2023 IEEE Pune Section International Conference (PuneCon)
COEP Technological University, Pune, India. Dec 14-16, 2023

A Deep Learning Approach to Irrigation Management in Smart Agriculture

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***Abstract*— This paper introduces a pioneering approach to modernize agricultural practices through the integration of Artificial Neural Networks (ANN) into irrigation management. The primary objectives include achieving accurate data analysis for precise irrigation control, implementing real-time data collection and monitoring, and developing a decision support system that leverages ANN insights to enhance crop health and resource efficiency. The utilization of ANN represents a cutting-edge advancement in smart agriculture, harnessing the capabilities of deep learning and attention mechanisms to optimize irrigation strategies. To build the ANN model, training data is collected and utilized to the objective is to train three models: The Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), along with the proposed Artificial Neural Network (ANN) model. This study assesses the efficacy of the suggested model and conducts a comparative analysis with the support provided by CNN and LSTM algorithms. The ANN model emerged as the standout performer across all metrics. With an accuracy of 97.24%, it outperformed both the LSTM (95.68%) and CNN (93.39%), showcasing its superior capability in accurately classifying temperature and moisture data, critical for precise irrigation management. Moreover, the ANN model demonstrated exceptional specificity and sensitivity values at 96.08% and 95.98%, respectively, surpassing both CNN and LSTM models.**

Keywords—Irrigation management, smart Agriculture, ANN, CNN, LSTM, Agriculture Technology, etc.

I. Introduction

Agriculture, as the backbone of global food production, faces increasing challenges in the 21st century. The world's population is Experiencing an unparalleled pace of growth, it is projected that by the year 2050, there will be over 9 billion mouths to feed. Coupled with climate change and resource constraints, this places immense pressure on the agricultural sector to boost productivity and sustainability. In this context, the concept of "smart agriculture" has emerged as a promising solution, leveraging technology, data, and advanced techniques to transform the way we grow and manage crops [1]. At the heart of this transformation lies the efficient and precise

Management of irrigation, a critical component for crop health and yield optimization. Traditional irrigation practices have often relied on scheduled watering or manual assessment of soil moisture levels, which can be inefficient, wasteful, and may not account for the dynamic environmental factors that affect crops. In response to these challenges, smart agriculture integrates cutting-edge technologies, data analytics, and machine learning to make irrigation more intelligent and resource-efficient. This article explores the application of deep learning, a subset of artificial intelligence (AI), to irrigation management within the context of smart agriculture[2].

Smart agriculture, Precision agriculture, also referred to as digital farming, signifies a fundamental change in our approach to the cultivation of food. The integration of technological advances, data analytics, as well as automation synergistically harnesses their respective capabilities optimize agricultural processes. Within this framework, irrigation management holds a pivotal role, as water is a finite and increasingly scarce resource. Moreover, inefficient or excessive irrigation not only strains water resources but can also lead to soil degradation and environmental pollution[3]. To address these challenges, smart agriculture utilizes a diverse array of technologies, including the Internet of Things (IoT), imagery collection, and data analytics, are being used. These technological advancements provide an ongoing record of soil conditions, meteorological patterns, and the overall well-being of crops in real-time, leading to data-driven decision-making. One of the most promising branches of AI employed Deep learning is the subject matter under consideration within this particular situation [4].

Deep learning, a subfield within the domains of machine learning and artificial intelligence, has demonstrated remarkable capabilities in various fields, from the domains of image and voice recognition to the field of medical diagnostics, a wide range of applications have emerged autonomous driving. In agriculture, deep learning has found applications in crop disease detection, yield prediction, pest control, and irrigation management. Its potential in irrigation management is particularly intriguing, as it the ability to analyze several data sources, including moisture levels in the soil meters, weather forecasts, and satellite imaging, enables the generation of accurate and detailed insights timely decisions about irrigation needs. This can optimize water usage, reduce costs, and minimize the environmental footprint of agriculture[5].

A. Deep Learning for Irrigation Management

Efficient irrigation management relies on a comprehensive understanding of the factors that influence soil moisture and crop water requirements. These factors include soil type, crop type, weather conditions, evapotranspiration rates, and historical irrigation practices. Deep learning models can ingest data from these sources and create complex, non-linear relationships, enabling accurate irrigation recommendations. One of the key benefits of using deep learning in irrigated management is its ability to enhance the capacity to efficiently handle and evaluate substantial quantities of data in real-time [6]. For example, soil moisture sensors placed at different

2023 IEEE Pune Section International Conference (PuneCon) | 979-8-3503-2420-4/23/$31.00 ©2023 IEEE | DOI: 10.1109/PUNECON58714.2023.10450129

depths in the field can provide continuous data on soil moisture content. Deep learning models can process this data and, based on historical information, make predictions about future moisture levels, thus informing when and how much to irrigate. These models can adapt to changing environmental conditions, providing a level of precision that traditional irrigation methods cannot achieve[7].

1) Objectives

- To incorporate the ANN model for accurate data analysis, enabling precise irrigation control.
- To implement real-time data collection and monitoring for immediate response to changing agricultural conditions.
- To develop a decision support system that leverages ANN insights to guide irrigation decisions, improving crop health and resource efficiency.

2) Organization of the study

The work may be broken down into the following sections: Background of the proposed methods are provided in Section 2, an explanation of the methodology that underpins the recommended algorithm is provided in Section 3, Section 4 delivers the findings of the study, and Section 5 provides a conclusion.

II. RELATED WORK

Conducted study addressing the incorporation of various machine learning techniques that have the potential to enhance irrigation decision management [8]. The aim of this study was to examine the current research direction and practical application of machine learning methods, as well as the use of resulting machine learning models, in order to support farmers in the field of sustainable irrigation management. [9] This research conducted an examination of current academic literature about the use of deep learning methodologies in the agricultural domain during the past five years. This investigation aimed to identify and emphasize the noteworthy advancements made in this domain, as well as the challenges that have been successfully addressed. In addition, the author conducted a study on agricultural parameters that were monitored using the internet of things (IoT) technology. These values were then inputted into a deep learning system designed for purposes of analysis. [10] emphasized the key restrictions to agricultural output, conventional irrigation scheduling techniques, as well as the accompanying problems, Various initiatives and advancements have been undertaken In order to optimize water use efficiency (WUE), implementing sustainable agricultural practices that optimize water use and minimize waste providing an overview of several smart irrigation alternatives.

[11] The inception of model predictive control (MPC) may be traced back to its first establishment, and its application in the field of precision irrigation is further elucidated. This paper provides a comprehensive analysis this study examines the use of data-driven modelling and predictive control models in the field of precision management of irrigation. Model predictive control (MPC) is being used in several applications related to irrigation canals, irrigation scheduling, stem water potential adjustment, soil moisture regulation, and plant disturbance prediction. [12] The main focus of this work revolves around the practical application of remote sensing technologies in the context of precision irrigation. The aforementioned methods are used to assess transpiration rates, including infrared thermography and the hydration status of crops agricultural characteristics. Precision agriculture has been incorporated as a vital component in the framework for reaching this aim. Using these strategies, the author may solve the issue of water scarcity, which is critical for agriculture.

III. BACKGROUND

This section provides an overview of various algorithms, including in this study, we used several machine learning algorithms, including random forests, Gaussian Naïve Bayes, and logistic regression CNN, by discussing their background and key features.

A. ANN

In the picture below, a neural network (ANN) model with two secret layers and partly linked nodes is shown. So many formative measurements are deciding factor in determining the number of input nodes. It is considered that there are I formative measures, which is denoted by the symbol $x_i\left(i=1,2,3,.....I\right)$. The overall input variables the amount of output variables both have a role when calculating the amount of neurons and layers that remain secret that are found in the hidden layer. It is presumable that there are W variables that are output to the system and N variables that are input to the system, denoted correspondingly as $\xi_w\left(w=1,2,3,.....,W\right)$ and $\eta_n\left(n=1,2,3,.....,N\right)$[13].Overall the total of neurons with results is given from assumption that there are O reflecting measures, which are denoted by $y_o\left(o=1,2,3,...O\right)$. The relationship between the measurements and the variables governs the connections between layers. The weights of the links among the input layer and hidden layer neurons are included in the $W\times I$ dimensional vector W^I, which is denoted as W^I. The linkage weights among buried layer neurons are included in the $N\times\left(W+N\right)$ dimensional vector,

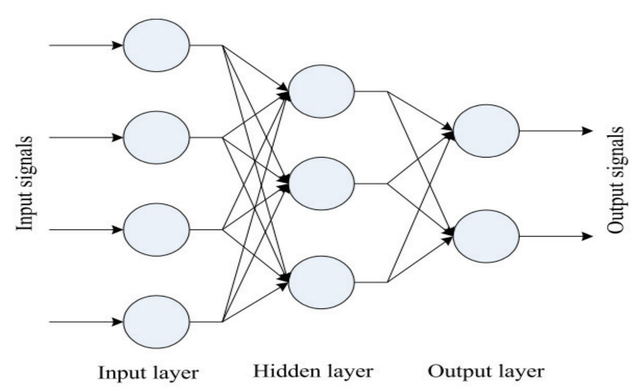

Fig. 1. ANN Architecture

designated as W^H. That linkage of weights between the results of the visible layer neurons and the neurons in the hidden layer are represented by the $O \times N$-dimensional vector abbreviated as W^o. In a neural network, each neuron has a nonlinear activation function.[14]

B. CNN

The convolutional neural network (CNN) is a kind of artificial neural network (ANN) frequently employed in the domain of deep learning to analyze visual images. The term "convolutional neural network" (CNN) is often used to refer to a specific kind of neural network that is frequently used in the field of deep learning for the purposes of image recognition and processing. A convolutional neural network (CNN) has left three separate layers: the input layer, the hidden layer, and the output layer [15]. The intermediate layers inside a neural network with a feed-forward structure are often denoted as hidden layers due to the fact that the activation function as well as final convolution disguise the inputs and results of these layers. Convolutional layers constitute a subset of the concealed layers inside a convolutional neural network, which execute convolutions[16].

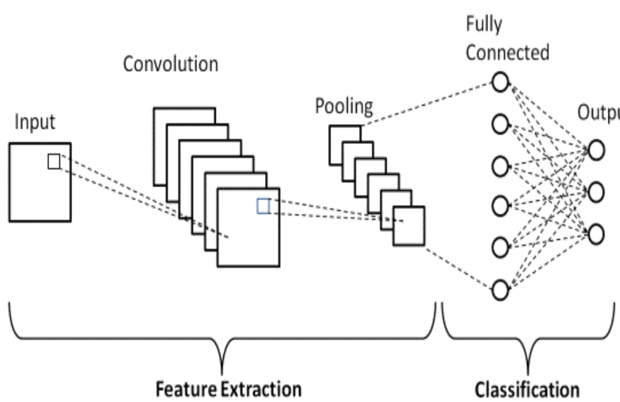

Fig. 2. CNN Architecture

C. LSTM

The model known as LSTM is used to identify whether network breaches have occurred. A specific extension of a recurrent neural network organisation, a DL model, is known as LSTM. For work on un-segmented data, relationship recognition patterns, voice recognition, including abnormal prediction in network traffic via IDSs, for example, LSTM may be utilised)[17]. The inputting gate, exit gate, remembering gate, and cell are the four basic parts of an LSTM system. Since cell memories usually only endure a limited time, three gates initially were used to define what information travels within and out of a cell. The figure below shows the LSTM for each phase of a cell. The horizontal uppermost line, which indicates the cell state, has a cell state implemented in it. As a result, when data has been completely regularised by gates in a cell state, the LSTM has no way to remove it. A cell contains important structural elements.[18].

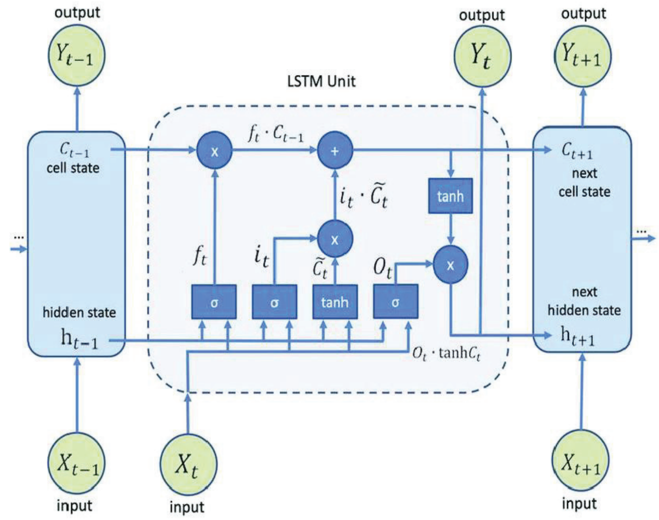

Fig. 3. structure of LSTM cell

IV. METHODOLOGY

The integration of ANN in irrigation management represents a cutting-edge advancement in smart agriculture. This methodology leverages the power of deep learning and attention mechanisms to optimize irrigation strategies. The objective is to dynamically schedule irrigation, enhance crop health, and conserve resources. The methodology encompasses data collection, pre-processing, ANN model training, real-time monitoring, and user-friendly interfaces for seamless interaction.

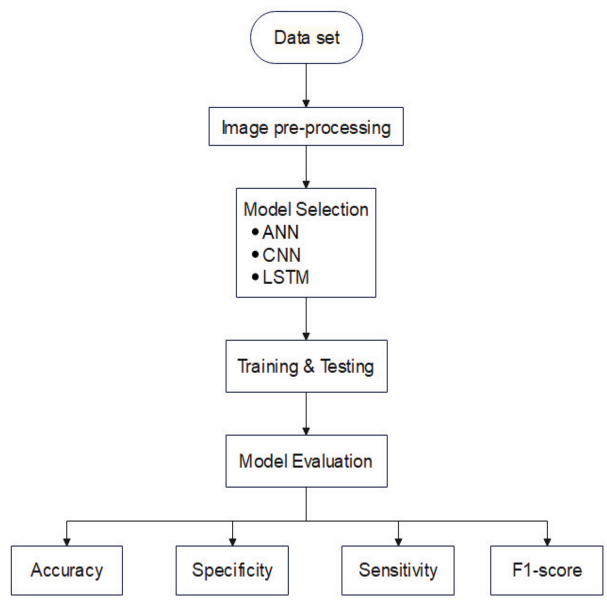

Fig. 4. Proposed Flowchart

A. Dataset Description

In this study, we collected data from below website:

https://www.kaggle.com/code/triptmann/irrigation-scheduling-for-smart-agriculture/input.

This dataset comprises a collection of images capturing moisture and temperature information. It includes numerical data representing various features such as meteorological conditions, soil moisture levels, and the identification of specific crop types. The primary goal of this system is to facilitate automatic water supply management based on the gathered information.

B. *Pre-processing steps for classification*

The objective is the objective of this research is to investigate the impact of various pre-processing techniques on the precision of the results many core convolutional networks. The next section presents a number of pre-processing approaches.

Eliminate noise:

The process of noise elimination, especially in image datasets, often involves various techniques and methods specific to the characteristics of the images. The information regarding which images are considered for noise elimination, the criteria for selection, or the methodology used to eliminate noise would typically be documented or described in the methodology section, associated documentation, or supplementary materials provided with the dataset.

To calm down the agitation whenever a function known as Gaussian is applied to blur an image, a blur that resembles a Gaussian is the result. One of the goals of this common graphics effect the objective is to reduce the level of visual clutter. Gaussian smoothing is often used as a preprocessing step in computer vision algorithms. This action is being undertaken with the purpose of to enhance visual architectures across different scales.

C. *Train _test split*

The dataset has been partitioned into separate test and training sets based upon the user-specified splitting ratio after all preparation procedures are finished. The models will then be validated using the test data after being properly trained using this segmented train data.

Train the network:

The train dataset is used for training the Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) algorithms, together with the suggested Artificial Neural Network (ANN) model. The effectiveness of the suggested model is evaluated and compared with the existing models assistance offered by CNN and LSTM.

The performance metrics enumerated below are utilized to assess the quality of the recommended algorithm.

D. *Performance metrics*

Metrics such Accuracy, sensibility, precision, along with the F1-score are often used as evaluation metrics to examine the performance of an algorithm in relation to the performance measures derived from the confusion matrix.

Accuracy: The term "identification rate" refers to the ratio of accurately identified individuals to the total count of disciplines.

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

Sensitivity: Recall, which is also referred to as sensitivity, denotes the proportion the computer system in question demonstrates a high level of accuracy in identifying and classifying labels as positive.

$$Sensitivity = \frac{TP}{TP + FN}$$

Precision: By considering the total count of accurate forecasts, it is possible to assess the level of accuracy in a forecast. This idea also goes by the name of predictive value.

$$\Pr ecision = \frac{TP}{TP + FP}$$

F1-Score: The F1-score is a quantitative metric that integrates both remembrance and accuracy.

$$F1 - score = 2 * \frac{\Pr ecisison * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$$

Specificity: The system has appropriately designated the negative as specificity.

$$Specificity = \frac{TN}{TN + FP}$$

Where,
TP= True Positive
TN= True Negative
FP= False Positive
FN= False Negative

V. RESULTS

ANN:

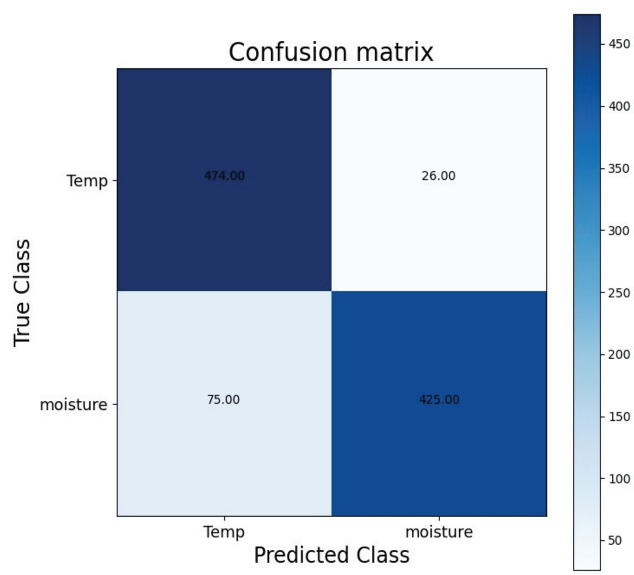

Fig. 5.

The confusion matrix of the proposed ANN architecture shows that Temp data are correctly identified 474 times and misclassified as moisture data 26 times. Moisture data are correctly predicted 475 times, with 25 misclassifications. The model exhibits good accuracy in distinguishing between non-defected and defected images.

CNN:

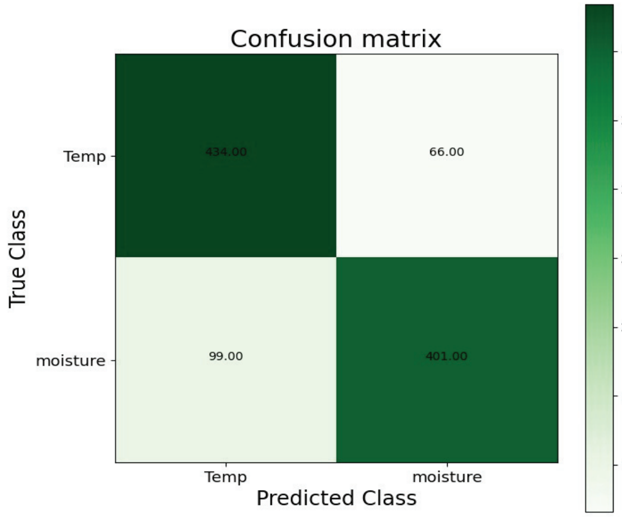

Fig. 6.

The provided confusion matrix illustrates the CNN architecture's performance in distinguishing between temp (0) and moisture (1) data. The proposed method correctly identified 434 temp data but misclassified 66 as moisture data. Additionally, it accurately predicted 401 moisture data but had 99 misclassifications. These results showcase the model's strengths in accurate identification while also revealing areas for potential refinement in reducing misclassifications.

LSTM:

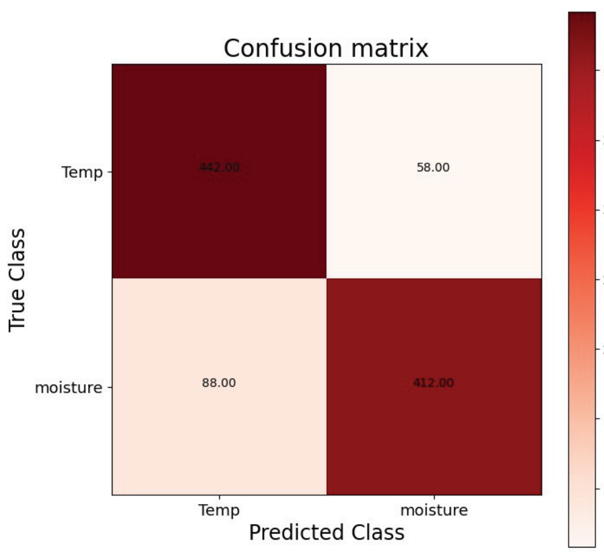

Fig. 7.

The confusion matrix for the LSTM architecture reveals that it correctly identified 442 temp data, but misclassified 58 as moisture data. For moisture data, it achieved 412 correct predictions, but there were 88 misclassifications. The model demonstrates a reasonably good performance in distinguishing between temp data and moisture data. However, it still exhibits certain classification errors. The model could be enhanced by investigating alternative hybrid deep learning models, which include the ANN model that has been given, in order to appropriately detect and tackle casting difficulties.

Performance indicators like Accuracy, Sensitivity, etc. Specificity are computed to assess the efficacy of the architectures. The results are shown as follows:

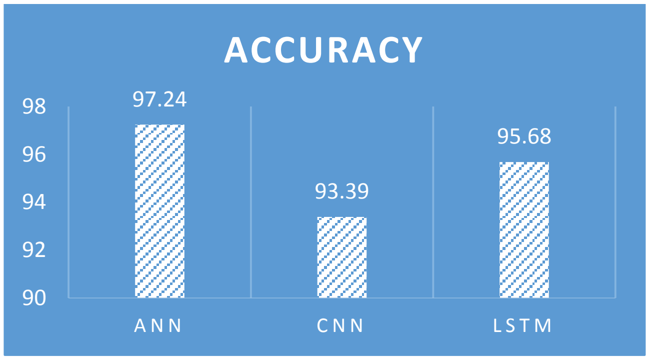

Fig. 8.

The previous graph makes it clear that The precision of the recommended artificial neural network (ANN) is The assessment and comparison were performed using two more models, namely the Convolutional Neural Network (CNN) as well as Long Short-Term Memory (LSTM). Consequence of this phenomenon is that proposed model beat the LSTM and CNN, producing an accuracy score of 97.24 as opposed to the recommended model's scores of 95.68 and 93.39.

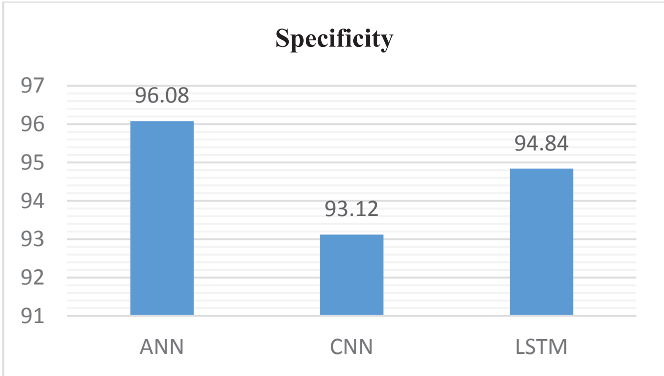

Fig. 9.

The performance of the recommended ANN The evaluation and comparison of the two more models, LSTM and CNN, is apparent from the given context following graph. The specificity value for ANN is 96.08. This led to the suggested model outperforming both CNN et LSTM, with specificity scores for the model suggested of 93.12, 94.84, respectively.

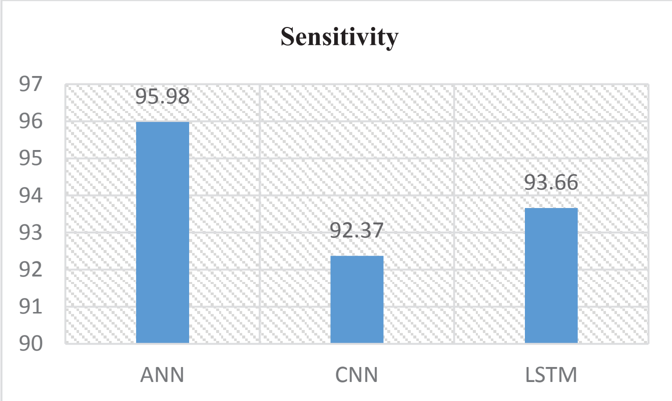

Fig. 10.

The accompanying graph compares and contrasts the performance of the CNN and LSTM models with that of the proposed model ANN. The sensitivity value for ANN is 95.98. The model that was suggested performed better than CNN (92.37) nor LSTM (93.66).

TABLE I. ARCHITECTURES AND VALUES

Architectures	Accuracy (%)	Specificity (%)	Sensitivity (%)
ANN	97.24	96.08	95.98
CNN	93.39	93.12	92.37
LSTM	95.68	94.84	93.66

VI. CONCLUSION

This paper presents a ground breaking advancement in modernizing agricultural practices by integrating Artificial Neural Networks (ANN) into irrigation management. The study's core objectives encompass achieving precise irrigation control through accurate data analysis, implementing real-time data collection and monitoring, and establishing a decision support system leveraging ANN insights to optimize crop health and resource utilization. This integration of ANN represents a significant leap in smart agriculture, harnessing deep learning and attention mechanisms to fine-tune irrigation strategies. The evaluation of three key models such as ANN, LSTM, and CNN revealed compelling insights into their performance. The ANN model emerged as the standout performer across all metrics. With an accuracy of 97.24%, it outperformed both the LSTM (95.68%) and CNN (93.39%). This higher accuracy underscores the ANN model's superior capability in accurately classifying temperature and moisture data. Furthermore, the specificity and sensitivity values of the ANN model, at 96.08% and 95.98% respectively, surpass those of both the CNN and LSTM models. These figures indicate the ANN's exceptional ability to distinguish between non-defected and defected images, providing critical insights for precise irrigation management. In terms of specificity, the ANN model excelled with a score of 96.08%, surpassing both the LSTM (94.84%) and CNN (93.12%) models. This highlights the ANN's effectiveness in correctly identifying non-defected images. Additionally, the ANN model demonstrated impressive sensitivity with a value of 95.98%. This further cements its superiority over both the CNN (92.37%) and LSTM (93.66%) models in accurately detecting defected images.

In summary, the ANN-based irrigation management system showcased in this study exhibits outstanding performance across all key metrics, making it the preferred choice for modernizing agricultural practices. Its exceptional accuracy, specificity, and sensitivity values indicate its potential to significantly enhance the sustainability and productivity of farming. By dynamically scheduling irrigation, improving crop health, and conserving resources, this approach holds immense promise for the future of agriculture. The integration of ANN technology presents a transformative path towards more efficient and sustainable agricultural practices.

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