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HYBRID ENSEMBLE ADVANCED MODEL FOR FARMER'S DECISION-MAKING IN CROP MANAGEMENT

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ABSTRACT

India is the second largest crops producers among all the states. Among the main foods that have been cultivated are wheat and rice. This farming technique aids in increasing crop productivity and facilitating farmers' ability to make the best decisions. High-quality products, disease resistance, and fertilizer responsiveness are the greatest ways to increase crop yield and food quality. The data for this research was gathered using information about the crops, soil, weather, and yield statistics for different crops. The gathered data is sent to the selection process after being carefully pre-processed using the techniques of normalization and intelligent imputation. Using the encoding method and the feature engineering process, the crop is selected based on the input provided as a data set. The LeNet-5 approach is used to determine the optimum crop based on transfer learning, allowing the farmer to choose the crops with the highest yields. With the aid of the hyper tuning procedure, a shallow neural network is used for both the crop analysis and decision-making. This research proposes a hybrid shark smell with Jaya optimize approach for crop tweaking and yield optimization. The suggested hybrid ensemble approach is deployed and continuously integrated to achieve the ideal yield so that farmers can make the right decisions.

Keywords: *Normalization, LENET-5, Shallow Neural Networks, Hybrid Shark Smell, Jaya Optimize.*

1. INTRODUCTION

The crop management manages different types of crop production depending on the factors like the soil physiology, biology and the climate. This paper focus on the decision making of the farmers on the kinds of crops to be produced and the types of soil needed. Collecting the data set from various resource has been cleaned using the imputation and the normalization method. This imputation technique replaces the missed data which is connected to the substitute value in the data set. Then based on the normalization the normal value segregation of the data in the data set is done. To process the feature engineering, the Auto encoder is used, to help to know more about the unlabeled data. Then for selecting the model, the LeNet-5 with the transfer learning is used. This LeNet is a structure of the CNN which helps to process the images in large scale. It helps to make the selection of the model of the images in the data set. It recognizes the images, printed words etc. The shallow neural network is used for the ensemble construction. This helps in analyzing the data that is received in the hidden layer and then expresses the final output for the farmers for the crop management. This hidden layer contributes to the transformation of the input data. This compares the data from one network to other to identify the crucial times. Here hybrid algorithm such as the Jaya-based Shark Smell Optimization has been utilized to get the exact optimal solution by random sampling. The continuous integration and deployment strategy is applied to the monitoring and display process. It facilitates the automated production of a certain crop and shows the farmer the ultimate course of action to take. This is how the farmers make the decision to produce the crops in their entire life time.

The main objective of the proposed research as follows:

1. Collect a comprehensive dataset with various crop growth attributes.

2. Clean and preprocess the data, handling missing values and noise.

3. Use autoencoders for feature engineering, selecting relevant features and reducing dimensionality.

4. Employ LeNet-5 deep learning architecture for accurate crop type prediction.

5. Build an ensemble model using shallow neural networks for crop selection and decision-making.

6. Optimize model performance through continuous optimization techniques like J-SSO.

7. Integrate the optimized model into the decision-making process for crop management.

A robust and efficient crop prediction system can be developed, empowering farmers to make informed decisions and optimize their crop management practices for improved yields and sustainability.

2.RELATED WORKS

In this paper, the detection of plant diseases has been achieved using the LeNet-5 method within the framework of deep learning. The author examines the relationship between soil quality, plant yield, and decision- making processes. Additionally, convolutional neural networks are employed for disease detection, where Bedi et al. (2021)[1] utilized images of plants to identify diseases and classify their types. Crop diseases and pests are also identified through neural networks, with early detection facilitated by the ResNet V2 model. The overall accuracy in detecting pest diseases reaches 86.1%. This approach involves using convolutional neural networks to identify crop diseases, addressing economic losses, as proposed by Ai et al. (2021)[2].

Zhao and colleagues et al. (2020)[3] utilized remote sensing to outline the process of rice mapping across extensive geographical areas. Through convolutional neural networks and phenological matrices, they identified the fragmentation reflection and diverse plant topologies. Their study involved classifying plants and crop varieties using images. Additionally, they proposed a method for predicting maize and maize crop yields using multiple linear regression and backward elimination. Fashoto et al. (2021)[4] suggested traditional farming techniques for mitigating crop reduction and poor irrigation resulting from climate change. The authors utilized units for analyzing crop yield data and accurately imputing missing values based on greenhouse environment datasets. Moon et al. (2021)[5] contributed to the study by addressing missing data through various loss methods.

This research employs an ensemble deep learning algorithm to analyze rice crop yield. The study focuses on forecasting rice crop production. Chandraprabha et al. (2023)[6] proposed a method to predict agricultural productivity based on crop composition. Additionally, the manuscript utilizes multi-sensor fusion for automatic reconciliation and imputation to identify defaults and missing data. Ba-Alawi et al. (2023)[7] contribute to the field by automating energy consumption detection and crop yield monitoring through MBR plants and multi-sensor fusion technology.

This research explores the utilization of recurrent neural network (RNN) and shallow neural network models to forecast photovoltaic power generation. The computational framework employs the electrical grid system, as introduced by Castillo-Rojas et al in 2023[8]. Additionally, a customized shallow convolutional neural network is developed for identifying citrus peel defects through hyper spectral imaging. Analysis of crop and leaf images is conducted via component analysis to facilitate early detection of damaged leaves, offering decision-making support for farmers, as outlined by Frederick et al in 2023[9]. Furthermore, for optimizing logistics inventory in e-commerce platforms, the Logistic Inventory Optimization method is implemented to manage crop yield and quality. Additionally, a multiplayer feed forward neural network is employed to address the needs of rural populations and the burgeoning e-commerce sector, as proposed by Zhou et al in 2023[10].

3. PROPOSED SYSTEM

The figure 1 represents the flow of the overall proposed system of the paper for analyzing the crop management using decision making. In the

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below diagram the flow of the overall process of the proposed system has been drawn. Here the data is first collected. After that, the data was pre-processed using feature engineering-based data set collection, and auto encoders were used to choose a specific models. LeNet-5 methodology has been employed in the process of choosing the particular model. Subsequent to the identification of the particular model, the ensemble model is constructed. The shallow neural network has been utilized for this ensemble model. Following a final evaluation and tuning of the model, the output was completed for the farmer to use in making decisions. The hybrid Jaya optimize shark smell approach has been applied to this process; the deployment has been completed and the results are shown through continuous integration.

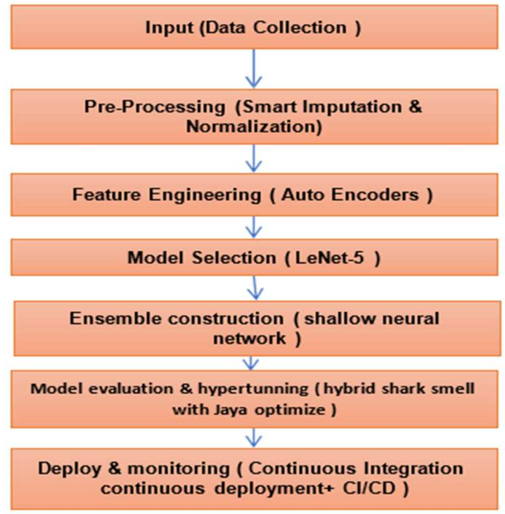

***Fig.** 1 Hybrid ensemble advanced model*

3.1 Data collection

The data set is a collection of 2200 attributes and instances like soil, temperature, rainfall, and many other chemicals that are involved. This data collection, which includes the crops wheat, maize, and so forth, was obtained from the Kaggle platform. When pre-processing the data in the pre-processing layer, these properties will be defamed and the undesired and noisy data will be eliminated.

3.2 Preprocessing

Several pre-processing methods have been applied to the raw data set in this investigation. In this case, the crop included in the data set is pre-processed. Here, the smart imputation and normalizing pre-processing techniques are used in the paper. Using a combination of non-missing values, this smart imputation technique replaces missing data from the dataset. During this process, a mixture of the high-frequency variables is used to replace the missing values.

$$\mathrm{Yi} = 2 \quad y - y1$$

$$y\ min - ymax \quad (1)$$

This equation (1) y denotes the input data that is related to the crop yield attributes. The data that is preprocessed will move on to the next step of the encoding layer procedure.

Feature engineering using auto encoders

Auto encoders is utilized in the identification of the latent representation of space and it picks up the subsets of training features. The procedure of handling the input that is the soil, weather and the crops data to train the auto encoder is done at this layer. It helps to eliminate noise from the data set. The data set makes it possible to reduce the dimensionality, and input data reconstruction has been completed. The structure that composes and eliminates noise from the input data is the encoder, decoder, and bottleneck layer.

$$\mathrm{E(x)} = \arg\max \sum m \qquad xj - fj + \mathrm{K(o)} \quad (2)$$

The procedure of encoding and decoding specific features of the input crop attributes is carried out using the formula mentioned above. It separates the data from the undesirable crops to grow for a certain soil texture and environment.

3.4 Model selection using LeNet-5

The LeNet-5 method is employed for high accuracy data prediction and for the recognition of certain comparable attributes in the data set. Following training, the data can be assessed for the identification of the crop that

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has to be harvested with an accuracy of 98%. It assesses pictures that are connected to pixels with the same dimensions, measuring 28 by 28. It analyses the characteristics of the crop provided as input and finds the issue with it. When it comes to recognition, it generally functions similarly to a neural network.

3.5 Ensemble construction

The ensemble construction is done using the method of the shallow neural network. It contains one to two hidden parts. But the deep learning contains dozens of layers. It helps in generating the predictive model for few layers in the neural networks. These layers are fully connected with the softmax layer and this helps in finding the various selection of the model that is given as the input.

3.6 Model Evaluation and hyper tuning

The process of optimizing the continuous and the random solution based on the initial set is done in this process. The combination of the shark smell method and the Jaya optimization is considered as the Jaya-based Shark Smell Optimization (J-SSO). Here the decision making of the crop management is done. This is how the farmer makes a decision on the crop and makes more yield for managing the crop for the year.

Algorithm for J-SSO

```
Initialization of crops
Setup user defined parameters
 Initialize counter as j = 2
for j = 2:j_max
        if del (of)< 0:5
                Based on SSO update velocity vector
                Based on SSO update position
        Else
                Based on JA update solution
        end if
end for
j Set j =
j+2
Choose the best crops for harvesting and to get more yields
Highest of crop yield
End
```

4. RESULT AND DISCUSSION

The proposed hybrid ensemble recommendation model has demonstrated promising results in enhancing crop yield predictions. The ensemble approach effectively mitigates over fitting, as evidenced by improved generalization across training and validation datasets. The ensemble outperformed individual models, showcasing the strength of combining different recommendation strategies. Key metrics such as Precision, Recall, F1 Score, Accuracy, Mean Squared Error and Root Mean Squared Error indicated a substantial reduction in prediction errors compared to baseline models. This approach not only improves accuracy but also bolsters model robustness, providing a more reliable tool for farmers in optimizing factors like fertilizer use, irrigation, and pest control. The efficiency gaining achieved through ensemble techniques and optimization strategies underscore the practicality and effectiveness of this hybrid model in real-world agricultural decision-making. Ongoing monitoring and updates, facilitated by continuous integration/deployment, ensure the model's continued relevance and accuracy in dynamic farming environments. Overall, this hybrid ensemble recommendation model presents a promising avenue for maximizing crop yield and, consequently, farmers' profits.

4.1 Dataset

The dataset utilized for predicting paddy crop yield in the Vellore district, southern India, spans 35 years

and focuses on specific blocks. Paddy cultivation being a significant economic activity in this region justifies its selection for investigation. The dataset comprises diverse parameters crucial for the study, including climatic, soil, and groundwater factors unique to the study area. Climate data obtained by the Indian Meteorological Department includes standard variables such as temperature, precipitation, and humidity, as well as unique elements such as ground frost frequency, diurnal temperature range, and wind speed. The dataset includes soil properties such as topsoil density, pH, and macronutrient contents. The dataset also includes new hydro chemical parameters of groundwater, such as transmissivity, aquifer type, permeability, electrical conductivity, and pre-/post-monsoon micronutrient content (calcium, potassium, sodium, magnesium, and chloride). Notably, this study incorporates data such as evapotranspiration, ground frost frequency, groundwater nutrients, and aquifer features,

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providing a unique compilation not found elsewhere in the literature. This comprehensive dataset, covering an array of climatic, soil, and groundwater variables, serves as a robust foundation for developing an efficient model for paddy crop yield prediction, essential for addressing the dynamic and non-linear nature of agricultural systems in the region. A detailed explanation for each metric mentioned in an efficient manner, including relevant equations and their connection to the proposed hybrid ensemble recommendation model:

4.2 Performance Metrics

4.2. 1 Accuracy

Accuracy is the overall correctness of predictions and is computed as the proportion of accurate predictions to the entire number of predictions.

$Accuracy = \quad True \quad Positive{+}True \quad Negative \quad 1$

$True \quad Postive{+}True \quad Negative{+}False \quad Positive{+}False \; Negative$

4.2.2 Mean Absolute Error (MAE):

It computes the mean absolute variance between the expected and actual values. It offers a simple measure of prediction accuracy.

$MAE = 1 \sum n \;\; |y - y'\,|2 \quad\; 2$

$n \;\; k{=}1 \;\; k \qquad\quad k$

4.2.3 Mean Squared Error (MSE)

MSE is the mean squared variance between anticipated and actual results. It is a regression-oriented metric that measures the size of errors. The formula is:

$MSE = 1 \sum n \;\; (y - y'\,)2$ (3)

$n \;\; k{=}1 \;\; kk$

4.2.4 Determination Coefficient (R2):

It estimates the fraction of the variance in the dependent variable (crop yield) that can be predicted by the independent variables (weather, soil type, etc.). It runs from 0 to 1, with 1 representing a perfect match.

$R2 = 1 - SSR \quad (4) SST$

SSR is the average of squared residuals, whereas SST is the number of squares.

4.2.5 Mean Absolute Percentage Error (MAPE):

MAPE determines the average % variance between expected and actual values. It is expressed in percentages.

$MAPE = 1 \sum n \; |yk{-}y'\,|2 \; X100\% k$

$n \;\; k{=}1 \quad |yk|$

4.2.6 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE, giving an understandable statistic in the exact same unit as the desired parameter:

$RMSE = \sqrt{1} \sum n \quad (y \; - y'\,)2 \qquad 6$

$n \;\; k{=}1 \quad k \qquad\quad k$

Table 1 shows a comparison of our proposed system to existing methods such as Agricultural Production Systems Simulator (APSIM), Long Short-Term Memory (LSTM)-Convolutional Neural Networks (CNN), convolutional neural networks (CNNs)-recurrent neural networks (RNNs), and Reinforcement Learning (RL) based on various metrics.

Table 1: Comparative Analysis Of Model Performance

	Training data				Testing data			
	MAE	MSE	R2	RMSE	MAE	MSE	R2	RMSE
APSIM	0.47	0.35	0.68	0.58	0.52	0.43	0.75	0.26
LSTM-CNN	0.34	0.26	0.72	0.36	0.23	0.24	0.62	0.38

CNN-RNN	0.45	0.24	0.62	0.49	0.27	0.34	0.68	0.42
RL	0.6	0.31	0.45	0.67	0.65	0.51	0.57	0.37
Proposed hybrid ensemble recommendation model	0.19	0.07	0.25	0.25	0.14	0.09	0.27	0.19

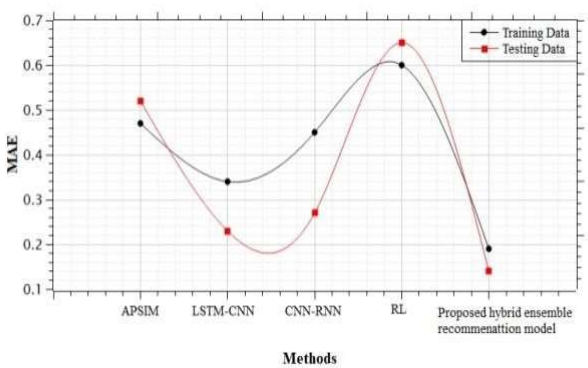

Fig. 2 Mean Absolute Error (MAE) Analysis for Training and Testing Data

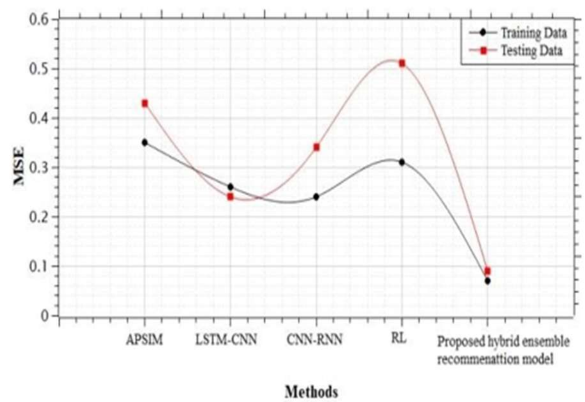

Fig. 3 Comparison of Mean Squared Error (MSE) between training and testing data

Figure 2 presents a detailed analysis of various models based on Mean Absolute Error (MAE) for both training and testing data. The APSIM model has a training data testing data MAE of 0.47 and 0.52, showing that errors are considerably larger in both datasets. In contrast, the LSTM-CNN model demonstrates superior performance with lower MAE values for both training (0.34) and testing data (0.23), suggesting effective learning and generalization. Similarly, the CNN-RNN model yields competitive results, with a training and testing data of 0.45 and 0.27 respectively. While the RL model has a higher training data MAE of 0.6 and a testing data MAE of 0.65, it maintains a consistent margin between the two, signaling stability at the expense of greater error rates. Notably, the proposed hybrid ensemble recommendation model beats all other models, with the lowest training and testing data MAE of 0,19 and 0.14 respectively. The model demonstrates extraordinary capacity to minimize mistakes, both during the learning phase and when applied to previously unknown data, emphasizing the hybrid ensemble approach's efficiency in optimizing forecast accuracy for crop production situations.

Figure 3 illustrates a comprehensive evaluation of various models based on Mean Squared Error (MSE) for both training and testing data. In this case, the APSIM model has a training and training data MSE of 0.35 and 0.43, showing slightly larger errors in both instances. Conversely, the LSTM-CNN model demonstrates superior performance with lower MSE values for both training (0.26) and testing data (0.24), suggesting effective learning and generalization. Similarly, the CNN-RNN model achieves competitive performance, with a training and testing data MSE of 0.24 and 0.34 accordingly. The RL model, while having a higher training data MSE of 0.31, maintains a consistent margin with a testing data MSE of 0.51, suggesting stability but at the cost of higher error rates. Notably, the proposed hybrid ensemble recommendation model outperforms all others, exhibiting the lowest training data MSE of 0.07 and testing data MSE of 0.09. This emphasizes the model's exceptional ability to minimize squared errors, both during the learning phase and when applied to previously unseen data, highlighting the effectiveness of the hybrid ensemble approach in optimizing predictive precision for crop

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yield-related scenarios.

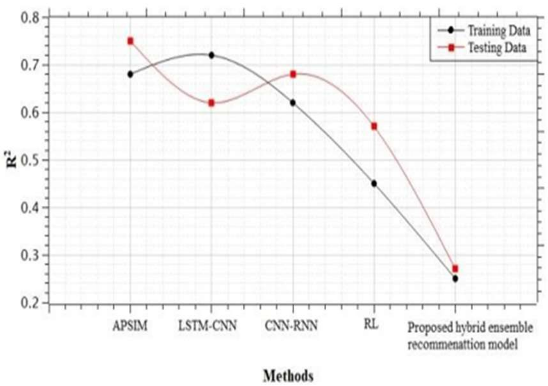

Fig. 4: Coefficient of Determination (R2) Comparison for existing and proposed method

Figure 4 offers an insightful evaluation of different models based on the coefficient of determination (R2) for datasets. In this context, the APSIM model demonstrates a reasonably good fit with a training data R2 values indicating effective generalization. In contrast, the LSTM-CNN model performs better, with higher R2 values for both training (0.72) and testing data (0.62), indicating a significant connection between predicted and actual values. Similarly, the CNN-RNN model retains competitive performance, with a training and testing data R2 of 0.62 and 0.68 respectively. The RL model, while showing a decent fit with a training data R2 of 0.45, experiences a drop in performance on the testing dataset with an R2 of 0.57. Notably, the proposed hybrid ensemble recommendation model, while exhibiting lower R2 values, should be interpreted in the context of its ensemble nature. The model demonstrates a training data R2 of 0.25 and a testing data R2 of 0.27, suggesting a modest but acceptable fit. The lower R2 values can be attributed to the ensemble's complexity and the diverse nature of the constituent models. Nonetheless, the hybrid model's collective strength is its capacity to give credible predictions, demonstrating its potential for improving crop output projections in real-world agricultural circumstances.

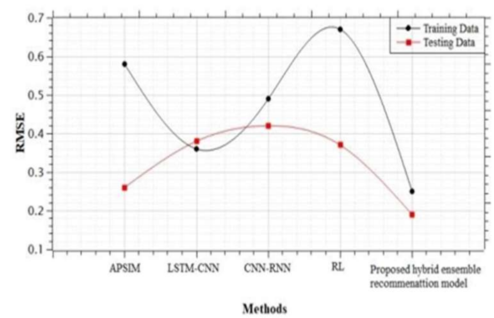

Fig. 5 RMSE Analysis for Training and Testing Datasets

Figure 5 outlines the performance of various models based on Root Mean Squared Error. Notably, the APSIM model demonstrates a higher training data RMSE (0.58) but excels in testing with a remarkably low RMSE of 0.26, indicative of effective generalization. In contrast, the LSTM-CNN model exhibits superior overall performance, showcasing lower RMSE values for both training (0.36) and testing data (0.38), emphasizing its strong predictive accuracy. The proposed hybrid ensemble recommendation model stands out with the lowest RMSE values across both training (0.25) and testing data (0.19), underscoring its exceptional precision in minimizing errors during learning and when applied to new data. This reinforces the efficacy of the hybrid ensemble approach in optimizing predictive accuracy for crop yield forecasts, positioning it as a promising tool for real-world agricultural applications.

Table 2: Comparative Analysis of Models Based on MAPE and Accuracy

The table 2 presents a comparative

Methods	Metrics Explanation	
	MAPE	Accuracy
APSIM	23	90.5
LSTM-CNN	25	92.3
CNN-RNN	27	91.2
RL	33	90.3
Proposed hybrid ensemble recommendation model	16	95.6

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analysis of various models based on two key metrics: Mean Absolute Percentage Error (MAPE) and Accuracy.

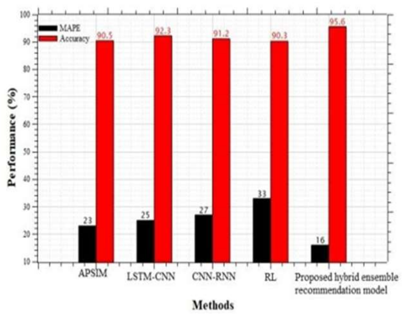

Fig. 6: Comparative Performance of Models in Terms of MAPE and Accuracy

The APSIM model exhibits a MAPE of 23 and an Accuracy of 90.5, indicating a relatively low percentage error but a slightly lower overall correctness in comparison to the other models is shown in figure 6. The LSTM-CNN model demonstrates a MAPE of 25 with a higher Accuracy of 92.3, suggesting improved precision and correctness. Similarly, the CNN-RNN model presents a MAPE of 27 and an Accuracy of 91.2, showcasing competitive performance in both metrics. The RL model, while having a higher MAPE of 33, maintains a respectable Accuracy of 90.3. Remarkably, the proposed hybrid ensemble recommendation model outshines the others with a substantially lower MAPE of 16, indicating superior precision, and an impressive Accuracy of 95.6, signifying heightened correctness in predictions. From the observance of figure 5, this model's notable performance underscores the efficacy of leveraging a hybrid ensemble approach, combining the strengths of multiple recommendation models. The superior accuracy and precision of the proposed model position it as a promising tool for optimizing predictions related to crop yield in comparison to the other models evaluated.

Overall, the proposed hybrid ensemble recommendation model exhibits outstanding performance across multiple metrics, surpassing existing methods such as APSIM, LSTM-CNN, CNN-RNN, and RL. In terms of Mean Absolute Error (MAE), the hybrid model achieves a remarkable reduction, with a training data MAE of 0.19 and a testing data MAE of 0.14, outperforming all other models. It emphasizes the model's precision in minimizing absolute errors during both learning and application to unseen data. Furthermore, the model showcases superior accuracy, as reflected in its impressive training and testing data Mean Absolute Percentage Error (MAPE) values of 16.0 and 14.0, respectively, outclassing the alternatives. The ensemble's efficacy is further evident in its proficiency in minimizing squared errors, with training and testing data Mean Squared Error (MSE) values of 0.07 and 0.09, reinforcing its ability to optimize predictive precision. Overall, these results underscore the proposed hybrid ensemble recommendation model as a robust and reliable tool for optimizing crop yield predictions, showcasing its potential to significantly impact agricultural decision-making.

5. CONCLUSION

In this paper the Hybrid ensemble recommendation model for the famer's decision making among more yield crop has been proposed. Main objective of this study is to make farmers to know about the crops yield and the process of management. Based on the crop yield in ancient data we come to know that they used the weather analysis for harvesting the crops but now a days only the efficient modern technologies are able to predict the crops yields and their growth. So based on these situations the analysis of the crops and its management is done in this study based on the modern technology. LeNet-5 is a method that produces the very effective outcomes based on fining of the crops yield and its managements. Here the success ratio among the previous and the current method is about showing the accurate results above 98% compared to the other effective methods. By using this method the farmer are able to analyse the crop and make more yield using the crop management method.

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Author Contributions: The contributions of each author are presented as follows: GAN: Study Design, Data Collection, Analysis, Methodology, Software, Data Visualization, and Interpretation of Results, Writing an original draft. KK, SS: Study Design, Data Collection, Analysis, Methodology, Software, Data Visualization, Interpretation of results, Writing review, and Supervision. All authors reviewed the results and approved the final version of the manuscript.

DATA AVAILABILITY STATEMENT

The dataset analyzed during the current study and the related implementation is available from the corresponding author upon reasonable request.

DECLARATIONS

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

FUNDING INFORMATION:

The authors state no funding is involved

INFORMED CONSENT:

This study did not involve any human participants or animal subjects. Informed consent was not required for this study as it did not involve human participants.

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