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INVESTIGATION ON THE IMPACT OF IoT AND MACHINE LEARNING IN URBAN PLANNING AND STRATEGIES FOR SUSTAINABLE COMMUNITY DEVELOPMENT

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Abstract

The present study is intended to model rice field to optimize the water management practices using Artificial Intelligence techniques to predict more Realtime effective rain and irrigation water requirements for rice. Results of the study indicate that the merit of predictive analytics for improving irrigation efficiency, and also combine predictions of irrigation demand using Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN) and Support Vector Machines (SVM) for various ML models. These models use data coming from temperature, humidity, and water level sensor that are deployed in paddy agriculture fields to forecast the crop irrigation needs. Taking all the factors into account, the results indicate that both the ANN and LSTM models can predict accurately with high percentage of precision, recall and F1 scores for water needs. In addition to this property, the ML-based systems are highly scalable and flexible in nature which allows it to be widely used in various crops and regions of farming. However, this research certainly underscores the need for data-driven advances to tackle some of the global challenges in agriculture around climate change and water shortage. Using the technology, we can interpret data that will deliver actionable insights around water conservation to increase efficiency and sustainability for farmers. It will be important to build on these systems, over time, with ongoing research and innovation, to continue advancing these systems and to rapidly respond to new threats, while also to increase the utility of digital approaches to food security informatics.

Keywords: Smart Irrigation, Rice Cultivation, Machine Learning, Sensor Technology, Water Management.

1. INTRODUCTION

In view of the rapid development of global water scarcity and the need to provide sustainable utilization of resources, it has become a major task for agriculture, above all in rice growing: optimization parameters for water managements on agroecosystems. These smart irrigation systems, which leverage state-of-the-art sensor technology and machine learning algorithms help in addressing this challenge by providing an efficient mechanism for an exact distribution of water wherever and whenever required based on the crop requirements.

The main objective of this research is to investigate the extent of machine learning models integrated with sensor technology for predicting water requirement model for rice crop at high accuracy [1], [2]. In recent years, smart irrigation systems have been recommended as the way to address water scarcity and sustainable water management in agriculture. These types of systems use sensor networks and Internet of Things (IoT) devices along with machine learning algorithms to control how agricultural irrigation is applied, which in turn enhances crop yields [3]–[5]. Smart irrigation systems have been high on the list of research topics to find solutions for sustainable agriculture by reducing amount of water used in rice farming and sustainability of smart irrigation systems are also investigated extensively in recent years [6], [7].

In the case of smart irrigation, sensors are very essential as they offer valuable data about the surroundings like moisture levels in soil, humidity & temperature or even rainfall etc as sensor technology helps to monitor in real-time. These sensors are equipped throughout the agricultural fields to record data about the water status of the crops and how well soil is maintained. Sensors collect data consistently, and then transmit it to a centralized control system that allow farmers to make better irrigation schedules, and manage their water more efficiently. Many research has proved that sensor-based irrigation systems exploring soil components and taking potential evapotranspiration's to reduce water use, eliminate resource waste and maximize crop production [8]–[10].

The growing need is now pushing machine learning algorithms into smart irrigation systems to enrich predictive ability and facilitate decision making. To generalize, machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees and Random Forests have been used to analyze data from sensors in order to accurately predict the irrigation needs of future. Machine learning models take historical data and use it to connect patterns, trends, and correlations for proactive irrigation management. Machine learning irrigation systems have been proven to save significantly more water at equal or greater crop yields when compared to traditional means of irrigation [11], [12].

Given that rice has high water requirements and is sensitive to water stress, smart irrigation systems provide a specific set of benefits for rice cultivation. Water: - It is grown in water-logged paddy fields so required due attention for its water management. Irrigation scheduling technologies designed specifically for rice production can assist in better managing irrigation water, preclude hydraulic lift and capillary rise occurrence as well as alleviate potential negative environmental outcomes related to river basin contamination through pollutants such as methane. Recent studies have demonstrated that sensor networks with machine learning models can be used to monitor soil moisture content, forecast water requirement and automatically provide irrigation schedule for paddy fields [13], [14].

By combining machine learning models with sensor tech in irrigation management, you can have adaptive strategies that adjust according to the environment and stage of crop growth. For instance, deep-learning algorithms can adapt irrigation schedules around the clock to real-time weather forecasts, evapotranspiration rates and crop water needs. Smart irrigation systems, via feedback loops and self-learning mechanisms continue to get better in their performance over time efficiently allocating resources and increasing agricultural productivity [15], [16]. Additionally, the scalability and relatively low pricing of smart irrigation technologies could make this solution available to even smallholder farmers in developing countries (water scarcity & food security are acute issues). By making use of such lower cost sensor networks along with open-source software and cloud-based platforms, the complete system for monitoring and control of irrigation is decentralized which helps farmers to monitor

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their farm from anywhere in this world. This decentralization allows them to see data in real-time accelerating their decision-making process while adapting itself continuously to climatic variabilities. Some of your research and technology transfer initiatives are needed to promote the adoption of smart irrigation interventions in different agricultural situations, which is essential for advancement towards sustainable goals [17], [18].

This research employing Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN) and Support Vector Machines (SVM) would help herald in an era of optimized irrigation, maximizing crop harvest and minimizing environment in the cultivation of rice. The AI research will explore real-time predictive models to predict when irrigation is required by analyzing data collected from environmental sensors including temperature, humidity and water level sensors deployed in the farming areas. The advent of machine-learning-based smart irrigation systems have ushered a new era in agricultural water management, providing technology to develop data-centric solutions for resource optimization to ensure the sustainability of farming. If this potential will be realized, these systems can transform water management in agriculture, support global food security and contribute to environmental sustainability by providing decision-advices based on predictive analytics to the farmers.

2. METHODOLOGY

In agricultural land administrations, sensor technologies have changed farming practices by making specific conditions that are vital for crop growth incredibly visible. This is necessary for the optimal use of various forms of farming resource-based wireless sensor technology like temperature sensors, humidity sensing unit and water level; knowledge measurement in rice growing where control-water becomes top priority. The sensors work as vigilant observers, continuously keeping tabs on the environmental conditions surrounding that are critical for cultivating rice. The methodology of the research are shown in figure 1.

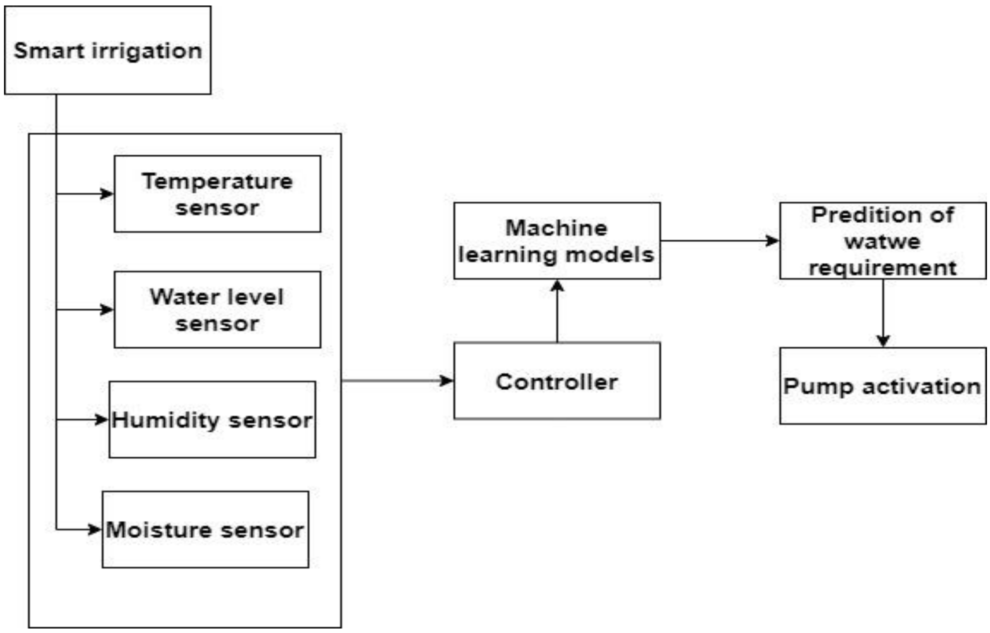

Fig 1: Working of the proposed system

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The sensors allow farmers to capture immediate weather and moisture conditions — temperature, humidity and water depth among others. Since the free-roaming sensors can be strategically placed anywhere on expansive farming spaces, full agricultural-landscape coverage of all-important environmental variables is achieved. With this massive data harvesting, farmers can make real-time decisions for irrigation timings and water management strategies that allow them to cultivate their fields economically as well as resource efficiently.

This detected data is collected as inputs to the center controller which works like brain of an automated irrigation. Once the controller has these sensor readings, it uses advanced algorithms (such as machine learning (ML) models) to process this data and make decisions on where to distribute water in an intelligent way. The controller, initially is designed to switch on or off the pump as per some derived threshold values from sensor data. When the soil-moisture sensor shows a decrease in irrigation below a certain point, and upon real-time signals; water is provided to cultivation by pump control triggered from controller.

But the real innovation is that it includes ML models in predicting the water needs of your plants in the future. The system is able to predict the water demand of crops with high accuracy using artificial neuron networks (ANNs), RNN, SVM along with LSTM. Based on various measurements from the sensor, such as moisture and environmental conditions, ML models are trained to learn how best predict the future water requirements of these plants. The use of ML to predict future water needs is a game changer for agricultural water management. Rather than waiting for a sensor reading to react, the system is proactive and “looks ahead” to know when water needs to be pumped even before the crop tells you it needs water. Moreover, ML algorithms allow the system to be adaptive and learn from its past experience thereby improving its predictions continuously over time thus increasing the efficiency of the system.

In addition to all of this, using ML models in the irrigation system reduces the risk of over-irrigation, making it an ideal solution for a need where over-irrigation is a significant issue as in conventional fields. With a prediction of the water demand, it will avoid waste when excess irrigation occurs and also prevent undesirable effects such as waterlogging or fertilizers leaching that are known for being harmful. This not only saves precious water resources but also ensures that the farming is done sustainably helping towards environmental conservation and long-term survival.

3. DATA COMMUNICATION

In the automated irrigation system, sensors communicate with the controller through WiFi technology, resulting in continual instant sensor data transmission. The sensors have WiFi connectivity which enables them to send their readings wirelessly to the centralized controller located in farming areas of rice cultivation.

When the condition change, for example decrease of humidity or liquid level, is detected by a sensor it notifies the controller over the WiFi provides information about the course of action for the event. As the decision-making brain of the irrigation system, it is this controller that has been programmed with algorithms to correctly interpret sensor data.

When the sensor readings are passed to a controller, this makes a comparison with predefined thresholds which signifies optimal environmental conditions for rice growth. Controller is used to automatically control various devices such as an irrigation system

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or a different device whenever its sensor data falls below, or exceeds prescribed thresholds. Having a human-in-the-loop to interpret sensor data and decide when to turn the pump on is not optimal, which suggests that using machine learning (ML) models inside of your controller decision process should be considered. These ML models such as RNNs, SVM and LSTM based models predict the patterns and trends of environmental conditions on analysing historical sensor data conducted from universal smart building. By learning from these insights, the ML models are able to accurately forecast its future water needs. The ML models predicts if the irrigation will be needed in a few hours, and inform the controller to activate sooner than necessary. Using ML into the decision which related to water with the help of embedded sensor system makes it more responsive and adaptive, leading to act before anything goes wrong and thereby conserving an optimized distribution of water needs by crops.

The small-scale land size of 0.5 acres is chosen to implement in this research for the stytem of smart irrigation for rice crop. This area has deployed various environmental sensors, and we have collected 1210 sensor readings from them. For these sensor readings, several machine learning (ML) models are being trained such as ANN, RNN, SVM and LSTM. In this regard, for training models in an efficient manner and exhaustive evaluation, 70% of the data is used to train the models, while the remaining 30% is kept aside for testing or evaluating Imation.

4. MACHINE LEARNING MODELS

In this research, a set of machine learning (ML) models were used to predict the crop water requirement for smart irrigation in rice cultivation. For machine learning models, the research used Artificial Neural Networks (ANN), Long Short-Term Memory and Recurrent Neural Networks LSTM-RNNs) and Support Vector Machines SVM). All of these models have their own advantages and are suited for different kinds of data and prediction problems.

Similarly, there are a series of nodes (neurons) in Artificial Neural Networks (ANN) which help in processing the input data and converting it into output predictions. These ANN models capturing non-linear relationships in the data and are employed broadly for regression, classification.

LSTM (Long short-term memory) networks is a type of RNN which is specialized in learning long-term dependencies and sequential data. Long-short term memories cells allow them to remember information over long periods of time and thus they are able to properly encode the temporal dynamics in the sensor data. Although there are many tasks it could perform, one of the most obvious tasks is time series prediction which fits well for forecasting things like weather, stock prices and so forth which is a great area of application regarding LSTM models.

Recurrent Neural Networks (RNN) — RNNs are a class of neural network models for sequence processing; they re-use activations at the current time step to deal with information coming in from the previous time steps, in effect exhibiting temporal dynamic behavior. Typically, this type of RNN used for sequences related problem like natural language processing, Time-series analysis and any other sequential data model tasks. Vector Machine (and Statistical Learning Theory) is a set of supervised learning methods used for classification and regression. SVM models are a type of classification and regression problem working to output the optimal hyperplane that separates different classes of data points on an n-dimensional feature space. Such

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models have a very good performance even if data is non-linear, and with the help of kernel functions can be applied to cases when you cannot correctly draw any straight line between 2 classes. They are heavily used in many fields such as bioinformatics, image classification and financial time series forecasting.

5. PREPROCESSING OF DATASET

Although in the case of this rice crop on a 0.5-acre land undergoing smart irrigation, preprocessing the sensor readings is an essential step before feeding into machine learning (ML) models for research purposes. The direct sensor data such as temperature, humidity, and water level sensors need to cleansed, transformed and formatted before performing analysis on the same — the primary conceptualization of any IoT project. The first step in this preprocessing pipeline was the data cleaning, where anomalies were detected and so they clean up their dataset, removing missing values; fixing outliers; suppression noise. Dataset with missing values may be in case of sensor defect or even a transmission error. These missing values of the data are often treated by imputation methods, in which they are filled with either mean or median, mode of the observed data, or through more advanced ways like K-nearest neighbors (KNN) imputation, linear interpolation to ensure the consistency but minimizing any bias into our dataset.

Outliers are extreme values that deviate significantly from other observations and are detected using statistical methods such as Z-score method method. When we detected these outliers, the next step was to remove them from the data set or transform them so that they become less influential. This preprocessing step is necessary because otherwise these abnormal values may end up contaminating the results of the ML models. Smoothing techniques like moving averages or exponential smoothing are utilized to mitigate noise in the sensor readings, as it represents random variations or errors and generates a more stable and predictive dataset.

Data Transformation After data cleaning, the next step is to transform it. The variety of units and scales results in that the sensor readings are normalized or standardized before they could be utilized for prediction. Normalization scales data to a fixed range, usually 0 to 1 while standardization changes the distribution of your data to have a mean of zero and variance of one. First, would be suitable techniques to align the data and help the ML models digest it in order learn from effectively. For example, temperature readings may need to be converted from Celsius to a standardized scale or humidity levels might have to mapped into so that all fall within the same range.

Adding or creating new features from the existing sensor readings is another important part of data preprocessing and it enhances-up the prediction of these models which we call as feature engineering. This includes the generation of interaction terms, polynomial features, aggregation of data on time windows to take into account temporal patterns. For instance, by averaging temperature and humidity readings to create a heat index feature, or computing rolling average for water leverage over the 7 days— to capture trends in irrigation need.

When the features are engineered, we divide the dataset into training and testing sets. In this research for training ML models, 70 % of the 1210 sensor readings are considered and the rest of their remaining 30% are reserved for performing testing and evaluation. This partition ensures that the models are trained on substantial data while also having unseen examples to test their performance accurately. Avoiding a bias from single split by k-fold cross validation. K-fold Cross-validation. It is a type in which we divide the data-set into k subset and then train the model k times on each subset of previous data as validation set, while leaving 1 part as test. This helps to have a better evaluation of the model performance by calculating the averages from all the folds.

In addition, the data is temporal and should be processed accordingly. For instance, in time-series data like sensor readings over a time-period —past values will affect re-occurring future values which is autocorrelation. To tackle this, time-series decomposition such techniques are used to split the data in three components: trend component, seasonal component and residual. Furthermore, lagged features that are based on past values of the sensors used as predictors for future readings to be able to account for time dependencies in the data.

6. RESULT AND DISCUSSION

The performances of all these models were evaluated in appropriate carefully and finally, the potential model was fixed according to its accuracy on the prediction of rice crop water requirements. It works by hiding the reserved 30% of the sensor readings in testing set that was kept aside and never shown to the models during training. The result of the performance evaluation is shown in figure 2. The artificial neural network (ANN) model delivers high performance, with an accuracy of 98.76%. The high accuracy achieved implies that the ANN model is highly capable in representing complex relations between the set of environmental variables and water requirement prediction of rice plants, hence it is a reliable predictive irrigation management tool.

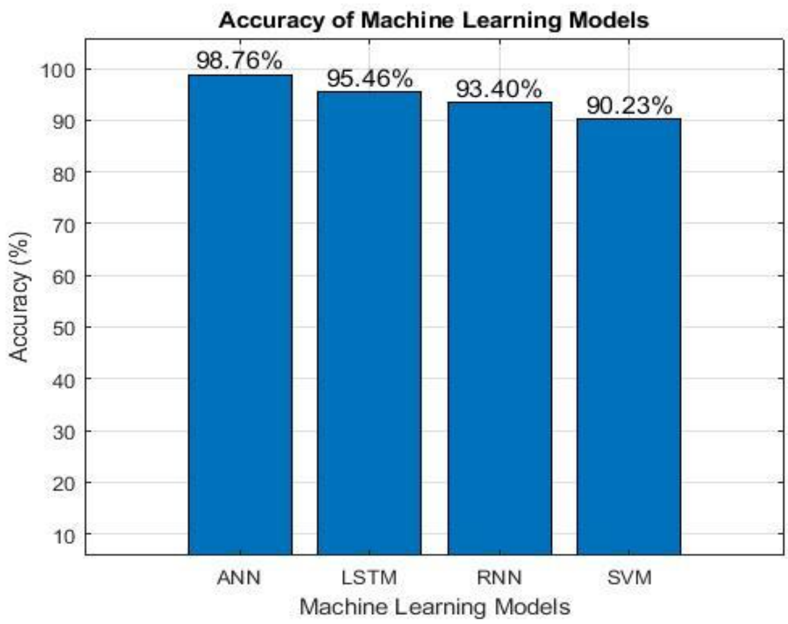

Fig 2: Accuracy of each model

Even the long short-term memory (LSTM) network, a strong sequential data and temporal dependency learner, is not far behind with an accuracy of 95.46%. This suggests that the LSTM model is good at detecting periodicity in sensor data and indeed able to make correct predictions on future water requirements. Another neural network, recurrent neural network (RNN) model designed for sequential data are also applied with the accuracy of 93.4%. Albeit with a little less accuracy than the LSTM, it still performs well suggesting that it can capture temporal dynamics in the data. Support Vector Machine (SVM) model, a powerful classification and regression tool, that makes an accuracy of 90.23%. It has the lowest performance among all tested models, but its accuracy is significant to work with the data produced by the sensor.

The performance of each model are further evaluated using the performance metrics and the results are shown in figure 3. The ANN model showed the best overall performance with an accuracy of 98.76% This means that 98.76% of the time, information was input into the ANN to correctly predict water needs and it did so correctly. The precision is 98.45% (i.e., correct in making a prediction of the requirement of watering through irrigation). As seen in the 98.78% F1 score, this trade-off between these precisions and recall values means it uses both of their strong points to signify robust performance. This is respectively high AUC-ROC of 99.05% to demonstrate its wonderful classifying skill (irrigation needed vs. not). LSTM model also perform good getting accuracy of 95.46%. It has a Precision of 95.10% which is lower than the Recall score (94.75%) meaning that its predictions tend to have minor false positives and it may lose sight of some actual needs for irrigation. A balanced F1 score of 94.92% An AUC-ROC of 95.30% demonstrates better prediction power than ANN but slightly less accurately

The performance of the RNN model is 93.40% accuracy, and precision is 93.20%, recall is at 93.60%. This implies that the identification of real irrigation requirements has a slight advantage over accurate predictions. Both the F1 score of 93.40% (Fig.8) and AUC-ROC of 93.55% confirms that our model is able to distinguish very well between the two classes which gives a balanced performance at both Positive and Negative instances. The SVM model has the lowest (but solid) accuracy of 90.23% The precision is 89.80% and recall rate reaches at 89.90%, which indicates a fairly good, but still slightly imbalanced predictions of the irrigate demands. A F1 score of 89.85% hints at reasonable balance and an AUC-ROC of 90.00% corroborates it as a sound classifier.

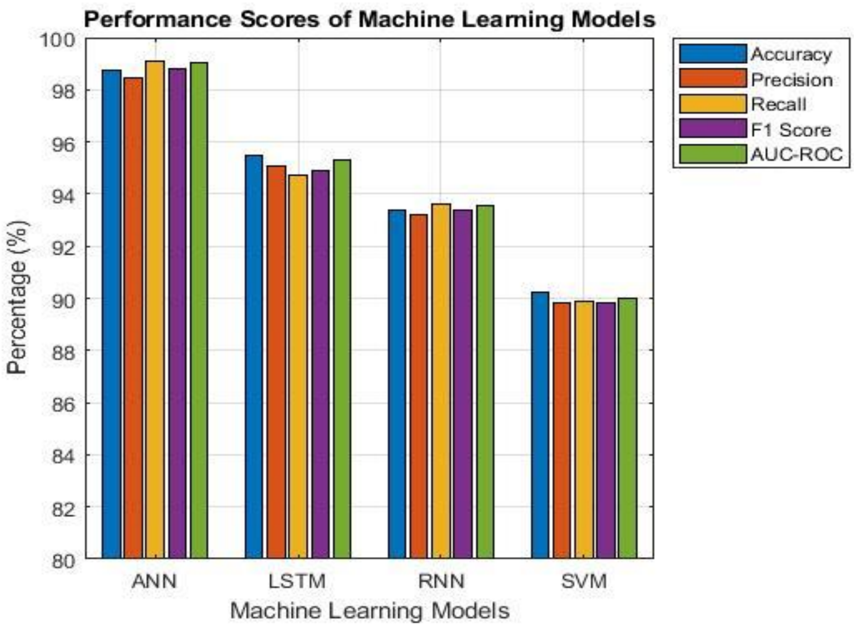

Fig 3: Performance score of each model

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The confusion matrices of each model in prediction are shown in figure 4. Confusion matrix for ANN model shows that out of 515 cases in which irrigation was not required (actual: no-irrigation), the model correctly predicted 500 cases as no-irrigation) TN Yet it misclassified 10 cases (false positive) as irrigation. In contrast, 5 instances of needing irrigation got the wrong prediction of not needing irrigation (false negatives) out of 700 actual cases of irrigation.

In the LSTM model, 480 out of 510 no irrigation instances were correctly classified (true negatives), while snapshot being taken to require irrigation have been wrongly classfied as a non-irrigation one (false positives). In the 700, yes that were irrigation there are true positives (665) as well false negatives (35).

Additionally, the RNN model properly classified 460 instances of no irrigation (true negatives) out of the dataset and misclassified another 50-requiring irrigation into not needed water. The RNN accurately predicted 655 of these cases (true positives) but misclassified the remaining 45 as not irrigation (false negatives).

True negatives refer to 450 of the no-irrigation instances correctly classified by SVM model out of total 510 wherein 60 has been incorrectly propagated as irrigation positives. Across 700 instances of irrigation, the SVM correctly classified 635 (true positives) but incorrectly predicted 65 (false negatives).

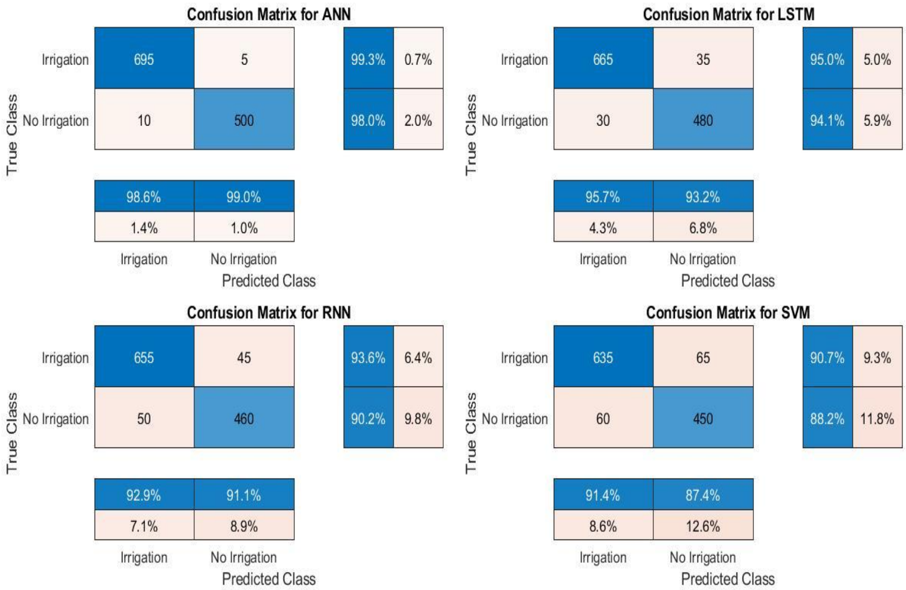

Fig 4: Confusion matrices of each model

7. CONCLUSION

This research has proven useful in the paradigm shift of the agriculture industry in water management where Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Support Vector Machines (SVM) have been adopted. These models can be harnessed to provide information to farmers and assist them with water resource management decisions that have input on irrigation scheduling, which in turn may lead to increased efficiency of water use, increases in crop yields and reduced potential environmental impacts. These results highlight the need for evidence-based strategies to mitigate the environmental challenges of climate change and water constraints faced in agriculture. In addition, given the scalability of these machine learning systems and their adaptability, these approaches hold promise for more extensive deployment across various types of crops and farming regions. With worldwide food demand on the increase, smart irrigation technologies driven by machine learning are set to take agricultural productivity to a whole new level, contribute to a sustainable sector, and lay the foundation for future generations to access food. While future advances in this field will require further investment and innovation in this area, this research helps in understanding how it is crucial to the development of better systems to meet the increasing demands for innovations and to achieve optimal effects in agriculture globally.

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