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A Novel Method for Prediction of Crop Yield Using Deep Neural Networks

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Abstract: The study of data mining is essential to obtain the significant information by exploiting the insightful information from the enormous data sources. Being a key industry in any country, the agriculture has direct impact on Gross Domestic Product (GDP). Financial production and market prices are the key factors in generating revenue in agriculture. Higher yields results in more money and profit. Whereas, the lower yields can cause the fall in agricultural GDP. As a result, the yield monitoring becomes crucial in boosting the countrys' economic resources. Early yield prediction models are based on manual computations, which occasionally had errors because of possible incorrect inputs. To address these issues, this paper provides a novel method by employing representative neural network models to evaluate the precision of yield predictions. This paper specifically investigate the use of hybrid and deep learning models, such as long short term memory (LSTM), convolutional neural network (CNN), and recurrent neural network (RNN) to choose the most precise model and evaluate yield prediction accuracy. Several tests are run by utilizing the farm production datasets collected from kaggle to assess the performance of these algorithms. The proposed method evaluates the predictive power of each model through these tests, providing insightful information for future projections of agricultural productivity. These findings have the potential to significantly increase the precision and dependability of yield projections, which would be advantageous for the agricultural industry and to boost the country's economy.

Keywords: *Short Term Memory, Convolutional Neural Network, Recurrent Neural Network, Deep Learning Model, Crop Yield.*

1. Introduction

This Planning for agriculture tries to maximize the agricultural productivity by utilizing scarce land resources. Algorithms for machine learning provide the intriguing ways to increase the agricultural yield and to reduce the losses during unfavourable conditions. Methods for crop selection are essential for maximizing the output under various circumstances, which benefits nations' economies. A thorough evaluation of seed quality is necessary to guarantee the excellent yields since the high-quality seeds have a major impact on crop productivity. Crop selection is aided by hybridization techniques, which enable higher yield rates in optimum conditions.

Crop production is influenced by a number of variables which includes soil type, crop choice, geographic location, meteorological conditions, and harvesting techniques. Classification and machine learning techniques are used to forecast ideal results in order to maximize agricultural productivity. Crop productivity is highly impacted by geographic factors including riverbeds, hills, and depths as well as by climatic variables like humidity, rainfall, temperature, and cloud cover. Crop growth is also influenced by the makeup of the soil, which contains nutrients like copper, potassium, phosphate, nitrogen, and others.

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Factors which affect the Crop Yield

Indeed, a number of different elements interact to affect the crop production, each of which has a big impact on the yield and general effectiveness of agricultural operations. The following are some of the major elements that affect crop production:

Soil Type: Crop growth and production are directly impacted by the different soil types' nutrient contents, water retention abilities, and drainage features.

Crop Selection: It's important to choose the right crops for a given area and environment. While some crops may not be well-suited to certain regions, this can have an impact on yield as a whole.

Location: The duration of the growing season, temperature changes, and the amount of sunlight are all influenced by the location's altitude and latitude, which has an impact on crop growth.

Meteorological Conditions: Climate variables including temperature, precipitation, humidity, and wind are essential for agricultural growth. Extreme weather conditions, such droughts or floods, can have a big impact on productivity.

Techniques for Harvesting: Crop yield and quality can be affected by harvesting timing and technique. Using the right harvesting techniques will maximize productivity and reduce losses.

Water availability and effective irrigation techniques are essential for maintaining crop development, particularly in areas with limited water supplies.

Pest and Disease control: To prevent crop damage and guarantee healthy yields, efficient pest and disease control measures are crucial.

Fertilization and nutrient management: It's important to apply fertilizers correctly and manage nutrients to give crops the nutrients they need for a healthy growth.

Crop rotation and intercropping: Using these approaches can improve soil fertility, lessen insect pressure, and maximize the use of available land.

Adoption of contemporary agricultural technologies, precise farming methods, and sustainable farming practices can increase crop output and resource efficiency.

Achieving optimal crop yield, guaranteeing food security, and promoting sustainable agriculture are depends on the proper management of these variables. To address issues and increase crop productivity, farmers, academics, and policymakers are always working to refine agricultural methods and to create innovative solutions.

The rest of the paper is organised as follows. In Section 2, literature review is presented. In section 3, existing system is presented with its limitations. The proposed methodology is described in Section 4. The results and discussions are outlined in Section 5.

1.1 Literature Review

Define This section attempts to define a list of models or strategies that are discussed in relation to proposed work and how to increase the crop yield based on several factors.

Barbedo J G A, (2018) [1],presents an investigation into the main factors that affect the design and effectiveness of deep neural nets applied to plant pathology. An in-depth analysis of the subject, in which advantages and shortcomings are highlighted, should lead to more realistic conclusions on the subject. The arguments used throughout the text are built upon both studies found in the literature and experiments carried out using an image database carefully built to reflect and reproduce many of the conditions expected to be found in practice. This database, which contains almost 50,000 images, is being made freely available for academic purposes.

Bu F and Wang X, (2019) [2], present a smart agriculture IoT system based on deep reinforcement learning which includes four layers, namely agricultural data collection layer, edge computing layer, agricultural data transmission layer, and cloud computing layer. The presented system integrates some advanced information techniques, especially artificial intelligence and cloud computing, with agricultural production to increase food production. Specially, the most advanced artificial intelligence model, deep reinforcement learning is combined in the cloud layer to make immediate smart decisions such as determining the amount of water needed to be irrigated for improving crop growth environment.

Zhang Z, Liu H, Meng Z, and Chen J, (2019) [3], to improve the Inception_v3 network, a network called AMT Net was designed and trained for automatic recognition of agricultural machinery images. Under the same experimental conditions, AMTNet achieved recognition accuracies of 97.83% and 100% on validation sets Top_1 and Top_5, respectively, demonstrating better performance than the classic networks ResNet_50 and Inception_v3. To further test the performance of AMTNet, 200 images of each of the 13 types of machine images were selected as test sets.

Frooq M and Pisante M, (2019) [4], it is the ready reference on sustainable agriculture and reinforce the understanding for its utilization to develop environmentally sustainable and profitable food production systems. It describes ecological sustainability of farming systems, present innovations for improving efficiency in the use of resources for sustainable agriculture and propose technological options and new areas of research in this very important area of agriculture.

C.Geetha et al., (2023) [5], described the major goal of putting the crop selection strategy into practice so that it may be applied to solve a number of problems that farmers and the agricultural sector face. As a result, crop yield rates are maximized, which is good for the Indian economy. Different types of land conditions. An ensemble of classifiers allows for better prediction decisions because it uses several classifiers.

A.K.Sharma et al., (2021) [6], discussed the importance of IOT and how the smart agriculture is examined using IOT. In order to fully automate the system, this research is primarily focused on enhancing the effectiveness of the current crop yield Prediction. The crop yield prediction carefully monitors the crop yield level. The sensor enables the camera to update the visible value and save it to the cloud as the crop yield level raises.

P.Shyamala Bharathi et al., (2021) [7], discussed a unique deep learning strategy referred to as the modified deep learning strategy (MDLS). It is developed to assist agricultural fields in accurately predicting crop output levels. This MDLS is derived from the K-nearest neighbour and decision tree algorithms, two common learning frameworks. The suggested method takes into account the factors like pesticide use, rainfall ratios, and temperature levels as prediction limits when examining agricultural yield characteristics. The subsequent section clearly illustrates using graphical representations the correct efficiency ratio of all the algorithms discussed. To measure the level of crop prediction, a fresh crop yield prediction dataset that is derived from the open source database called Kaggle.

Tripty Singh et al., (2022) [8], suggest to assist the farmers in determining the crop that would deliver a decent crop for a specific season by taking into account soil type, soil fertility, climatic conditions, rainfall, and the specific seed requirements. Using the provided data for various locations, this method employs deep learning techniques in the model to forecast the yield or success rate. In Phase 1, it uses a variety of machine learning techniques on the pre-processed data to forecast future weather conditions and rainfall (in mm). Phase 2 involved predicting crop success rates while taking into account soil and climatic inputs and achieved agricultural success rates for various crops, hence increasing yield at a location.

Swati Vashishtet al., (2022) [9] discussed that, the research on agricultural yield prediction has benefited from the use of a variety of deep learning methods, neural network topologies, and prediction models. This study suggests employing an upgraded version of the Extreme Linear Machine to predict crop yield. Data was pre-processed using the Kalman Filter Algorithm, some features are identified using Linear Discriminant Analysis, and crop prediction is carried out. Based on geography, season, and cultivation area, rice crop yield has been forecasted.

Anıl Suat Terliksizet al., (2022) [10], uses a 3D CNN model that takes advantage of spatiotemporal cues to estimate soybean yield in Lauderdale County, Alabama, USA. The yield is supplied for the years 2003–2016 by the USDA NASS Quick Stat tool. Google Earth Engine is used to acquire the satellite data from NASA's MODIS land products, which measure surface reflectance, land surface temperature, and land surface temperature. In order to compare the outcomes, the evaluation metric known as the root mean squared error (RMSE) is used.

Table 1. Sample of 10 References related to Crop Yield Prediction

Reference	Methodology Used	Work Done
Deep-LSTM Model for Wheat Crop Yield Prediction in India by Preeti Saini; Bharti Nagpal [11]	Deep-LSTM model	This will generate outcomes were assessed using Root Mean Square Error, Mean Square Error, and Comparison with the currently used machine learning techniques
An Approximation for A Relative Crop Yield Estimate from Field Images Using Deep Learning by Hulya Yalcin [12]	Deep Learning Model	To predict the crop yield from Farming Images collected from Remote Sensing Devices
Crop Yield Prediction Enhancement Utilizing Deep Learning and Ensemble Algorithms by Ohnmar Khin; Sung Keun Lee [13]	Linear Discriminant Analysis (LDA) Classifier, Quadratic Discriminant Analysis (QDA) Classifier, and Stochastic Gradient Boosting (SGB) Classifier	Enhance the performance of deep learning models for crop yield prediction
Crop Selection Method to maximize crop yield rate using machine learning technique by Rakesh Kumar; M.P. Singh; Prabhat Kumar; J.P. Singh [14]	Crop Selection Method (CSM)	To solve crop selection problem, and maximize net yield rate of crop over season and subsequently achieves maximum economic growth of the country

2. Existing System

In the existing systems, machine learning (ML) classification algorithms are used to identify the crop types and its diseases and how the crops are affected with several diseases. These algorithms accurately identify the diseases, but they couldn’t able to find the yield for the appropriate crops based on the crop quality. However, the limitations of the existing system are listed follows,

1. In recent years, all the countries are trying to increase the country’s GDP through agriculture.

2. In the recent days, the use of ML algorithms may not lead to identify the crop yield.
3. The ML algorithms failed to achieve accurate crop yield predictions.
4. For large dataset, ML algorithms are not accurate and efficient.

3. Methodology for Proposed System

Use Recurrent neural networks (RNN), convolutional neural networks (CNN), and long short-term memory (LSTM) models are all used in the proposed system to forecast the crop productivity. Utilizing the advantages of each model, the system will be able to discern spatial patterns from satellite imagery, capture temporal relationships in time-series data, and store long-term data for precise crop yield projections. The proposed system has the following advantages,

1. By using the deep neural networks, the crop yield can be easily identified.
2. The proposed system is able to classify which model is best in order to identify the crop yield.
3. It is identified that LSTM has more accuracy compared to other neural network models in order to predict the crop yield.

3.1. Algorithms

This section discusses about the current CNN model which is formed by combining several pre-trained models. This paper uses nearly 3 pre-trained techniques which are applied on agriculture production dataset collected from Kaggle. It try to use some deep learning and its hybrid techniques such as LSTM, CNN and RNN models for verifying the accurate yield prediction and then finally come to a conclusion which one gives best accurate report.

3.1.1. LSTM (Long – Short Term Memory) MODEL

If the input and output data are both sequences, LSTM networks are ideally suited for sequence-to-sequence applications. They have been effectively used in a variety of natural language processing (NLP) tasks, including speech recognition, sentiment analysis, language modeling, and machine translation. The main concept underlying LSTMs is to employ a memory cell with many gates that regulate the information flow inside the cell. The input gate, output gate, and forget gate are some of these gates. The LSTM cell is intended to select the data to be stored in the memory cell, the data to be deleted, and the timing of reading from it.

A high-level description of the LSTM cell is given below:

Input gate (i): The amount of fresh input data that should be saved in the memory cell is decided by theinput gate.

Forget Gate (f): This will selects the data to be erased from the memory cell.

Output gate (o): The output gate (o) regulates how much of the memory cell should be visible when the LSTM cell is output.

These gates serve as the foundation for the calculations inside an LSTM cell, which enable the model to selectively read from and write to the memory cell while preserving information over extended times.

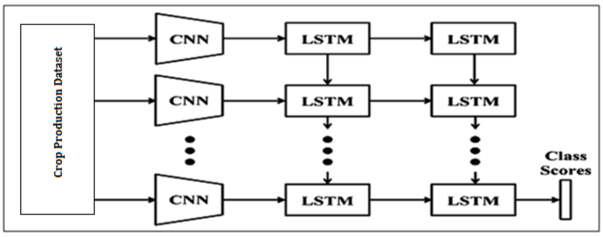


Fig. 1 Flow of LSTM for Crop Yield Prediction

Figure 1 illustrates the flow of an LSTM used to calculate agricultural production based on an input dataset. The time series data were analyzed using LSTM, and these attribute variables are periodically monitored. It provides an approximate estimate of the crop output. The one-dimensional convolutional network can be used to process the direct one-dimensional data. Due to the data format and processing, the network will require little time to train.

3.1.2. Proposed CNN Model

It is able to clearly see the proposed CNN model for yield prediction in Figure 2. CNN is a Feed Forward Neural Network with filters and pooling layers. We can include the following layers in this CNN model

1. Input Layer
2. Convolutional Layer
3. Pooling layer
4. Fully connected Layer
5. Regression Layer

An attempt is made to load the input into the CNN model by first loading the input as crop production, such as an excel file or cropped photos. The input is now entered into the hidden layers once the model has been loaded. Convolutional layer, pooling layer, fully connected layer, regression layer, and other intermediate layers are included in the hidden layer. The final output layer is achieved once the actions in the concealed layer are finished. In the top layer, the forecast of any crop illnesses that may be present based on the input data and it predict the yield based on the input data.

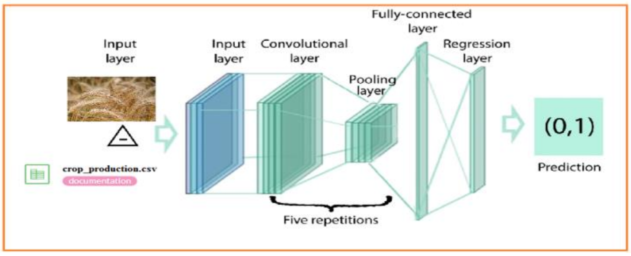


Fig. 2 Represents the Flow of CNN Model for Crop Yield Prediction

3.1.3. Recurrent Neural Network (RNN) Model

A sort of neural network architecture called a recurrent neural network (RNN) is ideally suited for sequence data, such time series data, where the order of inputs is important. An RNN can be used to examine historical data of different agricultural elements (such as weather, soil, planting dates, etc.) and estimate crop yields in the future based on the patterns and relationships found in the data. A step-by-step explanation of how an RNN can be applied to agricultural yield prediction is provided below:

Gather historical data about crop yields and any other relevant information, such as information about the weather (temperature, precipitation, humidity, etc.), the soil (nutrient levels, pH, etc.), and any other relevant variables. Preprocessing of this data is necessary, which may entail dividing the dataset into training, validation, and test sets as well as scaling, addressing missing values, and normalization.

Forming Sequences: Arrange the data into sequences. Each sequence is made up of a number of time steps, where each time step contains the values of several features for that particular period of time. For instance, you might produce monthly data sequences spanning several years.

RNN Architecture: Recurrent layers in the RNN architecture maintain a hidden state that collects data from earlier time steps and affects the prediction at the current time step. It is possible to utilize a straightforward RNN unit, but more sophisticated units, such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU), are frequently used since they can capture longer-term dependencies.

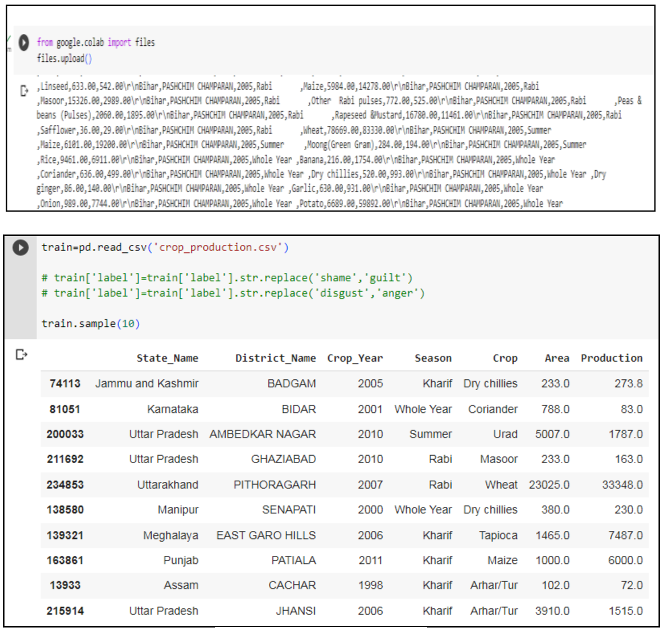
Model Training: Using a suitable loss function, such as mean squared error (MSE), the RNN is trained on the training data sequences. The RNN delivers an output at each time step after learning to change its internal hidden state in response to the input sequence. The anticipated crop production for that time step could be the output

4. Results and Discussion

This section try to check the performance of our pre-trained CNN models which are used for predicting the crop yield and then check which model gives more accuracy compared with other models and it also can get the accuracy of top 5 crops which yield more production.

5.1. Load Dataset and View the Dataset

Initially, try to load the input dataset into the application and try to verify the contents which are present in our input model. Once the input is loaded now we can able to check for the parameters which are present in that input dataset.



```
from google.colab import files
files.upload()
```

```
,Linseed,633.00,542.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi ,Maize,5984.00,14278.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi
,Masoor,15326.00,2989.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi ,Other Rabi pulses,772.00,525.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi ,Peas &
beans (Pulses),2060.00,1895.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi ,Rapeseed &Mustard,16780.00,11461.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi
,Safflower,36.00,29.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Rabi ,Wheat,78669.00,83330.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Summer
,Maize,6101.00,19200.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Summer ,Moong(Green Gram),284.00,194.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Summer
,Rice,9461.00,6911.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year ,Banana,216.00,1754.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year
,Coriander,636.00,499.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year ,Dry chillies,520.00,993.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year ,Dry
ginger,86.00,140.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year ,Garlic,630.00,931.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year
,Onion,989.00,7744.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year ,Potato,6689.00,59892.00\r\nBihar,PASHCHIM CHAMPARAN,2005,Whole Year
```

```
train=pd.read_csv('crop_production.csv')

# train['label']=train['label'].str.replace('shame','guilt')
# train['label']=train['label'].str.replace('disgust','anger')

train.sample(10)
```

	State_Name	District_Name	Crop_Year	Season	Crop	Area	Production
74113	Jammu and Kashmir	BADGAM	2005	Kharif	Dry chillies	233.0	273.8
81051	Karnataka	BIDAR	2001	Whole Year	Coriander	788.0	83.0
200033	Uttar Pradesh	AMBEDKAR NAGAR	2010	Summer	Urad	5007.0	1787.0
211692	Uttar Pradesh	GHAZIABAD	2010	Rabi	Masoor	233.0	163.0
234853	Uttarakhand	PITHORAGARH	2007	Rabi	Wheat	23025.0	33348.0
138580	Manipur	SENAPATI	2000	Whole Year	Dry chillies	380.0	230.0
139321	Meghalaya	EAST GARO HILLS	2006	Kharif	Tapioca	1465.0	7487.0
163861	Punjab	PATIALA	2011	Kharif	Maize	1000.0	6000.0
13933	Assam	CACHAR	1998	Kharif	Arhar/Tur	102.0	72.0
215914	Uttar Pradesh	JHANSI	2006	Kharif	Arhar/Tur	3910.0	1515.0

Fig. 3 Load Dataset

5.2. Load the Main Window

This is the main window to execute our problem. In this we can load the agriculture dataset and then check the performance of several models.

Fig. 4 Main User Interface

5.3 Upload the Dataset

From the above window we can clearly identify the dataset is loaded into the application Through User Interface which is created for our application.

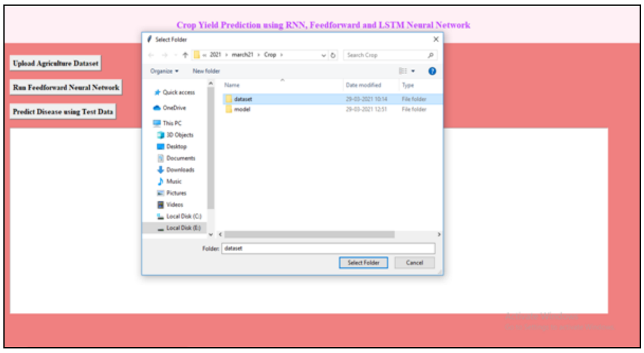


Fig. 5 Main User Interface

5.4. Data Pre-Processing Window

Here from the above window, we can see data is pre-processed successfully and any missing information is present inside the dataset will be removed and only useful contents will be displayed.

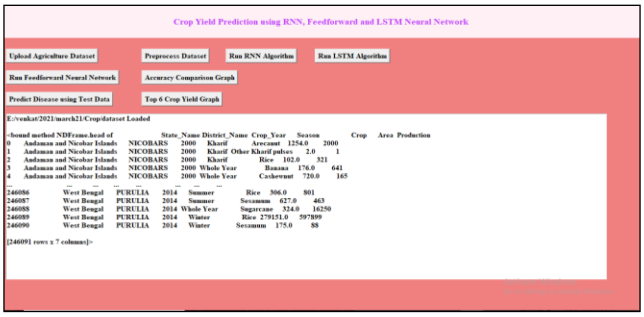


Fig. 6 Data Pre-Processing Window

5.5. RNN Model Prediction

In above screen RNN model generate with accuracy as 58% and now click on 'Run LSTM Algorithm' button to build LSTM model.

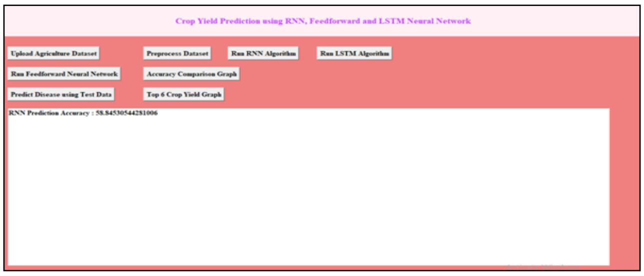


Fig. 7 RNN Model is Predicted

5.6. LSTM Model Prediction

In above screen LSTM model generated with accuracy 78% and now click on 'Run Feed Forward Neural Network' button to build feed forward model.

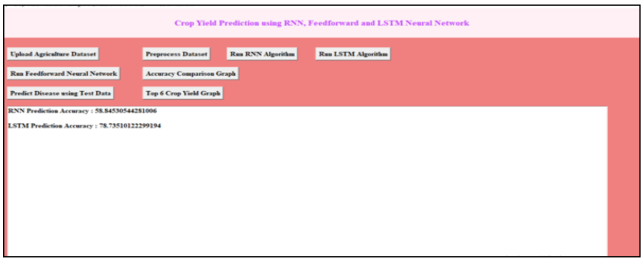


Fig. 8 LSTM Model Prediction Window

5.7. Model Comparison

In above graph x-axis represents algorithm name and y-axis represents accuracy of those algorithms and in all algorithms LSTM giving better prediction accuracy and now click on 'Predict Disease using Test Data' button to upload test data and then neural network will give below prediction result.

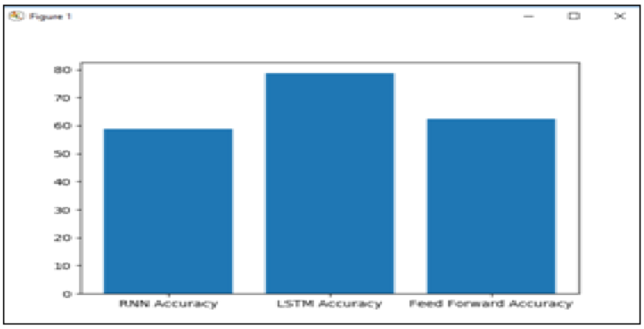


Fig. 9 Model Comparison Window

Table 2. Performance Analysis

Algorithm	RNN	CNN	LSTM
Accuracy	58 %	68 %	78 %

From the above table we can clearly get LSTM has more accuracy.

5. Conclusion

This paper create a predictive model to calculate crop yields based on a variety of variables, including soil type, climate, location, and crop-specific characteristics. Crop yield predictions are made using three deep learning models, RNN, CNN, and LSTM, for various circumstances. In terms of precisely forecasting crop yields, the study has demonstrated encouraging results. This has important implications for agricultural planning, resource management, and food security. For time series data, like trends in crop yield over time, RNN and LSTM models are ideally suited. The data is properly collected for long-term dependencies, and they produced precise predictions for different crop types. The CNN model successfully predicted crop yields using image data, particularly when assessing crop diseases and crop health monitoring. Through the use of data fusion, the combination of RNN, LSTM, and CNN models improved overall prediction accuracy and gave significant insights into the intricate relationships between many factors affecting crop yields. Finally, the proposed LSTM has more accuracy compared with other models. Future study could concentrate on a number of areas to improve the predictive models' precision, robustness, and practical usefulness. Following are some prospective research and development directions: Include new features, data augmentation, transfer learning, and other improvements to increase crop production prediction accuracy.

Conflicts of interest

The authors declare no conflicts of interest.

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