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Research Article

Multi-Modal Deep Learning for Crop Yield Prediction Network: Static and Temporal Feature Space

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ABSTRACT

In agriculture, crop yield prediction is the process of making yield estimates using data from crops, soil, and weather. Although ML models have been utilized before, they frequently depend on features that were manually created. So, a DL model like a 1D Convolutional Neural Network (1DCNN) can be employed. However, it struggles to learn temporal relations amongtime-series data. Therefore, a Deep learning-based Crop Yield prediction Network (DeepCropYNet) was designed using Long Short-Term Memory (LSTM) and Temporal Convolutional Network (TCN). However, this model struggles to learn significant features from complex datasets that involve multimodal inputs like time-series and image data.Thus, this paper proposes a Deep learning-based Multi-Modal CropYNet (DeepMMCropYNet) for crop yield prediction, which utilizes both time-series and image data related to crop yields. First, the dataset is pre-processed using a normalization technique to remove missing values and outliers. Then, the DeepMMCropYNet is trained using the pre-processed data to predict crop yields. This model comprises two branches: (i) LSTM-TCN for time-series data and (ii) multi-dimensional CNN for soil image data. This multi-dimensional CNN model comprises static and temporal feature extraction modules. The static module learns the static features from the soil images using 18 parallel 1DCNNs. The temporal module employs 16 parallel 2-dimensional CNNs (2DCNNs) to extract temporal features from soil images. The outputs of these modules are fused by the lateral connections. Moreover, each branch applies an attention strategy to assign the feature weights and find significant features. The features of each branch are then merged and given to a Fully Connected (FC) layer followed by an output layer to get a final prediction result of different crop yields.By comparing the DeepMMCropYNet model to previous models, the experimental findings demonstrate that it outperforms them in terms of Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient (R2). when it comes to predicting various crop yields.

Keywords: Crop yield prediction, 1DCNN, DeepCropYNet, Static and temporal features, Lateral connection, Attention strategy.

1 INTRODUCTION

Agriculture is a major social issue as it is the primary source of food. Many countries still suffer from food deficiencies due to high population growth rates [1]. The increasing population, global warming, and soil erosion require solutions to encourage smart farming and appropriate harvesting practices [2]. To realize this, accurate crop yield prediction is crucial, which addresses emerging difficulties in nutrient security, specifically in an era of global warming. Precise crop yield predictions not only support cultivators make cost-effective decisions but also assist famine avoidance efforts. A major problem in plant pathology is basic crop yield prediction, which is to realize how crop phenotype is determined by different factors such as genotype, locality, soil feature, irrigation quality, and climatic conditions [3]. In the ancient days, cultivators mostly relied on their expertise and historical data to forecast crop yields and make informed harvesting decisions. However, the emergence of new techniques such as crop modeling and Artificial Intelligence (AI) has allowed more precise crop yield prediction in recent years [4-5].

Linear models, ML models, and crop models are the three main types of modern approaches to predicting agricultural yields. Linear models are understandable by measuring the additive weight of all factors. In contrast, their prediction accuracy was low because they could not learn innately nonlinear relationships among each factor. Crop models are a kind of nonlinear model developed to predict crop yield [6]. These models offer explicit correlations between yield factors and weather conditions in multiple phases of the crop growth cycle. However, gathering yield data and adjusting model parameters can be time-consuming and labor-intensive. Low forecast accuracy was also seen. Multiple linear regression, decision trees, random forests, and artificial neural networks are some of the ML methods that have been used to forecast agricultural yields [7]. However, the prediction accuracy of these algorithms was low for large datasets. These algorithms require different and independent algorithms for feature extraction and prediction tasks, leading to high computation time. Also, the missing values in the dataset can impact the training of these algorithms and lead to unreliable predictions.

The use of DL models for crop yield prediction in recent years has helped alleviate these issues [8]. Scientists have compared the predictions made by ML algorithms with those made by Deep Neural Network (DNN) and Convolutional Neural Network (CNN) models when predicting various crop yields based on soil, weather, and yield data [9].DL models can unify feature learning and prediction tasks in a single framework. In this context, 1DCNNs was applied to gather more intricate relationships among yield and other aspects, thus enhancing the discriminability of various features [10]. However, this model was not well-suited for handling time-series crop yield data because it has inability to capture significant temporal correlations between various factors over period. This is mostly significant in understanding long-term environmental (i.e., weather) patterns to predict crop yields.To combat these challenges, a novel DeepCropYNet model was developed [11] using a customized dataset comprising historical information on weather, soil, and crop yields. This model hierarchically combined the LSTM and TCN. The first step was to normalize the time series of past yield and atmospheric data. Next, the data were fed into the LSTM network to learn temporal dependencies. Also, the TCN was 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 were forwarded to the FC layer to predict crop yields after specific periods.The problem is that this model has a hard time learning useful features from complicated data sources with multimodal inputs, like image and time series data.

As a result, this study proposes the DeepMMCropYNet model for crop yield prediction, that uses both time series and image data relevant to crop yields. First, the dataset is normalized to remove missing values and outliers. These data are used to train the DeepMMCropYNet, which predicts crop yield. This model has two branches: (i) LSTM-TCN for time-series data and (ii) multidimensional CNN for soil image data. This multidimensional CNN model includes static and temporal feature extraction modules. The static module applies 18 parallel 1DCNNs to learn static features from soil pictures, while the temporal module uses 16 concurrent 2DCNNs to extract temporal data from soil images. The lateral connection fuses the outputs of these modules. Furthermore, each branch uses an attention strategy to assign feature weights and obtain important features for accurate prediction. Moreover, the features from each branch are merged and passed to the FC layer with an output layer to predict the final crop yield.The following is a breakdown of the sections: Related works are covered in Section 2. Section 3 explains the DeepMMCYNet model, while Section 4 demonstrates how well it predicts crop yields. The complete study is summarized in Section 5.

2. LITERATURE SURVEY

This section discusses recent studies related to crop yield prediction using various ML and DL algorithms. A hybrid technique [12] based on the AquaCrop simulation model and regression algorithms was developed to predict tea crop yield from data related to weather, crop, and soil factors. However, the MAE and RMSE were high since these algorithms cannot capture the spatial and temporal relations among various factors. In [13], an ensemble ML algorithm was developed by the stacking regression and cascading regression using the wild blueberry dataset, comprising weather factors to predict wild blueberry yield. However, RMSE and MAE were very high. Also, it does not handle large datasets, comprising additional factors like soil and yield data. Extra Tree and AdaBoost algorithms [14] were employed to predict oil palm yield using the multisource data, consisting of soil moisture, weather, and oil palm fresh fruit bunch yield data. Conversely, R^2 was less since these algorithms cannot capture complex relations between weather, soil, and yield data.

In [15], a large dataset including meteorological, soil, and crop phenology variables was utilized to forecast winter wheat yields in several German nations using the CNN model. This model has a 1D convolution to extract the temporal dependencies of weather factors. However, the R^2 value was low. In [16], hybrid DL models, such as CNN-XGBoost, CNN-DNN, CNN-LSTM, and CNN-Recurrent Neural Network (RNN) were developed to forecast soybean yield based on weather and soil factors. However, the R^2 was low since these models may face challenges in seizing long-term dependencies from the noisy information.

In [17], a Functional Artificial Neural Network (FLANN) model was developed using a time-series agricultural crop yield dataset to predict rice, maize, and finger millet yield in Karnataka, India. This model can learn an empirical nonlinear correlation between crop yield and weather factors for crop yield prediction. Nonetheless, RMSE was high, and correlation coefficient was low. In [18], theImproved Optimizer Function with LSTM (IOF-LSTM) model was presented using the agricultural crop yield dataset to predict red gram, sugarcane,

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cereals, pulses, paddy, groundnut, and chilli crop yield in Andhra Pradesh, India. However, MAE and RMSE remained high.

2.1 Research Gap

In this literature, it can be observed that many studies emerged with various DL models for crop yield prediction using different factors. However, there are significant gaps that have yet to be addressed. Most of the existing studies rely on time-series data related to soil, weather, and crop yield. They fail to integrate image data with time series data, which could enrich the feature learning process and improve prediction performance. Despite the ability of hybrid DL models like CNN-BiLSTM, MFA-BiLSTM, IOF-LSTM, etc., to learn temporal relationships among environmental aspects and crop yield, their integration of multimodal informationlike images and time-series data remains limited. Also, their incapacity to acquire significant features leads to poor prediction performance. To address these gaps, this study develops the DeepMMCropYNet model by combining multimodal information for crop yield prediction.

3. PROPOSED METHODOLOGY

This section describes the overall framework of the proposed DeepMMCYNet approach. A pictorial representation of this study is illustrated in Fig. 1. Initially, an agricultural crop yield dataset is acquired, which comprises soil images and time-series sequential data related to yield, weather, and soil for various crops. Next, the dataset undergoes pre-processing to handle missing values and filter out any anomalies. These data are given to the DeepMMCYNet model for yield prediction. The predicted values are used to evaluate the DeepMMCYNet efficiency.

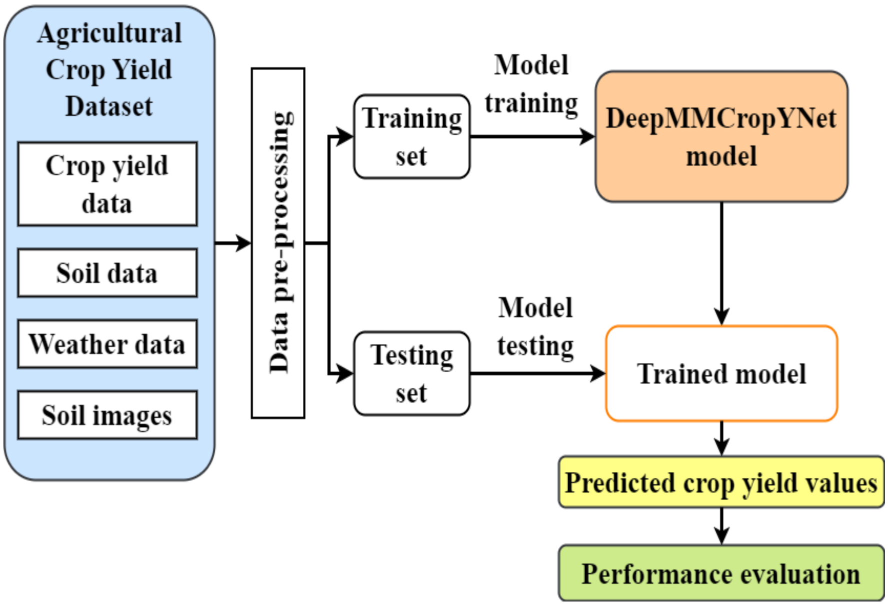

Figure 1.Diagrammatic Representation of this Study

3.1 Pre-processing

Data preprocessing plays a vital role in crop yield prediction, ensuring the DeepMMCYNet technique is trained effectively. It involves a normalization technique based on min-max scaling to convert the data to a specific range between 0 and 1 to handle missing values and ensure uniformityacross each feature (e.g., crop yield, soil, and weather data). It is defined in Eq. (1).

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

In Eq. (1), x_t^i is the i^{th} feature at time t, x_{max}^i and x_{min}^i are the maximum and minimum ranges of the corresponding feature. Based on this procedure, the pre-processed time-series crop yield dataset is obtained. Then, both soil image dataset and time-series crop yield dataset aredivided into training and testing sets. The training set is used to develop the prediction model based on the supervised learning mechanism. After the model is developed, the testing set is used to evaluate the model efficiency in predicting crop yields.

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3.2 Design of DeepMMCropYNet Model for Crop Yield Prediction

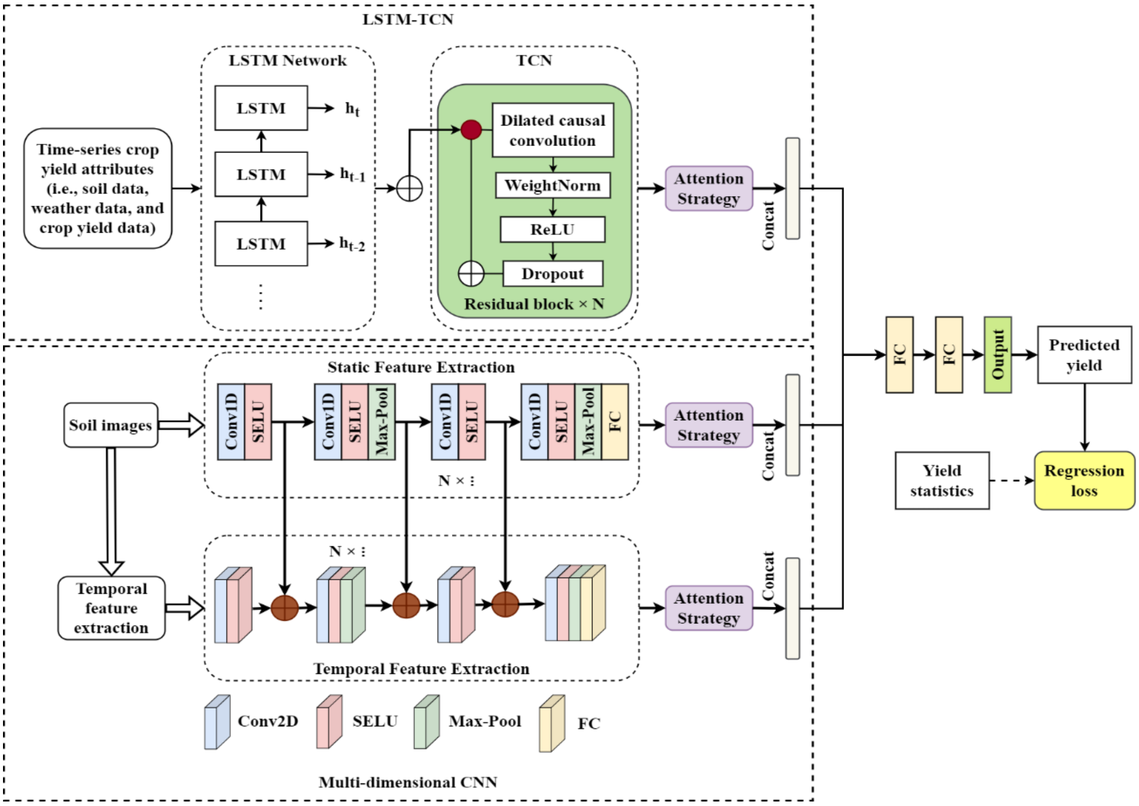

Figure 2. Structure of DeepMMCropYNet model

This DeepMMCropYNet model is designed by encompassing two branches: LSTM-TCN for the time-series crop yield dataset and multi-dimensional CNN for the soil image dataset. Also, an attention strategy is adopted to assign the feature weights and learn the significant features. These features are given to the FC with the output layer to obtain the final prediction results of crop yields. An entire structure of the DeepMMCropYNet is illustrated in Fig. 2.

3.2.1 LSTM-TCN for Time-Series Dataset

The LSTM-TCN aims to learn long-term temporal dependencies among time-series crop yield data. Considering crop yield, soil, and weather, their time series data of length N, represented by $x_{t-N}, \ldots, x_t$ is used as the input for the LSTM-TCN [11]. Here, x_t represents the observed values of yield, soil, and weather data during the specified period t. First, LSTMs are employed to capture temporal features, which are passed to the TCN for further processing. The TCN uses dilated causal convolutions on several residual blocks to learntemporal dependencies among crop yield, soil, and weather data at different time scales. This hierarchical approach enables the LSTM-TCN to efficiently learn both short-term and long-term dependencies, making it robust for handling complex temporal relationships in crop yield data.

3.2.2 Multi-Dimensional CNN for Soil Image Dataset

The multi-dimensional CNN involves two modules to extract static and temporal featuresfrom the soil image data related to crop yield.

- Staticfeature extraction module: In the field of time-series soil image analysis, 1DCNNs are effective in extracting temporal features. For N soil image inputs, N parallel 1DCNNsare proposed, each with 4 1D convolutional layers and 3 max-pooling layers. These Nparallel 1DCNNs process N soil images to capture their respective features of each soil image. The 1DCNNs use a 1D convolution kernelfor static feature extraction, as defined in Eq. (2).

$$v_{ij}^{x} = selu\left(b_{ij} + \sum_m \sum_{p=0}^{P_i-1} \omega_{ijm}^{p} v_{(i-1)m}^{(x+p)}\right) \quad (2)$$

In Eq. (2), P_i is the dimension of 1D convolution filter applied over the time axis, p is the total time steps, ω_{ijm}^{p} is thep^{th} kernel value linked to the m^{th} feature map in the previous layer and the unit value at the x^{th} time step

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on the j^{th}feature map in layer i (referred to as v_{ij}^{x}), b_{ij} is the feature map bias, and $selu(\cdot)$ is the Scaled Exponential Linear Unit (SELU) activation function.

- Temporal feature extraction module: In this module, N parallel 2DCNNs are utilized to extract temporal features from Nsoil image features over period, which consist of 2D convolution, SELU, max-pooling, and FC layers, as illustrated in Fig. 2.Suppose there is a pixel with coordinates(x, y)in a soil image at time$t$, and its feature value is denoted as$f(x, y)$. After a time interval Δt, the feature value at the new coordinate is represented as follows:

$$f(x + \Delta x, y + \Delta y) = f(x, y) \tag{3}$$

This indicates a temporal change in the feature distribution from (x, y) to $(x + \Delta x, y + \Delta y)$, forming a temporal feature vector $(\Delta x, \Delta y, \Delta t)$. Projecting this temporal feature vector onto the xy-plane yields the 2D vector $(\Delta x, \Delta y)$. By combining these temporal feature vectors across different positions in the soil image, a temporal feature field is represented as:

$$\vec{A}(M) = \vec{A}(x, y) = \big(P(x, y), Q(x, y)\big) \tag{4}$$

The temporal evolution of features at each position in the soil image between two time frames is represented using these vectors. Each vector is split into X-axis and Y-axis components. As multiple frames of soil images are analyzed, temporal features are extracted, which captures the temporal variations in the soil image feature distribution over period.

- Lateral connections: These connections are utilized to concatenate the outputs of two modules in each stage. These connections are added afterwards SELU1, Pool1, and SELU2. The modules differ in data dimensions but share the same channel count, so the lateral connections concatenate the features of these modules. The feature dimensions are (H, C) for the static features and $\{\alpha W, 2, C\}$ for the temporalfeatures. The $\{\alpha W, 2, C\}$ dimensions are reshaped and transposed to $\{2\alpha W, C\}$. Next, the result of the adjacentnetworks is combined to the temporal features by fusion.

3.2.3 Attention Strategy

In this study, the attention strategy is adopted in each branch to allocate larger weights to the crop yield, weather and soil data features with a high contribution to prediction. Overall spatial data is compressed into a feature descriptor, while global mean pooling generates feature-wise statistics. Each feature creates a statistic $z \in \mathbb{R}^c$, by reducing $U$where the c^{th} element of z is calculated as:

$$z_c = F_{sq}(u_c) = \frac{1}{N}\sum_{i=1}^{N} u_c(i) \tag{5}$$

In Eq. (5), $F_{sq}(\cdot)$ is the Squeeze operation and u_c is the c^{th}element. To generate weights for all features, a nonlinear correlation is learned. To ensure both complexity and generalizability, the model utilizes two fully connected layers and two sigmoid functions to measure the importance of each feature, expressed as:

$$S = F_{ex}(Z, W) = \sigma\big(g(Z, W)\big) = \sigma\big(W_2\delta(W_1 Z)\big) \tag{6}$$

In Eq. (6), $F_{ex}(\cdot)$ is the excitation operation, $\sigma(x)$ and $\delta(x)$ are the Sigmoid and Rectified Linear Unit (ReLU) activation functions. W_1 and W_2 represent the parameters of dimensionality-reducing and dimensionality-increasing layers, respectively. The input feature is weighted accordingly to produce the final output as:

$$\tilde{x}_c = F_{scale}(u_c, s_c) = s_c \cdot u_c \tag{7}$$

In Eq. (7), $\tilde{X} = [\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_c]$ and $F_{scale}(u_c, s_c)$ is the feature-wise multiplication amid the scalar s_c and feature map $u_c \in \mathbb{R}^c$.

3.2.4 Fully Connected Layer

Moreover, the results from two different branches are concatenated and flattened into a 1D vector. The FC layer receives this unified vector before the output layer makes the final estimation. The output layer uses Nneurons to forecast crop yield. Thus, the DeepMMCropYNet model is trained and utilized to predict different kinds of crop yield. The predicted yield values are later compared with the observed yield values to determine the regression loss such as MAE, MSE, and RMSE values.

Algorithm 1: Crop Yield Prediction Using DeepMMCropYNet Model

Input: Time-series crop yield dataset (Weather, Soil, and Yield data) and soil image dataset

Output: Predicted crop yields

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1. **Begin**
2. Normalize time-series data using Eq. (1);
3. Input the pre-processed data to the LSTM network for capturing long-term dependencies;
4. Feed the output of LSTM into the TCN to extract multi-scale temporal features;
5. Feed the soil image data to the multi-dimensional CNN;

Apply 18 parallel 1DCNN layers to capture static spatial features;
Use 16 parallel 2DCNN layers to capture temporal variations in soil images;
Fuse static & temporal features using lateral connections;
Apply global average pooling and use FC layers to learn feature importance;
Multiply attention weights with extracted features;

6. Merge features from LSTM-TCN and multi-dimensional CNN;
7. Pass concatenated features through FC layers;
8. Use the output layer with linear activation to predict crop yield;
9. Train the DeepMMCropYNet model using Adam optimizer;
10. Evaluate model performance by comparingthe predicted yield with actual yield;
11. Use the trained model for future predictions;
12. **End**

4. EXPERIMENTAL RESULTS

This section evaluates the efficiency of the DeepMMCropYNet model with existing models, such as 1DCNN [10], DeepCropYNet [11]

4.1 Simulation Environment

The crop yield prediction models were implemented in MATLAB 2019b. The experiments were carried out using a setup with an Intel® Core™ i5-4210 CPU (3GHz), 4GB RAM, and a 1TB HDD running Windows 10 (64-bit).Table 1 outlines the parameter settings for training various models.

4.2 Dataset Description

This study mainly focuses on predicting yield values of five major crops in Tamil Nadu, including groundnut, maize, moong, rice, and urad.The datasets for these crop yields werecreated by using multiple sources. A publicly available website, such as https://data.gov.in/was utilized to create a custom agricultural crop yield dataset. This dataset includes weather, yield, and soil data for the considered crops from 2016 to 2022. Also, a Kaggle dataset [22] was used, which containscrop names, years, harvesting periods, states, farming regions, manufacturingcapacities, annual rainfall, manure use, pesticide use, and considered yields.Besides, this study includes a soil image dataset. To create this dataset, the https://data.gov.in/website was used to identify soil types in specific regions by accessing geospatial and agricultural datasets. Then, corresponding soil images were collected from Kaggle datasets to support the crop yield prediction.

Thus, the collected soil image and time-series dataset for each crop contains 1012samples. By considering this, 80% of the datawere utilized for training and 20% were utilized for testing.

4.3 Evaluation Metrics

MAE: It is the mean absolute dissimilarity between estimated and observed values.

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

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

MSE: It measures the mean squared dissimilarity between estimated and observed values using Eq. (9).

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

RMSE: It is the square root of the MSE, provided that a mean magnitude of losses in Eq. (10).

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

Correlation coefficient (R²): It is used to assess the degree of association between predicted crop yields and actual crop yields.

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

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

Accuracy: It is calculated Eq. (12) by

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100 \tag{12}$$

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)) which is represented in Eq. (13).

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{13}$$

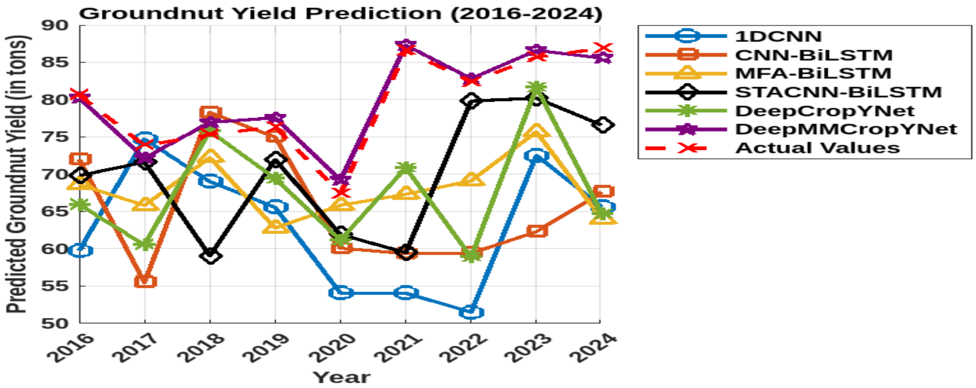
Recall: It is the percentage of exactly estimated positive instances (TP) to the sum of actual positive instances (TP + False Negatives (FN)).

$$Recall = \frac{TP}{TP+FN} \times 100 \tag{14}$$

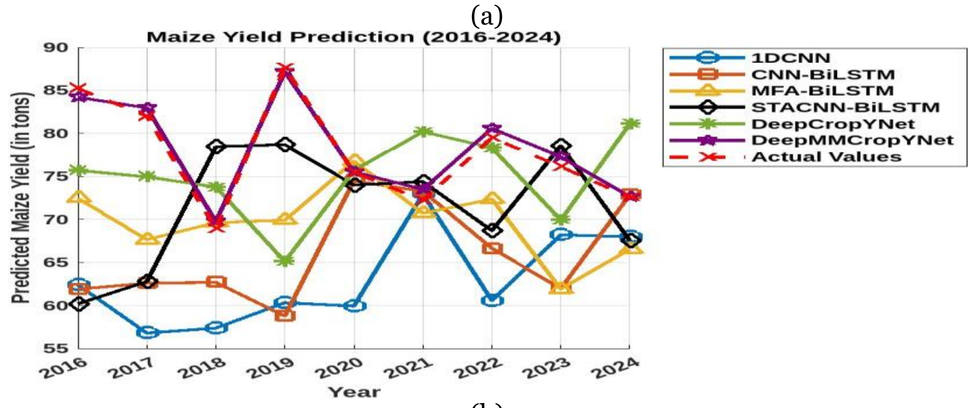
F-measure: It is determined by

$$F - measure = \frac{2\times Precision\times Recall}{Precision+Recall} \times 100 \tag{15}$$

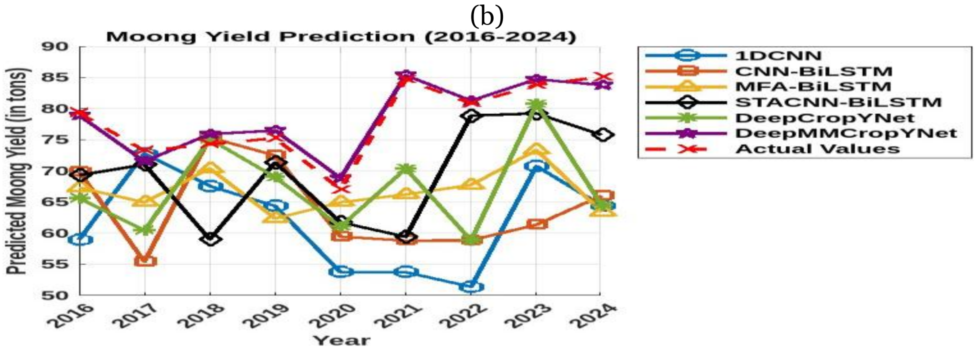
Figure 3 shows the time series comparisons of the DeepMMCropYNet model with existing models for crop yield prediction. The analysis reveals that the model closely aligns with the actual crop yield data, indicating its superior efficiency in predicting various crop yields.



(a)



(b)



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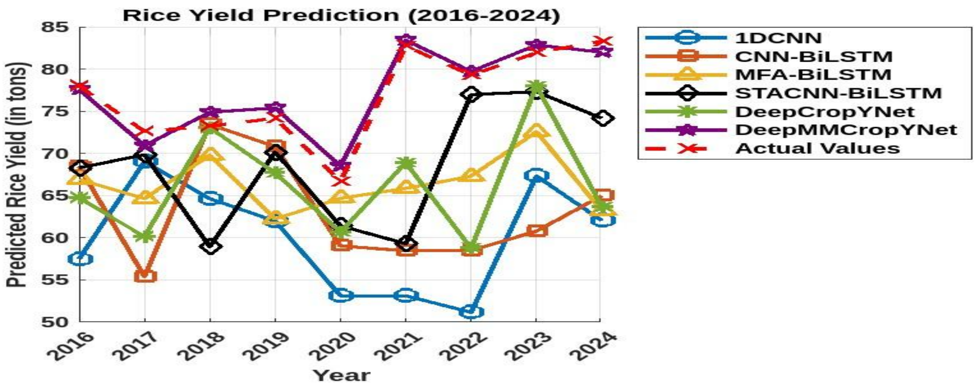

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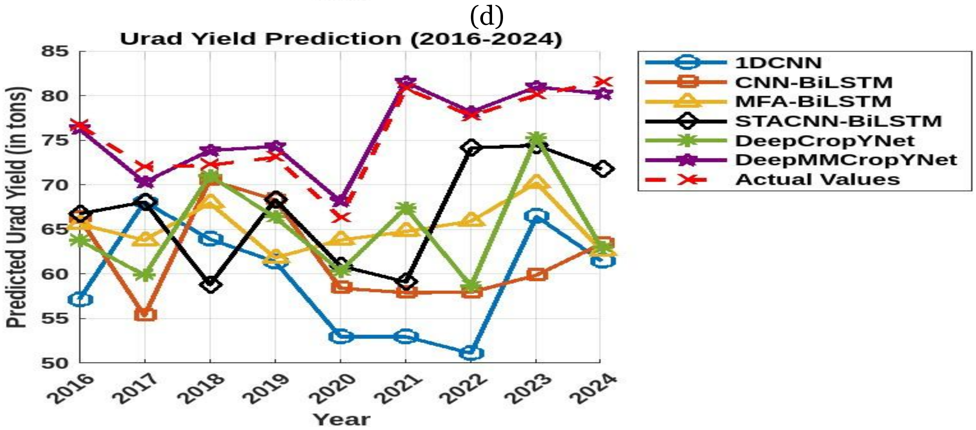

(e)

Figure. 3 Comparison of proposed and existing modelsfor crop yield prediction (in tons) from 2016 to 2024. (a)groundnut, (b) maize, (c) moong, (d) rice, and (e) urad

Table 1. Comparison of Different Models for Different Crop Yield Prediction

Crops	Models	1DCNN	DeepCropYNet	DeepMMCropYNet
Groundnut	MAE	0.081	0.0513	0.049
	MSE	0.0728	0.0469	0.043
	RMSE	0.2705	0.2166	0.2024
	R	0.8329	0.8617	0.8835
	Precision (%)	79.6	88	91
	Recall (%)	80	89	91.2
	F-measure (%)	79.8	88.5	91.1
	Accuracy (%)	80.1	88	91.4
Maize	MAE	0.0904	0.0586	0.0525
	MSE	0.1	0.0719	0.0683
	RMSE	0.3151	0.2681	0.2576
	R	0.8155	0.8459	0.8532
	Precision(%)	77.1	92	93.7
	Recall(%)	79.5	89	91
	F-measure(%)	78.3	90.5	92.35
	Accuracy(%)	79.5	90	91.6
Moong	MAE	0.0921	0.0612	0.0577
	MSE	0.0865	0.06	0.049

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	RMSE	0.2911	0.2449	0.2381
	R	0.8364	0.8644	0.8712
	Precision(%)	75.5	85	87
	Recall(%)	80	88	88.4
	F-measure(%)	77.75	87	87.7
	Accuracy(%)	77	86	88.5
Rice	MAE	0.0894	0.0576	0.054
	MSE	0.089	0.0552	0.051
	RMSE	0.2956	0.2349	0.2296
	R	0.8281	0.86	0.868
	Precision(%)	74.4	82	85.7
	Recall(%)	81	88	89
	F-measure(%)	77.7	86	87.35
	Accuracy(%)	77	84	86.2
Urad	MAE	0.1006	0.0741	0.07
	MSE	0.0998	0.0709	0.065
	RMSE	0.3172	0.2663	0.255
	R	0.8273	0.8587	0.862
	Precision(%)	73	80	82.3
	Recall(%)	76.5	85	87
	F-measure(%)	74.75	83	84.65
	Accuracy(%)	74	82	85

4.4 Performance Analysis for Groundnut Yield Prediction

This section presents the effectiveness of DeepMMCropYNet technique for forecasting groundnut yield compared to the existing models. Fig. 4 presents a performance comparison of various models when predicting groundnut yield. Compared to the 1DCNN and DeepCropYNet models, the DeepMMCropYNet reduces the MAE by 39.51% and 4.48%, respectively. It reduces the MSE by 40.93% and 8.32% compared to the 1DCNN and DeepCropYNet, respectively. It minimizes the RMSE by 25.18% and 6.56% compared to the 1DCNN and DeepCropYNet, respectively. It increases the correlation coefficient value by 6.08% and 2.53% compared to the 1DCNN and DeepCropYNet models, respectively.

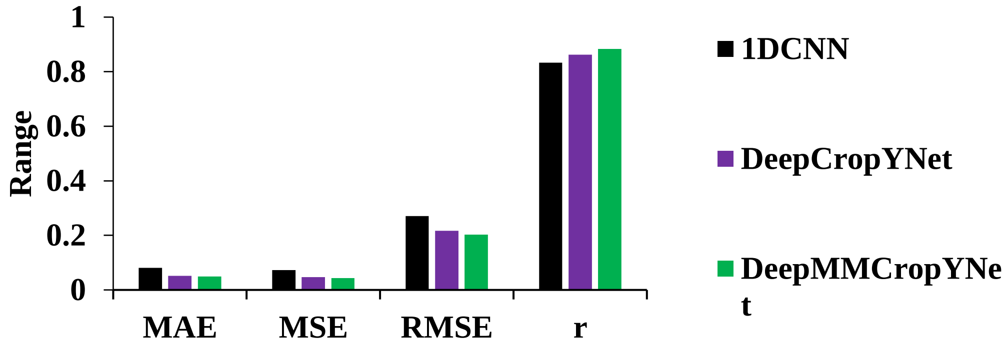

Figure. 4Performance analysis of yieldprediction models for groundnut yield prediction

Fig. 5 demonstrates that the DeepMMCropYNetincreases precision by 14.32% and 1.9% compared to the 1DCNN and DeepCropYNet models,respectively. The recall is 14%, and 1.33% higher than the 1DCNN and DeepCropYNet models, respectively. The f-measure is 14.16% and 1.62% higher than the 1DCNN and

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DeepCropYNet models, respectively. The accuracy is 14.11 and 3.86% higher than 1DCNN and DeepCropYNet models respectively.

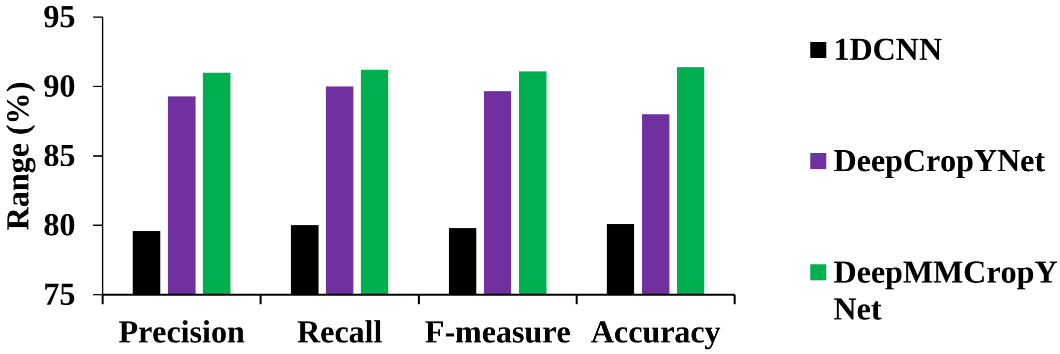

Figure. 5
Prediction efficiency of different yield prediction models for groundnut yield prediction

4.5 Performance Analysis for Maize Yield Prediction

This section presents the effectiveness of DeepMMCropYNet technique for forecasting maize yield compared to the existing models.

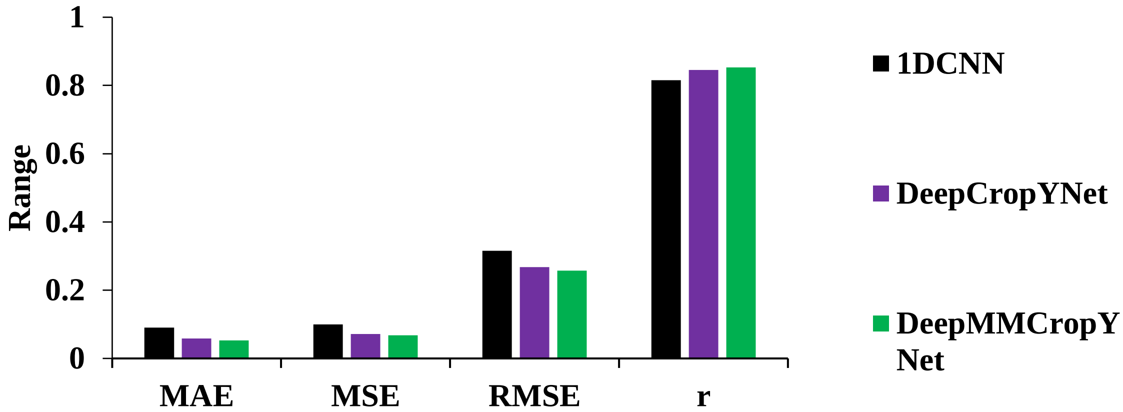

Figure. 6Performance analysis of different yield prediction models for maize yield prediction

Fig. 6 illustrates a performance comparison of various models for predicting maize yields. The MAE of DeepMMCropYNet is lowered by 41.92%, and 10.41% compared to the 1DCNN, and DeepCropYNet respectively. Similarly, the MSE is decreased by 31.7%, and 5.01%, respectively. The RMSE is lower than the 1DCNN and DeepCropYNet by 18.25%, 17.62%, 16.47%, 10.96%, and 3.92%, respectively. Compared to the 1DCNN, and DeepCropYNet, the correlation coefficient value increases by 4.62%, and 0.86%, respectively.

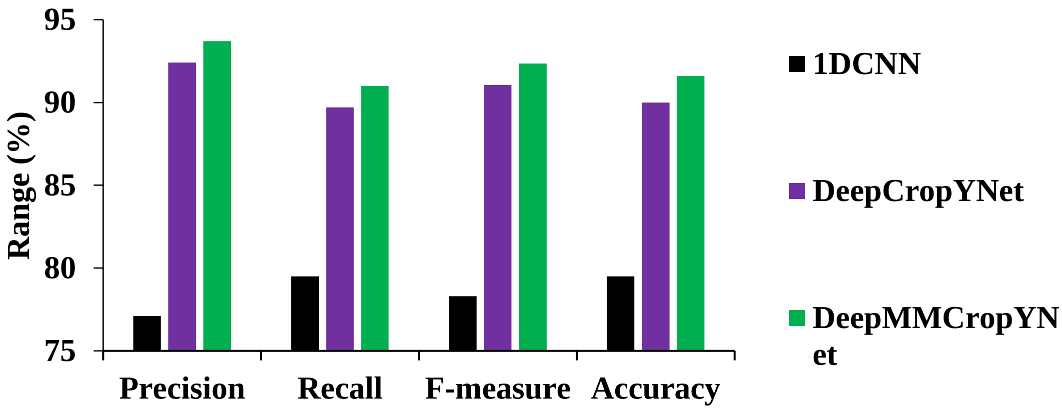

Figure. 7 Prediction efficiency of different yield prediction models for maize yield prediction

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Fig. 7 demonstrates that the DeepMMCropYNetincreases precision by 21.53%, and 1.41% compared to the 1DCNN, and DeepCropYNet models,respectively. The recall is 14.47%, and 1.45% greater than the 1DCNN and DeepCropYNet models,respectively. The f-measure is increased by 17.94%, and 1.43% compared to the 1DCNN, and DeepCropYNet models, respectively. The accuracy is increased by 15.22%, and 1.78% compared to the 1DCNN, and DeepCropYNet models,respectively.

4.6 Performance Analysis for Moong Yield Prediction

This section presents the effectiveness of DeepMMCropYNet technique for forecasting moong yield compared to the existing models.

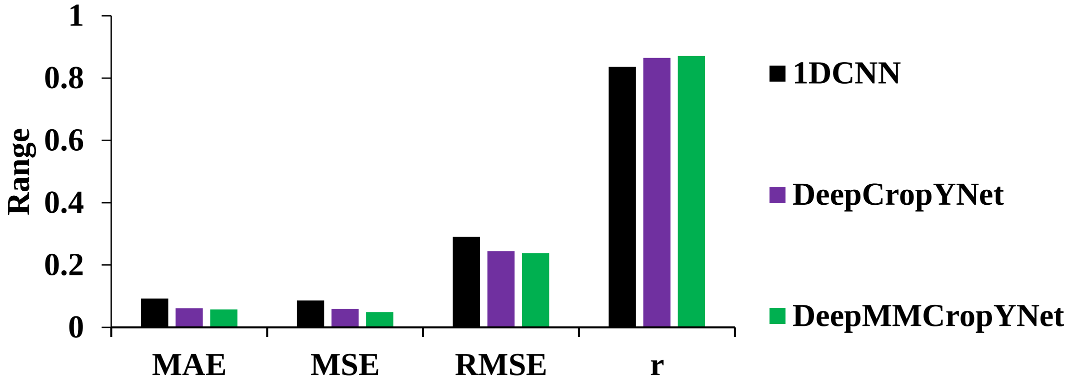

Figure. 8 Performance analysis of different yield prediction models for moong yield prediction

Fig. 8 shows a performance comparison of various models for predicting moong yields. Compared to the other models, the DeepMMCropYNet demonstrated superior prediction performance. The MAE is reduced by 37.35%, and 5.72% compared to the 1DCNN, and DeepCropYNet models, respectively. The MSE is 43.35%, and 18.33% lower than the same models. The RMSE is 18.21%, and 2.78% lower than the 1DCNN, and DeepCropYNet, respectively. The correlation coefficientvalue is 4.16%, and 0.79% higher than the 1DCNN, and DeepCropYNet, respectively.

Fig. 9 demonstrates that the DeepMMCropYNetincreases precision by 15.23%, and 2.35% compared to the 1DCNN, and DeepCropYNet models,respectively. The recall is 10.5%, and 1.61% greater than the 1DCNN, and DeepCropYNet models,respectively. The f-measure is increased by 12.8%, and 1.98% compared to the 1DCNN, and DeepCropYNet models, respectively. The accuracy is increased by 14.94%, and 2.91% compared to the 1DCNN, and DeepCropYNet models, respectively.

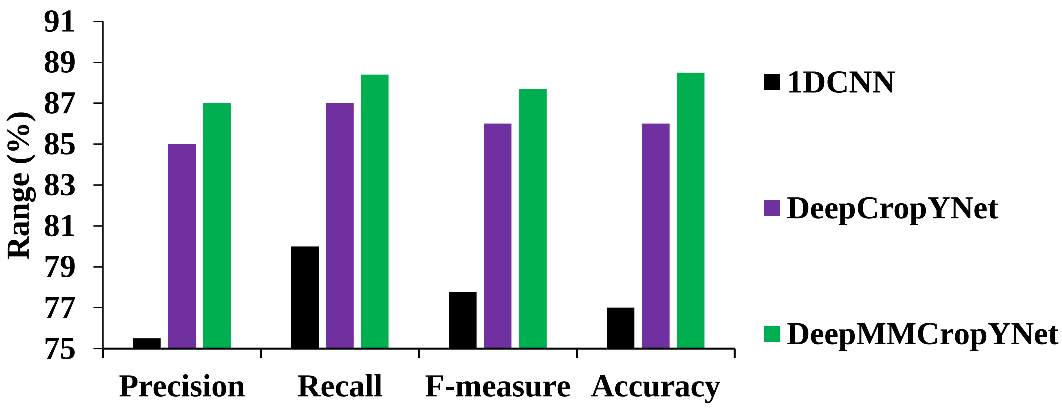

Figure. 9 Prediction efficiency of different yield prediction models for moong yield prediction

4.7 Performance Analysis for Rice Yield Prediction

This section presents the effectiveness of DeepMMCropYNet technique for forecasting rice yield compared to the existing models.

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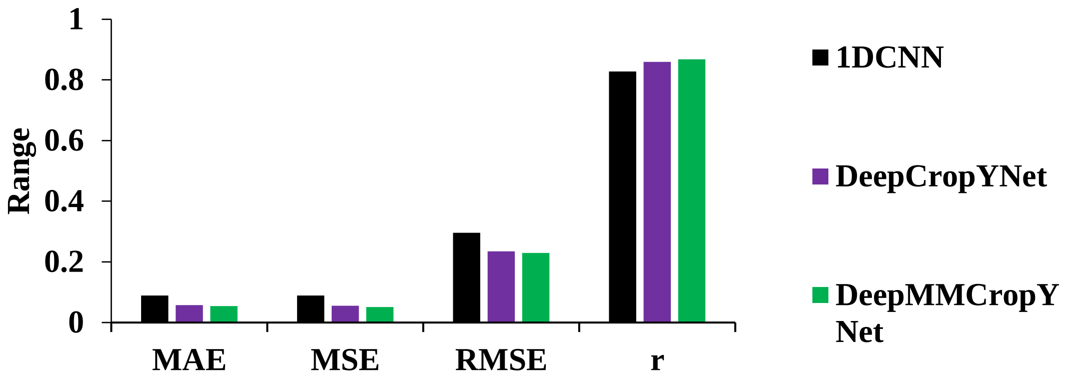

Figure. 10 Performance analysis of different yield prediction models for rice yield prediction

Fig. 10 illustrates a performance comparison of various models for predicting rice yields. It is noted that the DeepMMCropYNet achieved a higher performance compared to the others in rice yield prediction. The MAE of DeepMMCropYNet is 39.6%, and 6.25% lower than the 1DCNN, and DeepCropYNet, respectively. Similarly, the MSE is lowered by 42.7%, and 7.61%, respectively. The RMSE is lower than the 1DCNN and DeepCropYNet models by 22.33%, and 2.26%, respectively. The correlation coefficient value is increased by 4.82%, and 0.93% compared to the 1DCNN, and DeepCropYNet, respectively.

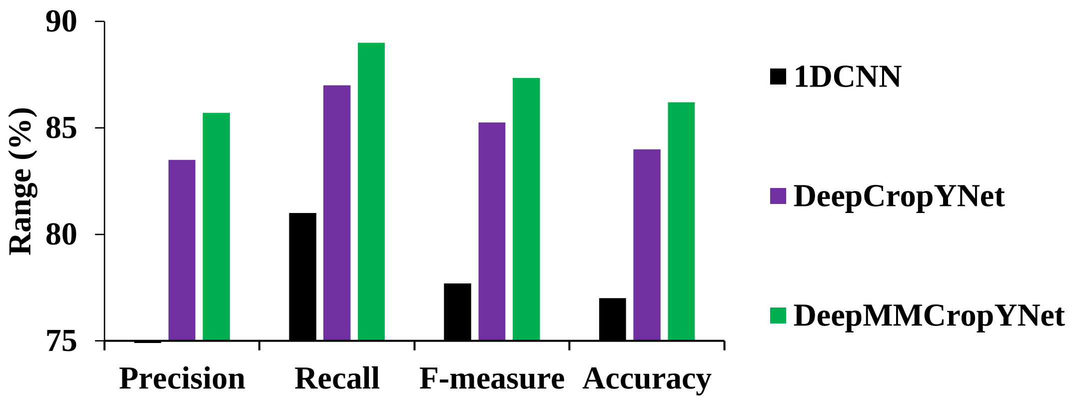

Figure. 11 Prediction efficiency of different yield prediction models for rice yield prediction

Fig. 11 demonstrates that the DeepMMCropYNetincreases precision by 15.19%, and 2.63% compared to the 1DCNN, and DeepCropYNet models,respectively. The recall is 9.88%, and 2.3% greater than the 1DCNN, and DeepCropYNet models,respectively. The f-measure is increased by 12.42%, and 2.46% compared to the 1DCNN, and DeepCropYNet models, respectively. The accuracy is increased by 11.95%, and 2.62% compared to the 1DCNN, and DeepCropYNet models,respectively.

4.8 Performance Analysis for Urad Yield Prediction

This section presents the effectiveness of DeepMMCropYNet technique for forecasting urad yield compared to the existing models.Fig. 12 demonstrates a performance comparison of various models for predicting urad yields. Compared to the 1DCNN, and DeepCropYNet, respectively, the DeepMMCropYNet reduced the MAE by 30.42%, and 5.53%. The DeepMMCropYNet reduces the MSE by 34.87and 8.32% in comparison to the 1DCNN, and DeepCropYNet, respectively. The RMSE is lower than the 1DCNN, and DeepCropYNet models by 19.61%, 17.74%, 15.51%, 11.7%, and 4.24%, respectively. Compared to the 1DCNN, and DeepCropYNet models, the correlation coefficient value increases by 4.19%, 3.84%, 3.54%, 1.88%, and 0.38%, correspondingly.

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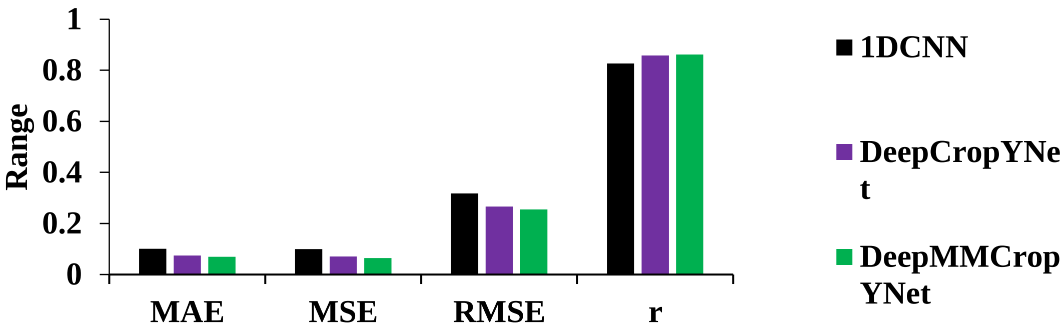

Figure. 12 Performance analysis of different yield prediction models for urad yield prediction

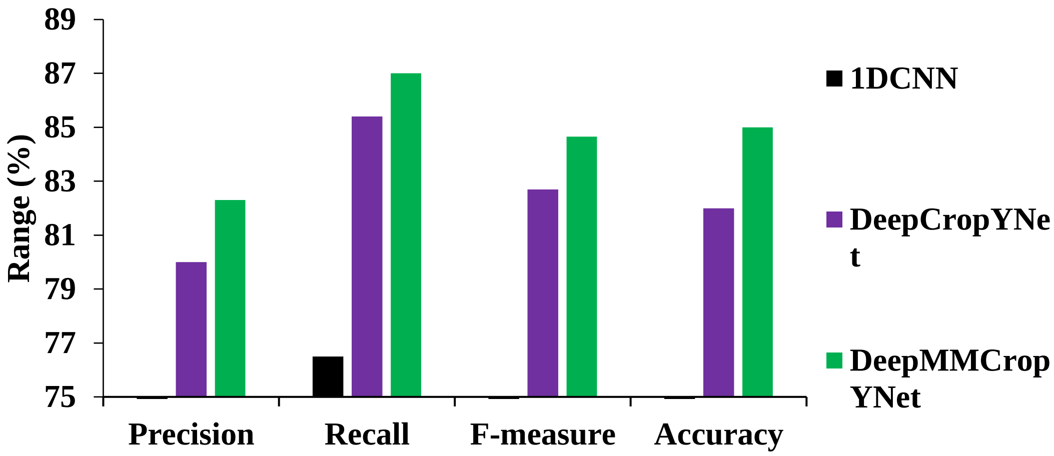

Figure. 13 Prediction efficiency of different yield prediction models for rice yield prediction

Fig. 13 demonstrates that the DeepMMCropYNetincreases precision by 12.74and 2.88% compared to the 1DCNN, and DeepCropYNet models,respectively. The recall is 13.73%, and 1.87% greater than the 1DCNN, and DeepCropYNet models,respectively. The f-measure is increased by 13.24%, and 2.36% compared to the 1DCNN, and DeepCropYNet models, respectively. The accuracy is increased by 14.86%, and 3.66% compared to the 1DCNN, and DeepCropYNet models,respectively.

These analyses clearly indicate that the DeepMMCropYNet model outperforms other models in accurately predicting different crop yields. This is due to its ability to capture fixed and adaptive 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 introduced the DeepMMCropYNet model for crop yield prediction using time series and image data. It involved two different networks such as LSTM-TCN for time-series and multi-dimensional CNN for soil images. The LSTM-TCN can extract long-term temporal features from the historical time-series crop yield data. The multi-dimensional CNN can extract static and temporal features from the soil images. In addition, an attention strategy was applied in each branch to allocate feature weights and learn significant features. Then, the FC with the output layer predicted the yields for different kinds of crops. Finally, experimental outcomes revealed that DeepMMCropYNet achieved a 0.049 MAE, 0.043 MSE, 0.2024 RMSE, and 0.8835 R^2 compared to the existing models in predicting groundnut yield. It attained 0.0525 MAE, 0.0683 MSE, 0.2576 RMSE, and 0.8532 correlation coefficient compared to the existing models in predicting maize yield. It achieved 0.0577 MAE, 0.049 MSE, 0.2381 RMSE, and 0.8712 correlation coefficient compared to the existing models in predicting moong yield. It achieved 0.054 MAE, 0.051 MSE, 0.2296 RMSE, and 0.868 correlation coefficient compared to the existing models in predicting rice yield. It attained 0.07 MAE, 0.065 MSE, 0.255 RMSE, and 0.862 correlation coefficient compared to the existing models in predicting urad yield.Forgroundnut, maize, moong, rice, and Urad crops,DeepMMCropYNet achieved precision values of 91%,93.7%, 87%, 85.7%, and 82.3%, recall values of 91.2%,91%, 88.4%, 89%, and 87%, f-measure values of91.1%, 92.35%, 87.7%, 87.35%, and 84.65%, and accuracy of91.4%, 91.6%, 88.5%, 86.2%, and 85%, respectively.

However, the performance of the model is limited by overlapping data from multiple crops in feature space, temporal, and spatial dimensions. These overlaps make it challenging to learn distinct patterns for each crop, leading to inaccurate predictions. Future research will explore the application of reinforcement learning to address data overlaps and uncertainties in crop yield prediction.

REFERENCES

[1] L. Xia, A. Robock, K. Scherrer, C.S. Harrison, B. L. Bodirsky, I. Weindl, ... andR. Heneghan, "Global Food Insecurity and Famine from Reduced Crop, Marine Fishery and Livestock Production due to Climate Disruption from Nuclear War Soot Injection", *Nature Food*, Vol. 3, No. 8, pp. 586-596, 2022.

[2] G. S. Malhi, M. Kaur, and P. Kaushik, "Impact of Climate Change on Agriculture and Its Mitigation Strategies: A Review", *Sustainability*, Vol. 13, No. 3, p. 1318, 2021.

[3] M. Ahmed, R. Hayat, M. Ahmad, M. Ul-Hassan, A. M. Kheir, F. Ul-Hassan, ... and S. Ahmad, "Impact of Climate Change on Dryland Agricultural Systems: A Review of Current Status, Potentials, and Further Work Need", *International Journal of Plant Production*, Vol. 16, No. 3, pp. 341-363, 2022.

[4] L. Zvobgo, P. Johnston, O. M. Olagbegi, N. P. Simpson, and C. H. Trisos, "Role of Indigenous and Local Knowledge in Seasonal Forecasts and Climate Adaptation: A Case Study of Smallholder Farmers in Chiredzi, Zimbabwe", *Environmental Science & Policy*, Vol. 145, pp. 13-28, 2023.

[5] M. H. Al-Adhaileh andT. H. Aldhyani, "Artificial Intelligence Framework for Modeling and Predicting Crop Yield to Enhance Food Security in Saudi Arabia", *PeerJ Computer Science*, Vol. 8, p. e1104, 2022.

[6] L. Luo, S. Sun, J. Xue, Z. Gao, J. Zhao, Y. Yin, ... and X. Luan, "Crop Yield Estimation Based on Assimilation of Crop Models and Remote Sensing Data: A Systematic Evaluation", *Agricultural Systems*, Vol. 210, p. 103711, 2023.

[7] T. A. Shaikh, T. Rasool, and F. R. Lone, "Towards Leveraging the Role of Machine Learning and Artificial Intelligence in Precision Agriculture and Smart Farming", *Computers and Electronics in Agriculture*, Vol. 198, p. 107119, 2022.

[8] T. Talaei Khoei, H. Ould Slimane, and N. Kaabouch, "Deep Learning: Systematic Review, Models, Challenges, and Research Directions", *Neural Computing and Applications*, Vol. 35, No. 31, pp. 23103-23124, 2023.

[9] M. Rashid, B. S. Bari, Y. Yusup, M. A. Kamaruddin, and N. Khan, "A Comprehensive Review of Crop Yield Prediction Using Machine Learning Approaches with Special Emphasis on Palm Oil Yield Prediction", *IEEE Access*, Vol. 9, pp. 63406-63439, 2021.

[10] D. Paudel, A. de Wit, H. Boogaard, D. Marcos, S. Osinga, and I. N. Athanasiadis, "Interpretability of Deep Learning Models for Crop Yield Forecasting", *Computers and Electronics in Agriculture*, Vol. 206, p. 107663, 2023.

[11] G. Pramela and R. Tamilselvi, "A Combined Long Short-Term Memory and Temporal Convolutional Network for Crop Yield Prediction", *Nanotechnology Perceptions*, Vol. 20, No. S12, pp. 319-335, 2024.

[12] D. Batool, M. Shahbaz, H. Shahzad Asif, K. Shaukat, T. M. Alam, I. A. Hameed, ... andS. Luo, "A Hybrid Approach to Tea Crop Yield Prediction Using Simulation Models and Machine Learning", *Plants*, Vol. 11, No. 15, p. 1925, 2022.

[13] H. R. Seireg, Y. M. Omar, F. E. Abd El-Samie, A. S. El-Fishawy, and A. Elmahalawy, "Ensemble Machine Learning Techniques Using Computer Simulation Data for Wild Blueberry Yield Prediction", *IEEE Access*, Vol. 10, pp. 64671-64687, 2022.

[14] N. Khan, M. A. Kamaruddin, U. Ullah Sheikh, M. H. Zawawi, Y. Yusup, M. P. Bakht, and N. Mohamed Noor, "Prediction of Oil Palm Yield Using Machine Learning in the Perspective of Fluctuating Weather and Soil Moisture Conditions: Evaluation of A Generic Workflow", *Plants*, Vol. 11, No. 13, pp. 1-19, 2022.

[15] A. K. Srivastava, N. Safaei, S. Khaki, G. Lopez, W. Zeng, F. Ewert, ... andJ. Rahimi, "Winter Wheat Yield Prediction Using Convolutional Neural Networks from Environmental and Phenological Data", *Scientific Reports*, Vol. 12, No. 1, p. 3215, 2022.

[16] A. Oikonomidis, C. Catal, and A. Kassahun, "Hybrid Deep Learning-Based Models for Crop Yield Prediction", *Applied Artificial Intelligence*, Vol. 36, No. 1, p. 2031822, 2022.

[17] P. R. Jena, B. Majhi, R. Kalli, and R. Majhi, "Prediction of Crop Yield Using Climate Variables in the South-Western Province of India: A Functional Artificial Neural Network Modeling (FLANN) Approach", *Environment, Development and Sustainability*, Vol. 25, No. 10, pp. 11033-11056, 2023.

[18] U. Bhimavarapu, G. Battineni, and N. Chintalapudi, "Improved Optimization Algorithm in LSTM to Predict Crop Yield", *Computers*, Vol. 12, No. 1, p. 10, 2023.

2025, 10(35s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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[19] P. Saini, B. Nagpal, P. Garg, and S. Kumar, "CNN-BI-LSTM-CYP: A Deep Learning Approach for Sugarcane Yield Prediction", *Sustainable Energy Technologies and Assessments*, Vol. 57, p. 103263, 2023.
[20] M. V. Krishna, K. Swaroopa, G. SwarnaLatha, and V. Yasaswani, "Crop Yield Prediction in India Based on Mayfly Optimization Empowered Attention-Bi-Directional Long Short-Term Memory (LSTM)", *Multimedia Tools and Applications*, Vol. 83, No. 10, pp. 29841-29858, 2024.
[21] K. S. Saravanan and V. Bhagavathiappan, "Prediction of Crop Yield in India Using Machine Learning and Hybrid Deep Learning Models", *Acta Geophysica*, pp. 1-20, 2024.
[22] https://www.kaggle.com/datasets/akshatgupta7/crop-yield-in-indian-states-dataset/data