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A Combined Long Short-Term Memory and Temporal Convolutional Network Model for Crop Yield Prediction

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Research in agriculture is growing, and predicting the best crops for an area depends on factors like moisture, rainfall, and temperature. Environmental changes have made farming more challenging, leading to the use of Deep Learning (DL) for prediction. Although DL models like Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) learn features from the given data, they cannot handle time-series or sequential data. They are not suitable for extracting features at different temporal scales, resulting in low performance in predicting future crop yields. As a result, in this paper, a novel DL-based future Crop Yield prediction Network called the DeepCropYNet model is proposed using a comprehensive dataset comprising historical information on weather, soil, and crop yields. This proposed DeepCropYNet employs a hierarchical integration of Long Short-Term Memory (LSTM) and Temporal Convolutional Network (TCN). The initial step involves the normalization of the time series of past yield and atmospheric data, followed by input to the LSTM network to distinguish temporal dependencies and extract representative features. Also, the TCN is constructed to apply a hierarchy of temporal convolutions across the input data, capturing features at various time scales. The resulting feature vectors from the TCN are forwarded to a Fully Connected (FC) layer for predicting future crop yields after specific periods. Finally, the experimental outcomes reveal that the DeepCropYNet model attains 88%, 90%, 86%, 84%, and 82% accuracy on groundnut, maize, moong, rice, and Urad crop datasets, contrasted with the conventional models.

Keywords: Crop yield prediction, Deep learning, Temporal scale, Long short-term memory, Temporal convolutional network.

1. Introduction

Agriculture is a major social issue as it is the primary source of food. Many countries still have populations suffering from food shortages and high population growth rates, leading to starvation [1]. The increasing population, temperature variability, soil erosion, and changing weather require solutions to ensure agricultural development and timely harvesting. It is also important to promote environmentally responsible farming and food production methods [2]. Accurate forecasting of agricultural yield, crop protection, and soil estimation is crucial for the nation's food supply [3]. Precise agricultural productivity predictions are also necessary for proper export and import evaluations to enhance public food safety [4].

Predicting crop productivity is a challenging task due to a multitude of complex factors. Location, soil quality, pests, genotype, water availability, temperature, rainfall, crop planning, and other variables all contribute to the success of agricultural output [5]. In the past, farmers relied on their expertise and historical data to forecast crop yields and make informed harvesting decisions [6-7]. However, the emergence of new technologies such as crop model simulation and Artificial Intelligence (AI) has allowed for more precise yield prediction in recent years [8-9].

Machine Learning (ML) algorithms like decision trees and their ensembles are easily interpretable methods, while neural networks may use feature attribution techniques to provide explanations for their predictions [10]. The study of making ML and AI more understandable is growing, and feature attribution approaches have made DL models easier to understand and analyse [11]. DL also offers the advantage of automatic feature learning such as learning complex associations among data, enhancing the discriminative ability of the learned features [12]. Numerous studies have employed DL models such as DNN and CNN to forecast crop yields, with some comparing their findings to those generated using traditional ML methods and analyzing the influence of different features [13-14]. However, these studies do not address the challenge of extracting the features at multiple temporal scales since the temporal convolutions across the input data are not considered in the standard CNN.

1.1 Main Contributions of the Paper

Therefore, this article introduces the DeepCropYNet model, a new deep network for predicting crop yields. The model uses historical weather, soil, and crop yield data to make predictions. It combines LSTM and TCN to extract features at different time scales. First, the historical yield and environmental data are normalized. Then, the LSTM captures temporal dependencies and extracts representative features. Additionally, the TCN applies temporal convolutions to extract features from multiple time scales. The resulting feature vectors are used to predict future crop yields. Thus, the DeepCropYNet model effectively captures spatial and temporal dependencies to improve prediction performance.

The following sections are structured as follows: Section II discusses earlier studies. Section III describes the DeepCropYNet model for crop yield prediction, and Section IV illustrates its performance. Section V provides a summary of the entire work.

2. Literature Survey

This section discusses recent studies related to predicting different crop yields using various ML and DL algorithms. Gavahi et al. [15] introduced DeepYield, a CNN combined with LSTM to enhance the precision of agricultural yield predictions. However, to improve its forecasting capability, it must consider additional variables such as weather and environmental conditions that impact crop development.

Shahhosseini et al. [16] introduced a hybrid approach that combines ML and crop modeling. Initially, crop modeling was used to determine features, which were then input into an ensemble ML algorithm for the final crop yield prediction. However, this method was unable to fully capture the complex relationships between yield and agrometeorological data. Ansarifar et al. [17] introduced a new predictive framework, the interaction regression model, to forecast crop yields based on the influence of weather, soil, management, and their interactions. However, the model's efficiency may be compromised as it struggles to identify robust features and interactions when dealing with larger datasets.

Paudel et al. [18] studied ML methods for predicting crop yield at various spatial levels. They compared regional crop yield predictions to a linear trend model over 5 years and analyzed the differences between observed and estimated yields for average and extreme harvests. They also combined local forecasts to the state level. However, the input data may not contain each parameter contributing to yield erraticism, such as inconsistencies in meteorological variables.

Nejad et al. [19] introduced a 3D-CNN and attention Convolutional LSTM (ConvLSTM) model for predicting multispectral agricultural yield. A series of CNNs were used to extract spectral-spatial characteristics, while a ConvLSTM was used to extract spatiotemporal features for estimating crop productivity. However, it cannot capture representative features at multiple scales. Oikonomidis et al. [20] developed hybrid DL models, including CNN-XGBoost, CNN-DNN, and CNN-LSTM, to forecast crop yield based on weather and soil factors. However, these models may face challenges in capturing long-term dependencies in data, particularly when dealing with intricate relationships in agricultural systems. They may not encompass all pertinent contextual information.

Khan et al. [21] introduced a new method for predicting oil palm yield using supervised ML algorithms. They collected data on soil moisture, climate, and fresh fruit bunch yield, removed duplicates, and trained tree and AdaBoost models to forecast oil palm yield. Conversely, it struggles to comprehend complex relationships among variables in agrometeorological and other multisource datasets. Batool et al. [22] utilized ML algorithms to predict tea crop yield based on climate, crop, soil, and agronomic information. However, such algorithms were unable to effectively capture the spatial and temporal relationships among the various data, resulting in inaccurate predictions.

Tripathi et al. [23] introduced a DL Multi-Layer Perceptron (DLMLP) and remote sensing for predicting soil health and crop yield. They utilized satellite data from Sentinel-1 and Sentinel-2, along with field data, to predict soil health attributes. These predicted soil factors were subsequently used to forecast wheat crop yield. However, the model was unable to capture the spatial and temporal relationships among different environmental factors.

Seireg et al. [24] utilized computer simulation data to develop an Ensemble ML Algorithm (EMLA) for predicting wild blueberry yield. The hyperparameters of the MLA were fine-tuned using a Bayesian optimizer. A combination of cascade and stacking approaches, along with feature selection algorithms, was employed to create a unique blend of MLA for yield prediction. However, the accuracy of the predictions decreased when dealing with large datasets.

Zhu et al. [25] introduced a new Deep-learning Adaptive Crop Model (DACM) designed to enable adaptive high-precision yield prediction in huge regions. The model focuses on adaptive learning of the spatial heterogeneity of crop development by completely capturing crop data. But it does not extract temporal correlations between environmental factors and crop yield at different periods. Srivastava et al. [26] utilized the CNN model, incorporating 1D convolution operation to capture the time dependencies of environmental and phenological factors to predict winter wheat yield. However, a major limitation was its black-box nature, resulting in poor prediction performance.

2.1 Research Gap

Based on these studies, it is clear that CNN models are effective at capturing spatial relationships within data. However, when it comes to tasks involving temporal relationships, such as predicting crop yield based on environmental attributes over time, CNNs may have limitations. They do not effectively extract features in different temporal scales or consider temporal convolutions across input sequences. Additionally, they operate on fixed-size input windows, making it difficult to capture patterns occurring over extended periods and handle irregular time intervals between data points. To address these challenges in crop yield prediction with temporal data, alternative architectures like LSTMs or hybrid models combining CNNs with recurrent layers may be more suitable. This study aims to address these challenges by adopting the TCN with the LSTM, which extracts representative features from different temporal scales.

3. Proposed Methodology

This section provides a brief explanation of the DeepCropYNet model for predicting future crop yields. A general layout of this study is illustrated in Figure 1. Initially, historical yield data and environmental data (e.g., CO2 concentration, temperature, humidity, soil pH, etc.) are gathered. These data are then pre-processed and input into the DeepCropYNet model to predict future crop yields. Further, the model's effectiveness is measured by evaluating the estimated crop yields with the observed crop yields. This methodology comprises pre-processing, LSTM, TCN, and FC layer modules, which are briefly described in the following subsections.

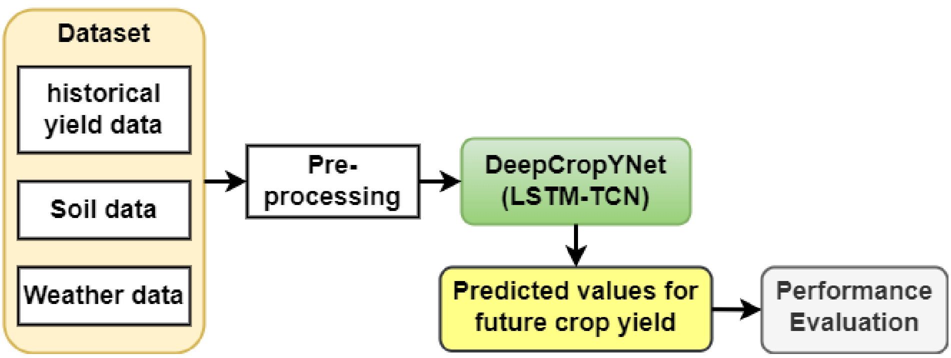

Figure 1 General Layout of this Study

3.1 Data Pre-processing

The goal is to estimate future crop yield after a specific duration using time-series data that includes past yield and atmospheric data. As depicted in Figure 2, the time-series of length N, represented by $x_{t-N}, \dots, x_t$ is used as the input for the network. The x_t in time-series is a vector that includes observed yield data, and environmental data recorded during period t. Initially, the data is normalized to a range between 0 and 1 by applying normalization to each factor (e.g., historical yield, soil parameters, and weather parameters) using Eq. (1).

$$\hat{x}_t^i = \frac{x_t^i - x_{min}^i}{x_{max}^i - x_{min}^i} \quad (1)$$

In Eq. (1), x_t^i is the i^{th} factor at t, x_{max}^i and x_{min}^i are the highest and lowest ranges for the corresponding factor.

3.2 Design of DeepCropYNet Model

Afterwards, the standardized time-series data is inputted into the many LSTM units, as depicted in Figure 2. In each LSTM unit, the following arithmetic operations are performed:

$$i_t = \sigma\left(W_{x_i}x_t + W_{h_i}h_{t-1} + W_{c_i}c_{t-1} + b_i\right) \quad (2)$$

$$f_t = \sigma\left(W_{x_f}x_t + W_{h_f}h_{t-1} + W_{c_f}c_{t-1} + b_f\right) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t \tanh \tanh \left(W_{x_c}x_t + W_{h_c}h_{t-1} + b_c\right) \quad (4)$$

$$o_t = \sigma\left(W_{x_o}x_t + W_{h_o}h_{t-1} + W_{c_o}c_{t-1} + b_o\right) \quad (5)$$

$$h_t = o_t \tanh \tanh \left(c_t\right) \quad (6)$$

In Eqns. (2) – (6), x_t, o_t, h_t are the input, output, and state of the LSTM related to the instance during t, respectively, c_t indicates the LSTM cell value signifying encoded past data acquired before t, $\sigma(\cdot)$,$\tanh \tanh (\cdot)$ are sigmoid and tanh functions, respectively, and other variables are corresponding weights and biases.

Thus, the LSTM network extracts representative features from the standardized input time-series as its states $[\cdots, h_{t-1}, h_t, h_{t+1}, \cdots]$, which are given to the TCN for further processing. The TCN module implements a series of temporal convolutions to its input data, capturing descriptive features at various time scales. As shown in Figure 2, the dilated TCN module comprises many residual blocks, each containing several dilated causal convolution layers. The dilated convolution layers perform dilated causal temporal convolution operations.

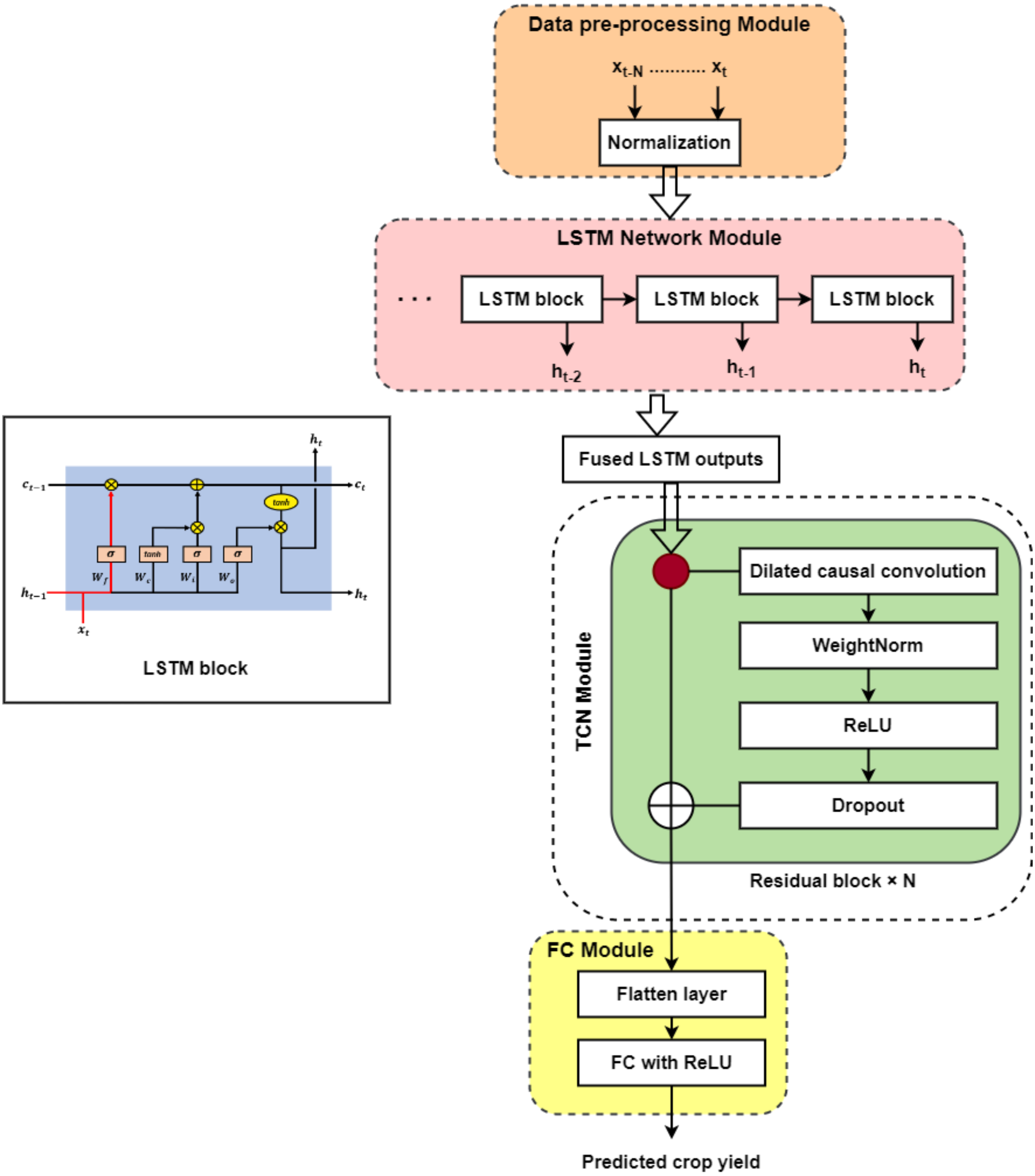

Figure 2 Architecture of DeepCropYNet Model

Specifically, the t^{th} result in the l^{th} layer and j^{th} block (represented by $S_t^{j,l}$) is determined from the previous layer using Eq. (7).

$$S_t^{j,l} = f\left(w_1 S_{t-s}^{j,l-1} + w_2 S_t^{j,l-1} + b\right) \tag{7}$$

In Eq. (7), $f(\cdot)$ is the Rectified Linear Unit (ReLU) activation function, w_1 and w_2 are weights, and b denotes the bias value.

During the training process, weight normalization is applied to the weights of a dilated convolution layer to aid in the convergence of the associated weight training algorithm such as the Adam. Additionally, to improve model generalizability, it is feasible to eliminate certain weights from the dilated convolution layers.

An extra 1D convolution process is applied to all residual blocks to align the size of the residual block input with that of the dilated causal convolution layer result, allowing them to be added together. The result of a specific residual block serves as the input for the subsequent block, and the result of the final residual block is the absolute result. The absolute yield prediction is produced by flattening the result of the TCN's final residual block and inputting it into the FC layer. Particularly, the FC layer contains a single result with a ReLU activation. The parameters of DeepCropYNet are listed in Table 1.

Table 1 Parameters of DeepCropYNet Model

Network	Parameters	Range
LSTM	No. of LSTM units	200
TCN	No. of dilated convolutional layers	3
	Kernel size	3
	Dilated rate	1
	No. of convolutional filters	250
	Activation function	ReLU
	Dropout rate	0.2
Training parameters	Learning rate	0.001
	Batch size	32
	No. of epochs	100
	Optimizer	Adam

Thus, the DeepCropYNet model is trained to predict future crop yield, and its performance is measured by comparing the predicted values to the actual crop yield values.

Algorithm 1: Future Crop Yield Prediction Using DeepCropYNet Model

Input: Historical yield data, soil parameters, and weather parameters

Output: Predicted crop yields

1. Begin
2. Normalize each input data using Eq. (1);
3. Train the LSTM network for feature learning;

//LSTM procedure:

Input: x_t, h_{t-1}, and c_{t-1};

Initialize parameters:

W_f, W_i, W_c, W_o: weight matrices for the forget, input, cell state, and output gates, correspondingly;

b_f, b_i, b_c, b_0: bias vectors for the forget, input, cell state, and output gates, correspondingly;

LSTM cell:

Function_LSTM_Cell(x_t, h_{t-1}, c_{t-1})

Forget gate f_t;

Input gate i_t;

Cell state update c_t;

Output gate o_t;

Hidden state h_t;

Return h_t, c_t

4. Concatenate LSTM outputs;
5. Train the TCN model;

//TCN procedure

Create dilated convolutional layers in the TCN;

Capture features with different receptive fields;

Apply weight normalization, ReLU, and dropout after convolutional layer;

6. Flatten the TCN outputs;
7. Apply FC with ReLU to predict future crop yields;
8. End

4. Experimental Results

This section evaluates the efficiency of the DeepCropYNet model with existing models in MATLAB 2019b. The experiment was conducted on a system with a quad-core Intel i5 2.20 GHz processor and 64 GB storage. Weather, crop, and soil data for groundnut, maize, moong (green gram), rice, and Urad (black gram) from May to December 2022 were obtained from sources [27], [28], and [29]. A total of 4730 data points were collected (946 data points for each crop) and divided into an 80-20 ratio for training and testing. For comparison analysis, existing models such as DeepYield [15], CNN-DNN [20], DLMLP [23], and DACM [25] were also implemented and tested using the dataset considered in this study.

- Mean Absolute Error (MAE): It represents the mean absolute dissimilarity between estimated and observed values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

In Eq. (8), n denotes total observations, y_i and $\hat{y}_i$ denote the observed and estimated values of i^{th} data, respectively.

- Mean Squared Error (MSE): It measures the mean squared dissimilarity between estimated and observed values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{9}$$

- Root Mean Squared Error (RMSE): It is the square root of the MSE, provided that a mean magnitude of losses.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

- Correlation coefficient (r): It is used to assess the degree of association between predicted crop yields and actual crop yields.

$$r = \sqrt{1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}_i\right)^2}} \quad (11)$$

In Eq. (11), $\underline{y}_i$ is the mean of the actual crop yield values.

- Accuracy: It is calculated by

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \times 100 \quad (12)$$

- Precision: It is the percentage of exactly estimated positive instances (True Positives (TP)) to the sum of instances predicted as positive (TP + False Positives (FP)).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \times 100 \quad (13)$$

- Recall: It is the percentage of exactly estimated positive instances (TP) to the sum of actual positive instances (TP + False Negatives (FN)).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \times 100 \quad (14)$$

- F-measure: It is determined by

$$\text{F} - \text{measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \times 100 \quad (15)$$

Table 2 presents a test results of different models for predicting future crop yields using the considered dataset.

Table 2 Test Results of Different Crop Yield Prediction Models

Crop type	Metrics	DLMLP	CNN-DNN	DACM	DeepYield	DeepCropYNet
Groundnut	MAE	0.1011	0.0864	0.0715	0.0608	0.0513
	MSE	0.0901	0.0796	0.0674	0.0582	0.0469
	RMSE	0.3002	0.2821	0.2596	0.2412	0.2166
	r	0.8150	0.8294	0.8386	0.8500	0.8617
	Precision (%)	72	78	81	84	88
	Recall (%)	78	79	82	85	89
	F-measure (%)	75	78.5	81.5	84.5	88.5
	Accuracy (%)	76	79	81	84	88
Maize	MAE	0.1143	0.0998	0.0802	0.0711	0.0586
	MSE	0.1107	0.1035	0.0951	0.0837	0.0719
	RMSE	0.3327	0.3217	0.3084	0.2893	0.2681
	r	0.8096	0.8114	0.8237	0.8311	0.8459
	Precision (%)	70	76	80	88	92
	Recall (%)	76	78	81	87	89
	F-measure (%)	73	77	80.5	87.5	90.5
	Accuracy (%)	75	77	82	85	90
Moong	MAE	0.1056	0.0966	0.0844	0.0730	0.0612
	MSE	0.0988	0.0904	0.0817	0.0705	0.0600
	RMSE	0.3143	0.3007	0.2858	0.2655	0.2449
	r	0.8178	0.8302	0.8411	0.8537	0.8644
	Precision (%)	72	75	78	80	85

	Recall (%)	78	80	81	85	88
	F-measure (%)	75	77	79	82	87
	Accuracy (%)	74	76	80	83	86
Rice	MAE	0.1028	0.0931	0.0817	0.0699	0.0576
	MSE	0.0989	0.0910	0.0800	0.0676	0.0552
	RMSE	0.3145	0.3017	0.2828	0.2600	0.2349
	r	0.8107	0.8213	0.8335	0.8479	0.8600
	Precision (%)	68	72	76	78	82
	Recall (%)	75	80	82	85	88
	F-measure (%)	71	76	79	81	86
	Accuracy (%)	70	74	78	80	84
Urad	MAE	0.1206	0.1094	0.0972	0.0855	0.0741
	MSE	0.1152	0.1035	0.0911	0.0834	0.0709
	RMSE	0.3394	0.3217	0.3018	0.2888	0.2663
	r	0.8095	0.8201	0.8325	0.8461	0.8587
	Precision (%)	68	70	74	76	80
	Recall (%)	72	75	78	80	85
	F-measure (%)	70	72	76	78	83
	Accuracy (%)	69	71	75	77	82

Figure 3(a) illustrates the test results for the DeepCropYNet in comparison to existing models for predicting future groundnut crop yield. The MAE of DeepCropYNet is 49.26%, 40.63%, 28.25%, and 15.63% lower than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The MSE is reduced by 47.95%, 41.08%, 30.42%, and 19.42% compared to the DLMLP, CNN-DNN, DACM, and DeepYield, respectively. The RMSE is 27.85%, 23.22%, 16.56%, and 10.2% lower than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the correlation coefficient is increased by 5.73%, 3.89%, 2.75%, and 1.38% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

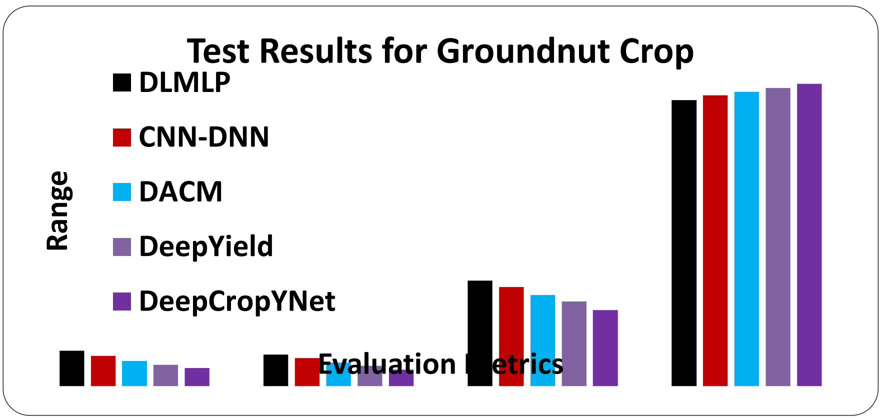

Figure 3(a) Performance Analysis of Different Yield Prediction Models for Groundnut Crop

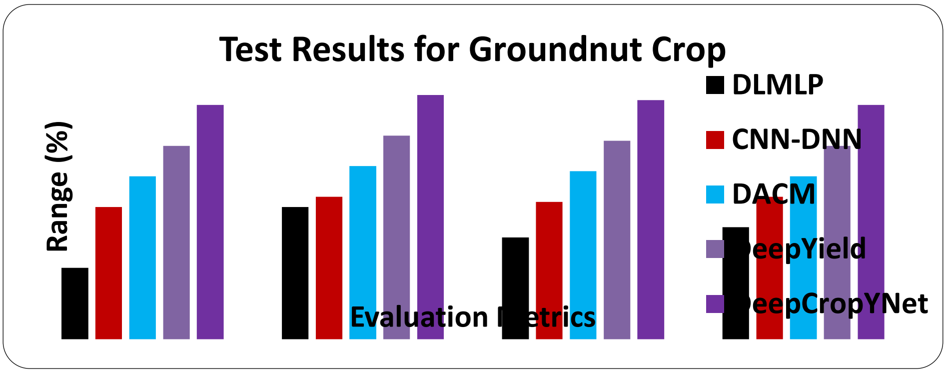

Figure 3(b) Prediction Efficiency of Different Yield Prediction Models for Groundnut Crop

Figure 3(b) demonstrates that the DeepCropYNet increases precision by 22.2%, 12.8%, 8.6%, and 4.8% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the recall is 14.1%, 12.7%, 8.5%, and 4.7% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The f-measure is also 18%, 12.7%, 8.6%, and 4.7% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Furthermore, the accuracy is 15.8%, 11.4%, 8.6%, and 4.8% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

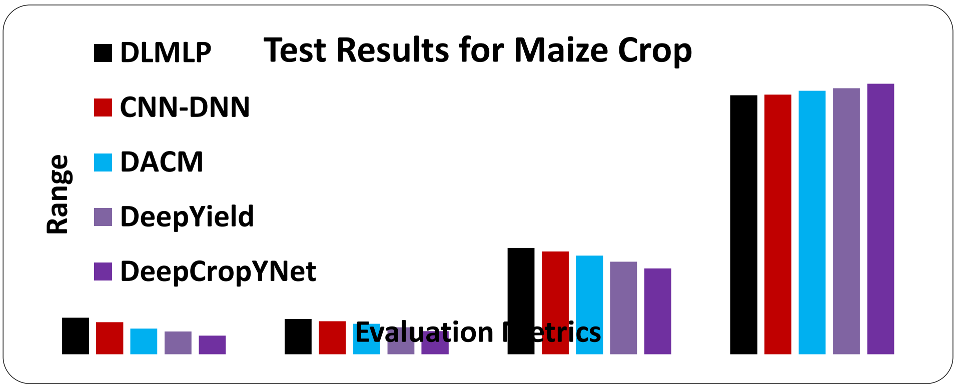

Figure 4(a) Performance Analysis of Different Yield Prediction Models for Maize Crop

Figure 4(a) shows the test results for the DeepCropYNet compared to other models for predicting future maize crop yield. The MAE of DeepCropYNet is lower than the DLMLP, CNN-DNN, DACM, and DeepYield models by 48.73%, 41.28%, 26.93%, and 17.58% respectively. The MSE of DeepCropYNet is reduced by 35.05%, 30.53%, 24.4%, and 14.1% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The RMSE is lower than the DLMLP, CNN-DNN, DACM, and DeepYield models by 19.42%, 16.66%, 13.07%, and 7.33% respectively. The correlation coefficient is increased by 4.48%, 4.25%, 2.7%, and 1.78% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

Figure 4(b) demonstrates that the DeepCropYNet increases precision by 31.4%, 21.1%, 15%, and 4.5% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

Additionally, the recall is 17.1%, 14.1%, 9.9%, and 2.3% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The f-measure is also 24%, 17.5%, 12.4%, and 3.4% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Furthermore, the accuracy is 20%, 16.9%, 9.8%, and 5.9% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

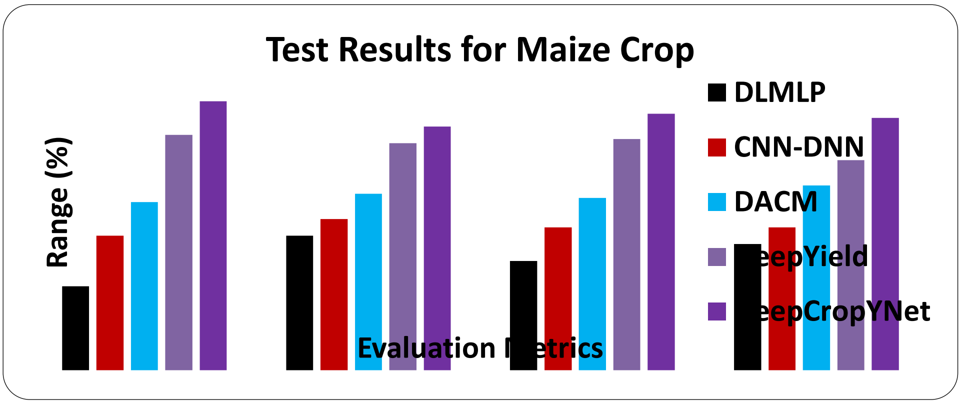

Figure 4(b) Prediction Efficiency of Different Yield Prediction Models for Maize Crop

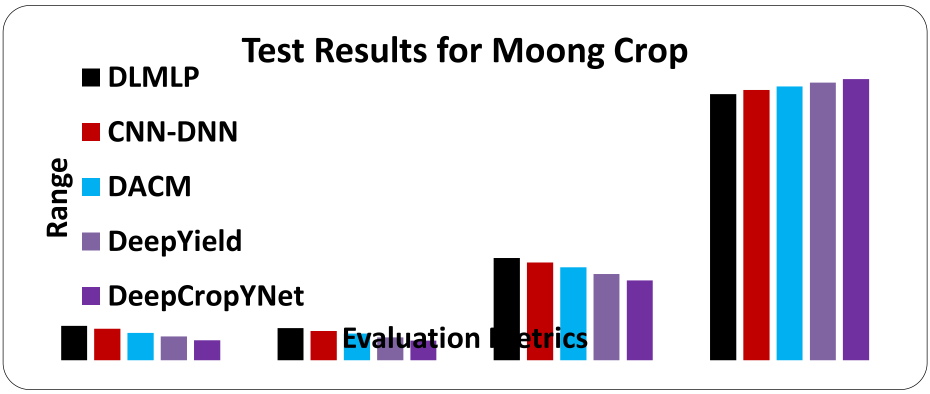

Figure 5(a) Performance Analysis of Different Yield Prediction Models for Moong Crop

Figure 5(a) shows the test results for the DeepCropYNet compared to other models for predicting future moong crop yield. The MAE of DeepCropYNet is significantly lower than the DLMLP, CNN-DNN, DACM, and DeepYield models, with reductions of 42.05%, 36.65%, 27.49%, and 16.16% respectively. The MSE is also reduced by 39.27%, 33.63%, 26.56%, and 14.89% compared to the same models. The RMSE is lower by 22.08%, 18.56%, 14.31%, and 7.76% respectively. Additionally, the correlation coefficient is increased by 5.7%, 4.12%, 2.77%, and 1.25% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models.

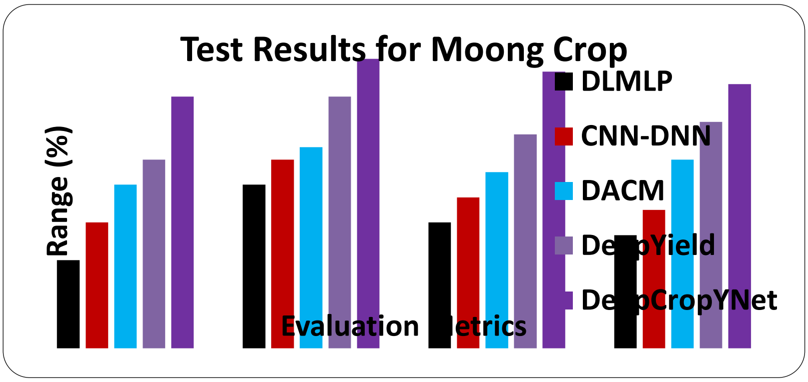

Figure 5(b) Prediction Efficiency of Different Yield Prediction Models for Moong Crop

Figure 5(b) demonstrates that the DeepCropYNet increases precision by 18.1%, 13.3%, 9%, and 6.3% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the recall is 12.8%, 10%, 8.6%, and 3.5% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The f-measure is also 16%, 13%, 10.1%, and 6.1% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Furthermore, the accuracy is 16.2%, 13.2%, 7.5%, and 3.6% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

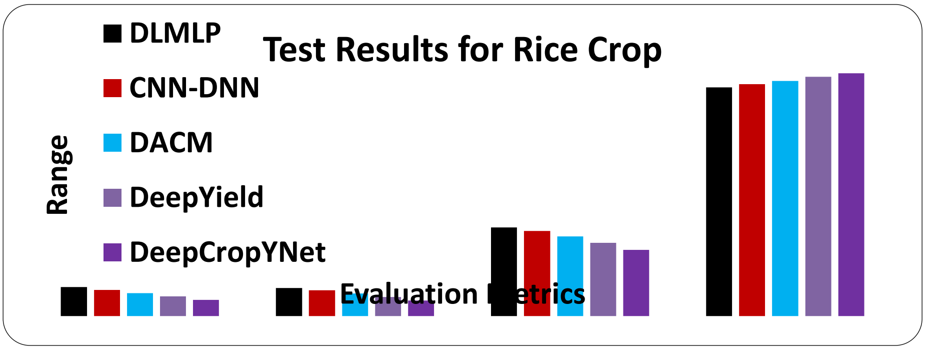

Figure 6(a) Performance Analysis of Different Yield Prediction Models for Rice Crop

Figure 6(a) illustrates the test results for the DeepCropYNet in comparison to other models for predicting future rice crop yield. The MAE of DeepCropYNet is 43.97%, 38.13%, 29.5%, and 17.6% lower than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the MSE of DeepCropYNet is reduced by 44.19%, 39.34%, 31%, and 18.34% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The RMSE is also lower than the DLMLP, CNN-DNN, DACM, and DeepYield models by 25.31%, 22.14%, 16.94%, and 9.65% respectively. Furthermore, the correlation coefficient is increased by 6.08%, 4.71%, 3.18%, and 1.43% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

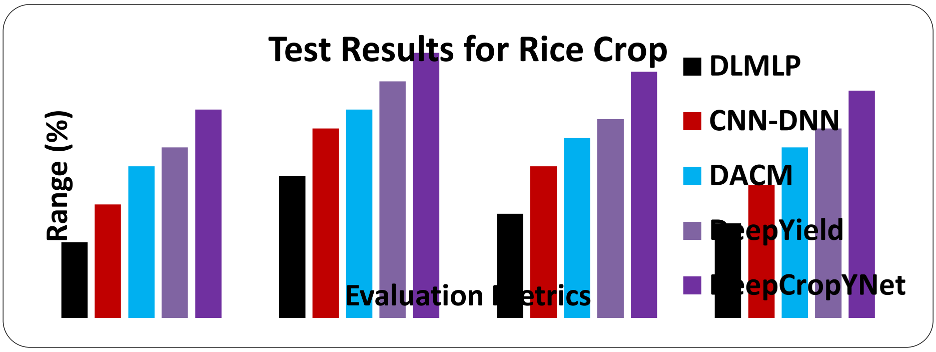

Figure 6(b) Prediction Efficiency of Different Yield Prediction Models for Rice Crop

Figure 6(b) demonstrates that the DeepCropYNet increases precision by 20.6%, 13.9%, 7.9%, and 5.1% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the recall is 17.3%, 10%, 7.3%, and 3.5% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The f-measure is also 21.1%, 13.2%, 8.9%, and 6.2% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Furthermore, the accuracy is 20%, 13.5%, 7.7%, and 5% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

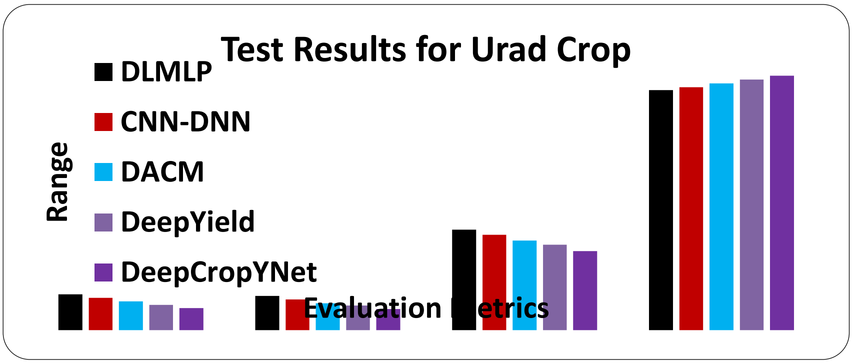

Figure 7(a) Performance Analysis of Different Yield Prediction Models for Urad Crop

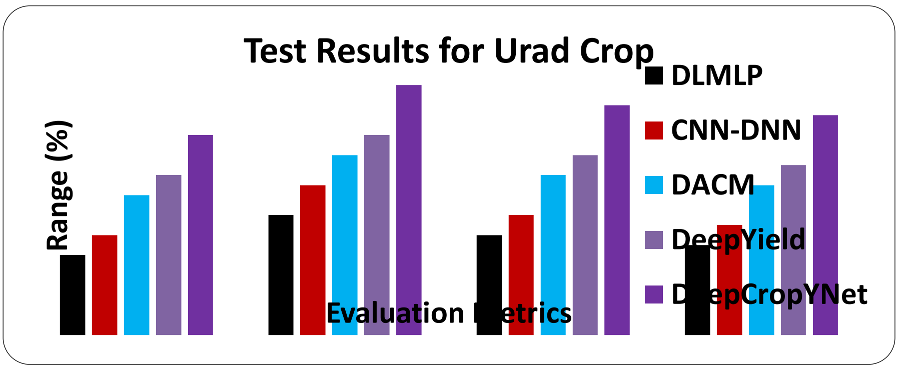

Figure 7(b) Prediction Efficiency of Different Yield Prediction Models for Urad Crop

Figure 7(a) demonstrates the test results for the DeepCropYNet in comparison to other models for predicting future Urad crop yield. The MAE of DeepCropYNet is 38.56%, 32.27%, 23.77%, and 13.33% lower than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the MSE of DeepCropYNet is reduced by 38.45%, 31.5%, 22.17%, and 14.99% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The RMSE is also lower than the DLMLP, CNN-DNN, DACM, and DeepYield models by 21.54%, 17.22%, 11.76%, and 7.79% respectively. The correlation coefficient is increased by 6.08%, 4.71%, 3.15%, and 1.49% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

Figure 7(b) demonstrates that the DeepCropYNet increases precision by 17.6%, 14.3%, 8.1%, and 5.3% compared to the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Additionally, the recall is 18.1%, 13.3%, 9%, and 6.3% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. The f-measure is also 18.6%, 15.3%, 9.2%, and 6.4% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively. Furthermore, the accuracy is 18.8%, 15.5%, 9.3%, and 6.5% higher than the DLMLP, CNN-DNN, DACM, and DeepYield models, respectively.

According to these analyses, it is evident that the DeepCropYNet model outperforms other models in accurately predicting future crop yields. This is due to its ability to capture both spatial and temporal dependencies among environmental data and crop yield at different periods. Therefore, this model can be beneficial for farmers in predicting yield productivity earlier based on weather and soil conditions.

5. Conclusion

This paper presents the DeepCropYNet model for predicting future crop yields from the historical data on weather, soil, and crop yields by combining the LSTM and TCN architectures. First, the collected yield and environmental data are normalized and given to the LSTM to extract representative features. The TCN is trained to capture temporal dependencies among different factors, and extract representative features at multiple scales. The resultant feature vector is then passed to the FC layer to accurately predict future crop yields. The experimental results confirm that DeepCropYNet outperforms existing models, making it an effective tool for precision agriculture and informed decision-making in crop yield prediction. The test results show that for groundnut, maize, moong, rice, and Urad crops, DeepCropYNet achieved MAE values of 0.0513, 0.0586, 0.0612, 0.0576, and 0.0741, MSE values of 0.0469, 0.0719, 0.06, 0.0552, and 0.0709, RMSE values of 0.2166, 0.2681, 0.2449, 0.2349, and 0.2663, and correlation coefficients of 0.8617, 0.8459, 0.8644, 0.86, and 0.8587, respectively. For groundnut, maize, moong, rice, and Urad crops, DeepCropYNet achieved precision values of 88%, 92%, 85%, 82%, and 80%, recall values of 89%, 89%, 88%, 88%, and 85%, f-measure values of 88.5%, 90.5%, 87%, 86%, and 83%, and accuracy of 88%, 90%, 86%, 84%, and 82%, respectively.

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