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OPTIMIZING CROP YIELD PREDICTION CROP YIELD PREDICTION: A HYBRID APPROACH INTEGRATING CNN AND LSTM NETWORKS

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ABSTRACT

Artificial Intelligence (AI) has proven successful in revolutionizing the agricultural sector, facilitating advancements in prediction, decision-making, and the monitoring and analysis of crops and soil. In this study, a hybrid model is introduced with the capability to predict crop yield. The proposed learning model combines the strengths of Convolutional Neural Network (CNN) with Recurrent Neural Network (RNN) models. CNN, recognized for its superior performance in feature extraction, is selected for its characteristic of considering a smaller number of parameters in the network, thereby reducing the risk of overfitting. Simultaneously, RNN serves as the prediction model, capitalizing on its inherent learning nature, feedback network, and ability to encode temporal sequence information. Addressing the short-term memory behaviour of RNN, the network is enhanced with LSTM cells, enabling effective long-term memory tasks. LSTM introduces memory blocks to resolve the exploding and vanishing gradient problem, differentiating itself from conventional RNN units. The best environment parameters have been identified by using the correlation where it shows the parameter that have the most significant relation with the crop production. The A Hybrid Approach Integrating CNN and LSTM Networks has achieved 74% accuracy in crop yield prediction.

Keywords: *Agriculture, Convolutional Neural Network, Crop Yield Prediction, Machine Learning, Recurrent Neural Network (RNN)*

1. INTRODUCTION

Nowadays, agricultural advancement stands as a critical component in meeting global food demand and driving economic growth on a global scale. Predicting crop yields is one of the most challenging tasks in agriculture [1,2]. Accurate yield predictions help farmers make informed economic and management decisions and can support famine-prevention efforts and the global food security[3]. Ansarifar et al. [4] emphasize the crucial role of crop yield prediction in addressing global food security concerns, highlighting various factors, including genotype, environment, and management, along with their intricate interactions, as significant obstacles. Concurrently, early crop yield prediction is identified by Al-Adhaileh et al. [5] as a pivotal element in mitigating famine risks and anticipating food availability for the growing global population. The World Health Organization reports that 820 million people still face insufficient food supply, underscoring the urgency of effective predictive measures.

With the rapid integration of science and technology into our daily lives [6]. Artificial Intelligence (AI) has emerged as a pivotal player in enhancing productivity and performance within the agriculture sector. Machine learning, which is a branch of Artificial Intelligence (AI) focusing on learning, is a practical approach that can provide better yield prediction based on several features [7]. Pursuing more accurate crop yield prediction techniques has and will continue to motivate innovation at the intersection of plant science and data analytics [3]. The traditional farming methods face challenges in meeting the escalating food demand driven by the increasing world population. Growers and farmers encounter difficulties in obtaining optimal environmental parameters to train models, resulting in significant disparities between predicted and actual crop yields [8]. Moreover, research indicates that non-hybrid crop yield prediction models exhibit inferior performance compared to their hybrid counterparts [9]. The persistent high demand for food coupled with inadequate supply has elevated concerns about food insecurity in various countries [12]

The research is essential due to the increasing global food demand, projected to surge as the population grows to 9.7 billion by 2050. Traditional crop yield prediction methods struggle to capture the complex interactions among genotype, environment, and management practices, leading to less accurate forecasts. With advancements in AI and machine learning, particularly in hybrid models, there is an opportunity to significantly enhance prediction accuracy. Hybrid models like CNN-LSTM can better analyze spatial and temporal data, providing more precise predictions. This accuracy is crucial for ensuring food security, enabling informed farming decisions, and supporting economic stability by optimizing resource use and mitigating famine risks.

2. RELATED WORKS

There are numerous types of crop yield prediction models and algorithms that have been introduced in the agriculture industry. However, there are some machine learning models that are more popular in the field of crop yield prediction On the other hand, Least Absolute Shrinkage and Selection Operator (LASSO), Long Short-Term Memory (LSTM) and hybrid model CNN-RNN or CNN-LSTM which is also algorithm that used in crop yield prediction. Therefore, LASSO, Random Forest, CNN, LSTM, and hybrid models will be reviewed.

2.1. LASSO

LASSO regression is a linear regression technique that employs shrinkage [10]. Khaki et al. [9] utilized LASSO in their study to predict corn and soybean yields across the entire Corn Belt, covering 13 states in the United States. The study compared the effects of linear and nonlinear weather and soil data on crop yield estimation using LASSO. The optimized L1 term coefficients ranged between 0.3 to 0.5, resulting in the most accurate predictions, with the best training Root Mean Square Error (RMSE) of 19.88 and the best validation RMSE of 27.06 for corn. For soybean prediction, the best training RMSE was 6.49, and the best validation RMSE was 7.66. Jiang et al. [11] employed various machine learning models, including LASSO, to predict country-scale maize yield, evaluating their performance based on Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). LASSO produced a prediction MAE of 4.76 bu/ac and MAPE of 2.72. Additionally, Anbananthen et al. [10] used LASSO to compare the performance of several popular machine learning models for crop yield prediction, including random forest regression, Gradient Boost Tree (GBT) regression, stacked regression, and hybrid machine learning. The LASSO model demonstrated an accuracy of 42% in their study.

2.2. Random Forest

Random Forest is a supervised learning algorithm used for classification and regression [13]. It operates as an ensemble learning method [14] combining multiple decision trees to form a random forest. Each individual training data generates a decision tree before being aggregated to produce the final output, employing a bagging method [14]. Moraye et al. [13] developed a Smart Farm application that uses a random forest training model with 20 decision trees for predicting crop yield, achieving 87% prediction accuracy through a 10-fold cross-validation technique. The review from Moya Gopal P.S, & Bhargavi. R [15] concluded that random forest outperformed other models like Artificial Neural Network, Support Vector Regression, and K-Nearest Neighbour in terms of accuracy. In this study, 70% of the data was randomly selected for training the model, with the remaining 30% used for testing. Features selection algorithms were applied to enhance computational efficiency, reduce model complexity, and improve accuracy.

2.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning algorithm comprising convolutional, pooling, and fully connected layers [16]. Srivastava et al. [17] applied CNN to predict winter wheat, capturing time dependencies of environmental variables using a proposed 1-dimensional convolution operation model. Their CNN model outperformed other machine learning models in terms of RMSE, MAE, and correlation coefficient.

Similarly, Karuna et al. [18] investigated the performance of CNN, RNN, and SNN for corn yield prediction. These learning models were trained with a dataset containing various environmental factors from 1980 to 2019 across 1176 countries, showcasing the versatility of CNN in capturing intricate relationships in prediction models.

2.4. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM), an enhanced cell of the Recurrent Neural Network (RNN), is designed to handle long-term correlation problems caused by vanishing gradient issues existing in recurrent neural networks [16]. LSTM can process data without treating each point independently, retaining previous data [16]. It excels in processing text, speech, and time-series data [16]. Tian et al. proposed an LSTM neural network for improving wheat yield forecasting [19]. They compared and analyzed the performance of the LSTM model with Support Vector Machine and propagation neural networks, showing that LSTM outperformed others with the highest RMSE (357.77 kg/ha) and R2 (0.83). Shen et al.[20] analyzed the performance of LSTM and LSTM-RF networks for wheat yield prediction[20]. LSTM yielded an RMSE of 684.1 kg/ha and R2 = 0.78. The structure of RNN incorporating the nonlinear relationship between yield and multi-feature inputs is cited as the reason for LSTM's superior performance.

Furthermore, Wang et al. [21] conducted research on winter wheat prediction using the LSTM model from MODIS LAI products. The results showed that LSTM provided better yield estimation compared to convolutional machine learning, with an RMSE of 522.3 kg/ha and R2 of 0.87.

Algorithms	LASSO	Random Forest	CNN	RNN (LSTM)	CNN-RNN (LSTM)
Accuracy (%)	42	87	Not Stated	Not Stated	89 (the best prediction performance)
R2	0.44	0.67	0.71	0.68	0.74
RMSE (bushels per acre)	7.66 (best performance)	8.61 (best performance)	Not Stated	Not Stated	4.15 (best performance)
Complexity	Moderate	Moderate	High	High	High

Table 1: Example Comparison of Characteristics between Algorithms

2.5. The hybrid CNN-RNN Model

A hybrid learning model combines a neural network with machine learning techniques [22]. The CNN part of the model consists of a W-CNN and an S-CNN model. W-CNN captures temporal dependencies of weather data, while S-CNN captures spatial dependencies of soil data. Both W-CNN and S-CNN have one-dimensional convolutional layers with four convolutional layers. Average pooling with a stride of 2 is applied for down sampling. The output of WCNN is fed to a fully connected layer with 60 neurons for corn yield prediction and 40 neurons for soybean yield prediction. Conversely, for S-CNN, the output is fed to a fully connected layer with 40 neurons. According to Khaki, the fully connected layer integrates with the output extracted by W-CNN and S-CNN, reducing the dimension of the CNN model's output. The RNN model is enhanced with LSTM cells to capture input with time, containing 64 hidden units.

The hybrid CNN-RNN model was trained for a maximum of 350,000 iterations, using a rectified linear unit (ReLU) activation function for CNNs and the fully connected layer. The training time for the designed CNN-RNN model took an hour on a CPU (i7-4790, 3.6 GHz). The best validation RMSE (bsh/ha) for corn yield prediction was in 2018 (RMSE = 11.48), while the best training RMSE was in 2017 (RMSE = 15.74). For soybean yield prediction, the best training RMSE was 3.08 (year 2017), and the best validation RMSE was 4.15 (year 2016).

On the other hand, Sun et al. [23] proposed a deep CNN-LSTM model for end-of-season and in-season soybean prediction at the country level. Results have shown that the performance of the proposed CNN-LSTM outperformed pure LSTM or CNN models in both in-season and end-of-season soybean yield predictions, with CNN having an average root-mean-square-error (RMSE) of 359.12, LSTM with an average of 636.15 RMSE, whereas the proposed CNN-LSTM has the least RMSE with an average of 329. Table 2 presents a comparison of characteristics between machine learning models from the literature review, including LASSO, Random Forest, CNN, RNN (LSTM), and the hybrid CNN-RNN (LSTM) [9, 23].

Traditional crop yield prediction methods fail to accurately forecast yields due to their inability to capture the complex, non-linear interactions among various factors like genotype, environment, and management practices. With escalating global food demand and persistent food insecurity issues, there is a pressing need for more accurate and robust prediction models. Current non-hybrid models exhibit inferior performance, underscoring the necessity for innovative solutions. This research addresses this gap by proposing a hybrid machine learning model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The hybrid CNN-LSTM model aims to improve crop yield predictions by effectively handling the diverse and dynamic nature of agricultural data, thereby enhancing prediction accuracy, contributing to food security, and advancing agricultural technology.

3. PROPOSED SOLUTION

The proposed solution consists of six stages: Data Collection, Data Processing, Data Transformation, splitting of data, and identify parameter, implementing CNN-RNN model and lastly model performance evaluation.

3.1 Data Collection

The current study uses online dataset from Kaggle https://www.kaggle.com/datasets/srinivas1/agricutu re-crops-production-in-india which is about historical crop yield. The dataset contains some parameter used for crop yield prediction. The dataset contains four different types of crops in Maharashtra with their corresponding environment parameters and their yield and production recorded. The attributes for this dataset include, area, wind speed, humidity, N (Nitrogen) value, P (Phosphorus) value, K (Potassium) value, soil type, production, yield, state name, district name, crop year, season name and crop name.

3.2 Data Preprocessing, Data Transformation, splitting of data, and identify parameter

In order to ensure the robustness and reliability of the dataset for model training and testing, several preprocessing steps were undertaken. First, missing values were addressed by filling them with appropriate measures to mitigate the impact on the model. This involved replacing missing values with the average, maximum, or minimum values, or in some cases, using zero values where applicable. Additionally, redundant or useless attributes were identified and removed from the dataset to prevent data bias problems and reduce the risk of invalid data errors during the training process.

Following the handling of missing values and attribute reduction, the dataset underwent normalization using min-max normalization, transforming the data to a uniform scale within the range of 0 to 1. This step was crucial to ensure that all features contribute equally to the model, preventing certain variables from dominating the training process due to differences in scale.

To further streamline the dataset, the identification of dependent and independent variables was conducted. This involved determining which variables are influenced by others (dependent) and which ones influence the former (independent). This distinction is essential for establishing the relationships within the dataset and forming the foundation for model training.

Next, the dataset was labeled to designate the yield data as either training or testing data. This labeling facilitates the supervised learning process, allowing the model to learn from the labeled data during training and then be evaluated on the testing data to assess its performance. These comprehensive preprocessing steps aim to enhance the quality and reliability of the dataset, laying a solid foundation for the subsequent stages of model development and evaluation.

A series of transformations were applied to the dataset, involving the extraction of essential attributes designated as target and predictor variables. This selection of attributes is crucial for building a meaningful predictive model. Subsequently, the data was randomly split into three sets: 80% for the training set, 10% for the validation set, and another 10% for the test set. The split function in Python was employed for this purpose, with the training set serving as the data for training the model, and the test set reserved for evaluating its performance.

To gain insights into the correlation among parameters, a heatmap analysis was conducted. This visualization technique allows for a comprehensive understanding of the relationships between different variables in the dataset. By identifying the correlation patterns through the heatmap, it becomes possible to assess how changes in one parameter may be associated with changes in another, providing valuable insights for model development and interpretation. This step contributes to the overall preparation of the data for the subsequent stages of machine learning model training and evaluation.

3.3 Implementing CNN-RNN model

In order to ensure the robustness and reliability of the dataset for model training and testing, several preprocessing steps were undertaken. First, missing

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values were addressed by filling them with appropriate measures to mitigate the impact on the model. This involved replacing missing values with the average, maximum, or minimum values, or in some cases, using zero values where applicable. Additionally, redundant or useless attributes were identified and removed from the dataset to prevent data bias problems and reduce the risk of invalid data errors during the training process.

The architecture of the proposed hybrid CNN-LSTM model is shown in Figure 1.

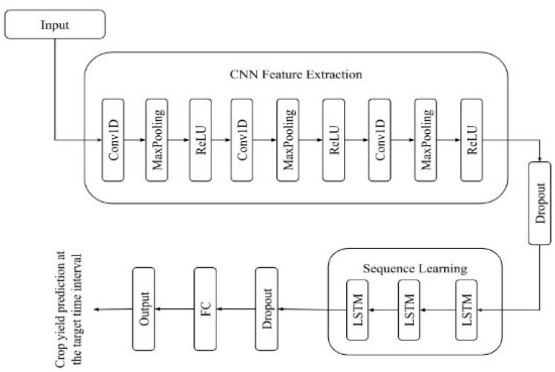

Figure 1: The architecture of the proposed hybrid CNN-LSTM model

The proposed hybrid model applies a combination of two deep learning algorithms: one-dimensional Convolutional Neural Network (CNN), also known as Conv1D, and Recurrent Neural Network (RNN) enhanced with LSTM cells. The model is structured into three phases: the analysis of historical crop yields based on environmental parameters, prediction of crop yield using the hybrid CNN-LSTM model to improve performance, and combining the CNN and RNN models for prediction.

In the fourth step of the process, a hybrid CNN-RNN model is constructed. To enhance the CNN component, a fully connected layer (FC) is implemented. This layer plays a crucial role in reducing the dimensionality of the CNN model, capturing intricate patterns akin to neural connections in the human brain. Utilizing a fully connected layer enables the model to discern complex relationships within the data, enhancing its ability to learn and extract meaningful features.

Simultaneously, the Recurrent Neural Network (RNN) component is established, incorporating Long Short-Term Memory (LSTM) cells. These LSTM cells excel at predicting crop yield in time series data by capturing and retaining information over extended sequences, making them well-suited for modeling temporal dependencies. By integrating both CNN and RNN elements, the model effectively analyzes spatial and temporal patterns, offering a comprehensive approach to crop yield prediction.

In this study, the integration of the MaxPooling layer and Rectified Linear Unit (ReLU) layer between the convolution layers is crucial. The CNN feature extraction block comprises three conv1D layers. A MaxPooling layer is introduced to down-sample feature maps, reducing computational load, while the ReLU activation function counters the vanishing gradient problem.

To address overfitting, a dropout layer is strategically placed between the CNN feature extraction block and the LSTM sequence learning phase, with a dropout probability set to 0.2. This layer randomly deactivates neurons during training, effectively mitigating overfitting.

Following the addition of the dropout layer, the output from the sequence learning block is connected to another dropout layer, succeeded by a fully connected layer and a tanh activation function, ultimately producing the final output. This architectural approach optimizes model performance by balancing computational efficiency, mitigating overfitting, and addressing gradient-related challenges. The output of the sequence learning block is connected to the dropout layer which is followed by a fully connected layer and tanh activation function to produce the final output as shown in equation (1).

$$O = \sum T t = 1\ h \quad (1)$$

where O is the output of hybrid module; ht is the output of the $t - th$ hidden unit of RNN module.

3.4 Evaluating Model Performance

Based on the trained CNN-RNN learning model, the performance of the model will then be evaluated using Root Mean Square Error (RMSE), R-Square (R2) and Accuracy as shown from formula (2) to (4):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (2)$$

where the yi is the predicted value, $\hat{y}i$ is the observed value, and n is the number of dataset samples.

$$R^2 = 1 - \frac{(\sum_{i=1}^{n}(y_i - \hat{y}_i)^2)/n}{(\sum_{i=1}^{n}\left(\underline{y}_i - t\hat{y}_i\right)^2)/n} \quad (3)$$

where $\hat{y}i$ is predictive value, yi is actual value, $\underline{y}_i$ is average value.

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$$Accuracy - \frac{FP+TP}{FP+FN+TP+TN} \quad (4)$$

False Positive (FP) - Number of yield samples labelled low, medium or high predicted as low, medium or high.

True Positive (TP) - Number of yield samples labelled medium predicted as high or low.

False Negative (FN) - Number of yield samples labelled low predicted as medium or high.

True Negative (TN) - Number of yield samples labelled high predicted as medium or low.

4. EXPERIMENTS

Dataset is splitted to training and testing set into 8:1:1 ratio which is 80% of train set, 10% of validation set, and 10% of test set. After building the model, it needs to be trained. The model is fitted with the training dataset and validated with the validation dataset. In this study, epochs of 16 and a batch size of 16 are used, implying that the learning process iterates 16 times, and the model weights are updated after each batch of 16 samples has been processed.

Next, the performance of the model needs to be measured as training epochs progress. Therefore, Mean Absolute Error is used to measure the loss of the model.

5. RESULTS AND DISCUSSION

This section discusses the results and analysis, as well as the impact of the findings.

5.1 Result and analysis

After testing for several combination of CNN-RNN (LSTM) hyperparameter, the resulted hyperparameter for CNN-RNN (LSTM) is obtained. Table 2 tabulates the use of parameter of CNN-LSTM crop yield prediction model in this project.

Table 2 : Parameter setting for CNN-RNN (LSTM) model

Layer	Kernel Size	Stride	Hidden neurons	Filters	Activation
Convolutional 1	48	1	-	3	ReLu
Convolutional 2	32	1	-	3	ReLu
Convolutional 3	16	1	-	3	-
LSTM 1	-	-	20	-	-
LSTM 2	-	-	20	-	-
LSTM 3	-	-	10	-	-
Fully Connected	-	-	1	True	Tanh

Correlation heatmap graph in Figure 2 shows the correlations between each parameter in the data. The heatmap shows that the environment parameter "area" has the highest correlation with the production of yield with the correlation of 0.9 hence it is the best environment parameter for prediction. Figure 3 shows the graph of actual crop yield value versus predicted yield value.

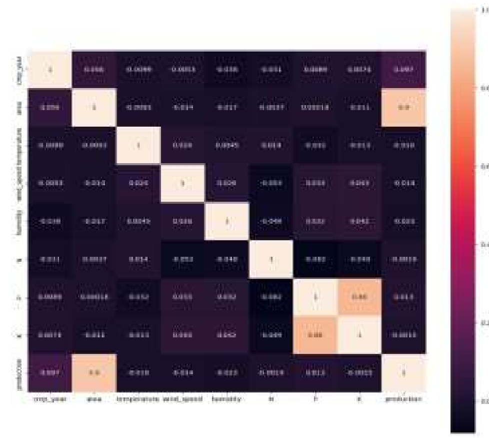

Figure 2: An Example of a Chart Represented in a Shaded Pattern (Heatmap graph)

In Figure 2, the correlation heatmap graph illustrates the correlations between each parameter in the dataset. The heatmap reveals that the environmental parameter "area" exhibits the highest correlation with yield production, with a correlation coefficient of 0.9. Therefore, it is considered the most effective parameter for predicting crop yield.

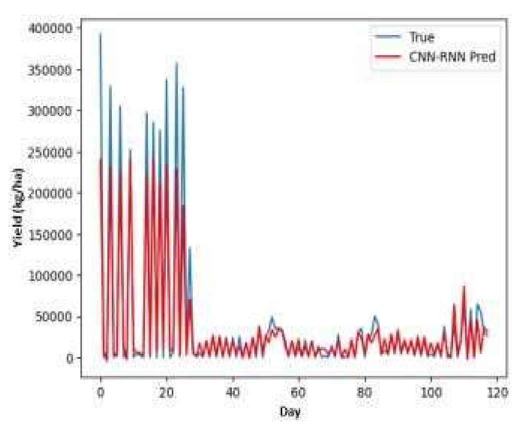

Figure 3: An Example of a Chart Represented in a Shaded Pattern (Prediction result)

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Figure 3 shows the results of the graph plotting, with the red line representing the predicted values and the blue lines indicating the actual values. From the graph, it is evident that there is a slight difference between the predicted and actual values, suggesting that the model performs predictions effectively.

CNN and RNN model with same dataset, epoch and batch size was trained and Table 3 tabulate the model performance of the trained CNN, RNN (LSTM) and CNN-RNN (LSTM).

Table 3: Comparison of model's performance.

Model	RMSE	R2	Accuracy (%)
CNN	0.10	0.77	72
RNN (LSTM)	0.13	0.65	53
Proposed CNN-RNN (LSTM)	0.08	0.87	74

Figure 4 shows the prediction results of the actual crop yield and the crop yield predicted by CNN, RNN (LSTM) and CNN-RNN (LSTM).

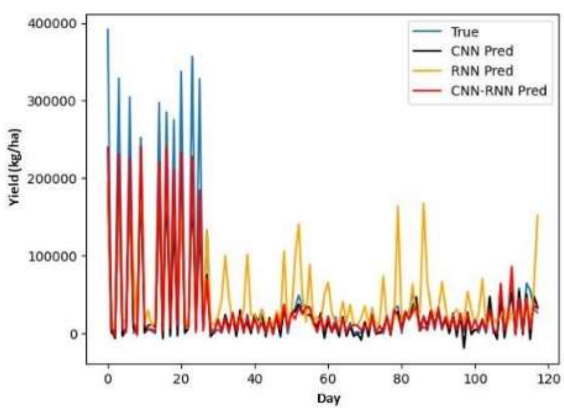

Figure 4: Prediction result for CNN, RNN (LSTM) and CNN-RNN (LSTM) and actual yield

It can be concluded that the hybrid. CNN-RNN (LSTM) can predict the crop yield better than CNN and RNN (LSTM) model.

The accuracy graph for CNN, RNN (LSTM) and CNN-RNN (LSTM) is shown at Figure 5. It can be concluded that the hybrid CNN-RNN (LSTM) had outperformed the traditional CNN and RNN (LSTM) model, with low RMSE, high R2 and high accuracy.

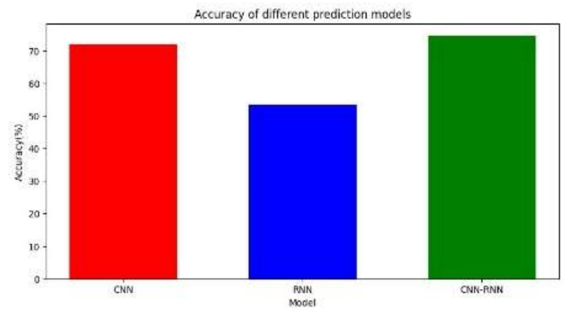

Figure 5: Accuracy graph of CNN, RNN (LSTM) and CNN-RNN (LSTM) model

The conclusion regarding the research problem of crop yield prediction was reached by evaluating several key criteria. The performance of the hybrid CNN-RNN model was assessed using metrics such as Root Mean Square Error (RMSE), R-Square (R^2), and accuracy. The model demonstrated superior performance with lower RMSE and higher R^2 values compared to other models like LASSO, Random Forest, standalone CNN, and standalone LSTM, indicating better prediction accuracy. The model's consistency was validated by testing it on both training and testing datasets, ensuring it was not overfitting and could generalize well to new, unseen data. Additionally, a correlation heatmap was used to identify the most influential environmental parameters, which were then selected as features for the model. The practical applicability of the model was confirmed through experimental validation, where its predictions closely matched actual crop yield data. Furthermore, the model's efficiency and scalability were taken into account, proving that it could be trained and used with standard computational resources, making it suitable for large-scale applications. These criteria collectively demonstrated that the hybrid CNN-RNN model significantly enhanced crop yield prediction, making it a valuable tool for agricultural decision-making.

5.2 Impact of Findings

This research markedly advances agricultural technology by introducing a hybrid CNN-LSTM model that significantly improves prediction accuracy through its integrated approach to analyzing spatial and temporal data. By leveraging CNNs for spatial analysis and LSTMs for time-series data, the model reveals intricate patterns and trends, leading to more precise crop yield forecasts. These enhanced predictions enable farmers to make better-informed management decisions, boosting productivity while minimizing environmental impact. Furthermore, the model's reliable forecasts support global food security by informing effective

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policy decisions and strategies to combat food shortages, demonstrating the transformative potential of AI in agriculture and setting the stage for future technological innovations.

6. CONCLUSION

The proposed hybrid CNN-RNN (LSTM) model is intended to provide crop yield prediction for farmer to make better crop management system. The design principle of the model is to benefits growers and farmers to make better crop management decision by knowing the crop yield in advance. This research contributes to agricultural technology by developing a hybrid CNN-LSTM model that offers enhanced prediction accuracy through comprehensive data analysis. By integrating CNNs for spatial data and LSTMs for time-series data, the model can identify complex patterns and trends, leading to more accurate crop yield forecasts. These predictions help farmers make better management decisions, increasing productivity and reducing environmental impact. Additionally, the research supports global food security by providing reliable forecasts that inform policy decisions and strategies to address food shortages. The innovative approach advances the application of AI in agriculture, setting the stage for future technological developments.

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