone to the overall cognitive solution, providing farmers with accurate predictions of rainfall to know when and when not to irrigate using motors.

A programmable chip with an internal soil moisture sensor for automatic watering based on whether detected soil moisture is dry or not was designed by [18]. Utilizing this device enables farmers to not manually water the land. The device is only fed a soil moisture sensor and is only concerned with moist levels. However, according to [19], other soil properties such as temperature and water flow in soil need to be considered prior to irrigation. The proposed study considers these properties, as the soil may always be dry due to water flow.

Extending the work of [18], [20] introduced image processing to further identify plants affected with diseases or lacking sufficient water. To achieve this, K-means clustering was employed to find differences between affected and unaffected parts of the plant. However, plants may be subjected to diseases resulting from little watering or over-watering, of which is what the proposed study aims to address. Crops are sensitive and it is important to know when to give crops the accurate amount of water, considering soil properties and other factors such water level and flow.

An IoT-based remote monitoring system for irrigation by [21] utilized temperature, humidity, and rain sensors. These sensors communicate with the Arduino microcontroller through a Wi-Fi module. The system provides required levels of water to the farmer, as informed through sensor input data to ensure that water is preserved. Although the farmer may still override the system by manually turning on the motors, it is important for farmers to have weather conditions insights prior to utilizing the system. The proposed study provides the farmer with rainfall prediction knowledge, and to systematically put on hold the auto irrigation to preserve water and crop life.

In a real-time irrigation scheduling system by [22], artificial intelligence algorithms were deployed to learn dynamics of soil moisture, and specifically, neural networks were used to predict moisture of soil to determine water amount needed for irrigation. The prediction of soil moisture dynamics is successful only during crop growing season, as the climate data used was collected during main season of growing crops. The focus of their work was to accurately predict soil moisture in certain seasons to schedule irrigation, thus, implying that this system can only be used during crop growing season. In the proposed study, to ensure water is utilized efficiently, the Auto Regressive Integrated Moving Average model was used to perform analysis and time series prediction of rainfall.

There is clear evidence that the farmers of Limpopo province can benefit from the proposed system to help preserve water. There is not much research in providing farmers with accurate weather alerts such as rainfall predictions, to which this study adds to the body of knowledge. This can consequently benefit farmers in adequately irrigating their farms based not only on soil parameters visualized on a mobile application. Additionally, the proposed system makes use of humidity, rain, temperature, and soil sensors that act as an input source of data to reduce labour and save time in initiating the irrigation process. In the following section, the methodology is discussed, and how all these components come together to result in an automated farming irrigation system.

The following is how the paper is set up: Section 2 outlines the methodology used to prepare the data, including data comprehension, selection, transformation, and model development. The results' interpretation and assessment are discussed in Section 3. Section 4 then reviews the findings and makes recommendations for further research.

2. METHODS

In this section we observe how the components that make up the automated irrigation system are assembled. To provide clarity of each component, a block diagram of the proposed irrigation system is presented in Figure 1 below. The proposed prototype consists of hardware components, and an application as part of an automated farming irrigation system. The hardware is an Arduino ESP microcontroller with relay switches connected to it that were used to control the two motors. Motor 1 and 2 will be for irrigating the crops, and for refilling the tank respectively. The power supply plug to the microcontroller powers it up with 5 volts. The Arduino has built in Wi-Fi capabilities that connects to the soil moist sensor, water level sensor, temperature sensor and water flow sensor. The minicomputer then transmits these values to the smartphone application through the Wi-Fi interface. The smartphone application will be used to alert the farmer to current sensor readings and rainfall predictions.

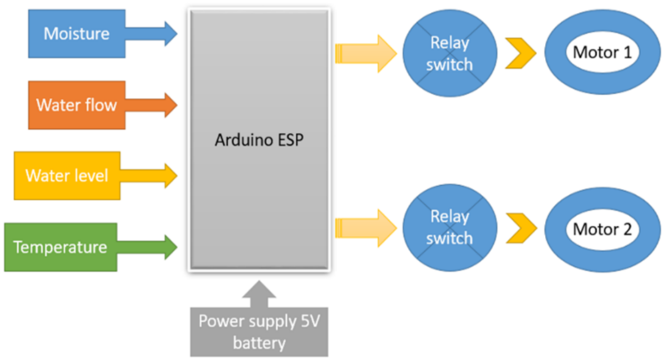

Figure 1. Block diagram of the proposed hardware components

DOI: doi.org/10.35970/jinita.v6i1.2187

In developing the system, the authors opted for an adapted design science research methodology (DSRM) [23], as depicted in figure 2 below. DSRM is a method for guiding researchers to develop artefacts (prototypes and models) in a research paper [24]. DSRM consists of 6 stages, which are problem identification, objectives definition, design and development, demonstration, evaluation, and communication. However, stage one and two have already been done in the previous section and will therefore not be mentioned here. Stage 3, which is *Design and Development*, will be covered by this section (section 2 – methods) where we provide a collection of tools and technologies utilized. Stages 4 and 5, *Demonstration* and *Evaluation*, will be shown in section 3, where we show the overall implementation of the system using the tools and technologies described in this section. Furthermore, the results emanating from the implementation are provided, and evaluated. The remaining stage, stage 6 – communication, will be covered by section 4, where a brief discussion and conclusion are provided.

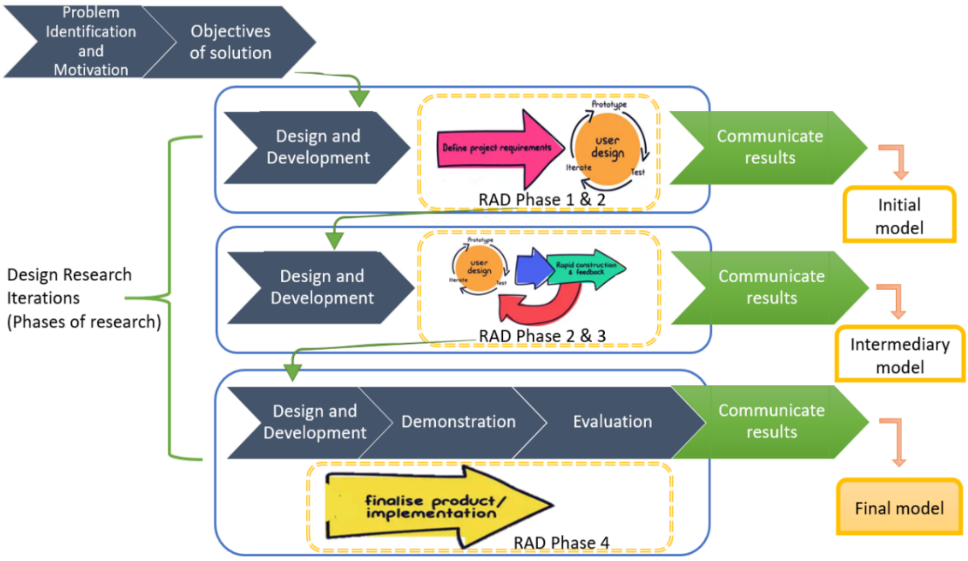

Figure 2. DSRM adapted by [25] from [26].

2.1. Design and Development – Stage 3 of DSRM

In this stage, an artifact, which is a smartphone application, and a prediction model were developed and implemented respectively. The end goal is to have the application depict sensor data and notify the farmers of rainfall alerts, which derive from the prediction model. Below we describe the two separate creation processes and later combine them to form one output, which is the automated irrigation system. First, let us explain each component utilized in the development of proposed prototype.

As shown in the block diagram in figure 1, several components and sensors were utilized for acquiring environmental data. Below is a brief discussion of each component and sensor.

i) Arduino ESP Microcontroller

The Arduino ESP8266 is a micro-controller board with Wi-Fi capabilities that acts as a circuit board to components. It is considered a microchip that performs computations [27], as shown in figure 3 below. All the other components are powered and processed by this chip.

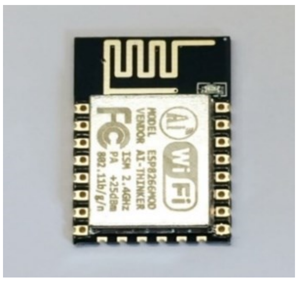

Figure 3. ESP8266 chip.

ii) Sensors

Various sensors were used in this design to acquire a vast amount of soil and environmental data to ensure accurate readings are utilized. These sensors are:

- Temperature sensor

The resistance temperature detectors (RTDs) solely measure resistance and use a conversion factor to find the temperature. The higher the resistance implies the higher the temperature, and this is called the positive temperature coefficient. The range of the temperature is 0 – 110 degrees Celsius. The measuring process is illustrated in figure 4 below.

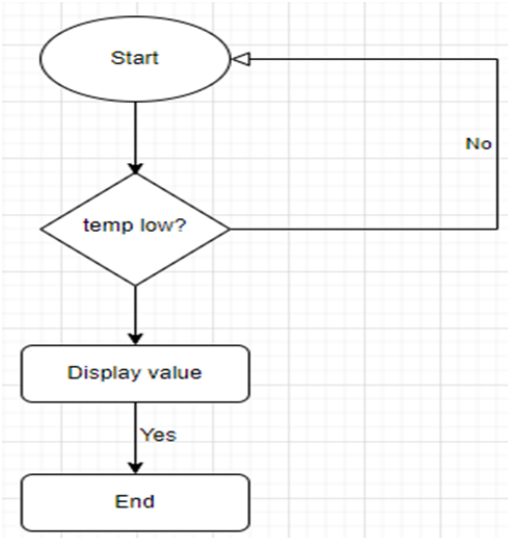

Figure 4. Temperature capacitance measuring process.

- Soil Moisture Sensors

Low cost and user-friendly devices used to observe soil moisture value through capacitance. The function of the dielectric permittivity in the soil is the water content. The soil moisture value will farmers how much water is present on the farm, to use available water accordingly [28]. The usage process of this sensor is depicted in figure 5 below. The soil moisture sensor consistently monitors soil moisture and sends data to the micro controller. The sensor plays a vital role on the system for decision making for the system to irrigate.

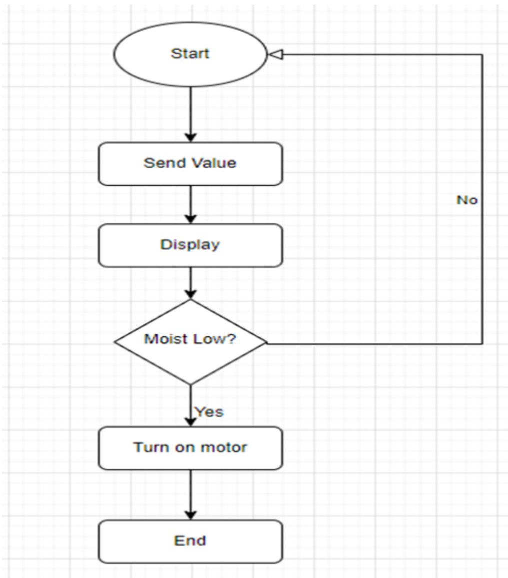

Figure 5. Soil sensor measuring process.

DOI: doi.org/10.35970/jinita.v6i1.2187

- Water flow sensor

The water flow sensor checks if there are leaks on the pipes by monitoring the water flow on the main pipe while the irrigation is turned off. Its process is depicted in Figure 6 below.

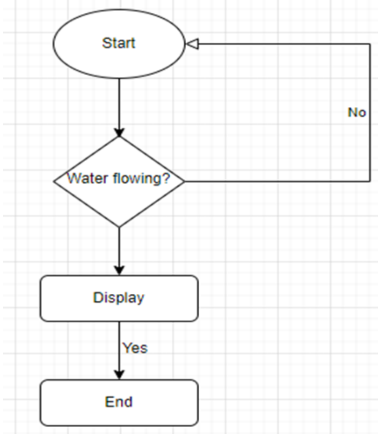

Figure 6. Water flow sensor process to monitor pipe leaks.

iii) Other components

- Motors

Rotates from 0 – 180 and controls the angular movement of the pipes to circulate water accordingly.

- Power Supply

5V power supply was used.

iv) Application development and modelling tools

- Arduino IDE

Arduino IDE is an open-source software used to write code or programs that is supplied to the Arduino board [29]. The IDE consists of a text editor section, where a traditional C++ programming language is used to write code. Another section is a text section, to display text representing messages and errors. Additionally, a console toolbar that displays menu buttons for saving projects. This is used to write code that collects sensor readings and sends them from the ESP to the smartphone through the Wi-Fi.

- Android Studio

Android Studio is also an integrated development environment (IDE) for android application development through Java or Kotlin. It provides a platform for designing applications, providing functionality to applications, and integrating with other external components such as data stores and machine learning tools. The data store we will use is Firebase Real-time database, and the machine learning tool we will use is TensorFlow lite.

- TensorFlow lite

TensorFlow lite is an open-source library that allows machine learning models to be run on android applications. Machine learning, which is a field that enables computers, systems, and software applications (machine) to learn by themselves leveraging historical data [30]. This historical data from Kaggle, along with the sensor data is fed into the TensorLite environment, as tensors, to allow the model to make predictions. Figure 7 below depicts this architecture's flow of execution. This will allow the creation of the rainfall prediction model and application development to be executed in the same environment, which will reduce model export issues and inaccuracies.

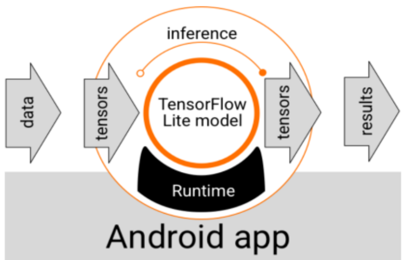

Figure 7. TensorFlow lite flow of execution.

The overall architecture of the proposed system utilizing all processes and components is shown in figure 8 below. The flow of the architecture covers the processes data input, pre-processing, storage, dataset generation, input, prediction, and output. These processes are described below in detail and represented by figure 8.

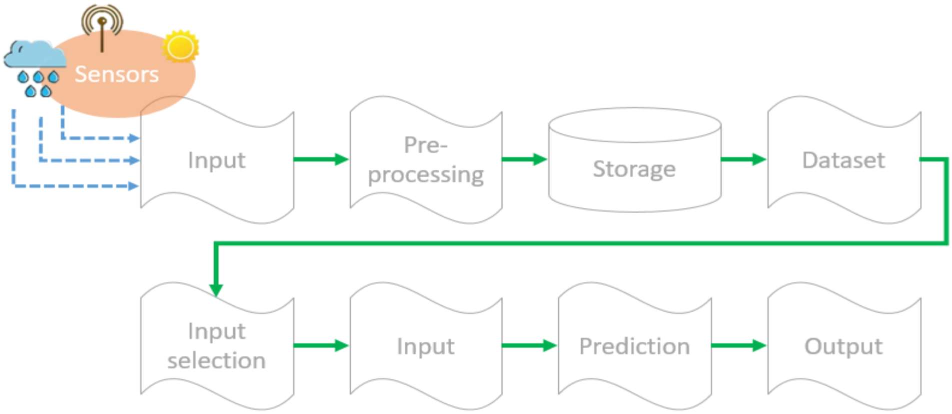

Figure 8. Flow of the Architecture of the proposed system.

i) Data Input

Initially, data is collected from burial sensor which measures temperature and degree of soil moisture every 4 hours. This data is regarded as meteorological data of the Limpopo province in South Africa once collected. Data were compiled as a table in a CSV file depicting attributes such as nature of environment and soil type. Other important attributes include month which is the planting season, temperature, morning weather humidity which is the degree of humidity in the early morning, midnight humidity which is the degree of humidity in the late afternoon, the noon weather humidity which is the degree of humidity in the afternoon, soil moisture which is the degree of moisture in the soil of agricultural lands, Soil salinity which is the percentage of salts in agricultural lands, evaporation transpiration (m3 / donum / month) which is the amount of water that one dunum of agricultural land loses in a month as a result of its evaporation, Average daily water consumption (mm) which is the amount of water a plant needs to reach the degree of hydration. This data was therefore combined with the datasets we collected from Kaggle, for the model to have sufficient data for better prediction accuracy.

ii) Pre-processing, Storage, Dataset Generation

In this process, a target data set was created from the meteorological data in the previous process by selecting a subset of variables (Soil Humidity, Soil Moisture, and Temperature) that directly affect the irrigation process. The selected data was processed, analyzed, and correlated using TensorFlow lite. The dataset was now ready for queries and generation of input for the next process to perform forecasting.

iii) Input Selection & Prediction

From the pre-processed data, using Multilayer Perceptron, significant data is extracted and used as inputs for classification and prediction purposes. The prediction of rainfall was determined. The selected significant input was used to make the predictions.

iv) Output

This is the process where results were generated. From the sensor data buried depth of 3-5 inches below the areas of roots spread in green lands, part of the data was used for testing the model and the other part for training the model.

In putting it all together, the system will be used to maximize production with minimal water resources. The system uses a microcontroller for soil and environmental data collection, and to control the motors to irrigate the farm or refill the tanks when necessary. Different sensors (moisture, water flow, water level, temperature sensors) to check different measures as input are employed, then pre-processed for feature selection. The selected inputs are therefore forwarded to the smartphone application, which consists of a TensorFlow lite API that then utilizes the data to create a prediction model. The output of from TensorFlow lite, which is the created model, is deployed on the Android application and ready to send notifications to the farmer whenever the prediction of rainfall is above a threshold of 75% chance of precipitation. Moreover, the application displays soil moisture levels, humidity, and temperature values.

3. IMPLEMENTATION AND EVALUATION

In this section, the automated irrigation system is presented as a solution to overcome the daily water crisis Limpopo farmers are facing in the country. Moreover, the results emanating from the model and mobile application are presented and discussed. This section holistically shows how each tool, technology, and component was utilized to make up the proposed system. This section delivers on the fourth and fifth stages of DSRM, *Demonstration* and *Evaluation*, as previously indicated.

3.1. Demonstration and Evaluation (Stage 4 and 5 of DSRM)

To demonstrate the proposed system, a prototype was designed using the components described in section 2 previously. The prototype shows a switch, in place of a motor, a power supply, the ESP8266 chip, the soil and temperature sensors, and a small pipe to water the soil. This is depicted in figure 9 below. The phases of the prototype are subsequently described.

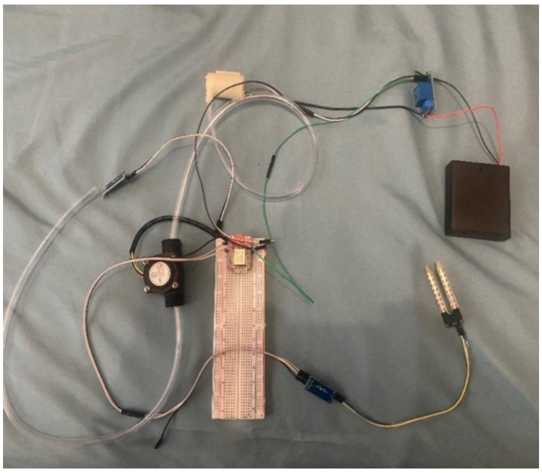

Figure 9. A prototype of the automated farming irrigation system.

1. Inputs are given based on soil moisture, temperature, and water levels constantly for every 4 hours.
2. The Wi-Fi module is used as receiver to disseminate the data.
3. A rise or drop in temperature triggers the relay switches to turn on or off. The farmer is also alerted to override the action when required.
4. Water requirement for crops can be calculated following Romyan's method [31]:
   - Calculate time required for watering crops for a type of soil.
   - 1 cu m of soil with x cu m of water is equalized so that it makes into 100% humidity level.
   - N * M per square meter crops is considered present.
   - The area is Y square meters.
   - For each stage, the depth of root immersed in the soil is Z meter.
   - P is considered power consumption of motor in hose power.
   - 1 Gallon of water is required (0.3mm)
   - F is the soil factor.
   - Thus, an ideal case would be as follows:

$$Wreq = (N * M) * Y * Z * X \quad (1)$$

Prior to the prototype watering the soil, a rainfall prediction is determined. This paper applied Auto Regressive Integrated Moving Average (ARIMA) model to perform time series prediction and analysis, and forecasting of rainfall to ensure water is used accordingly in farms [32]. A type of the ARIMA model, Box-Jenkins, consists of four steps, which are depicted below in figure 10.

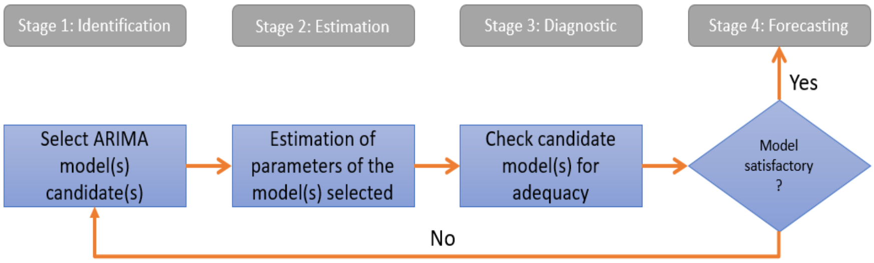

Figure 10. Auto Regressive Integrated Moving Average (ARIMA) stages [33].

a) Stage 1: Identification
   - In this step, a series of responses used in calculating the time series and autocorrelations are identified. The statement used to achieve this task is Identify.

b) Stage 2: Estimation
   - Estimation of previously identified variables is performed. Additionally, parameters are estimated. The statement used to achieve this task is Estimate.

c) Stage 3: Diagnostics
   - In this stage, a diagnostic check of variables and parameters collected in the above stages is performed.

d) Stage 4: Forecasting
   - In this stage, predicting values of time series are forecasted. The parameters used in this model describe the number of log observations, degree of difference, and the moving average order.

We further used Artificial Neuron Network (ANN), which uses specially organized computer elements to learn from data [34]. ANN computes and recognizes patterns like the brain. A dataset with inputs and outputs trains a backpropagation neural network (NN). Initial input is given to NN. NN receives untrained random weights between -1 and +1. Weight training reduces NN errors and allows output. Backpropagation NN has input, hidden, and output layers. NN has 32 inputs and 185 hidden layer neurons [35]. These neurons are linked to each NN layer. The ARIMA model determines that the ANN is suitable for rainfall prediction using deep learning techniques which are Multilayer Perceptron, for classification and prediction tasks, and Auto-Encoders for time series forecasting by performing feature extraction. The performance of this methodology will be evaluated using Root Mean Square Error (Root MSE). Figure 11 shows how the inputs of the auto-encoder network are connected to the multilayer perceptron.

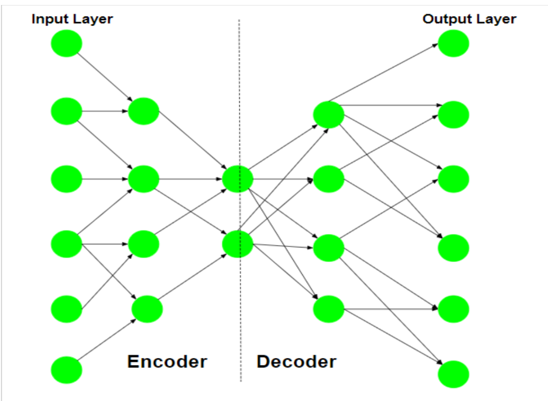

Figure 11. Auto-Encoder Architecture.

The ARIMA model and the Auto-Encoder architecture ensured that the rainfall prediction model was trained and tested with combined sensor data and datasets from Kaggle, which were split into 80:20. After splitting the data, the training process was done by measuring the temperature and degree of soil moisture through burial sensors. The sensors work on measuring the humidity and temperature in the soil every 4 hours, it prevents automatic irrigation process if the humidity is high and permitted if the humidity is low. In testing phase, the testing dataset was entered as inputs for the designed model then compared the results between the assumption and the result predicted by the model. The mobile application which is hosted on the smartphone utilizes the rainfall prediction model from TensorFlow lite, to accurately guide farmers of irrigation requirements. In putting it all together, figure 12 below provides a bird view of the joint processes of AI and IoT to deliver the said AIoT solution to the agricultural sector. The following sub-section displays the results of the model, as it plays an integral part in the overall system.

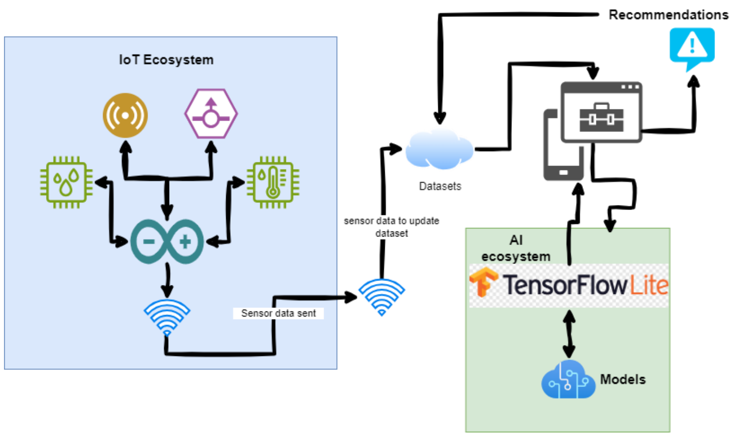

Figure 12. Bird view illustration of AI and IoT.

4. RESULTS AND DISCUSSION

It is useful to control water consumption, especially in the agriculture sector as it demands greater water resources. With the current climate state, rainfall in Limpopo province is inconsistent with regards to the weather seasons. Farmers need to adequately use the correct amount of water to not negatively affect the quality of production of fruits or vegetables which in turn increases profits. In this paper, an automatic irrigation system has been designed for agriculture, working by measuring soil moisture and temperatures to determine the amount of water required to water the crops having knowing rain predictions. Using this system, farmers can succeed in their agricultural endeavours while making profit and participating in the country's economy. Economically, the proposed system is feasible and somewhat inexpensive to adopt.

This section delivers on the sixth stage of DSRM, *Communication*, implementation and demonstration of the proposed model and prototype respectively.

4.1. Communication (Stage six of DSRM)

The Arduino microcontroller was set up successfully, as it was able to indicate sensor readings from the sensors installed. The sensor readings (data) were analyzed using machine learning; deep learning technique, named Multi-Layer Perceptron (MLP) model. Through ARIMA, MLP model was selected to make predictions from the sensor readings as to whether the motors need to be turned on or off. Selection of MLP was based on the MSE value, which is indicated in table 1, as well as in figure 13. As a result, farmers can use this model to analyze soil data and plan for the water reserved, as also concurred by [36] and [37]. There is a significant need to apply more of these machine learning methods to make predictions and recommendations, especially in the agricultural area.

Table 1. Stratified Cross Validation

Accuracy	Precision	Recall	F1	Score	MSE
0.85	0.87	0.9	0.91	0.91	0.1465
1.0	0.74	0.5	0.6	0.6	

An MSE value of 0.1 implies that the MLP model's ability to predict correctly using sensor data has better chances than chances of incorrect predictions. This results in a robust prototype that can accurately water the soil adequately due to successful automated motors. Detailed report on the MLP model is illustrated below, which demonstrates 85% accuracy score.

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
print("The accuracy score using MLP is {}".format(accuracy_score(Y_test, y_pred)))

print(classification_report(Y_test, y_pred))
```

```
The accuracy score using MLP is 0.8534304963563867
              precision    recall  f1-score   support

           0       0.87      0.95      0.91     22726
           1       0.74      0.50      0.60      6366

    accuracy                           0.85     29092
   macro avg       0.81      0.73      0.76     29092
weighted avg       0.84      0.85      0.84     29092
```

Figure 13. Classification report of MLP model.

Figure 14 below illustrates a calculated final root mean squared error score (RMSE) for the predictions, providing a point of comparison for other ARIMA configurations. A line plot was created showing the expected values (blue) compared to the rolling forecast predictions (red). We observe that the values show some trends and are in the correct scale, as shown in figure 15.

```
predicted=343.272180, expected=342.300000
predicted=293.329674, expected=339.700000
predicted=368.668956, expected=440.400000
predicted=335.044741, expected=315.900000
predicted=363.220221, expected=439.300000
predicted=357.645324, expected=401.300000
predicted=443.047835, expected=437.400000
predicted=378.365674, expected=575.500000
predicted=459.415021, expected=407.600000
predicted=526.890876, expected=682.000000
predicted=457.231275, expected=475.300000
predicted=672.914944, expected=581.300000
predicted=531.541449, expected=646.900000
Test RMSE: 89.021
```

Figure 14. RMSE for predictions.

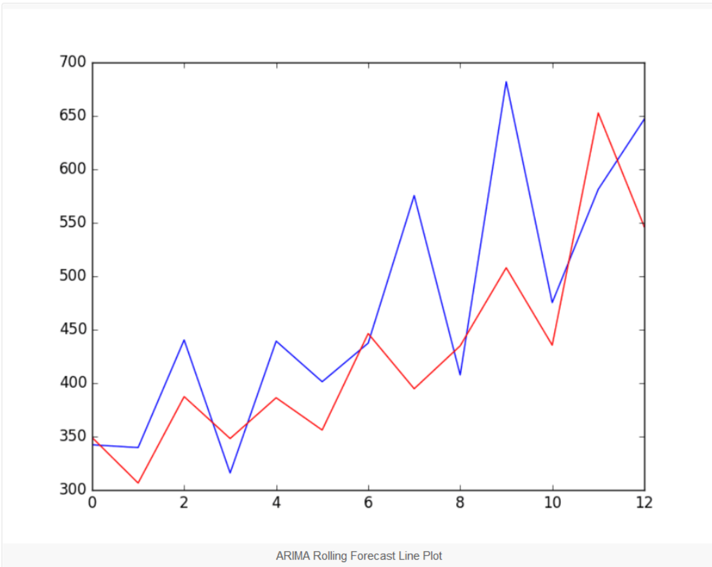

Figure 15. Rolling Forecast Prediction.

For the Arduino ESP microcontroller to share the readings with the smartphone application, the microcontroller was set up as a Web server using the WebServer ExpressIf library. The smartphone needs to be on the same network (Wi-Fi) as the Arduino ESP for data to be exchanged. The Web server setup allowed the Arduino to additionally act as an access point, for which the smartphone connected to. Once connected, the access point's IP address becomes the web where the response messages and data from the Arduino will be directed to. The smartphone application used an HTTP library to download data posted by the Arduino from the web server, then display it in a neat format to the farmer.

The readings obtained by the sensors are displayed on the microcontroller, which are then sent to the web server in JSON format. Accessing the web server through the IP address of the ESP's access point, the application extracts these data for displaying purposes. Figure 16 below is a representation of the extracted data from the web server.

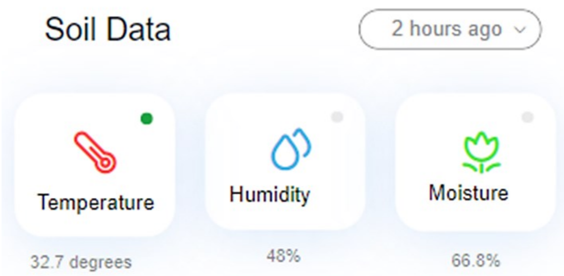

Figure 16. Representation of sensor soil data in-app.

The figure above indicates the temperature is below the threshold, which is 56 degrees Celsius, as declared by [38]. The motors are not triggered in this instance. Additionally, humidity readings indicated a significant amount which is nearly 50%. According to [39], humidity needs to be balanced, reason being that high humidity causes water usage by the plant is to be slow and compromises quality. Likewise, if humidity is very low and subsequent transpiration is too high, the plant closes its stomatal openings to minimize water loss and wilting [28] and [40]. The soil moisture sensor measures the amount of water in the soil [41][42]. Soil moisture is represented in percentage using the formula *Moisture in percentage = 100 – (Analog output * 100)*. The obtained readings were 340 AC. The ESP8266 Arduino deployed uses a 10-bit resolution, thus the analog output was divided by 1023, which is the highest AC in a 10-bit microcontroller [43]. Thus, substituting *Moisture in percentage = 100 – (340/1023) * 100)* gave 66.8% moisture level. As concurred by [41], 41% to 80% demonstrates significant level in crops, thus, the motors did not need to be turned for irrigation.

When the soil moisture percentage stays the same or increases during the same day, as the sensor readings occur every 4 hours until evening, the application makes the deduction that there is a pipe leak as the soil always has more or the same level of water. Figures 17 and 18 show an updated user interface for when there is normal flow of water, and when a pipe leak is determined.

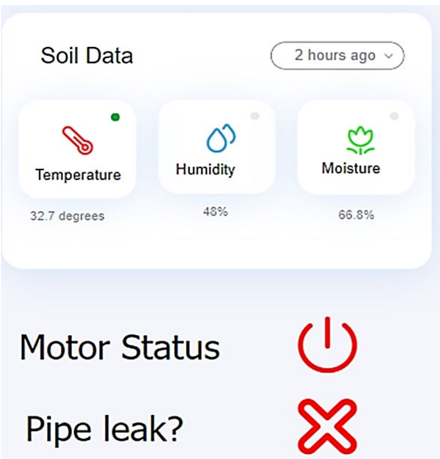

Figure 17. Output of motor status resulting from soil parameters.

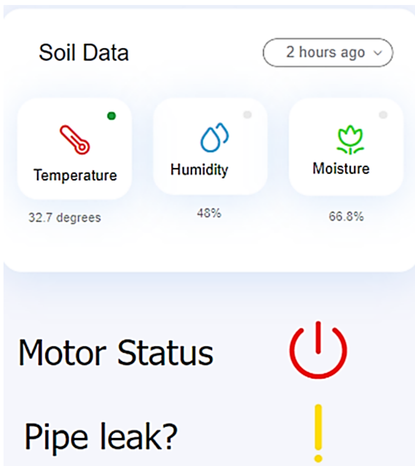

Figure 18. App alerting user of possible pipe leak resulting from soil parameters.

The results obtained in this proposed study reflect those of [36, 43, 44]. As concurred by [45], machine learning models and Internet of Things can change agricultural processes and make it dynamic, thus enabling increased production of food. Although the work in this study is in line with those in the literature, in comparison, this study emphasizes that farmers could further save more water when they have knowledge of rainfall prediction, which is what makes the study novel. After careful investigation of the literature, there is no work depicting integration of model prediction, on a smartphone application.

5. CONCLUSION

The provision of water has a high priority in the agriculture sector as it is the most water consuming sector. Due to the critical situation of available water resources in the Limpopo province, attention should be paid to the issue of water needs of plants and scheduling the appropriate irrigation to spread the right ways in the management of modern irrigation and effectively transfer rainfall prediction knowledge to the farmers. In this paper, an automated irrigation system for Limpopo farmers was designed to assist in effectively and efficiently utilizing water in the farms. We utilized Machine learning and Internet of Things concepts to propose an Artificial Intelligence of Things (AIoT) solution that can greatly improve the agricultural processes offered at lower costs and without requiring heavy machinery. The sensors deployed in the fields can accurately collect different soil parameters such as temperature and humidity. Through the micro-controller's WiFi module, these readings are sent to the locally stored dataset for processing, which was initially obtained from Kaggle. This is to ensure that the application always works with recent data for accurate predictions. With the application built on top of a TensorFlow lite environment, ML algorithms and models such as ARIMA and ANN are readily available to process the sensor readings in real-time, offering farmers with on-the-spot recommendations, such as whether to have motors switched on or off based on the prediction percentage. In addition, the application utilizes these readings to inform the farmer of the level of the soil parameters.

The results of this study and those of related works suggest that these systems can promote efficient water usage. In future work, Long Range (LoRa) technology of IoT could be adopted to target big farms as this technology could span over 10 kilometers. This would enable soil properties of the entire farm's spectrum to be monitored and irrigated accordingly by the accurately displaced motors. It is important to note that using mobile applications could anchor the system due to battery life issues and connectivity issues. It is recommended that the smartphone application be backed up by a web application which can be accessed by any device with Internet access. Moreover, we are targeting short-term predictions of rainfall, and in future, we may look at other suitable models for long-term predictions. This would ensure that the MLP execution is reduced and in turn saves battery life of the smartphone.

ACKNOWLEDGEMENTS

We would like to thank all the authors involved in ensuring the success and completion of this work through diverse knowledge and expertise. We further acknowledge Tshwane University of Technology for all the components acquired for this work.

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