A Time-Series Based Yield Forecasting Model Using Stacked Lstm To Predict The Yield Of Paddy In Cauvery Delta Zone In Tamilnadu

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Abstract— **Cauvery delta zone in Tamilnadu is called as "Nerkazhanchiyam" (the land of Paddy) of the state, as it has the potential to produce paddy in huge quantity that can be suffice the need of the state. This zone includes the districts such as Thanjavur, Tiruvarur, Nagapattinam, Trichy and Cuddalore. These districts account for about 53% of production of paddy in the state. Increasing the production of paddy in Cauvery Delta Zone would satisfy the requirement of rice in the state on the whole. This will also have a substantial influence on both the farmer's and the nation's economy. Forecasting the production of crops beforehand could assist the farmers in improving their productivity. This necessitates the design of a precise crop yield prediction model. Crop production in agriculture is primarily determined by a variety of factors that falls under three categories: technological (agricultural techniques, managerial decisions, etc.), biological (diseases, insects, pests, etc.), and environmental (climate change, etc.). Among these factors environmental factors pose a great challenge to the decision makers in developing a precise prediction model. Hence, it is proposed to develop a suitable yield prediction model to predict the yield of paddy in Cauvery delta region considering the environmental factors along with the supplied nutrients. The proposed prediction model makes use of Long Short Term Memory (LSTM) algorithm which is a popular deep learning algorithm, to forecast the yield of paddy. LSTM is well known for its better prediction using time series data. Performance of the proposed prediction model is measured using the training loss and validation loss.**

Keywords- Crop Yield, Deep Learning, Artificial Intelligence, Agriculture, Long Short Term Memory(LSTM).

I. INTRODUCTION

Agriculture plays a major role in deciding the economy of any country. Increasing the productivity of the crops aids the government in taking necessary steps to improve food security. Increase in population in any country necessitates increase in the yield of grains and pulses to satisfy the growing demand. Cauvery Delta zone [1,2] in Tamilnadu contributes to the major share of pulses in the entire state. It is well known for its production of paddy and hence it is also called as "Nerkalanchiyam" of Tamilnadu. Increasing the production of paddy in this Zone could help in satisfying the demand in future. Forecasting the yield of crops could help the farmers in increasing the production in future. Conventionally, the farmers make use of their past experience to forecast the yield of crops. But, these forecasts would not be precise, as the crop growth and yield are highly dependent on various factors such as area of cultivation, level of irrigation, climatic conditions, fertilizers consumption and different government policies. Developing a precise yield prediction model that considers the above factors could assist the farmers and the policy makers in improving the crop yield thereby meeting the demand of the growing population. Earlier, the researchers have studied the performance of various machine learning algorithms [4,5] in performing the prediction. In recent days, they have turned their attention towards analysing and applying deep learning (DL) techniques to both classification and regression problems.

Deep Learning has found its applications in diverse domains such as medical image processing [6-8], disease identification in plant leaves in agriculture [9-11], security and surveillance [] and so on. Deep learning (DL) is an Artificial Intelligence (AI) function that works like a human brain in pre-processing the data and creating patterns for use in decision making [15,16]. The word Deep in Deep Learning refers to the use of multiple layers in the network. It teaches the computer to filter the inputs through multiple layers, to learn how to predict and classify the information. The observations can be in the form of text, sound or images. Deep Learning is also known as Deep Neural Learning or Deep Neural Network (DNN).

Forecasting the crop yield mainly depends on the previous history about the various parameters that affect the yield. The conventional Feed-forward Neural Network does not consider

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the previous history while performing the prediction. This shortfall has been overcome by the Recurrent Neural Networks that takes in to account the time dependent data during the prediction. But it is able to remember only the data of short duration from the history. Long Short-Term Memory (LSTM) [15-17] network is a class of recurrent neural network, which is capable of learning from the previous history and remembering the learned patterns for a longer duration. It is also capable of selectively remembering or forgetting data so that it reduces the memory requirement for computation. LSTM networks are widely used for solving problems based on time series data. This makes LSTM as an appropriate solution to design a suitable crop yield prediction model. Hence, to increase the benefits for farmers, this project focuses on predicting the yield of crops using LSTM.

The rest of the paper is organized as follows: In Chapter II, various existing crop yield prediction models are reviewed. Chapter III describes the proposed crop yield prediction model and Chapter IV demonstrates the experimental evaluation of the proposed model. Finally, Chapter V presents the summary of the proposed work and its future scope.

II. LITERATURE REVIEW

This section explores the various attempts made by the research community in developing a suitable crop yield prediction model using machine learning and deep learning approaches. Accurate yield projections are critical in enhancing any agricultural industry's production plans, increasing agricultural product sales, and determining the industry's performance. As a result, a review of existing crop yield prediction models was conducted in order to find the suitable aspects that could aid in the development of a better prediction model as well as the identification of flaws in existing approaches.

Cai et al. [18] made use of a regression model named LASSO and three machine learning algorithms such as SVM, Random Forest, and Neural Networks to build a precise prediction model to forecast the yield of wheat crop in Australia. They tested the prediction model using enhanced vegetation index (EVI) from MODIS and solar-induced chlorophyll fluorescence (SIF) from GOME-2. The experiments conducted revealed that the machine learning methods showed improved performance than the LASSO regression model. Preethi Tiwari [19] used CNN (Convolutional neural networks) to check the collected raw data from satellites such as NDVI (Normalized Difference Vegetation Index) and SPI (Soil Potential Index) parameters. It takes spatial features as input and has been trained by propagation to reduce prediction error. The experiment was carried out using genuine data from real geospatial resources. When the suggested modified CNN's results are compared to those of earlier approaches, it is discovered that the proposed modified CNN outperforms them on many parameters.

Wang et al. [20] proposed a deep learning based crop yield model to predict the yield of soybean crop in Argentina. The model is developed using deep transfer learning algorithm with little amount of training data. They trained and tested their model using the dataset obtained from MODIS satellite image. Performance of the model is measured using R2 and RMSE and it is found that the proposed model resulted in a better prediction when compared to the existing deep learning approaches. Sun et al. [21] used the CNN-LSTM model to predict soybean yields at the country level for both the end of the season and the beginning of the season. They employed a variety of data in this method, including MODIS Land Surface Temperature (LST) and MODIS Surface Reflectance (SR) data. With the help of weather and corn dataset, Crane-Droesch designed a crop yield prediction model using deep neural network to predict the yield of corn in US Midwest. Performance of the model has been improved over the test set through hyperparameter tunning.

Elavarasan and Vincent [22] used deep reinforcement learning to combine parametric features with a threshold to predict the production of crop. This learning obtains an aggregate score for the activities completed by minimizing error and maximizing forecast accuracy. By accurately conserving the original data distribution, the proposed model outperforms existing models in accurately predicting crop yield. Khosla et al. [23] predicted the amount of monsoon rainfall and the yield of Kharif crops in Vishakapatnam using Modular Artificial Neural Network (MANN) and Support Vector Machine (SVM), respectively. First, they predicted the monsoon rainfall using MANN. This predicted rainfall and the cultivated area are fed as input to SVM inorder to prediction the yield of Kharif crops.

Gong et al. [24] applied temporal sequencing process by integrating two state-of-the-art networks. The proposed approach used various datasets gathered from multiple real greenhouse sites over the growth season to create a temporal convolutional network (TCN) and a recurrent neural network (RNN). They employed Root Mean Square Errors (RMSEs) between anticipated and actual crop yields to test the performance of the suggested system, which produces better yield prediction performance than standard deep neural networks. Bi and Hu [25] proposed a genetic algorithm (GA)-assisted deep learning solution approach for crop yield prediction is proposed in this research. The proposed method is divided into two phases: a global search phase and a local search phase. GA is utilized in the global search phase to get the best starting weights for the neural network. Random perturbation is applied to the local search phase to prevent the local optimum and vanishing gradient difficulties. To compare the proposed method to other gradient-based algorithms, a case study of agricultural yield prediction is done. The results reveal that in terms of convergence speed and prediction accuracy, the suggested method beats gradient-based methods. Maimaitijiang et al. [26] developed an yield prediction model to predict the yield of soy bean in Columbia using multimodal data fusion and Deep Neural Network. Multimodal data such as canopy spectral, structure, thermal and texture features extracted through Unmanned Aerial Vehicle (UAV) platform has been used to train the model. Performance of the model is tested using Root Mean Square Error (RMSE) and it is found that the model resulted in about 15.9% RMSE. Hence, it is valid that DNN based yield prediction model outperforms the machine learning based models.

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III. PREDICTION OF PADDY YIELD USING LSTM

Precision agriculture is required by farmers in order to improve their farming and productivity. As a result, an accurate crop yield prediction model is required to assist farmers in forecasting the production of their crops. The suggested system is an LSTM-based Deep Learning yield prediction model. The LSTM model is the proposed model for forecasting crop yield prediction. In comparison to other deep learning algorithms, this model is more efficient and produces superior results. It has the ability to recall old data and compare it to current information to produce superior results. The dataset contains a total of 12 features, 11 of which are independent and one of which is the dependent variable, known as 'RICE-TQ.' The 'RICE TQ' feature contains values related to crop production in quintals. It begins by loading the dataset and dividing it into training and testing data. Therefore, it is proposed to develop an LSTM based prediction model to predict the yield of paddy crop. The proposed prediction model consists of the following five phases:

1. Pre-Processing Phase
2. Split the dataset into training and testing dataset
3. Create the Stacked LSTM model
4. Training and Testing the model

A. Pre-Processing Phase

All adjustments done on the raw data before delivering them to the deep learning algorithm are referred to as preprocessing. Initially, the dataset has been downloaded and pre-processed for enhancing the data for further processes. Data preprocessing is critical because it allows researchers to improve the quality of raw experimental data. It also aids the machine's ability to analyze data quickly. In this crop yield prediction model, the input parameters in the dataset such as fertilizer consumption, production area, production quantity and other such parameters contain NULL values. These values should be replaced with appropriate values. Here, these values have been replaced by the average value. Followed by this, the values in the dataset are normalized, as the value of each feature falls under different ranges. This will result in reduced error rate during prediction. Hence, normalization has been done to scale down the values of all the features in the range 0 – 1. Here, Min-Max scalar is used to scale down the values.

B. Split The Dataset in to Training and Testing Dataset

After preprocessing, the complete dataset is divided into training and testing datasets. The training dataset accounts for 65 percent of the total, while the remaining 35 percent is used to test the dataset. One advantage of dividing a dataset into a ratio of training and testing groups is that it prevents 'overfitting,' which occurs when a model becomes too finely tuned to the data it is given and is unable to make accurate predictions on data it hasn't been trained on.

C. Create the Stacked LSTM MODEL

An LSTM model containing multiple LSTM layers is known as a stacked LSTM architecture which is depicted in Fig. 1. An LSTM layer above sends a sequence of values to the LSTM layer below, rather than a single value. Specifically, instead of one output time step for all input time steps, one output time step per input time step is used. Two layers of LSTM are utilized, with the optimizer being used to minimize error function (loss function) or increase production efficiency. For training deep learning models, the Adam optimizer is employed as a substitute optimization technique for stochastic gradient descent. In the vast majority of circumstances, Adam is the best adaptive optimizer.

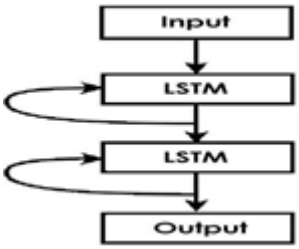


Fig. 1. Stacked LSTM Architecture

D. Training and Testing the Model

The model is trained on the pre-processed data. Fig. 2 and Fig. 3 depict the predicted yield for the training and test dataset, respectively. Fig. 4 shows how well the predicted values coincide with the actual values for the training dataset. From the graph it is understood that the proposed prediction model has done a precise prediction of the yield of paddy.

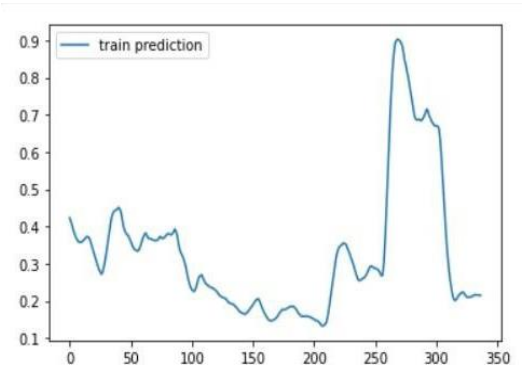


Fig. 2. Predicted Yield for the Training Data

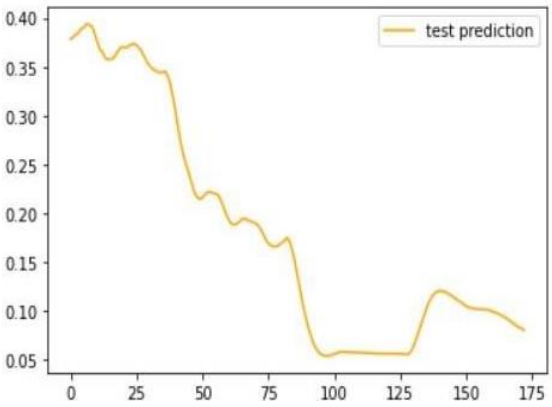


Fig. 3. Predicted Yield for the Testing Dataset

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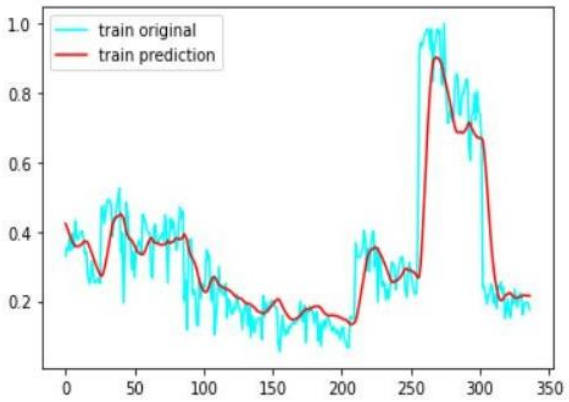


Fig. 4. Observed vs Actual Yield for the Training Data

IV. EXPERIMENTAL RESULTS

A. Dataset Description

TABLE I. DATASET DESCRIPTION

Name of the Attribute	Description about the Attribute
Year	Year during which the crop production measured
District	The district which produces crop yield.
NIA	Net irrigated area
AVG_RF	Average amount of rainfall in a particular district per year.
N_TC	Total consumption of nitrogen
P_TC	Total consumption of Potassium
K_TC	Total consumption of Phosphate
Canals	Net irrigated area of canals
Tanks	Net irrigated area of Tanks
Tube well	Net irrigated area of Tube well
Other well	Net irrigated area of other well
Other sources	Net irrigated area of other sources
RICE_TA	The total cultivated area of the rice crop
RICE_TQ	Total production of rice made by the particular district

The crop dataset for this research was obtained from the ICRISAT website 'vdsa.icrisat.ac.in,' which is part of the Village Dynamics in South Asia (VDSA) project. The Bill and Melinda Gates Foundation (BMGF) established ICRISAT with the goal of engaging stakeholders in studying the dynamics of village poverty. It also has a database of information on farming activities in order to help South Asia's agriculture improve. The data has been gathered with the goal of predicting paddy production in the districts of the Cauvery Delta Zone. The features present in the dataset are listed in Table I. There are a total of 12 independent features and one dependent feature, 'RICE TQ,' which represents total rice production in terms of Quintal in a given year. The sample dataset, which spans the years 1966 to 1980, is shown in Table 6. However, the real collection contains 552 records from 12 districts. Table II presents the experimental setup under which the proposed prediction model has been trained and tested. The model is trained and tested repeatedly by varying the number of epochs, the optimizer function, and the batch size.

TABLE II. EXPERIMENTAL SETUP

Parameter	Value
Epoch	25, 50, 100
Optimizer	Adam, RMS Prop, Nadam
Batch Size	64, 72

B. Performance Analysis

Performance of the proposed model has been analyzed using the important metrices: training loss and validation loss. Training loss and validation loss over time are two of the most commonly utilised measurement combinations. The training loss is a measurement of how well the model fits the data. The validation loss, on the other hand, reveals how well the model matches new data. Training loss will gradually reduce, and the validation loss will be less than the training loss. Each epoch's training loss is measured, while validation loss is measured after each epoch. The training and validation losses obtained by the proposed model are depicted in Fig 5.

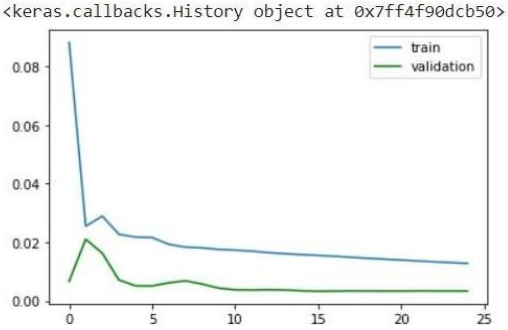


Fig 5. Training Loss vs Validation Loss

Tables III and IV present the training and validation losses obtained under different experimental setups. From the loss values, it is understood that the proposed model does not fit the training data in all situations. It is also evident that the model best fits the training data for the batch size of 64 with the Adam and RMS Prop optimizers. The model is characterized as overfit, underfit, or best fit based on the value of training and validation loss. If the training loss is less than the validation loss, the model is said to be overfitting; if the training loss is more than the validation loss, it is said to be underfitting; and if the training loss and validation loss are nearly equal, then the model best fits the training data. Underfitting denotes the poor generation of data and poor performance while best fit denotes the center of curve and gives high accuracy.

TABLE III. TRAINING AND VALIDATION LOSS OBTAINED FOR A BATCH SIZE OF 64

Batch Size	Epoch	Optimizer	Training Loss	Validation Loss	Type of Fit
64	25	Adam	0.0762-0.0082	0.0072-0.0015	Best fit
	50		0.0014-0.0051	0.0125-0.0012	Best fit
	100		0.0626-0.0050	0.0206-0.0013	Best fit
	25	RMS Prop	0.0860-0.0110	0.0124-0.0022	Best fit

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	50		0.0112-0.0075	0.0022-0.0016	Best fit
	100		0.0882-0.0096	0.0101-0.0026	Best fit
	25	Nadam	0.0787-0.0112	0.0070-0.0034	Underfit
	50		01537-0.0100	0.0169-0.0028	Underfit
	100		0.0412-0.0068	0.0071-0.0019	Best fit

TABLE IV. TRAINING AND VALIDATION LOSS OBTAINED FOR A BATCH SIZE OF 72

Batch Size	Epoch	Optimizer	Training Loss	Validation Loss	Type of Fit
72	25	Adam	0.1797-0.0128	0.0235-0.0044	Underfit
	50		0.0507-0.0100	0.0077-0.0027	Underfit
	100		0.0851-0.0078	0.0070-0.0023	Best fit
	25	RMS Prop	0.0732-0.0137	0.0094-0.0027	Underfit
	50		0.0771-0.0119	0.0092-0.0024	Underfit
	100		0.1021-0.0147	0.0084-0.0035	Underfit
	25	Nadam	0.1420-0.0194	0.0148-0.0045	Underfit
	50		0.0140-0.0103	0.0042-0.0030	Underfit
	100		0.0096-0.0083	0.0025-0.0021	Best fit

V. CONCLUSION AND FUTURE WORK

The need for food in our state is getting steadily increased due to the growth in population. Cauvery Delta zone in Tamilnadu has the potential of producing food grains particularly paddy to meet the demand. There is a much lower possibility of improving productivity if contemporary technologies are not used. To anticipate paddy production in the Cauvery Delta zone, a deep learning-based crop yield prediction model using LSTM is proposed. The model is well trained by fine tuning the main parameters such as epochs, batch size, and optimizer. Comparing the batch size 72 with 64, it is found that the model best fits the training data for 64. This reveals that a higher batch value does not imply greater accuracy; rather, a smaller batch value ensures that the model fits appropriately. In future, the model can be trained with large size of datasets with additional feature such as weather, rainfall, and humidity of the soil.

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