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Prediction on field crops yield based on analysis of deep learning model

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ABSTRACT

Agriculture has a key role in the overall economic development of the country. Climate change, irregular rainfall, changes in the nutrient content of the soil, and other environmental changes are seen as a severe problem in crop yield prediction. Using deep learning (DL) models that incorporate multiple factors can be viewed as an essential strategy for attaining accurate and effective solutions to this issue. The crop yield can be predicted using yield data obtained from a historical source that includes information about the weather, soil nutrient content, soil type, the season in which the crop was grown, and its yield. In order to train the model and achieve high accuracy, a large set of data including multiple factors would be required. This research aims to forecast the yield of a certain crop using long short-term memory (LSTM) time series analysis and the information currently available. The data used to construct the models was obtained from a reputable source and contains correct numbers. Before growing a crop that has been sown on a piece of agricultural land, the yield prediction utilizing advanced methodologies can assist farmers predict the yield of a specific crop.

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1. INTRODUCTION

Crop yield is considered as a difficult and complex trait that can be determined by various factors which are the soil type, physical environment, and the changes occurring in it. To predict crop yield continuously, it needs a lot of information that can be used to investigate the relation between obtained crop yield and other parameters. In order to understand these dependencies, it is essential to know about the extensive datasets as well as the algorithms that might be incorporated [1]. Time can be considered as an essential parameter that might be taken into consideration if the model has to forecast anything, be it the expected stock price, the amount of crop yield or the amount of rainfall that might fall at a particular location. For instance, a condition can be quite fascinating wherein the model can predict the time which would be having the most consumption in electricity. It may allow us control the consumption expenses so that we'll be able to produce more electricity during the peak time and could even save resources when not needed [2].

To understand time series, we can consider it as a simple continuous data that are arranged based on the time. While implementing this method, the role of time is generally considered as a non-dependent entity whose main objective generally emphasizes on forecasting. By using time series analysis one can predict the future outcomes on the basis of past data [3]. Seasonality is one of the aspects of time series analysis which can be referred as a periodic fluctuation. In order to understand it we can take following example into consideration, different types of crops grow in different seasons. It could be studied and understood by a relation and find if it is in a sinusoidal shape. It can be observed from the complete duration of a season [4].

Stationarity can be considered as one of the most crucial aspect. In the method, it can be called as stationary only when all of the statistical attributes remains the same over a period of time. Also, can be inferred that there is a constant mean and variance. Therefore, the related variance can be considered as it is independent of time. There are various ways in order to model a time series so as to make predictions. Some of them are:

- Moving average: This model has general approach for the models that are related to time-series. It also states that the forth coming values will be the mean of all the values that were observed in the past.
- Exponential smoothing: It is the model which uses the same logic which is used in moving average but the only difference is that variable weights that are arranged in descending orderare given for respective observations. Therefore, considerably less significanceis provided to values that were observed as the model keeps on processing till the future. One of its kind is double expo. Smoothing which is also implemented in this time series model. We use this method only when a simple continuous implementation of this smoothing two times is required.
- SARIMA: It is model that is having the combination of simple models and combines them in order to form a model that is complex enough and can be used in various time series related traits.

The proposed work is sumfold into two categotries:

- Prepocessing-eliminating the null values, reduntant data and discarding the non-relevant factors related to crop.
- Model-several deep learning (DL) models are applied to evaluate the performance of crop yield predictions. The proposed work enhances the long short-term memory (LSTM) method to predict the crop yield.

Section 2 describes about the survey of yield predictions techniques. Section 3 deals about the deep learning models and dataset descriptions. Section 4 deals about the proposed reconstruction strategy of LSTM. Section 5 deals about the results and discussions of yield prediction.

2. RELATED WORKS

Some of the works discussed in the paper [5] had the remote sensing mechanism included for gathering the data along with the moderate resolution imaging spectroradiometer (MODIS) satellite imagery. Remote sensing images [6] which includes the radiometric calibration and the geological corrections, were overcome by the use of the software called environment for visualizing images (ENVI) and the module used was fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) [7]. It was observed that building a single level model for each crop was a better option so as to make things simple [8]. Once all the crop models are having a high accuracy in the yield prediction, then merge all the simple models into some complex models [9]. Also the calendars [10] based information must also be taken into consideration as one of the parameter to keep a track of sowing cycle and to obtain valuable information on land use and crop phenology. Collecting ground-based data for training is challenging and takes a lot of time. To overcome that remote sensing based satellites [11] started playing an essential role. Kussul *et al*. [12], predictions on the basis of in-situ data from previous year and tuned with neural networks with an accuracy of 85.9%. In the same year, Zhong *et al*. [13] used MODIS normalized difference vegetation index (NDVI) and LSTM [14] for the prediction of vegetation dynamics with root mean square error (RMSE) lesser than 0.03. The dataset was divided into 3 segments which are as follows training, validation and the testing. Using this method, prediction of any vegetation changes is well adapted and precautions can be taken for safety of these crop beforehand [15].

To make the model more dynamic, identification of the crops can also be added which was also a key feature in the research which was done in the year of 2019. In order to achieve this, various methods of machine learning can be used like support vector machines. Once the VI is calculated for a particular soil, it can be used for the prediction with a lot of accuracy. A lot of other parameters like leaf area index (LAI) and low-noise amplifier (LNA) can also be calculated for a better and more accurate predictions. One of the models like source address validation improvements (SAVI) was at a time considered as accurate because it calculated a lot of parameters and conditions. The model was faster than the previously made models and also gave a high accuracy output [16] also tried adding some additional variables to the already existing conventional methods with applications of random forest regression algorithm which gave even better results in terms of accuracy. In the same year, Zhou [17] used convolutional neural network (CNN) to design a model based on NDVI and RGB for crop prediction from data obtained from unmanned aerial vehicle (UAV). As a result, the CNNs were far better than NDVI and red-green-blue (RGB) in performance [18]. Optical sensor imaging is considered as an efficient method in order to monitor the various parameters that are necessary to predict the crop yield [19]. The data obtained from the optical sensor might sometimes be ineffective due to cloud covering, which can be overcome by using synthetic aperture radar (SAR) sensors.

Trinks and Felden [20] tried to bridge the gap between the optical data and SAR sensors using MCNN-Seq. In other words, it is an extension of conventional CNN-recurrent neural networks (RNN). This shows the efficiency of multi layered CNNs over single layered CNNs. The accuracy achieved by this model was higher than CNN or RNN in terms of R^2 and RMSE [21]. Apart from predicting the crop yield, protecting it from crop related diseases is equally important. Wang [22] focussed on the diagnosis of the crop yield, a model named SqueezeNet with plant village is used and a performance accuracy of 98.49% was achieved [23]. As a result, made his focal point to predict the seeding, maturation and harvest dates to maximize the production. Senthil-1 satellite was used to extract the time series data [24]. SAR backscattering and interferometric synthetic aperture radar (InSAR) coherence provided the crop seeding dates with 85% and harvest dates with 56% accuracy respectively. Another research using time series data extracted with Senthil-1 was done by [25], conducting an analysis on cross polarisation (VH/VV). This enhanced the prediction of seeding, maturation states of the currently growing crop and harvest dates.

As the years pass, the number of parameters increased and the dependency of the model increased on all these parameters and the accuracy of the model increased because features like climate change prediction, and various other parameters can be used in order to make our model efficient [26]. To the best of my knowledge, the crop yield is highly depend on the phenotype or environmental factors rather than the genotype factors. The results of the study [27] also reveals that environmental factors plays a predominant role in the crop yield affecting parameters when compared to the genotype factors [28]. Multipath delay commutator fast Fourier transform has been proposed for enhancing the throughput [29]. Cooperative routing using the fresher encounter algorithm to improve energy-efficiency and solves the node dead issues [30].

3. DEEP LEARNING METHODS

3.1. Dataset details

For the purpose of training the model and enhancing its efficacy, a high-quality data set is required to produce accurate results. Due to the fact that the model's output is produced from the training dataset alone, the properties of the dataset and the size of the dataset also play a crucial part in testing the model. The crop data should include numerous parameters that can be weighed throughout the feature selection procedure.

The dataset under consideration contains data from several locations in India. This data set contains about eighty thousand records, which were collected between 2014 to 2019. This data collection takes into consideration numerous climate and soil characteristics. When calculating a field's crop yield, the field's area is taken into account. Crop production in the specific field over the years. Rainfall is a significant aspect in agricultural yield forecast since it is a primary climatic factor that, in excess, can harm the crop, and even in insufficient amounts, can destroy the yield. This examination of the crop takes into account a variety of seasons. Each crop grows throughout a distinct season, which provides it with an appropriate growing environment. Temperature is also essential in relation to the type of crop that has been planted. Various types of crops namely, Moong, Wheat, Maize, and Urad, are used to analyse and train the model. Also critical are soil conditions; different types of soil vary in pH, nitrogen content, and electrical conductivity. Here, for each data point, these values are examined because crop health depends on them.

3.2. Data pre-processing

Data pre-processing helps to convert raw text data into numerical values. In addition, it also eliminates the missing values, and redundant features in the dataset. This research work consist of yield prediction, though some of the features in the dataset are represented as text. For eg district, seasons are the feature that are represented in text. These categorical values are converted into numbers before applying the DL Models. This dataset also consist of some missing values and are eliminated by using python libraries. This dataset does not contain any reduntant feature. After completing the pre-processing process, the dataset is ready to apply the DL models to estimate the accuracy and finding the best one.

3.3. Deep neural network (DNN)

Two models of deep neural network (DNN) namely, recurrent neural networks (RNN) and long short-term memory (LSTM) are analyzed in the proposed work for the yield prediction of field crops. Nodes are generally considered as the small component that are present in the system. They can be generalized as neurons that is present in the brain of a human. As soon as a stimulant interacts them, a response to stimuli takes place within these nodes. A lot of them can be related and could be identified by the mark. However, in a general scenario, the nodes could further be classified into various layers. The Figure 1 explains a DNN layers.

The mechanism should handle the layers of knowledge and manage it between the input and output in order to successfully complete a task. There are numerous layers present and it's to a particular method through which it needs to induce the final output. The more deep the network goes, better it works and all the instances are taken into account. A DNN can be considered as helpful when there is a need to reduce the human labour. DNN many time compels and intimates that it has a tendency to replace human labour. DNN thus has an autonomous work profile which can hardly compromise its potency. The DNN usage in various sectors will make everyone understand its varied applications in real time scenario.

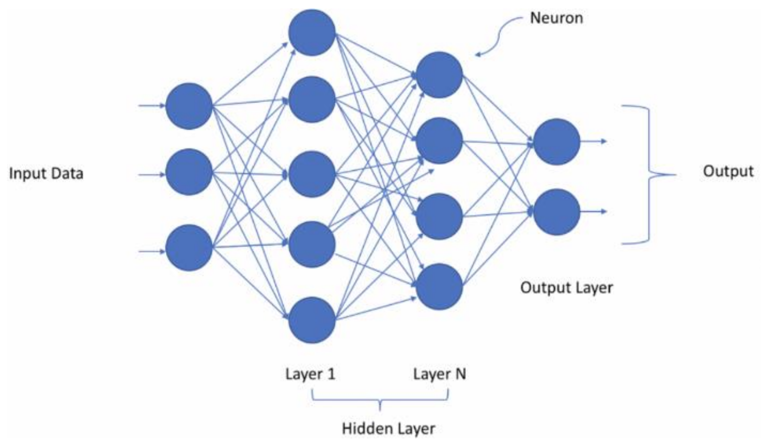

Figure 1. Representation of DNN Layers

3.3.1. Recurrent neural network (RNN)

The RNN model was created to take into consideration the temporal dependence of agricultural output across a number of years. Two contradicting observations necessitated the deployment of the RNN model. On the one hand, field crops (maize, wheat, urad. and moong) yield have increased over the last four decades. This is partly attributable to the continued improvement of genetics and management practices as a result of significant investments in breeding and agricultural techniques. However, genetic information was not available to the public for this prediction study. Consequently, utilizing the available data, the effect of genotype must be addressed indirectly in the model. This paper addressed the RNN technique to predict the yield for different crops based on the environmental factors. The performance of RNN is discussed in the results and discussion section.

3.3.2. Long short-term memory (LSTM)

LSTM can be considered as an artificial neural network (ANN) that keeps on recurring and is also used in the field of deep learning. Sequence problems are considered as one of hardest problem in deep learning. These includes variety of problems like stock prediction, sales prediction, and crop prediction. LSTM is edge over CNN, RNN and feed-forward neural networks in many ways. LSTM modifies the information by multiplications and addition is shown in Figure 2. It has a mechanism in which the information flows, called as cell state.

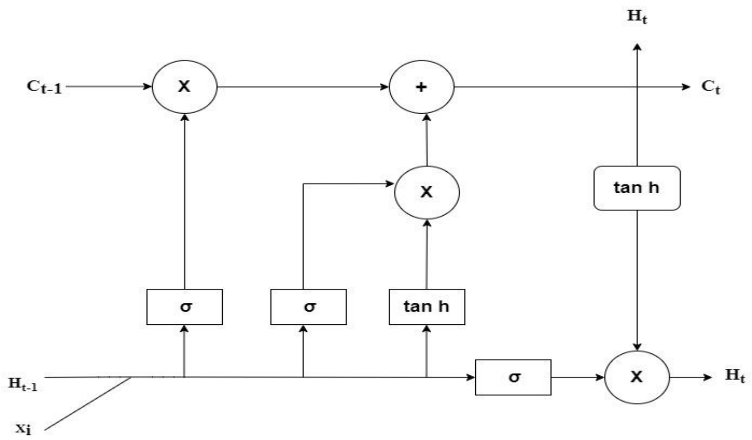

Figure 2. Working principle of LSTM

Symbols namely orange rectangle represents layers, arrow represent the copy operation, circle represents point wise operations. In Figure 2, X_i is a vector considered as input, H_{t-1} - output of previous cell, C_{t-1} - memory of previous cell, H_t-output of current cell, C_t-memory of current cell, *-multiplication, + - addition, W, U-weights.

These can be classified into three states:

- Previous State has the information present in the memory after previous step.
- Previous hidden state gives same output as the previous state.
- Input state which stores new information.

Figure 3 represents the LSTM states. Even though the accuracy with the LSTM is higher for weekly data and is more reliable than other model but the complexity of the code also increases. A higher number of data inputs is also needed for training the dataset used for LSTM. Therefore, DNN is used so that the complexity decreases, lesser amount of data is needed to train the model and also it outperformed LSTM for daily data.

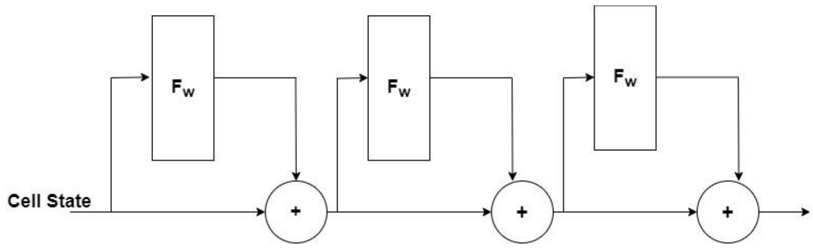

Figure 3. Representation of LSTM states

4. PROPOSED METHOD

The proposed method make use of reconstructive mechanism of LSTM. The proposed architecture is shown in Figure 4. Out of all the models analyzed, the LSTM was giving high accuracy when a huge dataset was taken into account in various other researches. The use of LSTM in order to make a model that works on the large time series data might even give good outputs with a better accuracy. Since the whole time series dataset would be having multiple parameters like rainfall, area, season in which the crop was sown, pH value of the soil, nitrogen content inside the soil that should be taken into account.

The methods that are currently running have a lot of flaws be it the lack of accurate data or the inadequacy while processing of all the essential parameters that are needed in order to forecast the yield. Also, the usage of the current methodologies is refined to some well-developed areas where in the farmers having a good source of income can benefit themselves using the models as they are in a good financial state.

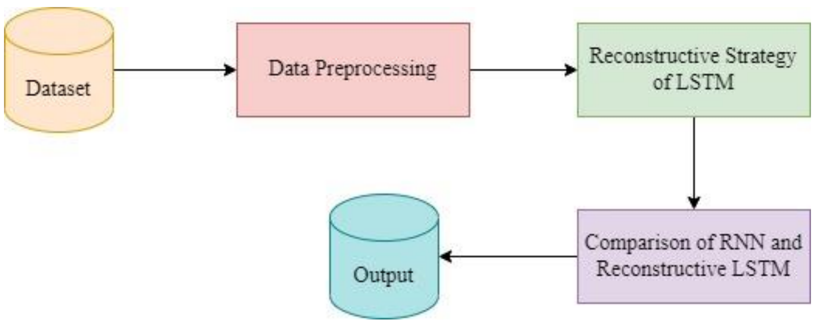

Figure 4. Proposed architecture of crop yield prediction

The data pre-processing phase should also be reconstructed. The dataset that is to be used in the training process should be filtered in such a way that there should not be any null values. Apart from the null values, it has to be taken care of that all the column values are having a same datatype. It is also necessary to identify the important attributes that are to be considered in order to train the model accurately.

Once all the pre-processing is done, the model can be trained using the key attributes using which the yield or the total production of the crop can be forecasted. It has to be taken into account that since the dataset is huge, there might be some possibilities of overfitting which might in turn affect the accuracy of the model. Some functionality should be added so as to avoid it. As soon as all this is done, the model can be tested on the test dataset.

The values of this test dataset are already known but it is used to check the accuracy of the model and if there is a case of less accuracy, then necessary actions could be taken. As soon as a good accuracy is attained, the model can be used on the dataset having the essential values of the crops that will be grown in future. Based on this data, the model should predict the yield of the crop in a particular season.

5. RESULTS AND DISCUSSIONS

The LSTM model has a tendency to handle the information given to it and has the ability to add or remove the information that is sent to the cell states. The functionality is regulated by a lot of gates that allows the model to train in a much efficient way. So, the model will be taking in the training datasets and will be processing all the information. Once all the training processes are carried out, the model can now be tested on the datasets having information that is known and the yield value can be cross checked.

While developing the model in order to forecast the yield, following things must be taken into consideration:

- Input from the user should have the same parameter which was used while training the model.
- There should be a proper use of the layers in order to get correct outputs and avoid overfitting.
- Area, season, crop sown and the nutritional values present in the soil should be given importance. Figure 5 demonstrates the season and production graph.

Firstly, for analysis and better understanding of the data. A graphical representation of the crop with respective production in specific conditions is plotted. During the process of analyzing the dataset of the crop, there are a lot of parameters that might play a vital role in predicting the yield for a particular season. Since there are a lot of parameters on which the yield of the crop depends upon, it is needed to process the data first so that it can be easily used for further analysis.

Figure 6 shows a Season vs temperature graph. Like this, production graph is plotted for other features also like temperature, season and rainfall. The data is then checked for any null values in it. The isna() gives the count of any null value present in the training dataset for individual column. In case any null value is found it has to be omitted or processed correctly so that it does not affect the prediction. Similarly, same is done with the test data.

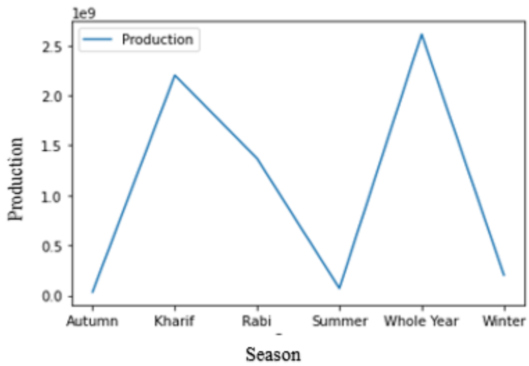

Figure 5. Season vs production graph

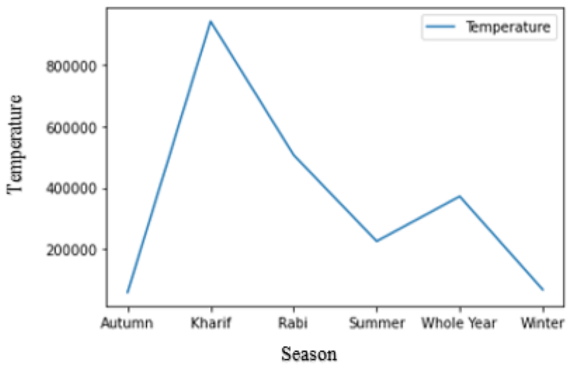

Figure 6. Season vs temperature graph

Figure 7 demonstrates a season-rainfall graph. From the training and the testing dataset, production column is stored in variables and the column is dropped from the original datasets, with this the dataset becomes independent of the production values. Then using one hot encoder and column transformer it is fitted into an array which has the values of every row. Similarly, it is repeated for the test dataset. Table 1 described the training data, whereas Table 2 illustrates the test data. Tables 1 and 2 clearly depicts the features used to predict the crop yield. The output of the dataset is to predict the crop production which is not present in the test data.

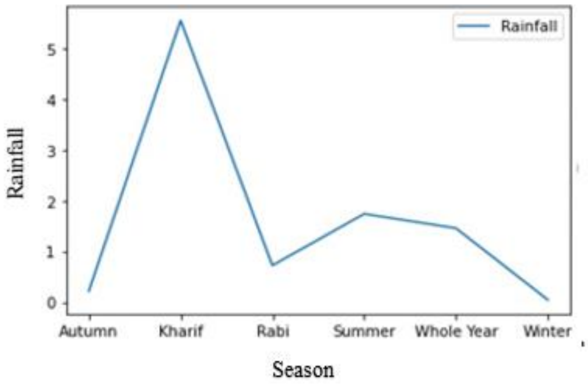

Figure 7. Season-rainfall graph

Table 1. Training data

Area	Production	Rainfall	Season	Temperature	Crop	pH	Nitrogen (kh/ha)	Electrical conductivity (ds/m)	Year
7800.00	3200.0	30.400333	Kharif	28.007000	Moong	6.5	497	4.1	2014
39922.0	75572.0	111.90100	Khariif	27.232333	Maize	5.6	473	3.9	2014
44656.0	49099.0	3.396500	Rabi	20.277000	Wheat	7.3	366	4.9	2014
6540.0	3945.0	30.932500	Rabi	24.241500	Wheat	5.3	417	3.8	2014
2911.0	2062.0	189.208333	Kharif	27.456333	maize	6.3	267	3.5	2014

Table 2. Test data

Area	District	Season	Rainfall	Temperature	Crop	pH	Nitrogen (kh/ha)	Electrical conductivity (ds/m)	Year
10803	Bairampur	Kharif	0.215	0.214	Urad	7.0	267	2.9	2020
84190	Bairampur	Kharif	1.428	1.458	Urad	7.3	320	5.6	2020
43539	Bairampur	Kharif	6.952	2.145	Sugarcane	6.7	305	4.0	2020
90246	Bairampur	Winter	2.152	6.952	Wheat	5.7	279	2.1	2020
18087	Bairampur	Whole Year	8.546	1.976	Wheat	6.4	252	2.5	2020

Figure 8 is plotted based on the multiple crops that were grown in all the six seasons i.e. summer, winter, autumn, kharif, rabi and whole year. The x-axis holds the season value and the production value is marked on the y-axis. Each colour represents a specific crop. In order to train the model, we have used four dense layers having an activation function ‘relu’ and the dropout of 0.2 and 0.3 is added so as to avoid the overfitting. Figure 9 attained after plotting the values that we got from the training and testing datasets. The equation y=a+b x was taken into consideration wherein x contains the data from the training dataset and y contains the data from the test dataset, b is the slope of the line and a is the y intercept value. Figure 8 demonstratesax_train, y_train linear regression graph.

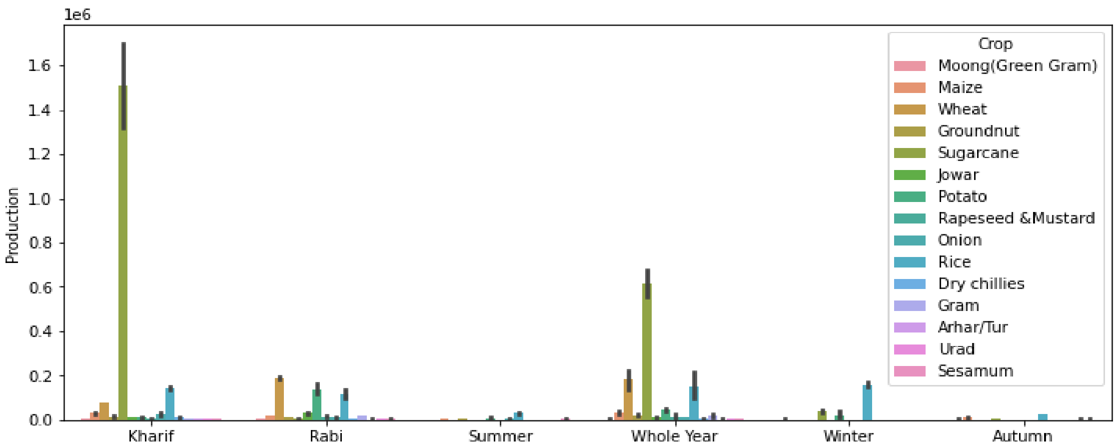

Figure 8. Season wise crop-production bar graph

Table 3 accuracy and the loss percentage in test data. Table 3 predicts the accuracy using RNN and LSTM neural networks. The model is trained and tested using 10 epochs. After 10 epochs, the accuracy is not increasing much. The model is trained till 20 epochs, minimal amount of accuracy gets increased. Table 3 clearly depicts comparison of accuracy in each epochs using RNN and LSTM networks. Our findings shows that both LSTM and RNN achieve satisfactory result in this dataset. But LSTM outperforms the best result compared to the RNN.

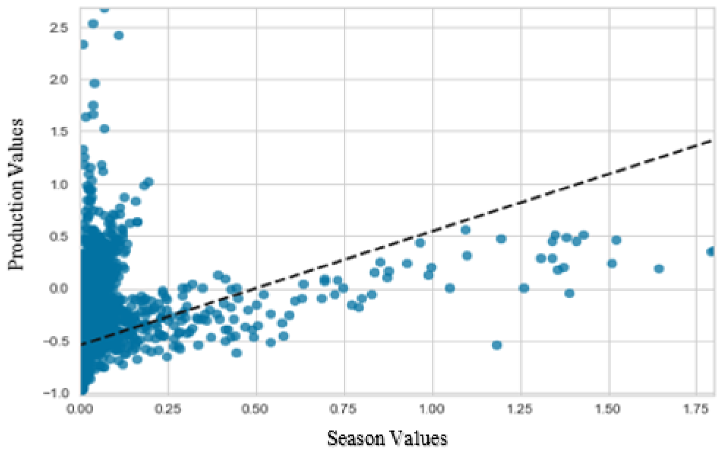

Figure 9. Linear regression of x_train and y_train

Table 3. Accuracy in test data of each epoch

Epoch	RNN Accuracy	RNN Loss	LSTM Accuracy	LSTM Loss
1	0.81	19.12	0.93	7.01
2	0.74	26.31	0.86	14.01
3	0.76	24.14	0.88	12.21
4	0.82	18.13	0.91	9.12
5	0.80	20.00	0.92	8.00
6	0.80	20.00	0.92	8.00
7	0.80	20.00	0.92	8.00
8	0.75	25.17	0.87	13.21
9	0.77	23.14	0.89	11.02
10	0.81	19.13	0.93	7.01

6. CONCLUSION

The study shows that a variety of features are being used in the model proposed by the researchers of the various publications that were selected for the study. Each paper focused on the yield prediction of various crops using various techniques like RNN and LSTM. Through the study, it was found out that the datasets used by various publishers differ in size as well as geographical location thus limiting the features of the model. Despite the usage of the various algorithms in the study, it can be concluded that the accuracy given by the LSTM algorithm was remarkable when compared with RNN in order to predict the yield of the field crop. The accuracy of the model was found out to be around 93% in LSTM. The future directions of this research work is to focus on ensemling techniques to minimize the error on this dataset.

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