ISSN: 2752-3829 Vol. 3 No.2, (December, 2023)

Stochastic Modelling and Computational Sciences

ENHANCING AGRICULTURAL DECISION-MAKING WITH DEEP LEARNING CROP YIELD PREDICTION MODELS

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ABSTRACT

Important in agriculture is the ability to predict crop yield. For decision-making and planning purposes, planners and farmers can gain a great deal from quick and accurate crop yield forecasts. Utilising statistical models to predict agricultural productivity is typically a laborious and time-consuming process. Machine learning and deep learning are beginning to make significant advancements in their respective fields. As a result of their inherent ability to extract characteristics from vast datasets, deep learning models are better adapted for prediction. Several elements, such as genotype, environment, as well as interaction between them, impact crop yield. Understanding of the correlation between these interaction factors along with yield is required for yield prediction. Several methods based on deep learning are used to collect relevant crop data for forecasting. Models based on deep learning can naturally extract features from large datasets, which is of great benefit to predictive models. Using techniques of deep learning, the objective of this study is to predict the yield of a crop. In this study, we forecast agricultural productivity using a Deep Learning-based CNN-LSTM model with modifications, the present study also employed other approaches based on deep learning RNN-LSTM, ANN and compare proposed model with another model. According to the findings, the proposed model CNN-LSTM gives superior performance in all metrices as compared to other technique.

Keywords: Deep learning, crop yield prediction, CNN-LSTM, RNN-LSTM, ANN

1. INTRODUCTION

Agriculture is among the most economically, environmentally, and sustainably significant industries in the United States. In the modern world, the significance of agriculture, as well as the need for it, has been growing in tandem with the rise in the global population. In order to achieve a sustainable equilibrium, agricultural productivity will need to undergo significant improvement. Numerous factors, including soil, water, climate, and environment, are significant determinants of sustainable crop production (Frooq M. and Pisante, 2019). The success of the farming operation might be judged by the amount of crops it produced. The agricultural elements play the most important role in determining the crop output. The ever-increasing population of the world is creating a significant obstacle for all people on the planet in the shape of a lack of food that can satisfy their needs. The practice of farming that causes the least amount of harm to the environment and maximizes the harvest of important food crops is known as "sustainable farming." Agricultural researchers from throughout the world are working on this problem **(Tyagi 2016)**. One of the most significant uses of agricultural yield forecasting is predicting the quantity of food that will be readily available for sustaining the growing global population.

However, crop production forecast is difficult due to various complex aspects. Several factors affect agricultural productivity, including genotype, meteorological conditions, soil quality, parasite infestations, harvest planning, and landscapes (Xanthoula, 2016; Mauro E Holzman, 2018; Arti Singh, 2016). Crop yield methodologies and processes are inherently nonlinear & dependent on time (Rebecca Whetton, 2017). These strategies are also complex due to the numerous interdependent characteristics they contain, all of which are determined & influenced by external, uncontrollable variables (Yajnaseni Dash, 2018; Wendy Wieder, 2018).

Numerous factors influence crop productivity, making it difficult to establish an accurate forecasting model using conventional methods. Nonetheless, a novel method for predicting agricultural yields has been devised and trained as a result of advances in computer technology (Kheir et al., 2021). Deep learning is a key technology that is widely employed in agriculture because to its diverse data technologies and high-performance computation **(Sarker, I.H. 2021)**. In the past, producers predicted crop yields using precise historical knowledge and personal experience. On the basis of these projections, crucial production decisions were made. However, it appears that recent innovations such as deep learning and crop model simulation can now more accurately predict yield. In addition, the ability of high-performance computing to analyse large volumes of data has facilitated this growth (Anna Chlingaryan et al., 2018; Bruno et al., 2019; Mohsen et al., 2019; Mohsen et al., 2020).

The main contributions of this paper are four-fold shown as follows:

- We developed several hybrid deep learning-based crop yield prediction models and investigated their performance on public datasets.
- We investigated the performance of hybrid deep learning-based CNN-LSTM algorithm and compared its performance against existing method.
- We evaluated the effects of several feature engineering methods on the performance of crop yield prediction models.
- We demonstrated that the hybrid CNN-LSTM model provides the best performance among others.

The remaining parts of this report are organized as follows: Section 2 provides the related work. Section 3 presents the problem formulation and section 4 discussed about the methodology. Section 5 explains the experimental results. Section 6 the conclusion and future scope of the study.

2. REVIEW OF LIETRATURE

Suresh, G., Kumar, et al (2021) discussed The investigation of a machine learning-based crop yield recommendation system that is effective in digital agriculture. Agriculture drives India's economy, which also supports a thriving agribusiness sector. Seventy percent of Indians' primary source of income is agriculture. Our investigation seeks to aid farmers in determining the nutritional value of their soil through examination of all the different soil parameters and utilising the resulting data to inform crop decisions. The efficacy of the Produce Suggestion Framework is improved by the Help Vector Machine's Arrangement computation. The structure maps soil and yield data to determine the legally permissible extraction range for a particular soil type and provides information on insufficient soil supplements for a specific harvest.

Van Klompenburg et al. (2020) employed Integrating SLR & utilising machine learning to predict agricultural products. They discovered that the neural networks are frequently utilised in crop yield forecasts, particularly CNN, LSTM, and DNN. They added that the number of features varies depending on research.

Sun et al. (2020) examined In order to forecast the end-of-season agricultural output, We compared the effectiveness of the CNN-LSTM technique to that of the CNN and LSTM techniques. During a five-year durationThe CNN-LSTM end-of-season model outperformed the alternative method. It subsequently emerged that the CNN-LSTM-based model was considerably influenced by the MODIS surface luminosity compared to other environmental variables.

P. Saini et al. (2020) conducted a Thanks to deep neural network analysis, it is possible to accurately foresee the Kharif harvest. Using an innovative DNN-LSTM technique, we forecast the Bajra yield in Rewari, Haryana. MSE as well as RMSE differ from conventional machine learning strategies are utilised to estimate experimental results. Deep Neural Network generates more accurate forecasts with a lower RMSE of 81.91 than conventional methods.

Khaki et al. (2020) proposed a Using environmental data and management strategies, a framework based on deep learning predicts crop production. The framework incorporates CNNs & RNNs. In order to predict maize and soybean crop yields in the 13-state maize area of the The CNN-RNN model has been recommended as well as incorporated into commonly employed techniques like random forest (RF), deep neural networks with full connections (DFNN), and LASSO for United States data for the years 2016, 2017, and 2018. With RMSE values of 8% & 9% of average yields, respectively, the novel model outperformed all previously evaluated strategies.

Nevavuori et al. 2019 studied on the basis of weather conditions and photoperiod profiles, to estimate crop yield, a region-specific model employing deep learning has been developed. Convolutional neural network systems (CNNs), a system for deep learning that specialises in image classification, are used for categorising photographs this study develops agricultural productivity prediction models. These models are founded on RGB and NDVI data collected by UAVs. CNN components that influence prediction accuracy include the training procedure, network depth, regularisation technique, and hyperparameter modification. By employing June 2017 data since the growth period was 25%, the Adadelta training approach, regularisation in early termination, and a CNN with six convolution layers had the capacity to estimate the production rate with an average absolute error of 484.3 kg/ha and a mean absolute error percentage of 8.8%. The MAE was calculated to be 624.3% kg/ha based on data collected during the period of above 25% growth in July and August 2017. RGB data demonstrated greater CNN architecture efficacy than NDVI data.

N. Gandhi et al. (2016) conducted Estimating rice production yield as well as the contributing factors influencing rice cultivation yields in Maharashtra, India using neural networks. The findings indicated that the test was accurate 97.5% of the time, with a sensitivity of 96.3 and a specificity of 98.1. In addition, for this particular research endeavor. Mean absolute error, its square root, relatively pure error, and the corresponding square root of relative proportional error have been determined.

3. PROBLEM FORMULATION

Many climatic elements have an impact on agricultural productivity. In the same way as meteorological variables (such as rainfall, regional rain, irrigated, and temp) and pedological variables (such as soil moisture, permeability, and nutrient content) are measured and recorded, so too are metrological variables (such as humidity (PH, organic carbon, phosphorus, fiber, etc.). In addition, everything is a mess because of the persistent climate change. When it comes to farming, many Indian farmers are still using age-old methods. On the other hand, everything ran smoothly and on schedule in the distant past because of the relatively mild climate. But, owing to global warming and other circumstances, almost everything has now altered. A lack of regular, timely rainfall is the primary obstacle facing India's agricultural sector. Plants need some humidity, but the current levels are too high and are a negative factor. There has been widespread damage to Rabi crops because of the disruption to the winter season. The heavy winter rains over the last several years have been completely normal. We need a framework that can unearth obscured facts, outcomes, patterns, and insights to solve the problems listed above. The farmer can plan and understand what to plant to maximize yield. To aid farmers in their decision-making, the suggested system employs data analytics methods to examine information about agricultural output. It is for this reason that we provide a generic framework built on a machine-learning model for making reliable yield predictions.

4. RESEARCH METHODOLOGY

The following is a description of the procedures that need to be completed to accurately predict crop yields that is using an approach based on deep learning. In the beginning, agricultural data is employed for crop yield prediction. After that, the data is subjected to pre-processing to cleanse any noisy data. The data that has already been pre-processed are then put through a process called feature extraction. This process involves the collection of features such as information about the soil, nutrients, and field management, among other features. These features are then used by deep learning algorithms to perform classification. This research strategy utilizes a one-of-a-kind deep learning (DL) method, which is a modified CNN-LSTM model, in order to classify crop predictions and offer more accurate findings. This method also helps to improve overall accuracy.

4.1 Proposed work flow

Figure 1 shows a flowchart of the steps involved in training a CNN-LSTM model. Here's a step-by-step explanation:

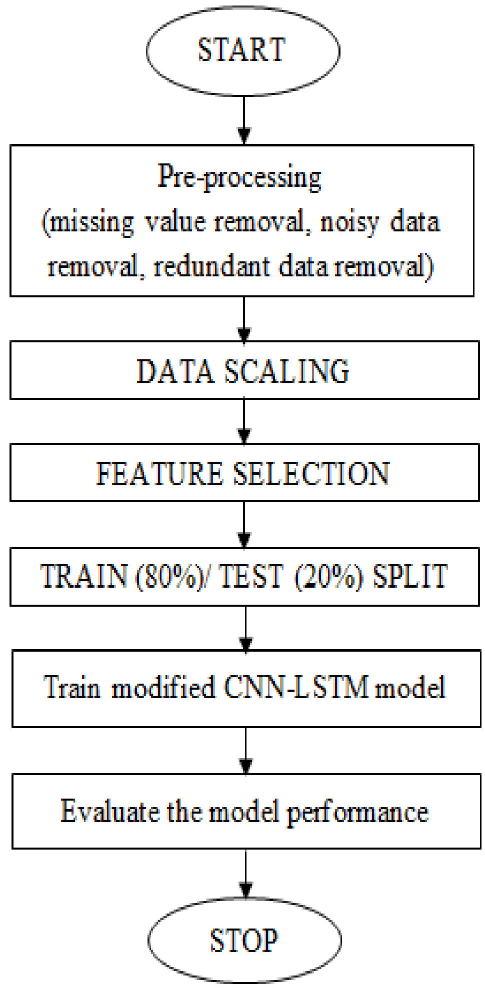


Figure 1. Flowchart of proposed framework

1. **Start Training:** The process begins with the start training signal. This could be a manual trigger or an automated process based on certain criteria.
2. **Pre-processing:** The next step is to pre-process the data. This can involve a variety of tasks, such as removing missing values, removing noisy data, and removing redundant data. The goal of pre-processing is to ensure that the data is clean and in a format that can be used by the model.
3. **Data Scaling:** After pre-processing, the data is scaled. This involves transforming the data to a common scale so that all features have a similar range of values. This can help to improve the performance of the model.
4. **Feature Selection:** The next step is to select features. This involves identifying the features that are most relevant to the task at hand. This can be done using a variety of techniques, such as statistical analysis or machine learning algorithms.
5. **Train/Test Split:** The data is then split into two sets: a training set and a test set. The training set is used to train the model, while the test set is used to evaluate the performance of the model. The typical ratio for splitting the data is 80% for training and 20% for testing.

6. **Train Model:** The training set is used to train the CNN-LSTM model. This is an iterative process that involves feeding the data into the model and making adjustments to the model's parameters based on the results.
7. **Evaluate Model Performance:** After training, the model is evaluated on the test set. This involves measuring the model's accuracy on the test data. The evaluation results are used to assess the performance of the model and to identify areas for improvement.
8. **Stop Training:** The training process is stopped when the model reaches a desired level of performance or when the model stops improving.

If the model performance is not satisfactory, the process can go back to step 2 and repeat the data pre-processing, scaling, and feature selection steps. This may involve trying different techniques or parameters to improve the quality of the data or the model itself.

4.2 DEEP LEARNING TECHNIQUES

- **Recurrent Neural Networks:** RNNs are a type of artificial neural networks designed exclusively for sequence input processing. Because RNNs are able to remember an encoded representation of their history, they are ideally suited for modeling data that is presented in a sequential fashion.
- **RNN-LSTM:** The RNN-LSTM addresses the challenges faced by regression, ANN, ANFIS, and machine learning approaches. Four layers comprise the proposed model: Sequence input layers, completely connected LSTM, and regression output. In the sequence input layer, four inputs with an hourly resolution are present. Layer 2 is an LSTM layer that collaborates with a completely linked layer to enhance the effectiveness of the model. The completely connected layer provides a variety of answers, whereas the LSTM layer analyses a vast number of hidden units. Last to be captured by the regression layer is the output.
- **Artificial Neural Network:** Each stratum of a neural network serves a specific function. As model complexity increases, so does the number of model layers. In a neural network, three layers exist, including the input layer, the concealed layer, and the output layer. With the additional data, the artificial neural network performs well and avoids overfitting. The ANN algorithm consists of an input layer, an intermediate layer, and a conclusion layer.

4.2.1 Proposed Hybrid CNN-LSTM model

The paper proposed a CNN-LSTM network based on CNN and RNN's achievements. CNN can infer numerous details from a picture like the human brain. An LSTM may bridge significant input latencies across any time span. LSTM improves the analysis of crop growing cycles of varying durations by presenting temporal patterns at different frequencies. In addition to the following, we will examine key performance indicators including F1-score, precision, precision, and support indicator value: and this revised CNN-LSTM model would be utilized to make predictions about crop records. Figure 2 depict the architecture of Hybrid CNN-LSTM model as shown below.

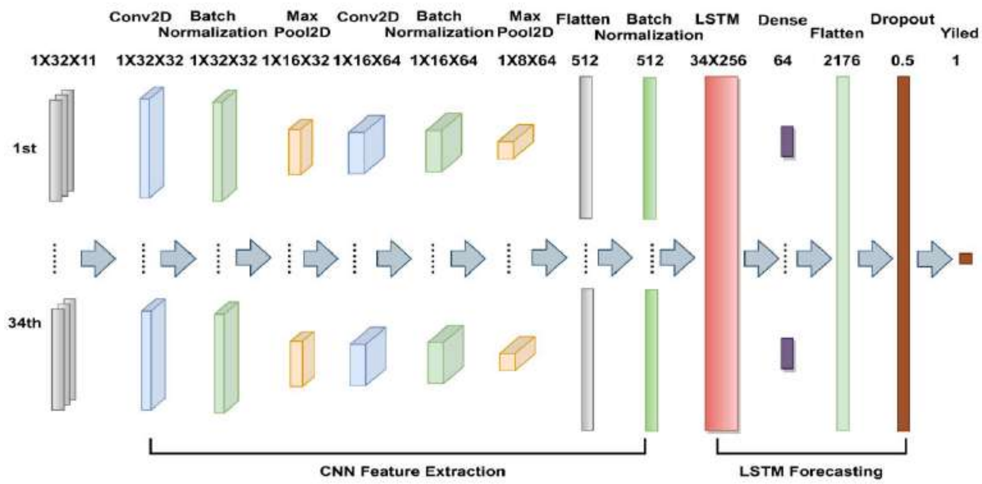


Fig 2: The architecture pf the proposed CNN-LSTM model

4.3 Dataset

This research made use of the dataset that had previously been collected, processed, and used by (Khaki & Wang, 2019). This dataset's research focus pertains to the soybean harvest in nine US states. Soil, weather, and management information make up the dataset. In particular, information about the average observed yield from 1980 to 2018 is available. Also included is weekly data on the total percentage of planted fields in each state. This data is updated annually beginning in April. Among the characteristics of meteorological data are the following: minimum and maximum temperatures, vapour pressure, snow water equivalent, solar radiation, and precipitation. The following properties are included in the soil data: wet bulk density, dry bulk density, clay percentage, hydraulic conductivity, organic matter percentage, pH, sand %, saturated volumetric water content, and the upper and lower limits of plant-available water content. Different depths (i.e., 0-5, 5-15, 15-30, 30-60, 60-100, and 100-200 cm) were used to measure all the soil characteristics with a resolution of 250 m2. The field's slope in percent, the average national commodity crop productivity index, and the depth of the crop root zone were some of the soil characteristics that were also recorded on the soil's surface. The dataset has 25,345 samples and 395 characteristics in total.

4.4 Performance metrices

In this study, there are various parameters which has been used in this study for predict the outcomes such as precision, accuracy, recall, f1 score, RMSE, MAE as described given below.

1. **Precision:** Precision is the proportion of correctly predicted positive observations in relation to the total number of positively predicted data.

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \quad (1)$$

2. **Recall:** Recall is the proportion of correctly anticipated positive findings relative to all positively anticipated data that can be reliably predicted.

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \quad (2)$$

3. **Accuracy:** Accuracy is the simplest logical performance metric to compute, as it is just the ratio of correctly anticipated observations to the total number of observations.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (3)$$

4. **F1 score:** Calculating the standard deviation weighted difference between the recall and accuracy values yields the F1 Score. As such, this score accounts for the possibility of both false negatives and false positives.

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \quad (4)$$

5. **Mean square error (MSE):** The average square sum of errors is used to avoid cancelling positive and negative errors. The effect of significant mistake value increased since the absolute error was squarred. MSE is used to check how close estimates or predictions are to actual value by using this formula.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

6. **Root mean square error (RMSE):** In order to predict the performance more accurately, we use the RMSE evaluation model determine the standard error through the prediction results.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (6)$$

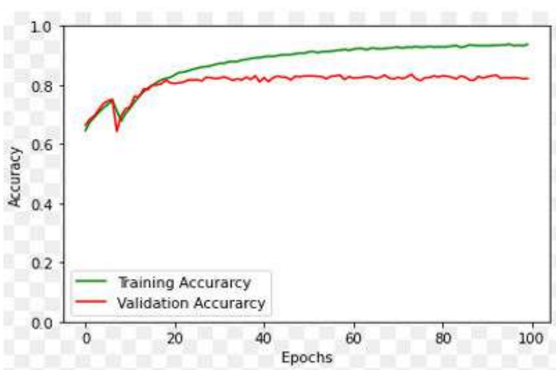
7. **MAE:** The absolute difference between expected and actual values is referred to as the mean absolute error, or MAE. This statistic is used to compare two observations of the same event.

$$MAE = \left(\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{(n)(\bar{y})}\right) \quad (7)$$

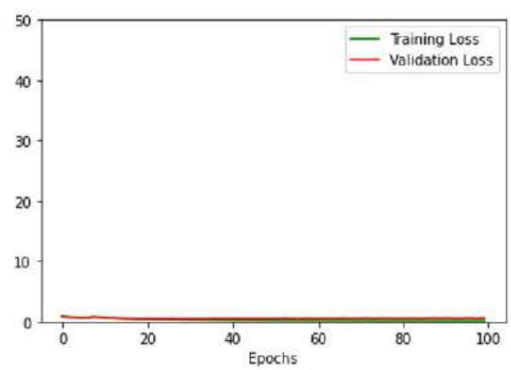
5. RESULT & DISCUSSION

In this section, the findings of this study have been analysed and studied which is described given below. The proposed method is compared to all other existing method as seen below.

Figure 3 depict the training and validity of our work. Fig. 3(a) shows the training and validation accuracy which is indicate by two different lines. In Fig. 3(a) as we can see that the training accuracy is continuously increasing as shown below. Fig.3(b) depict the training and validation loss which is represent by green and red line. In Fig.3(b), as we can see that the training and validation loss is continuously decreasing as shown below.



(a)



(b)

Figure 3. (a) Training and validation accuracy and **3(b)** Training and validation loss

Figure 4 depict the comparison of confusion matrix of proposed model as shown below.

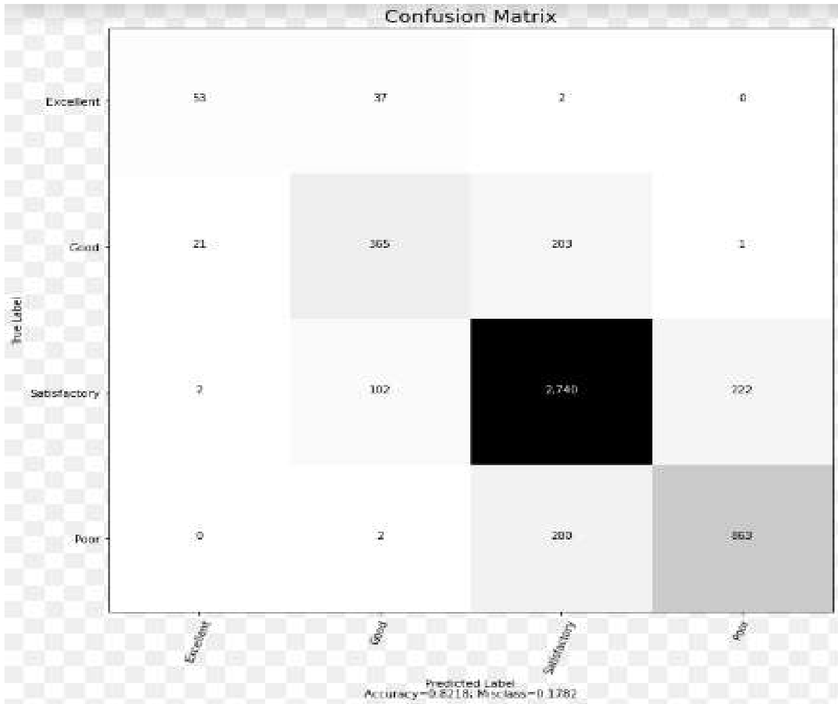


Fig 4: Confusion matrix comparison of the proposed model and previous research models

Figure 5 demonstrate the comparative analysis based on various parameters as shown below. In Fig.5, the value of precision 0.70 is indicate by excellent, 0.72 represent ty the Good, while 0.85 signify the satisfactory. The remaining value of parameter such as recall, f1-score, and support is also indicated by different sign like excellent, good, satisfactory, and poor as shown below.

	precision	recall	f1-score	support
Excellent	0.70	0.58	0.63	92
Good	0.72	0.62	0.67	590
Satisfactory	0.85	0.89	0.87	3066
Poor	0.79	0.75	0.77	1145
accuracy			0.82	4893
macro avg	0.77	0.71	0.74	4893
weighted avg	0.82	0.82	0.82	4893

Fig 5: Comparative analysis based on various parameters

Table 1 depict the performance of proposed model with respect to different technique as shown below. From Fig.1, the RNN-LSTM model attained the RMSE is 0.393, MSE is 0.386, MAE is 0.097 and accuracy is 0.78. ANN models obtained the accuracy is 0.79, RMSE is 0.398, MSE is 0.397, MAE is 0.098. Random Forest technique attained high accuracy, RMSE, MSE, MAE as compared to RNN-LSTM, ANN. Hence, the proposed model CNN-LSTM achieved high accuracy 0.821, RMSE 0.189, MSE 0.0357, and MAE is 0.0357 which gives superior performance as compared to other existing method.

Table 1. Performance or proposed model with respect to different methods.

Models	RMSE	MSE	MAE	Accuracy
Proposed model/CNN-LSTM	0.189117	0.03576	0.03576	0.8217
RNN-LSTM	0.3932	0.3972	0.0927	0.7872
ANN	0.3981	0.3972	0.988	0.7943
Random Forest	0.3981	0.3963	0.09846	0.7798
Multivariate Linear Regression	0.3989	0.39782	0.0990	0.7928

5.1 Comparative analysis

Figure 7 illustrates the comparison graph of proposed model with different techniques as shown below. From Fig. 7, RNN-LSTM model has attained less accuracy, Random Forest method has obtained low accuracy as compared to all other method. Multivariate linear regression model achieved high accuracy as compared to Random Forest and RNN-LSTM model. Therefore, it is clear that the proposed model achieved high accuracy as compared to all other methods and it gives superior performance against other methods.

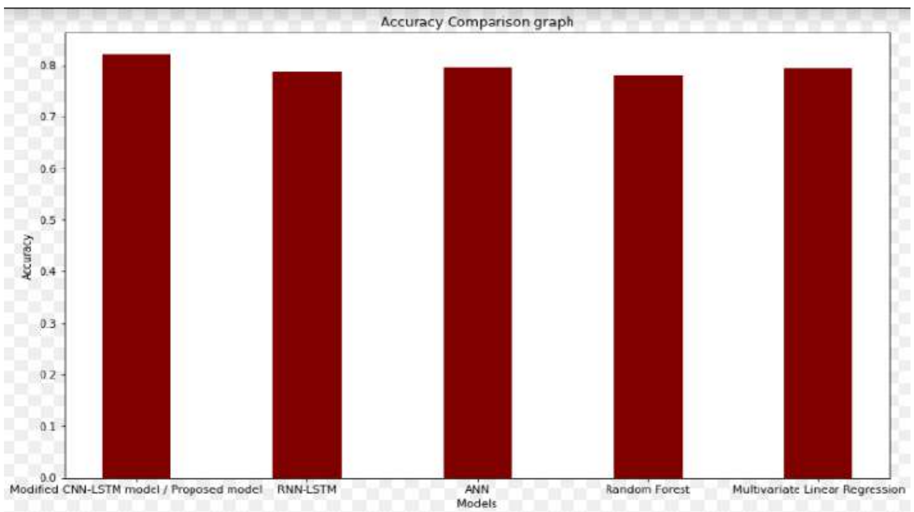


Fig 7: Accuracy comparison graph between the proposed model and earlier research models

6. CONCLUSION AND FUTURE SCOPE

This research aimed to identify an efficient deep learning technique for predicting wheat crop yields. The choice of the modified CNN-LSTM model as the study's foundation was deliberate, taking into account the demonstrated efficiency of CNN and LSTM in managing time series data. CNN has been given an advantage thanks to LSTM models, able to represent both short-term and long-term memory. LSTM models provide a solution to the problem of vanishing gradients encountered by RNN approaches. Standard performance evaluation measures were used to assess the precision of the predictions that were generated by the various methods. According to the findings, the proposed model CNN-LSTM attained high accuracy, precision, recall, and f1-score as compared all other technique. Future research should investigate more deep learning models to improve analysis and efficiency.

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