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Autonomous Smart Irrigation for Paddy Farming Using AI-Enhanced Dense Neural Networks and IoT-Based Soil Moisture Control

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ABSTRACT: This study focuses on the use of artificial intelligence (AI), in the form of dense neural networks (DNNs) to the improvement of irrigation practices in paddy agriculture. To obtain a high fidelity data set with 420 time ordered data records which include temperature, relative humidity, wind velocity, atmospheric pressure, meteorological parameters and soil moisture tension, a customized Internet of Things (IoT) based data acquisition system was designed and deployed in the field. A specialized DNN, considering the binary cross-entropy loss function, was used to predict the irrigation requirements with five hidden dense layers mixed with dropouts to overcome over fitting to represent a methodology for supplementing crop monitoring and management in the smart farming concept. Performance evaluation, which was done on the basis of accuracy, precision, recall, and F1 score, provided 99.17 percent accuracy, 99.25 percent precision, 99.12 percent recall, and 99.19 percent F1 score, which proved the model's ability to predict the irrigation necessity with great efficiency. The findings highlight the potential of DNNs in enabling data-driven, temporally accurate decision-making in agriculture, with the benefit of improved yield and water consumption. System autonomy is ensured by the activation of a water pump when soil moisture tension drops below 10 kPa and the termination of irrigation when moisture reaches or exceeds the threshold value, having precise water delivery. Moreover, the study highlights the synergy of IoT and AI as a route towards sustainable farming, as well as water conservation, optimization of resources, development of efficient and technology-based agricultural methods.

KEYWORDS: Plant Irrigation, Deep Neural Networks, Binary Cross-Entropy, Dense Neural Network, Smart Farming, Internet of Things.

1. INTRODUCTION

Paddy rice farming forms an integral part of the global food security; however, the need for wise consumption of water calls for sustainable interventions and mitigation approaches to cope with the environmental impacts [1]. Employing reduced volumes, reusing and recycling of water within the paddy systems is indispensable for resource conservation, climate resilience, biodiversity preservation [2], especially when incorporated in food - system development with guiding principles of sustainable practices and policy frameworks with integrity [3], thus strengthening global efforts for agricultural resilience and sustainability [4]. Yet, rice cultivated in puddle paddies is not exempted from these limitations, particularly in terms of water use, agricultural water competition and exploitation of resources [5]. It is interesting to note that climate change is making the need to have energy-intensive water management strategies even more pressing [6]. Without innovative technologies and systematic assessments of alternative water use schemes for crop growth, the prospects for crop production with paddy rice look bleak [7]. AI is also influencing rice cultivation through remote sensing and precision agriculture technology that enhances monitoring, disease detection, watering and fertilization, better allocation of resources, crop yield predictions and smart harvesting through accurate weather prediction [8, 9]. Analytic smartphone applications also contribute to effective field surveillance. AI's adoption for reduced environmental effects and market analysis is ushering in a new era toward lesser resource-intensive and more responsible data-centric paddy farming that, thus, improves the quality of crops, their yields, and food security. Besides, AI models perform very well in analyzing sequential data: they have become good choices for time series, language processing, and speech tasks by using feedback loops to capture temporal dependencies [10]. SVM specializes in both classification problems and regression in high-dimensional space, focusing on optimal hyperplane separation [11]. Random Forest works on the ensemble principle and combines the predictions of various decision trees for different tasks, thereby helping in determining the importance of features [12]. k-Nearest Neighbors (KNN) works in a straight-line way to perform effective and efficient assignments of classes or averages on the basis of a nearby neighbor and fits the profile of recommendation systems and anomaly detection techniques [13]. On the other hand, Logistic Regression, which is capable of doing binary classification, describes probabilities by means of logistic functions and finds application in the medical and financial areas [14]. In addition, the model augments the monitoring of paddy farms by assisting in the informed decision-making and optimizing resource allocation based on the water levels in soils, thereby enhancing the efficiency and yield of rice cultivation [15, 16]. Growing of paddy requires very careful management of water, temperature, soil, and pests for a successful harvest [17, 18]. Such model is apt for monitoring paddy farms because they have specialization in sequential data, which feed in its results from the weather stations and soil moisture sensors that guide on irrigation needs [19, 20]. Additionally, the structure can provide feedback on water-saving measures for paddy farming amid limited resources and sustainable agricultural practices. Given the needs of paddy fields for large volumes of water with an optimum at 10 kPa (kilopascal) to maintain moisture without suffocating the plants [21, 22], the importance of water-efficient management for sustainable agricultural practices arises. Through AI-driven advance conditioning, precision agriculture and sustainability add more to yield and food safety. Parfitt, et al. [21] recommended sprinkler irrigation as the best replacement for flood irrigation operation on areas that are uneven by ensuring very careful and meticulous management of waters coupled with fertilizers and by recommending specific soil water tensions at certain growth stages. Moreover, Aziz et al. [22] developed an IoT-based smart farming system for monitoring paddy field using sensor network and cloud storage in order to optimize irrigation regimes. Meanwhile, Jha, et al. [23] have stood behind agricultural automation technologies, such as IoT and AI, which are promising developments in precision farming and intelligent systems. On top of that, in the work of Adhikari, et al. [24], they proposed a vision-based approach to identifying crop rows on paddy fields against low-level methods via coupled deep neural networks. Liu, et al. [25] focused on experimenting on different capabilities of models (REG, ANN, GEP) in predicting growth of rice and concluded that GEP was the most reliable model regardless of climates and rice variety. However, there was a lack of evidence on the literature related to optimization and measurement of water in Rice growing in relation to AI. Importantly, the approach adopted in this study is analogous to what has been taken in [22] that uses multi-sensor network and cloud-based repository. This study proposes an automatic closed-loop smart irrigation system based on the real-time soil moisture tension (kPa) as the control variable to fill this gap. Autonomous and efficient water management is done in accordance with the crop's requirement, as irrigation is activated when the moisture level falls below -10 kPa and halted when the level exceeds or is equal to -10.This allows for autonomous, efficient water management, appropriate for the crop's water requirement, by triggering irrigation when moisture becomes less than -10 kPa and stopping irrigation when moisture is at or greater than -10 kPa.

This manuscript presents a local model built based on the internet of things and artificial intelligence for predicting the irrigability of soils in the city of Kirkuk in the North of Iraq, during the months of July-August 2023. The data was collected from a customized Internet of Things (IoT) sensor network system with a dual microcontroller architecture comprising of an Arduino Uno and a NodeMCU ESP8266, which was connected by a voltage divider circuit as a way to assure the hardware compatibility. The autonomous sensing apparatus continuously monitored six pertinent environmental measurements: temperature, relative humidity, wind speed, atmospheric pressure, derived meteorological indices and the soil moisture tension, with some 400+ temporally sequential observations available for time series prognostication.

The rest of the paper is organized as follows: Section 1 enunciates the significance of paddy cultivation with the help of artificial intelligence in the field of agriculture. The methodology framework is detailed in section 2, and comprised of a data acquisition and control subsystem based on the Internet of Things (IoT) (2.1) and the creation and testing of the AI model (2.2). The findings and discussions of the empirical study are presented in Section 3 while Section 4 concludes the manuscript.

2. METHOD

This research utilizes a methodologically strict two-stage procedure. In the first stage an IoT based data acquisition system is customized and implemented in order to collect a high fidelity, temporally resolved dataset from a paddy field. The second stage uses this filtered data set to create, train and test a special type of deep neural network (DNN) model that is designed to predict soil irrigation needs.

2.1. IoT-Based Data Acquisition and Control System

Modelling in the artificial intelligence system is always reliable and consistent, the production of a reliable and consistent dataset is a prerequisite. The system architecture has been deliberately designed in a dual microcontroller approach, to break the limitation of the input pins common in Wi-Fi development boards and to provide a stable and long-term operation.

The hardware configuration was an arduino uno microcontroller, which is an affordable sensor hub dedicated to the purpose. This board was chosen because of its large number of analog and digital input pins, thus allowing the easy and parallel connection of all the required environmental sensors. The built-in sensors were: DHT22 (ambient temperature in Celsius and humidity in Percentage); capacitive soil moisture sensor whose analog output was programmed processed to give soil water tension in kilopascals kPa; anemomer analog, Adafruit cup type (for wind speed in m/s); BMP280 sensor (for ambient pressure in hPa) with I2C communication. A standalone NodeMCU ESP8266 board was used to serve only as a network communication gateway that received the collected sensor data from the Arduino Uno and communicated it wirelessly with a cloud server [22].

The two microcontrollers were connected through a serial connection (UART). The transmit (TX) pin of Arduino Uno was connected to the receive (RX) pin of the NodeMCU, while the ground (GND) pins of both the boards were connected to create a common reference. Due to the fact that the Arduino Uno is a 5 V logic device but our NodeMCU is a 3.3V device, a voltage divider circuit was necessary in order to lower the signal voltage safely. This circuit which includes a 1kohm resistor (R1) and a 2kohm resistor (R2) was connected between the TX pin on the Uno and the RX pin on the NodeMCU. The voltage divider helped to ensure that the 5V signal from the Arduino was stepped down to about 3.3V signal before it reached the NodeMCU, to avoid any potential damage to the input pin of NodeMCU. The output voltage (Vout) was calculated by applying the formula of a voltage divider shown in Equation (1).

$$V_{out} = \frac{R_1}{R_1 + R_2} \times V_{in}$$

Where (V_{in}) is the input voltage (5V from the Arduino Uno Tx pin), (R_1) is the first resistor in series (1 $k\Omega$), (R_2) is the second resistor connected to ground (2 $k\Omega$), and (V_{out}) is the resulting voltage at the node between R_1 and R_2, which connects to the NodeMCU Rx pin. Substituting the values ensured a safe logic level for the 3.3V NodeMCU as given in Equation (2).

$$V_{out} = \frac{2000}{1000 + 2000} \times 5 \approx 3.33\ V$$

The entire system was powered autonomously by a solar-charged battery bank, enabling off-grid operation for the duration of the data collection campaign. The complete hardware and signal flow configuration is illustrated in Figure 1.

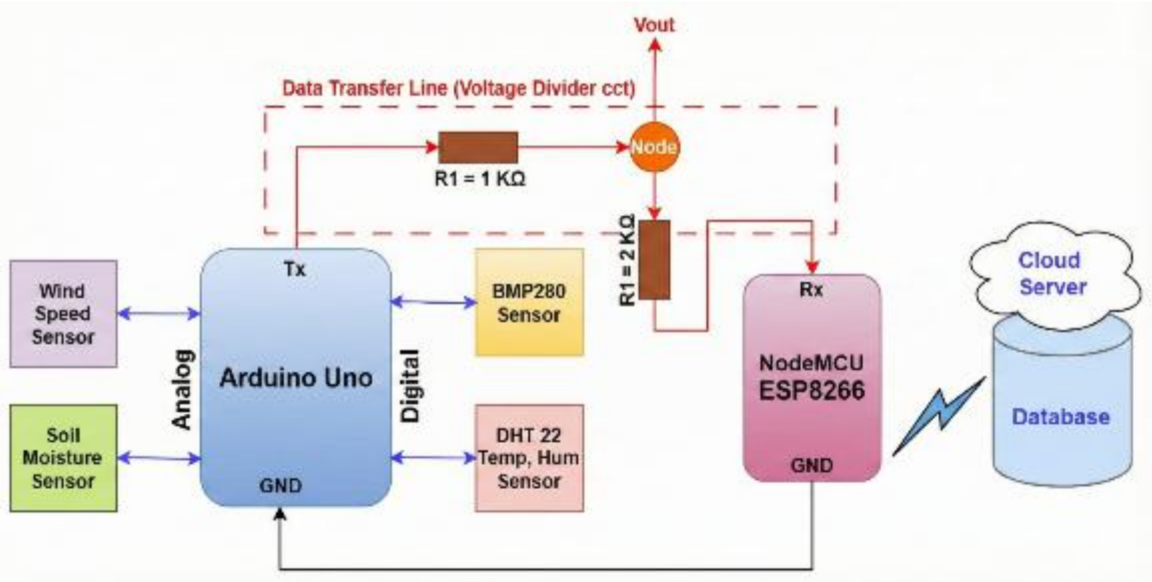

Figure 1: IoT-Based Data Acquisition System Architecture

The sampling interval was set to 30 minutes to produce a time-series data. An Arduino, UNO was used to read out all sensors in sequence, convert the raw sensor readings (for instance, convert the soil moisture voltage to kilopascals) and algorithmically determine a categorical label, Weather-Condition (such as sunny, cloudy, rainy) using heuristic rules on the sensor readings at each cycle. These regulations analyzed the trend of temperature and humidity and soil-moisture tension with the assumption that a high humidity and the increasing soil-moisture tension would have indicated Rainy weather and a constant high temperature with low humidity, would have indicated Sunny weather. At a set time the Weather-Condition and direct parameters (Temperature, Humidity, Wind Speed, Atmospheric Pressure, Soil Moisture) were collected and stored in a data-packet. This packet was sent over to a NodeMCU through the serial interface where a complete packet was received followed by the opening of a Wi-Fi connection and transmitting the data to a secure cloud database via a standard HTTP POST request [22]. This transmission protocol was able to deliver good data logging on a remote server, and thus the final curated dataset of 420 sequential records of the environment.

There were many points of validation to guarantee data integrity, including sanity checking the values on the sensors in the firmware, the NodeMCU would re-transmit if upload failed, and there was some preprocessing on the server. The latter preprocessing consisted of the normalization of all the numerical features in the {0, 1} range, and the formalization of the data in time series format that would later be used for the training of the AI models.

This is an IoT based smart irrigation system that continually measures the capacitive soil moisture sensor installed in the soil and converts the soil moisture tension in kilopascal. The basic control logic has been developed to keep the soil moisture at an optimum set point of 10kPa. When the moisture goes below this set point, irrigation is turned on, and when it comes up, irrigation is turned off [21, 22]. A hysteresis band was added to prevent the pump from rapid cycling caused by sensor noise and sensor fluctuations. In particular, the water pump is triggered at a lower water tension of 9.7 kPa when the soil moisture tension falls below this level. Irrigation is continued until irrigation water moisture is greater than an upper limit of 10.3 kPa, which causes the pump to turn off. 0.6 kPa hysteresis around the 10 kPa setpoint ensures minimal unnecessary actuation, prevents damage to the pump hardware, and offers better system control. This control logic is implemented in a microcontroller, which takes the real-time sensor data, runs a preprogrammed conversion algorithm to convert the raw moisture data to kPa units, and then uses the kPa amount to actuate the pumps. System would also be equipped with auxiliary sensors such as ultrasonic water-level sensor, which would monitor the water level in tanks and ensure a constant flow of water. All the information gathered by the sensors are uploaded to a cloud repository through a custom-designed IoT platform where they are stored, analyzed and visualized via web interface, for remote supervision and to track past. The system saves a lot of water by keeping the soil moist within desired values of about 10 kPa of moisture (Figure 2) saving energy and enhancing sustainable agricultural output without the need to have human hand-control.

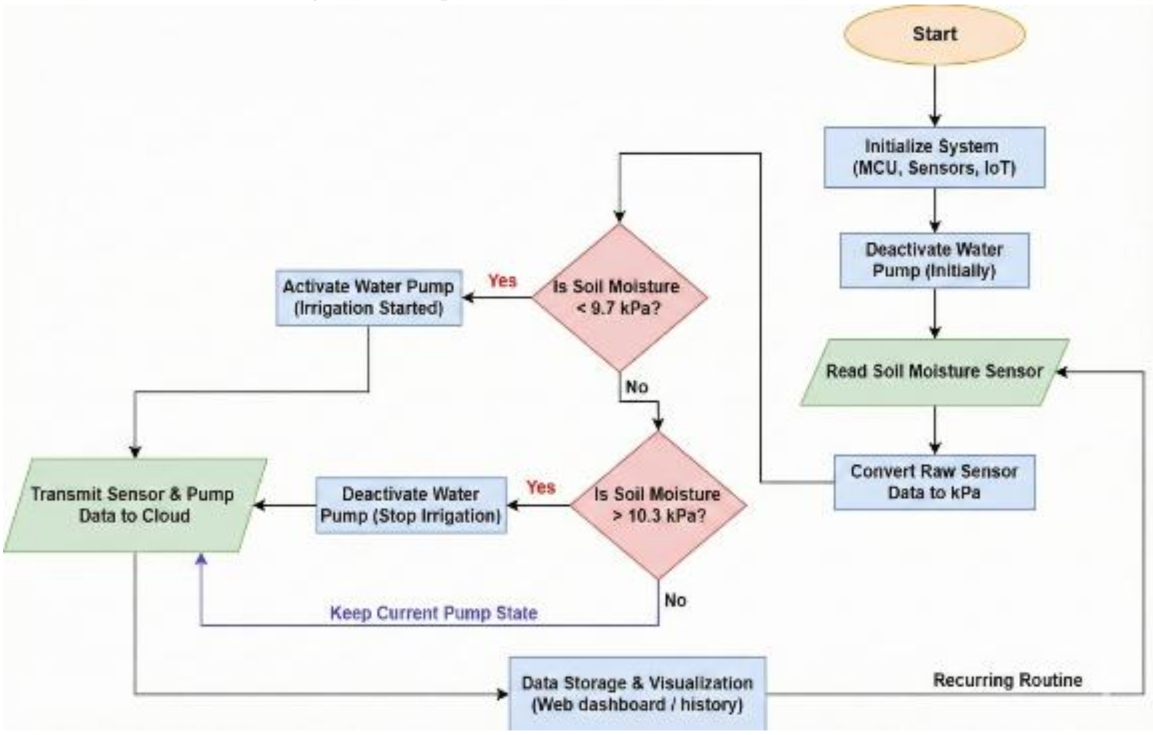

Figure2: Flowchart of the IoT-based smart irrigation control system

2.2. AI Model Development and Evaluation

The dataset of 420 records got from and preprocessed by the IoT system described in Section 2.1 formed the empirical base for the predictive Deep Neural Network model construction. The primary aim of this investigation was to develop a binary classification model to distinguish the need for irrigation in the near future with high reliability using the strength of multivariate environmental inputs. A range of metrics, including accuracy, precision, recall and f1-score were used to assess performance, with particular focus on balanced datasets to gain an overall picture of the strengths and limitations of the model. Accuracy provides an overall performance measure of correctness, however it may not adequately reflect the behaviour of models when there is class imbalance – in this case, precision, recall and F1-score are more informative and nuanced ways of evaluating model performance. Precision measures how well the model is able to minimize the number of false positive incidents, while recall measures how well the model is able to accurately flag positive cases. TheF1 is the harmonic mean of precision and recall and is the balance between false positives and false negatives. This balance is of utmost importance when we assess models because improvement in one measure often causes degradation in the other measure so the F1-score is particularly useful for assessing this balance.

Certainly, the model will pivot around the precision versus recall trade-off, and hence, F1 provides an aggregated measure based on a specific objective. The relative relationship between precision and recall brings together the F1-measure to provide a common basis for selecting models based on specific objectives. While assessing models, precision, recall, and F1-score will assist in choosing the model that precisely matches the application's requirements as it best depicts the trade-off between precision and recall. For clarity, those formulas for accuracy, precision, recall, and F1-score are summarized in Equations (3-6) [26].

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{3}$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{4}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{5}$$

$$F1 - Score = 2 \times \frac{Precision \times\ Recall}{Precision +\ Recall} \tag{6}$$

In a classification problem, True Positives (TP) are positives and predicted positives. True Negatives (TN) are negatives and predicted negatives that are recognized as intended. If negatives are predicted positives, they are false positives (FP); if positives are predicted negatives, they are false negatives (FN). These four will be required to establish how accurate the model is at predicting positives and negatives (or, in this case, excess irrigation vs. non-excess irrigation) and required to understand precision, recall, and the F1-score

The information retrieved through the IoT infrastructure was further processed in order to make it friendly to a deep neural network training. Despite the fact that the hardware platform performed initial validation and normalization, the observations needed to be transformed through the aid of auxiliary transformations into the format of binary classification. The instances were labeled based on the soil moisture tension; the ones with a lower 10 kPa were labeled as requiring irrigation (label 1) and the ones with a 10 kPa or higher were labeled as not requiring irrigation (label 0). Such dichotomous labelling is the dependent variable of supervised learning. This gave a data set that had an almost equal distribution within the two classes with 56 percent of the data falling in the positive class (irrigation required) and 44 percent falling in the negative class. This kind of balance counteracts the threat of class-specific bias when training models. All six explanatory variables including the temperature, humidity, wind speed, atmospheric pressure, derived weather condition, and soil moisture were rescaled using min-max normalization to a range between 0 and 1. The process normalizes the weightings of each feature and accelerates network training through the use of the gradient-descent optimization.

The environmental parameters gathered by the IoT system have a direct physiological relevance to the needs of irrigation. Humidity affects the rate of evapotranspiration, with increased humidity normally reducing the amount of moisture lost by the soil and possibly lowering the frequency of irrigation needed. Temperature directly influences evapotranspiration (generally high temperatures will increase water demand). Wind speed increases the evaporation of soil from its surface, especially when in exposed field conditions. Atmospheric pressure is an index of the imminent changes in weather conditions, and the reduction of atmospheric pressure is often followed by precipitation phenomena which may reduce the need for irrigation. Soil moisture tension, measured in kilopascals, is the best available index of water stress on plants, for paddy cultivation, a moisture tension of 10 kPa is determined to be the optimum water tension level. These interrelated parameters together provide information in irrigation decisions and thus make them adequate features for forecasting models. This research introduces a tailored Deep Neural Network (DNN) designed to forecast soil irrigation requirements based on data gathered from local sources. Figure 3 illustrates the architecture of this AI model.

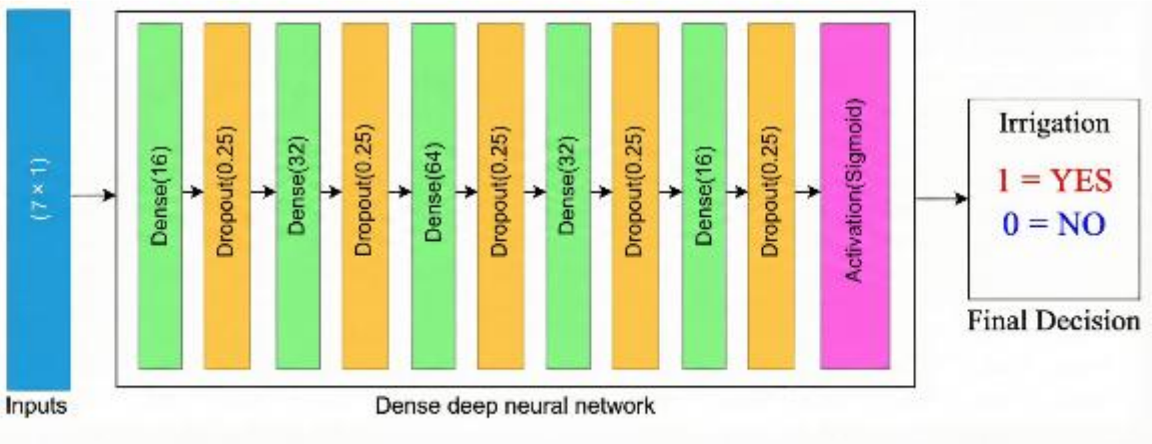

Figure 3: Design framework of the proposed model

Thirty characteristics are fed to the model (see List 1). In it, a deep neural network is used which consists of 5 hidden dense layers (16, 32, 64, 32, 16) in a specific order. The training process is designed to minimize overfitting by include a dropout layer after each dense layer with a probability of 0.25. The last layer is sigmoid because it is the ideal activation function for binary classification (soil irrigation required or not). In this framework, a binary cross-entropy loss function (Equation 7) is used for binary classification [27].

$$L_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (7)$$

Where, N is the number of samples, y_i is the correct class label of the i^{th} sample (a binary label 0 or 1), and $\hat{y}_i$ is the model's prediction of the probability that the i^{th} sample is from class 1. BCE loss function plays a very important role in binary classification. Measures the distance between predicted probabilities by the model and actual outcomes. It is a window into the model's probability estimation and as a consequence serves as a feedback signal during training, a push towards increasing the accuracy. Thus, the objective of training is simple: minimize BCE. The less it gets, the better the model learns to predict matching true with predicted labels. However, binary classification is for two classes, it is actually the model should predict how near each point is to the positive class. In both scenarios the BCE would punish the model by assigning low probability to its prediction of the true 1, and high probability to its prediction of 0 when it is a 1, and vice versa. The loses are contributed by each and every individual data point, and averaged to provide an overall sense of the model's performance. The next step is optimization; the model parameters are typically tweaked until the series of iterations of gradient descent make the probability predictions just miss the actual binary outcomes. This entire process is narrowing that gap and lowering BCE and strengthening prediction in definition and confidence.

3. RESULTS AND DISCUSSION

Explaining The proposed AI model is developed and trained using KERAS and COLAB. The dataset is divided 80% for training and 20% for validation. The training process is executed for 500 epochs with the settings presented in Table 1.

Table 1. Configuration settings for training

Parameter	Value
Learning rate	1×10^{-4}
Epochs	500
Optimizer	Adam Optimizer
Beta 1	0.9
Beta 2	0.999
Loss function	Weighted Binary Cross entropy
Metric	Accuracy, Precision, Recall, F1-Score
Train dataset size	80%
Test dataset size	20%
Trainable parameters	5,409

The proposed model has demonstrated superior performance in evaluating the test set after being trained for 500 epochs, producing a test loss of 0.0565 and a 99.17% overall assessment of its performance as measured by each of the evaluation metrics (accuracy: 99.17%, recall: 99.12%, precision: 99.25%, and F1-score: 99.19%), as depicted in Figures 3. Specifically, these figures show the trends of training and validation accuracy over the 500 epochs of training, showing that the model’s predictive accuracy improves incrementally as it becomes exposed to the dataset. The training accuracy is indicative of the number of correctly classified instances from the training dataset, while the validation accuracy is representative of the model’s performance on an independent validation dataset that is used exclusively for assessing the model’s performance on unseen data. Therefore, the difference between training and validation accuracy is referred to as the generalization gap; when there is a small generalization gap, as shown in Figure 4, the model is able to avoid overfitting and generalize well to new data.

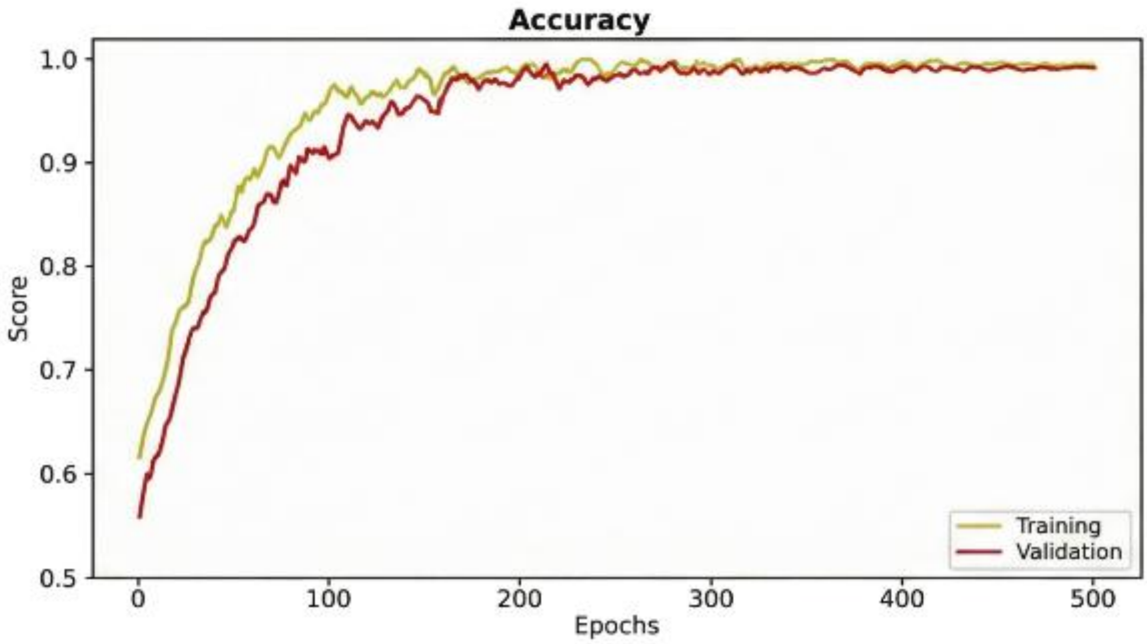

Figure 4: Training and validation accuracy for paddy plant irrigation

Recall is used to measure the model's effectiveness in identifying positive instances from the training data, and the model's ability to recognize such instances from a separate, held-out dataset. As depicted in Figure 5, both training and validation recall are improving over time as the model continues to train, demonstrating the model's increasing ability to recognize positive examples as training occurs.

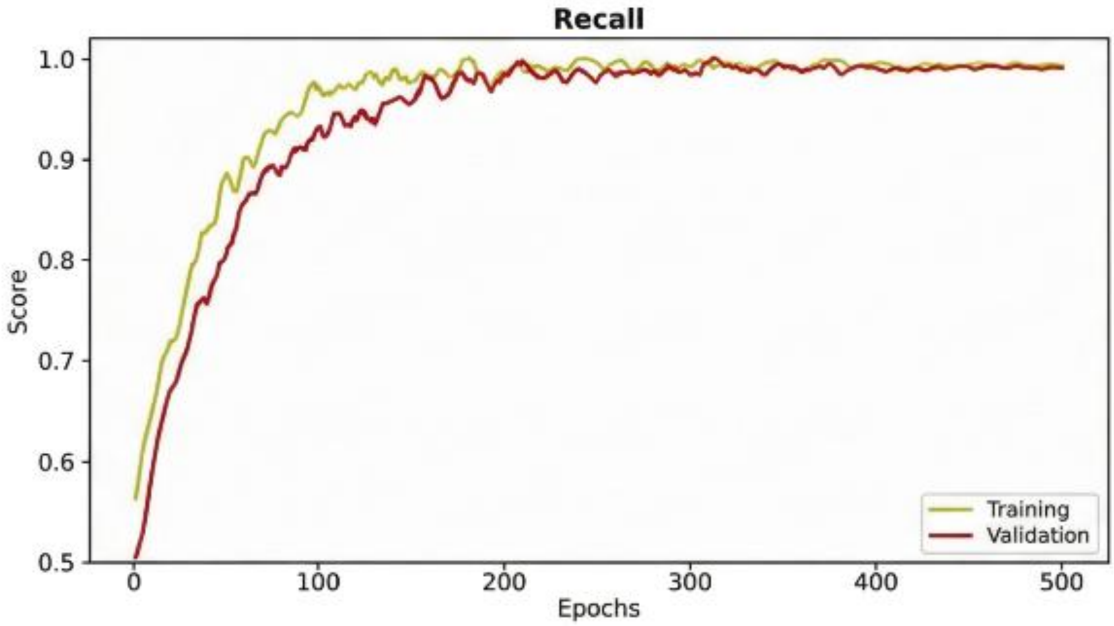

Figure 5: Training and validation recall for paddy plant irrigation

Precision is defined as the proportion of true positives relative to all predicted positive instances, and is utilized to assess whether or not the model is able to predict positive instances without also incorrectly predicting negative instances as positive. As depicted in Figure 6 precision improves steadily throughout the training process as epochs continue to occur, with validation precision first increasing then stabilizing at approximately 200 epochs. Therefore, the trend of both training and validation precision demonstrate that the model is continuing to learn and generalize effectively.

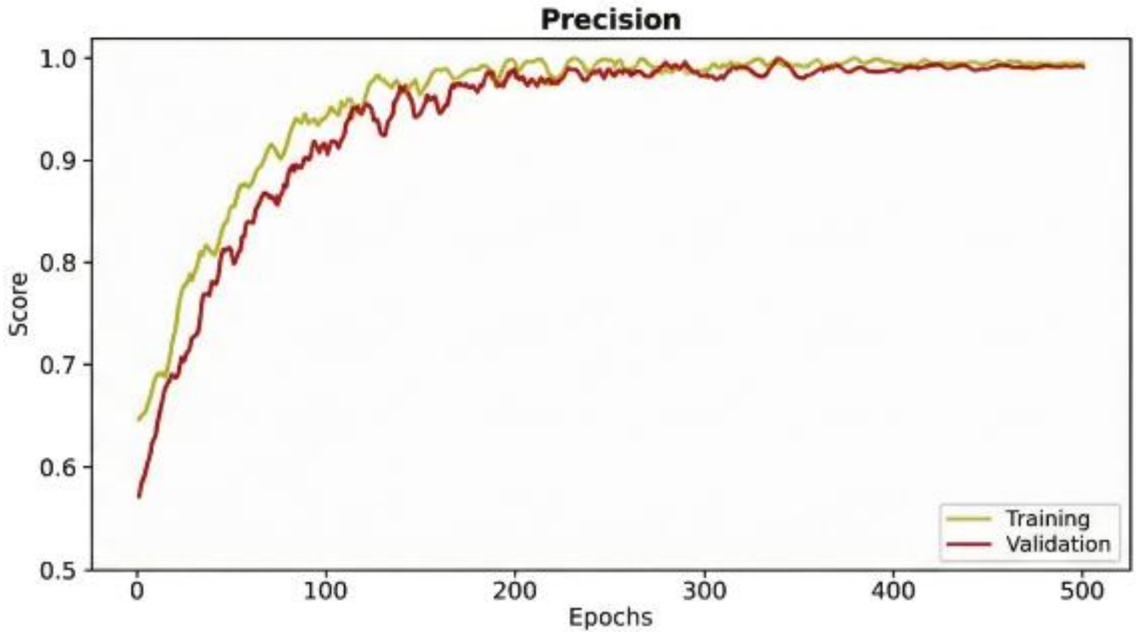

Figure 6: Training and validation precision for paddy plant irrigation

For Figure 7, the F1-score, which indicates combined precision and recall, reveals increasing training and validation F1-scores across epochs. The validation F1-score was obtained from test data not used by the model, validated so that learning could not occur based solely on test data (which may overfit training to gain a value on training). Evaluating training data where the model had no opportunity to learn from it means that the model could not learn to effectively gain value on just this one data set. Still, the values derive from the model are supportive of its potential to work effectively on other unseen data.

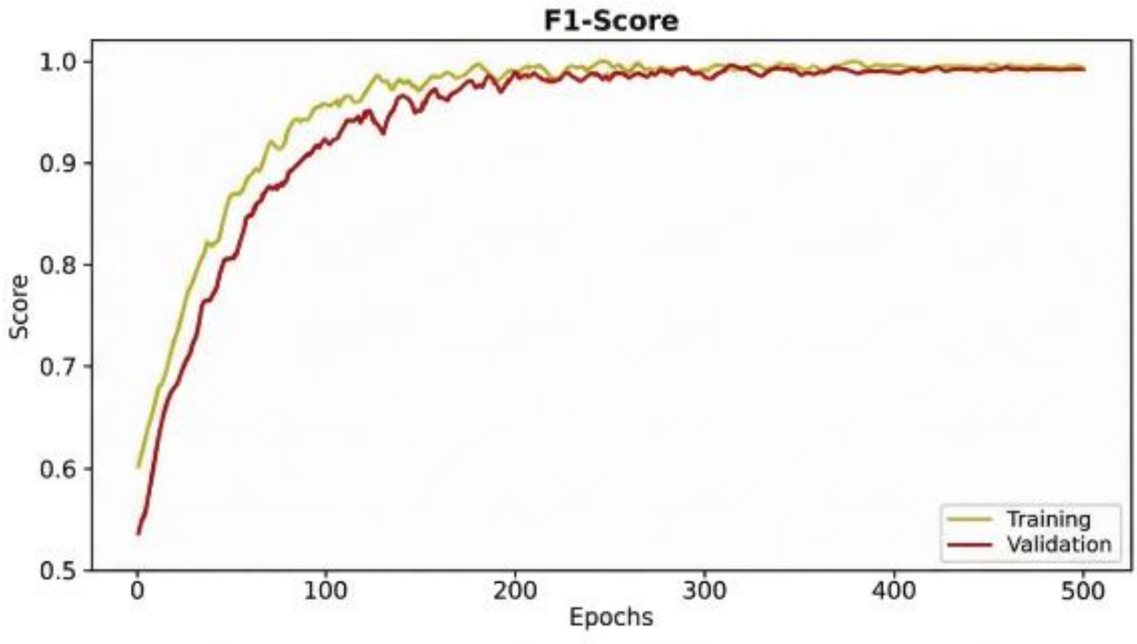

Figure 7: Training and validation F1-score for paddy plant irrigation

Training loss tracks the model's improvement in fitting the training set, whereas validation loss tracks the model's ability to fit new or unseen data. In Figure 8, a progressive decline in both the training loss and the validation loss is observed with each epoch. As training continues, it becomes evident that the model is adapting to the training data and applying that knowledge to fit unseen data. Training loss shows a rapid drop-off at first; however, after this point, the training loss levels off and reaches a stable lower value. The validation loss drops off gradually but at a similar rate as the training loss. These results suggest that the model has adapted to learn and generalize from the data.

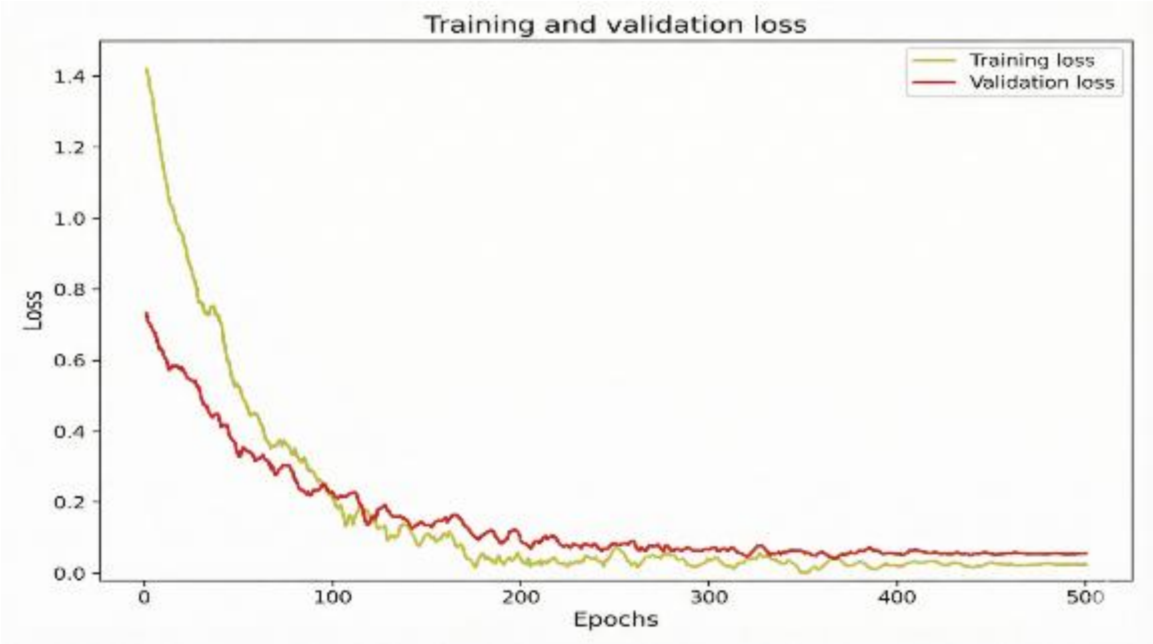

Figure 8: Training and validation loss for paddy plant irrigation

In order to evaluate how well these different AI models performed compared to one another, four additional AI models (SVM, Random Forest, KNN, and Logistic Regression) were tested with the exact same dataset used to train and test the DNN. The results clearly demonstrate that the proposed DNN model significantly outperformed the other AI models in terms of all three metrics (i.e., accuracy, recall, and precision), with the DNN model performing flawlessly at 99.17%. On the contrary, the other AI models did not perform nearly as well as the proposed DNN model, therefore, it is reasonable to conclude that the proposed DNN model will provide a great deal of support when making decisions related to irrigation in this field. In addition, the study suggests that DNNs may be a promising solution for text classification tasks. Results and discussion notes that all the examples discussed in the comparative texts were correctly classified by the proposed DNN model with 99.17% accuracy meaning there are no false negatives. In addition, there was a 99.12% recall rate meaning all text examples for positive examples were rightly identified. Finally, the proposed DNN model received a 99.25% precision meaning that every identified example that was flagged as a positive example was indeed a positive example. The F1-Score of the proposed DNN model was 99.19% which is a statistical score that combines the precision and recall score to find an average balance between them. Thus, the results show that the proposed DNN model shows support for accuracy, recall, precision and F1-Scores making the model suitable for sentiment analysis and topic classification amongst different applications. The comparative performance of all models across accuracy, precision, recall, and F1-Score is summarized in Table 2.

Table 2. Evaluation metrics for the test dataset

Metric	SVM	Random Forest	KNN (k=5)	Logistic Regression	**Prop (DNN)**	
					Training	**Validation**
Accuracy (%)	83.33	98.2	88.09	89.28	**99.53**	**99.17**
Precision (%)	89.65	92.3	93.54	91.17	**99.59**	**99.25**
Recall (%)	70.27	96.4	78.37	83.78	**99.39**	**99.12**
F1-Score (%)	78.78	94.3	85.29	87.32	**99.49**	**99.19**

In the context of smart irrigation, the model's binary output (class 1 for irrigation needed, class 0 otherwise) is directly used to control the water pump. When the DNN predicts moisture below 10 kPa, the pump is activated; when moisture is predicted at or above 10 kPa, irrigation ceases. Furthermore, the implemented hysteresis control (activating at 9.7 kPa, deactivating at 10.3 kPa) ensured stable pump operation in the field by preventing rapid on-off cycles caused by minor sensor fluctuations around the 10 kPa setpoint. This seamless integration of AI prediction with IoT-based actuation ensures that water is applied precisely when needed, maintaining optimal soil conditions while minimizing waste.

4. CONCLUSION

The study was able to develop and validate the integrated IoT and AI solution for irrigation forecasting in paddy fields. The methodology included the design and implementation of a custom IoT-based data acquisition system, which collected a high fidelity data set comprising a total of 420 environmental records. This system used a dual microcontroller system using Arduino Uno as a sensor hub and NodeMCU ESP8266 as a Wi-Fi gateway with a voltage divider circuit ensuring safe communication (5V to 3.3V serial communication). The model of deep neural network with 5 hidden dense layers (16, 32, 64, 32, 16 neurons) proved to be very powerful for our problem with accuracy of 99.17%, precision of 99.25%, recall of 99.12%, and F1-score of 99.19% on the validation data. These results significantly outperformed comparative models, such as support vector machines, random forests, k-Nearest Neighbors and logistic regression, thus establishing the proposed DNN as a superior tool for this classification task. The results confirm the possibilities of a combination of robust and low-cost sensor hardware with deep learning methods to provide accurate agricultural water management. The proposed artificial intelligence model especially DNNs has a huge potential for improvement in crop monitoring for smart farming and other agriculture applications. Real-time estimation of water irrigation needs of soil can help farmers to improve their methods: improve the crops while minimizing water use or encourage the agricultural sustainable development. The system works on its own by turning on the irrigation system when the soil moisture is less than 10 kPa and stopping when the threshold is reached to provide a responsive and water-efficient control loop. This practical application of IoT and AI is an example of how intelligent automation can help agriculture to be sustainable by means of accurate water management that is based on data.

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