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IoT-Enabled Intelligent Irrigation System with Machine Learning-Based Monitoring, for Effective Rice Cultivation

Riyajuddin Yakub Mujawar[1*], R. Lakshminarayanan[2], Jyothi A. P.[3], Shanmuga Prabha P.[4], Sumagna Patnaik[5], K. Dhayalini[6]

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Abstract: The objective of this study is to examine how IoT-enabled intelligent irrigation systems can be used in rice agriculture. The study uses sensors to gather environmental data in real time, such as temperature, water level, humidity, and humidity sensors. Machine learning models, such as artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), and random forests (RF), are then used to process the data in order to predict future water demand. Experimental findings The efficacy of the system indicates , where ANN demonstrates the greatest accuracy of 95.6%, followed closely by SVM of 93.2%, DT of 88.7%, and RF of 86.5% These performance indicators indicate the robustness and accuracy of the model in forecasting environmental conditions for irrigation highlighting the positive. The effectiveness of each model is further demonstrated by confusion matrices, which provide instances of true positives, false positives, true negatives, and false negatives. Achieving a successful integration of IoT and machine learning ensures a proactive response to changing field conditions and lowers the risk of resource misuse through precise adjustments to the water supply. The results emphasise the potential of technology-driven solutions to increase precision agriculture, leading to sustainable practices that optimise yields while conserving resources. The study offers vital insights for agricultural stakeholders, opening the road for flexible and adaptable solutions that solve the problems of contemporary rice production in the face of altering climates and global food.

Keywords— *IoT, machine learning, intelligent irrigation, rice cultivation, sustainable agriculture*

1. Introduction

Rice farming, a crucial aspect of international agriculture, has issues linked to environmental unpredictability, usable resource utilisation, and the requirement for sustainable approaches to serve expanding food demands [1], [2]. In tackling these difficult scenarios, precision agriculture, enabled with the help of the Internet of Things (IoT) and system acquiring knowledge of, emerges as a disruptive way for boosting crop productiveness. This study strives to offer to the sector by building and assessing an IoT-enabled smart irrigation system primarily tailor-made for rice agriculture. By combining superior sensors and machine learning algorithms, this system targets to dynamically react to real-time environmental variables, improving irrigation tactics to make sure premier increase and beneficial resource performance [3], [4]. As international weather patterns vary and water shortage becomes ever more well-known, the necessity for technologically advanced solutions in agriculture becomes clear. Thus, the point of interest of these investigations is in leveraging the potential of IoT and machine learning to know to solve the complexity of rice production, imparting a scalable and adaptable framework for sustainable agricultural methods [5]–[7].

The integration of IoT in agriculture has observed a booming passion in last years, altering old agricultural processes. Smart agricultural structures, utilising IoT

1Bharati Vidyapeeth (Deemed to be University), Institute of Management and Rural Development Administration, Sangli, Maharashtra, India
2Department of Networking and Communications, SRM Institute of Science and Technology, Kattankulathur. Tamil Nadu, India
3Department of Computer Science and Engineering, M. S. Ramaiah University of Applied Sciences, Bengaluru, Karnataka, India
4Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India
5Department of Computer Science and Engineering, Bhaskar Engineering College, Hyderabad, Telangana, India
6Department of Electrical and Electronics Engineering, K.Ramakrishnan College of Engineering (Autonomous), Tiruchirappalli, Tamil Nadu, India
Corresponding: riyajuddin1676@gmail.com
Emails: riyajuddin1676@gmail.com; lakshmir4@srmist.edu.in; jyothi.cs.et@msruas.ac.in; prabhaspalanivel@gmail.com; sumagnapa72@gmail.com; dhaya2k@gmail.com

technology, has proven significant in actual-time records collection and monitoring of different environmental indicators vital for crop fitness [5], [8]. In rice agriculture, the implementation of IoT has confirmed promising findings in improving irrigation, pest control, and universal crop management. The power to capture and analyze information from sensors put within the region gives farmers with actionable insights, creating an allowance for rapid interventions and resource-green selection-making [9], [10].

Machine learning, especially in the form of predictive modeling, has demonstrated amazing capabilities in precision agriculture. Various methods, inclusive of Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF), have been used to are anticipating agricultural results, disease occurrences, and irrigation needs. These models, trained on prior facts, understand complicated patterns and correlations, enabling them to make smart choices in actual-time. In the context of rice production, the usefulness of machine learningto know models offers promise for optimizing irrigation schedules, minimising water loss, and enhancing typical crop yield.

Rice, the primary staple of a vast section of the world's population, needs special environmental attention for optimum growth [11], [12]. Such are the difficulties such changing temperatures, water availability, soil suitability impacting agricultural production and intensification. Furthermore, these difficulties are further compounded by the unpredictability generated by climate change, which requires for complex solutions that adapt to shifting agricultural environments [13]–[15].

Several research explored intelligent irrigation systems integrating IoT and systems intelligence for various kinds of plants. However, the major need of rice farming demands a correct method [16], [17]. Existing technologies show promise to boost resource efficiency, minimise environmental impact, and improve total agricultural production. Understanding the strengths and limits of these structures informs the creation of a tailored solution for rice fields, including elements such as water degree management, humidity control, and soil moisture optimization [18], [19].

Despite the gains in IoT-enabled agricultural and system researching applications, a full and customised intelligent irrigation system for rice farming remains an underexplored region [20], [21]. This study tries to bridge this gap by use of constructing a system that not handiest takes actual-time facts from the field but additionally applies machine learning to know algorithms to predict and optimize water requires specific to rice plants. The ultimate purpose is to establish a scalable and flexible system that solves the specific demanding conditions of rice agriculture, contributing to sustainable agricultural practices and worldwide meals protection [22], [23].

2. Methodology

The approach used in this study involves the incorporation of many sensors to gather crucial environmental data in order to enhance the efficiency of rice agriculture via irrigation optimisation. The used sensors include temperature sensors, water level sensors, humidity sensors, and moisture sensors. These sensors are strategically placed in the agricultural field to collect real-time data on the prevailing environmental conditions. The selection of these sensors is based on their application in enhancing and advancing rice cultivation. Temperature, water levels, humidity, and soil moisture are main parameters that have a significant influence on crop productivity.

The data collected by those sensors is then communicated to a central controller, which functions as the central hub of the IoT-enabled intelligent irrigation system. The controller functions as the decision-making unit, analysing incoming data and making educated decisions based on specified set point values. For instance, the temperature sensor provides information about the surrounding temperature, assisting the system in determining if the circumstances are suitable for high-quality rice growing. Similarly, the water stage sensor measures the water levels in the region, allowing the system to activate the water pump as necessary to maintain the correct moisture level in the soil.

The primary purpose of the device is to activate the water pump according to the predetermined values obtained from the sensor data. This guarantees a flexible and reactive watering method that adjusts to the specific needs of the rice plants. Moreover, the system is built to communicate this information to the cloud in real-time. The cloud connection provides a twofold cause – it allows non-stop monitoring of the rural environment and enables remote gain entry to for stakeholders. Through the cloud interface, those interested in the rice growing method may acquire actual-time facts on temperature, water ranges, humidity, and soil moisture from anyplace, supplying them with important insights into the ongoing problems inside the location. The architecture of the proposed IoT system is shown in figure 1.

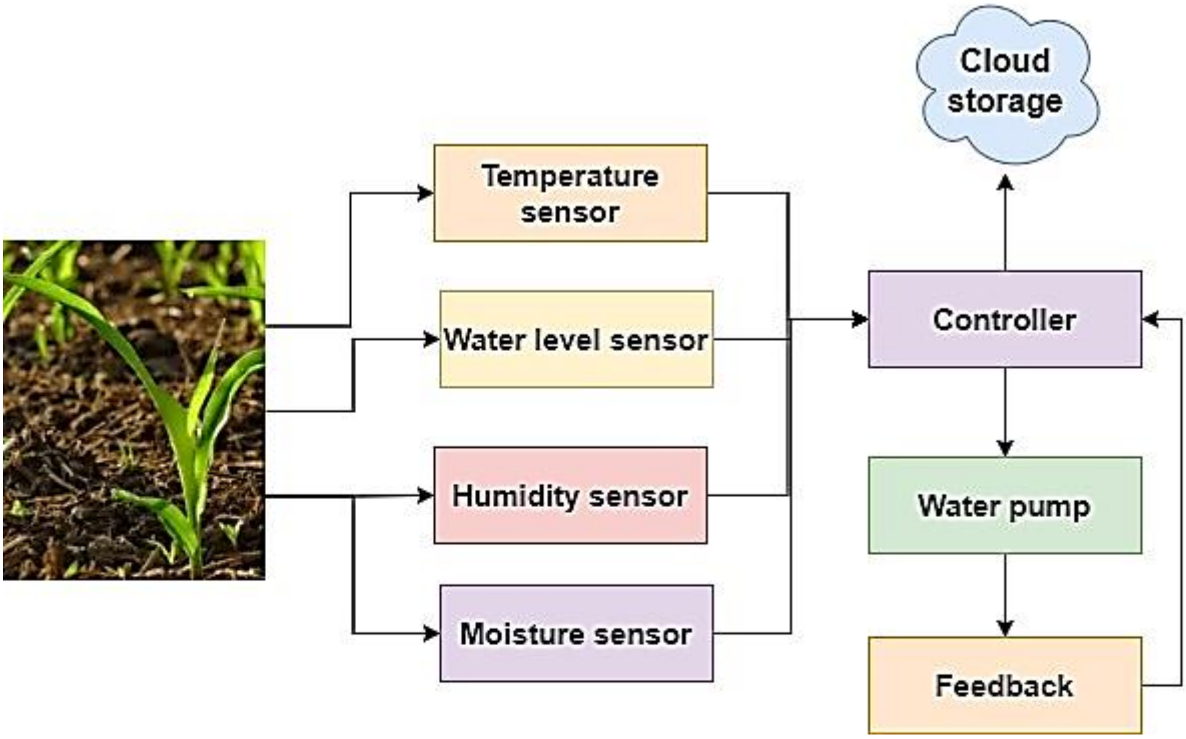

Fig 1 Architecture of the proposed system

2.1 Need for machine learning

In addition to real-time remarks from sensors, continual system surveillance is important for making sure the efficacy and balance of the intelligent irrigation system. To meet with this necessity, machine learning (ML) models have been introduced into the study approach. These ML models are educated the utilisation of historic sensor readings, permitting them to are anticipating future environmental conditions dependent entirely at the present sensor facts. The predictive abilties of the ML models play a crucial part in proactively waiting for changes in temperature, water degrees, humidity, and soil moisture. By leveraging those forecasts, the ML models contribute to the decision-making way of the essential controller, which, in flip, controls the operating of the water pump.

The addition of ML techniques offers a layer of intelligence to the system, enabling it to react dynamically to altering environmental settings. This predictive feature assists in preventing oscillations in the machine via proactively modifying irrigation settings depending on projected alterations. By teaching the ML models on a dataset including sensor readings and relevant consequences, the machine may analyse sophisticated correlations and patterns, letting it to generate knowledgeable choices even in the absence of instantaneously sensor remarks. This proactive strategy currently not most effective compliments the general performance of the sensible irrigation system but also mitigates the danger of over- or underneath-irrigation, resulting to more sustainable and optimal rice farming techniques.

In this study, a many set of machine learning methods are used, which incorporate Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF), are utilised to anticipate environmental situations based on sensor data. The utilisation of several models complements the resilience and accuracy of predictions by using the particular strengths of each set of rules. ANN shines in taking photos challenging patterns, SVM supplies strong categorization, DT gives interpretability, and RF harnesses machine learning to know for better generalization. This thorough strategy guarantees a nuanced understanding of the rural surroundings, helping to more accurate and adaptable selection-making in the shrewd irrigation system.

2.1.1. Artificial Neural Network

Artificial Neural Networks (ANN) comprise an essential element within the technological examining framework utilised in this research for forecasting environmental factors in rice production. ANNs are quite effective at modelling the dynamic and interrelated variables present in agricultural contexts because they are particularly well-suited for capturing complex and non-linear interactions within complex datasets. In the context of the smart irrigation system, ANNs function an effective method for detecting patterns and dependencies amongst temperature, water levels, humidity, and soil moisture. The community's design, consisting layers of linked nodes, allows it to evaluate and react to the intricacies of the sensor recordings, permitting the extraction of crucial insights as shown in figure 2.

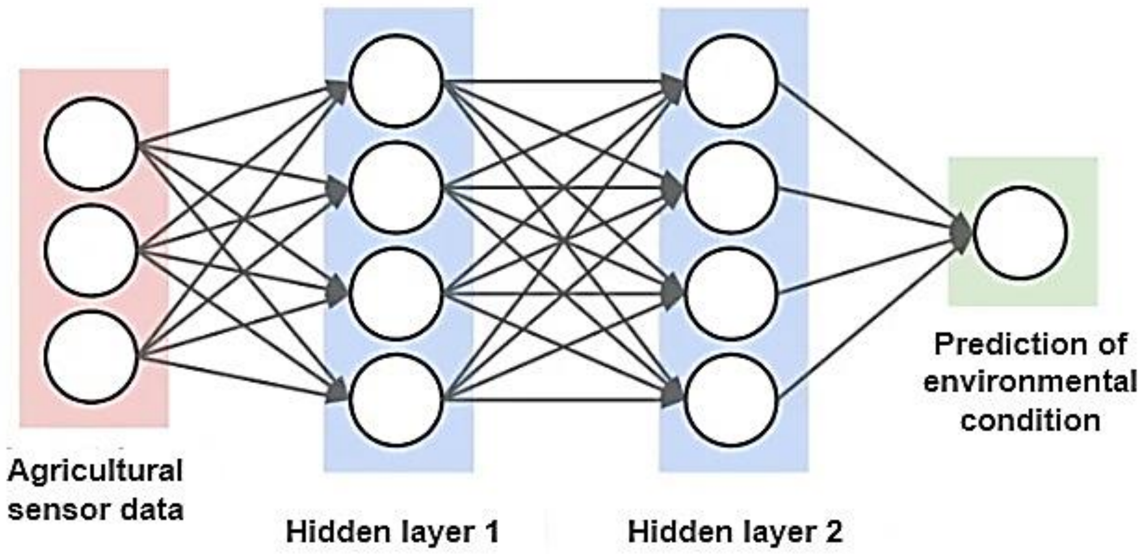

Fig 2 Structure of ANN model

The training strategy comprises exposing the ANN to previous sensor data and their accompanying repercussions, enabling the community to alter its inner settings to enhance forecast accuracy. The intrinsic capacity of ANNs to generalize from training records makes them effective at projecting future environmental conditions based on real-time sensor inputs. This predictive feature considerably enhances the machine's reactivity, enabling perfectly timed modifications to watering settings. Furthermore, the ability of ANNs encompasses the developing character of agricultural settings, making sure adaptation to different eventualities. By incorporating ANN into the research approach, the smart irrigation system may harness modern facilities learning mechanisms, adding to a more complex knowledge of the agricultural environment and improving the accuracy of decision-making for most effective rice cultivation consequences.

2.1.2 Support Vector Machine

Support Vector Machines (SVM) perform a critical part inside the study, serving as a strong and adaptable machine gaining knowledge of version for forecasting environmental circumstances within the context of rice agriculture. SVM is notably properly-acceptable for type duties and regression analysis, making it an excellent desire for recognising patterns and correlations within the sensor facts obtained within the agricultural field. SVM functions by figuring out a hyperplane that first-class divides one of a kind classes or forecasts continuous consequences. In the intelligent irrigation system, SVM is educated using previous sensor facts to produce a selection boundary that best classifies and forecasts variations in temperature, water degrees, humidity, and soil wetness.

The strength of SVM stems in its capacity to manage excessive-dimensional information and non-linear associations, letting it to catch intricate dependencies within the environmental variables. By utilising the kernel method, SVM may remodel the sensor information right into a higher-dimensional space, in which sophisticated patterns turn out to be additional discernible. This permits the version to generate reliable predictions even in scenarios in which the connections between variables are non-linear. Additionally, SVM delivers great generalization, guaranteeing that the predictive powers grow beyond the training dataset to produce correct predictions on fresh, unexplored data. In the clever irrigation system, the utilisation of SVM helps to the robustness and dependability of the general predictive version, offering a wonderful complement to other machine learning techniques.

2.1.3 Decision Tree

Decision Trees (DT) perform a fundamental machine learning to know version in this investigations, gambling a significant role in forecasting environmental variables for strong rice production. DTs are acclaimed for their interpretability and ability to simulate intricate selection-making methods. In the context of the smart irrigation machine, DTs are recruited to discover patterns and correlations in the sensor recordings. The hierarchical form of a selection tree comprises a succession of binary choices mostly based on entry attributes, leading to the remaining prediction of environmental scenarios. This realistic portrayal no longer only offers a clear awareness of the selection-making approach but also lets in for the extraction of essential information into the elements impacting the rural environment.

The training of the DT entails exposing the version to previous sensor facts, enabling it to recursively divide the information space relying entirely on feature values. Each node in the tree indicates a decision based on a specified attribute, while the leaves offer the very final predictions. This intrinsic interpretability makes DTs especially important in agricultural initiatives, in which stakeholders are searching for intelligible insights into the elements driving crop development. Moreover, DTs excel in dealing with each numerical and categorical information, making them adaptable for collecting different variables of environmental conditions.

2.1.4 Random Forest

Random Forests (RF) play a crucial position on this look at, giving away a robust machine learning to know strategy for predicting environmental variables in the situation of rice farming. RF is a collection of decision trees, individually educated on a distinct portion of the dataset and providing independent predictions. The final prediction is then formed by means of a majority vote or average, producing a solid and dependable model. In the intelligent irrigation system, RF utilises the abilties of ensemble gaining knowledge of to increase the overall prediction overall performance with the help of avoiding overfitting and increasing generalization.

One of the major advantages of RF rests in its capacity to manage excessive-dimensional information and grab intricate relationships among various variables. By merging the predictions of several selection trees, RF supplies a more consistent and honest prediction, lowering the effect of noise and outliers within the sensor facts. Moreover, RF automatically addresses the variation in environmental conditions, offering a response that is less challenge to individual tree changes. The addition of RF within the examination technique increases the system's flexibility and resilience, primary to a stronger and precise prognosis of temperature, water stages, humidity, and soil moisture.

Table 1 Experimental Results

Time	Temperature (°C)	Water Level (%)	Humidity (%)	Moisture (%)	Pump Response
09:00 AM	25.5	70	60	35	On
09:30 AM	26.0	68	62	34	On
10:00 AM	27.2	65	58	36	On
10:30 AM	28.0	62	55	38	Off
11:00 AM	28.5	60	57	37	Off
11:30 AM	29.2	58	59	35	On
12:00 PM	30.0	55	61	33	On

12:30 PM	31.5	52	63	32	On
01:00 PM	32.0	50	65	30	Off
01:30 PM	32.8	48	67	28	Off
02:00 PM	33.5	45	70	27	On
02:30 PM	34.0	42	72	26	On
03:00 PM	33.7	40	75	25	On
03:30 PM	33.2	38	78	24	Off
04:00 PM	32.5	35	80	22	Off
04:30 PM	31.8	32	82	20	On
05:00 PM	30.5	30	85	18	Off

3. Result And Discussion

Table 1 offers a thorough evaluation of sensor readings and pump reactions at 30-minute intervals from 9:00 AM to 5:00 PM, representing the environmental dynamics within the context of rice production. The temperature data, measured in degrees Celsius, reflect the changes in environmental circumstances at some moment in the day. The water level, stated as a percentage, represents the relative amount of water within the discipline, vital for keeping most beneficial soil moisture. Humidity, supplied as a percentage, represents the atmospheric moisture content material, while soil moisture measurements suggest the moisture level in the soil vital for healthy crop development. The pump response column clearly illustrates the system's option to spark off ('On') or deactivate ('Off') the water pump largely based on real-time sensor inputs and established set factor values. For example, the pump may be brought on when soil moisture decreases beneath a particular threshold. This table presents a precious picture of the dynamic interplay between environmental variables and the system's responsiveness, serving as a foundation for in addition evaluation and insights into the overall performance of the IoT-enabled shrewd irrigation system in facilitating effective rice cultivation.

Data acquired over a one-month period serves as the foundation for training machine learning models. Models comprising ANN, SVM, DT, and RF evaluate this data set and anticipate drops and increases in sensor values. By recognising trends in previous data, each model acquires insight into changing environmental circumstances. These numbers revealed are crucial markers for estimating future water consumption in rice farming. Machine learning models learn to predict changing crop demands by recognising particular patterns in temperature, moisture content, humidity and soil moisture using self-training algorithms This predictive capacity delivers water a clever irrigation can dynamically change water supply, assuring the most efficient and practical method. The performance evaluation of the machine learning models in the test phase demonstrated a remarkable degree of accuracy in forecasting water consumption as shown in Figure 3. In particular, the artificial neural network (ANN) reveals a remarkable accuracy of 95.6%, an example of the data that illustrates its ability in detecting complicated objects.

Following closely, the Support Vector Machine (SVM) demonstrates an accuracy of 93.2%, indicating its usefulness in environmental condition categorization and prediction Decision Tree (DT) and The Random Forest (RF) model displays appropriate accuracies of 88.7% and 86.5%, respectively. These findings illustrate the durability of utilising machine learning models, and ANN has emerged as an accurate predictor of water demand for smart irrigation systems for rice farming

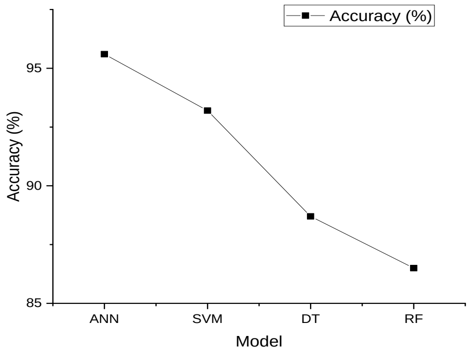

Fig 3 Accuracy of each model

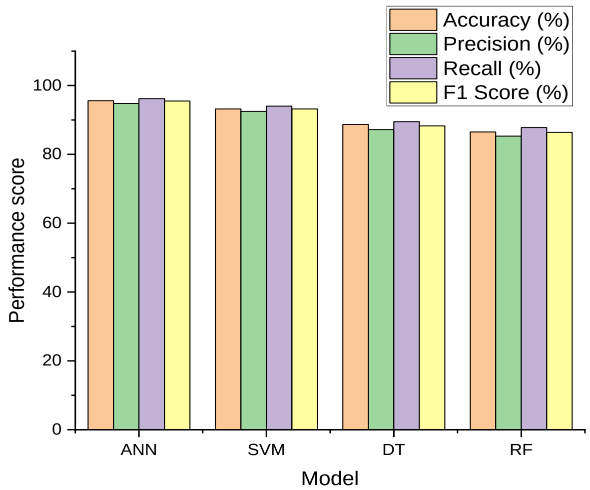

Fig 4 Performance score of each machine learning model

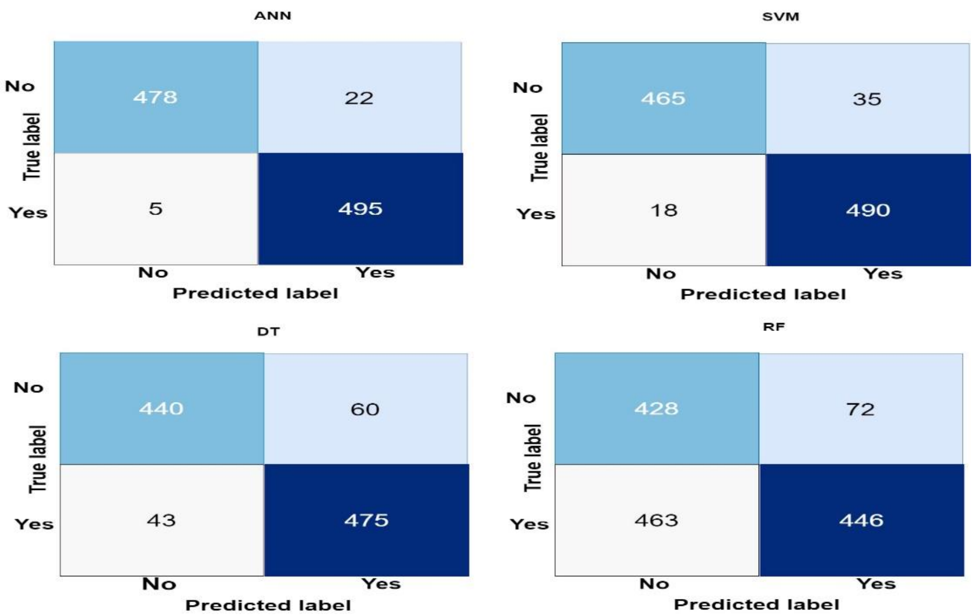

Fig 5 Confusion Matrices of each model

Figure 4 presents the performance ratings of five different machine learning models to forecast water needs for rice growth. Metrics include Accuracy, Precision, Recall, and F1 Score, offering a complete study of the efficacy of each model. Artificial Neural Network (ANN) emerges as the highest performing model with an astounding accuracy of 95.6%, displaying proficiency in pattern recognition followed closely by Support Vector Machine (SVM) with 93.2% accuracy, and creating its validation of trustworthy distribution skills. Decision tree and random forest demonstrate appropriate accuracies of 88.7% and 86.5%, respectively. Together, these measures give useful information into the predictive capacity of each model in improving irrigation systems.

The provided Figure 5 shows the confusion matrices for each machine learning model, offering a thorough breakdown of their prediction performance in terms of true positives, false positives, true negatives, and false negatives e.g. They received a false-pa. Similarly, the Support Vector Machine (SVM) yielded 465 true positives and 35 false positives. These values provide insight into the models' capacity to effectively categorise water demand data and emphasise their strengths and limits in handling true and false predictions, which are vital for the examination of a real-world applications for irrigation efficiency for rice farming.

Conclusion

In conclusion, this research gives thorough insights into IoT-enabled smart irrigation systems and its applications for effective rice farming. The integration of numerous factors such as temperature, humidity, humidity and humidity sensors provides real-time data gathering, allowing the system to respond robustly to ambient circumstances a modifying it Artificial neural networks (ANN), support vector machines (SVM), decision trees (DT), Using machine learning methods like as random forests (RF) enhances the prediction capacity of the system size, allowing for dynamic flexibility in irrigation plans. The performance study reveals that ANN demonstrates the best accuracy of 95.6%, followed closely by SVM, DT, and RF. Together, these models assist avoid over- or insufficient irrigation, and increase soil moisture for effective rice farming.

Confusion matrices expose the inner details of model performance, revealing true positives, false positives, true negatives, and false negatives. The capacity of the system to precisely estimate water needs is vital for effective resource management and sustainable agriculture practices. Overall, the research underlines the relevance of integrating IoT and machine learning into precision agriculture, enabling scalable and adaptable solutions to solve the complex issues of rice cultivation. The results give useful insights into the future developments of technology in agriculture, designed to increase agricultural yields, resource efficiency, and environmental sustainability further investigation and development of these intelligent systems promises to change agricultural methods.

References

[1] L. Tian, C. Wang, H. Li, and H. Sun, "Yield prediction model of rice and wheat crops based on ecological distance algorithm," *Environmental Technology and Innovation*, vol. 20, p. 101132, 2020, doi: 10.1016/j.eti.2020.101132.

[2] N. Kitpo and M. Inoue, "Early rice disease detection and position mapping system using drone and IoT architecture," *Proceedings - 12th SEATUC Symposium, SEATUC 2018*, pp. 0–4, 2018, doi: 10.1109/SEATUC.2018.8788863.

[3] H. Arumugam, B. Krishnasamy, G. Perumal, A. D. A, M. I. Abdul Aleem, and A. Muthukaruppan, "Bio-composites of rice husk and saw dust reinforced bio-benzoxazine/epoxy hybridized matrices: Thermal, mechanical, electrical resistance and acoustic absorption properties," *Construction and Building Materials*, vol. 312, no. November, p. 125381, 2021, doi: 10.1016/j.conbuildmat.2021.125381.

[4] B. S. Bari *et al.*, "A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework," *PeerJ Computer Science*, vol. 7, pp. 1–27, 2021, doi: 10.7717/PEERJ-CS.432.

[5] G. Marques, J. Rencoret, A. Gutiérrez, and J. C. del Río, "Lipophilic compounds from maize fiber and rice husk residues – An abundant and inexpensive source of valuable phytochemicals," *Industrial Crops and Products*, vol. 146, no. November 2019, p. 112203, 2020, doi: 10.1016/j.indcrop.2020.112203.

[6] S. D. Saravanan and M. Senthilkumar, "Prediction of tribological behaviour of rice husk ash reinforced aluminum alloy matrix composites using artificial neural network," *Russian Journal of Non-Ferrous Metals*, vol. 56, no. 1, pp. 97–106, 2015, doi: 10.3103/S1067821215010174.

[7] N. Balaji, J. V. S. P. Kumar, G. Ramesh, V. Dhinakaran, N. Gobu, and T. Maridurai, "Investigation on DMA, Fatigue and Creep Behaviour of Rice Husk Ash Biosilica-Prickly Pear Short Fibre-

Reinforced Epoxy Resin Composite," *Silicon*, vol. 14, no. 18, pp. 12773–12779, 2022, doi: 10.1007/s12633-022-01981-4.

[8] Q. Li *et al.*, "Low risk of category misdiagnosis of rice syrup adulteration in three botanical origin honey by ATR-FTIR and general model," *Food Chemistry*, vol. 332, no. March, p. 127356, 2020, doi: 10.1016/j.foodchem.2020.127356.

[9] H. Pallathadka *et al.*, "Application of machine learning techniques in rice leaf disease detection," *Materials Today: Proceedings*, vol. 51, pp. 2277–2280, 2022, doi: 10.1016/j.matpr.2021.11.398.

[10] X. Dai and D. Li, "Research on rice pests and diseases warning based on CBR," *Proceedings - 2013 International Conference on Computational and Information Sciences, ICCIS 2013*, pp. 1740–1742, 2013, doi: 10.1109/ICCIS.2013.454.

[11] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li, "Image recognition of four rice leaf diseases based on deep learning and support vector machine," *Computers and Electronics in Agriculture*, vol. 179, no. August, p. 105824, 2020, doi: 10.1016/j.compag.2020.105824.

[12] S. Jain and D. Ramesh, "AI based hybrid CNN-LSTM model for crop disease prediction: An ML advent for rice crop," *2021 12th International Conference on Computing Communication and Networking Technologies, ICCCNT 2021*, 2021, doi: 10.1109/ICCCNT51525.2021.9579587.

[13] H. Alshahrani, G. Pathinettampadian, A. K. Gujba, and A. Prakash Vincent Rethnam, "Effect of palmyra sprout fiber and biosilica on mechanical, wear, thermal and hydrophobic behavior of epoxy resin composite," *Journal of Industrial Textiles*, vol. 52, 2022, doi: 10.1177/15280837221137382.

[14] J. Pant, R. P. Pant, M. Kumar Singh, D. Pratap Singh, and H. Pant, "Analysis of agricultural crop yield prediction using statistical techniques of machine learning," *Materials Today: Proceedings*, vol. 46, pp. 10922–10926, 2021, doi: 10.1016/j.matpr.2021.01.948.

[15] K. Rachineni, V. M. Rao Kakita, N. P. Awasthi, V. S. Shirke, R. V. Hosur, and S. Chandra Shukla, "Identifying type of sugar adulterants in honey: Combined application of NMR spectroscopy and supervised machine learning classification," *Current Research in Food Science*, vol. 5, pp. 272–277, 2022, doi: 10.1016/j.crfs.2022.01.008.

[16] M. Lastra-Mejías, M. Izquierdo, E. González-Flores, J. C. Cancilla, J. G. Izquierdo, and J. S. Torrecilla, "Honey exposed to laser-induced breakdown spectroscopy for chaos-based botanical classification and fraud assessment," *Chemometrics and Intelligent Laboratory Systems*, vol. 199, no. January, 2020, doi: 10.1016/j.chemolab.2020.103939.

[17] H. S. Yang, H. J. Kim, H. J. Park, B. J. Lee, and T. S. Hwang, "Water absorption behavior and mechanical properties of lignocellulosic filler-polyolefin bio-composites," *Composite Structures*, vol. 72, no. 4, pp. 429–437, 2006, doi: 10.1016/j.compstruct.2005.01.013.

[18] Z. Li, L. Ding, and D. Xu, "Exploring the potential role of environmental and multi-source satellite data in crop yield prediction across Northeast China," *Science of the Total Environment*, vol. 815, p. 152880, 2022, doi: 10.1016/j.scitotenv.2021.152880.

[19] S. Pawar, S. Shedge, N. Panigrahi, A. P. Jyoti, P. Thorave, and S. Sayyad, "Leaf Disease Detection of Multiple Plants Using Deep Learning," *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing, COM-IT-CON 2022*, no. May, pp. 241–245, 2022, doi: 10.1109/COM-IT-CON54601.2022.9850899.

[20] S. Poomathi and S. S. S. Roji, "Experimental investigations on Palmyra sprout fiber and biosilica-toughened epoxy bio composite," *Biomass Conversion and Biorefinery*, no. 0123456789, 2022, doi: 10.1007/s13399-022-02867-6.

[21] A. J. Rau, J. Sankar, A. R. Mohan, D. Das Krishna, and J. Mathew, "IoT based smart irrigation system and nutrient detection with disease analysis," *TENSYMP 2017 - IEEE International Symposium on Technologies for Smart Cities*, pp. 3–6, 2017, doi: 10.1109/TENCONSpring.2017.8070100.

[22] R. Hesse, F. Krull, and S. Antonyuk, "Prediction of random packing density and flowability for non-spherical particles by deep convolutional neural networks and Discrete Element Method simulations," *Powder Technology*, vol. 393, pp. 559–581, 2021, doi: 10.1016/j.powtec.2021.07.056.

[23] M. Duque-Acevedo, I. Lancellotti, F. Andreola, L. Barbieri, L. J. Belmonte-Ureña, and F. Camacho-Ferre, "Management of agricultural waste biomass as raw material for the construction sector: an analysis of sustainable and circular alternatives," *Environmental Sciences Europe*, vol. 34, no. 1, 2022, doi: 10.1186/s12302-022-00655-7.