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Deep Multi-Modal Reinforcement Learning-Based Multi-Modal Crop Yield Prediction Network

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ABSTRACT
In agriculture, one of the most challenging tasks is predicting crop yield based on different factors, including weather, soil, and crop parameters. To solve this issue, many Deep Learning (DL) models have been developed in the past decades. Among them, the DL-based Multi-Modal Crop Yield prediction Network (DeepMMCropYNet) model takes into account time-series weather, crop, and soil data along with the soil images of specific regions to predict crop yield. This model was built by integrating the Long Short-Term Memory (LSTM)-Temporal Convolutional Networks (TCN) and multi-dimensional Convolutional Neural Networks (CNNs), that support both spatial and temporal feature extraction. However, overlapping data from multiple crops, which can occur in feature space, temporal, and spatial dimensions, limits its performance. These overlaps make it difficult to learn unique patterns for each crop, resulting in inaccurate predictions. Therefore, this article develops the Deep Multi-Modal Reinforcement Learning-based CropYNet (DeepMMRLCropYNet) model by integrating the DeepMMCropYNet with the deep Q-learning (DQL) for crop yield estimation. Initially, the actual output values of the DeepMMCropYNet are mapped into the Q values. After that, the parametric features are integrated with the threshold by the Q-learning agent to forecast crop yield. The agent obtains a consolidated score for its activities by reducing error and enhancing its ability to predict with the best rewarding iterations. Moreover, the total incentives dictate the agents' capacity for learning. Extensive experiments reveal that the DeepMMRLCropYNet achieves a higher efficiency for predicting different crop yields compared to the existing models in terms of Cohen's Kappa, Mean Square Error (MSE), Mean Squared Logarithmic Error (MSLE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Correlation Coefficient (R).
Keywords: *Crop yield prediction, DeepMMCropYNet, Reinforcement learning, Deep Q-learning, Rewards*

1. INTRODUCTION

Food productivity must increase faster so that they can stay up with the growing population. The worldwide population is expected to reach 9.3 billion by 2050, requiring food productivity to increase by 70-100% to encountersupply and demand [1]. Rising temperatures and erratic rainfall pose a threat to crop productivity. Agriculture has become a very susceptible sector due to unstable climate patterns, prompting experts to anticipate yield to plan suitable policy responses [2]. On the contrary, crop yield prediction is challenging since it involves both farmer choices or actions as well as climate and weather elements. Crop yield changes regionally, exhibiting unexpected patterns. Crop simulation [3] and data-driven models [4] are commonly used tools for estimating the impact of different factors influencing crop production. Crop simulation models are highly effective at predicting yields because they incorporate empirical information relevant to each site, geographical measurement, and measurements at the plot level. However, they tend to be expensive, take a long time to create, and are only suitable for specific crops. Also, these on-siteoutcomes confront hurdles once applied to the plot since farmer conduct, cropping patterns, and land features vary [5]. Furthermore, adjusting models for crop simulations necessitates substantial amounts of data derived from multiple experiments. Instead, to overcome the above issues, data-driven methods are used to forecast crop yield. Previous research suggests that data-driven models are more adaptable to agricultural development than crop development methods because of their ease of installation and superior efficiency [6]. Data-driven techniques forecast crop yield sensitivity to climatic parameters determined by past data on the rate of change in yields. A simple way to classify these models is as either linear or nonlinear.

Linear methods highlight the use of parameters-based statistical techniques to evaluate the effects of climate change on agricultural crop yields [7].In practice, the statistical method predicts the worldwide, national, and local impacts by analyzing historical data. Because the correlation between weather and crop yields changes over time, the fact that these models only produce one estimated association parameter for the entire study period is undesirable. Furthermore, the estimations from statistical methods may be unfair, resulting in decreased predictive accuracy. Alternatively, nonlinear models, such as Machine Learning (ML) models, handle the complex connection between weather conditions and crop yields by mathematically expanding the objective function [8]. The popular ML technique is the Artificial Neural Network (ANN), that has a nonparametric structure [9].In contrast, the predictive accuracy of this method was poor for extensive datasets. This technique necessitates distinct and autonomous algorithms for feature extraction and prediction tasks, resulting in longer computation time. The absence of values in the dataset can adversely affect the training of these algorithms, resulting in unreliable predictions. DLtechniquesare utilized for crop yield estimation in recent years [10] to resolve the limitations in ML techniques. Several studies employed Deep Neural Network (DNN) and CNNmethods to estimate various agricultural yields based on characteristics such as soil, weather, and yield data. These models can integrate feature learning and prediction tasks into a singular framework. In this context, 1-Dimensional CNNs (1DCNN) were utilized to elucidate more intricate correlations between yield and other variables, hence augmenting the discriminability of diverse aspects [11]. However, this model proved unfit to manage time-series crop yield data due to its inability to capture substantial temporal correlations among numerous components over time. This is primarily important for comprehending long-term environmental (i.e., meteorological) patterns to forecast agricultural yields.

So, a novel DeepCropYNet model was created with a tailored dataset that includes historical data on weather, soil, and crop yields [12]. This model hierarchically integrated the LSTM and TCN. The initial stage involved normalizing the time series of historical yield and atmospheric data. Subsequently, the data were input into the LSTM network to acquire temporal dependencies. The TCN was designed to implement a hierarchy of temporal convolutions on the input data, thereby capturing information at several time scales. The feature vectors generated by the TCN were transmitted to the FC layer to forecast crop yields after designated intervals. This model has difficulties in extracting appropriate characteristics from intricate data sources that include multimodal inputs like time series and image data.

To solve this problem, the DeepMMCropYNet model has been developed for predicting crop yields, utilizing both time series and image data for crop yields [13]. This model involved two components: (i) LSTM-TCN for time-series data and (ii) multidimensional CNN for soil image data. This multidimensional CNN model has static and temporal feature extraction modules. The static module uses 18 simultaneous 1DCNNs to learn static features from soil images, whereas the temporal module utilizes 16 concurrent 2D-CNNs to extract temporal information from soil images. The lateral connection fuses the outputs of these modules. Additionally, each branch employs an attention mechanism to allocate feature weights and identify significant information for precise prediction. The extracted features from each branch are fused and passed to the Fully Connected (FC) layer with a softmax to estimate the final crop yield.

However, its ability was failed when dealing with overlapped data of multiple crops.Overlap can occur in various cases, including feature space, temporal, and spatial dimensions. Feature space overlap happens when input features for different crops share similar values. Temporal overlap arises when time-series data for multiple crops have overlapping periods with similar patterns. Spatial overlap occurs when crops in neighboring regions share environmental and agricultural conditions. These overlaps make it challenging for the model to learn distinct patterns for each crop, resulting in inaccurate predictions.

1.1 Main Contributions

This article proposes the DeepMMRLCropYNet model by integrating the DeepMMCropYNet with the Q-learning technique for crop yield estimation. This research integrates reinforcement learning and DL to create an effective crop yield estimation method that maps raw data to estimate values.This model applies DQL to construct a crop yield estimation setting, taking into account the input features. A linear layer initially converts the DeepMMCropYNet's real output values into Q values. The Q-learning agent then uses the threshold in conjunction with parametric features to forecast the yield. By maximizing accurate predictions and reducing error with the best rewarding iterations, the agent earns a unified score for the activities accomplished. More importantly, the sum of all incentives dictates how well the agents learn. As a result, the agents and the model experience inconsistent input as they adjust their efficiency. Consequently, this method of learning compels the agent to become more effective by revealing the profound differences in crop yields.

The following segments are organized as: Section 2 discusses similar works. Section 3 describesthe DeepMMRLCropYNet for crop yield prediction, and Section 4 demonstrates its performance. Section 5 concludes the study.

2. LITERATURE SURVEY

Sivanantham et al. [14] developed a new Quantile Regressive Empirical correlative Functioned Deep Feed-Forward Multilayer Perceptron Classification (QRECF-DFFMPC) model for crop yield estimation. The input layer used apractical orthogonal function for identifying pertinent attributes. Then, quantile regression was employed in the hidden layer to generate the regression value for each data point. Moreover, these values were sent to the output layer to forecast crop yield. However, this model cannot fit time-series data since it fails to extract temporal correlations among the yield data.Abbaszadeh et al. [15] presented a model based on the Bayesian Model Averaging (BMA) and a collection of copula functions for combining the results of several DNNs (3D-CNN, ConvLSTM, etc.) for soybean crop yield prediction. However, it cannot handle overlapping data in multiple crops.

Qiao et al. [16] suggested a Knowledge-guided Spatial-Temporal Attention Graph Network (KSTAGE) for crop yield prediction. First, they used a 3D-CNN to incorporate the first spectral characteristics. Then, a Knowledge-guided Temporal Multi-head Attention Algorithm (KTMA) was utilizedto create temporal attention weights using self-attention strategy. Also, a new strategy was applied to align self-attention scores by prior distribution. Furthermore, a location-aware spatial attention graph network using geospatial knowledge was introduced to combine the spatial neighborhood attributesto predict final yield. However, it fails to consider uncertainty when interpreting ambiguous inputs.

Abdel-salam et al. [17] developed a new model by unifying a fusion feature selection method and an improved SVR for predicting crop yields. They first applied data normalization and then used K-means clustering with the correlation-based filter to create a dimension-condensed dataset. Then, a fusion FMIG-RFE method was adopted for selecting attributes. Moreover, an Improved Crayfish Optimization Algorithm (ICOA) was used to fine-tune the hyperparameters of the SVR method for predicting crop yields. However, R^2 was low due to a lack of crop yield data.

Saravanan et al. [18] presented a hybrid DL model based on the Spatio-Temporal Attention-based CNN (STACNN)and BiLSTM to extract features from the crop yield dataset and predict the crop yield in Indian states. However, MAE and RMSE remained high.Krishna et al. [19] developed theMayFly Algorithm empowered attention-BiLSTM (MFA-BiLSTM) model using agricultural crop yield dataset to predict rice, sugarcane, wheat, and maize yields. However, RMSE was high.Punitha&Geetha [20] developed a Gorilla Troops Optimization with DL-based Crop Recommendation and Yield Prediction Model (GTODL-CRYPM). Initially, the LSTM network was used to recommend suitable crops, whereas to choose the best LSTM parameters, the GTO is used. Next, in order to make an accurate prediction of crop yield, the Deep Belief Network (DBN) was performed. Conversely, MAE and RMSE were high.

2.1 Research Gap

From the literature, it can be inferred that earlier models fail to address uncertainties and lack robustness in handling large-scale datasets with ambiguous or noisy inputs. To resolve this issue, this study develops a new DL model incorporated on top of the deep reinforcement learning algorithm for crop yield estimation with a minimum prediction error while effectively managing data overlaps and uncertainties.

3. PROPOSED METHODOLOGY

This section provides an explanation of the DeepMMRLCropYNet model for crop production prediction. Fig. 1 provides a visual representation of this study. First, a dataset of agricultural crop yield is obtained, which includes soil photos and time-series sequential data about soil, weather, and yield for different crops. The dataset is then pre-processed to eliminate outliers and missing values. The dataset is fed into the DeepMMRLCropYNet model to forecast yield. The model's performance is assessed using the estimated values.

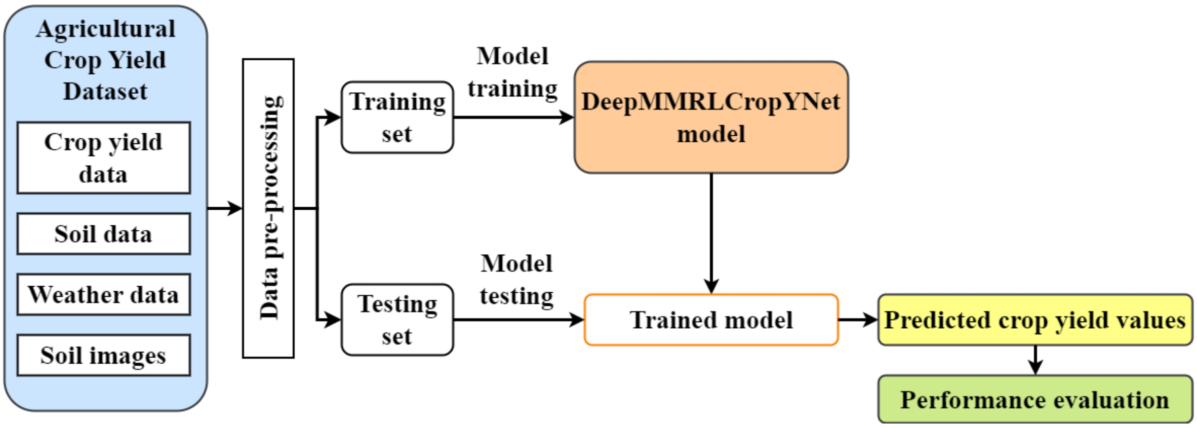


Figure 1. Pipeline of the Proposed Study

3.1 Data Pre-processing

To effectively train the DeepMMCropYNet model for crop yield prediction, data preparation is an essential step. To deal with missing values and guarantee consistency across all features (such as crop yield, soil, and weather data), a normalization method based on min-max scaling is used to transform the data into a particular range between 0 and 1. It is represented as follows:

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

In Eq. (1), x_t^i is the i^{th} feature at time t, x_{max}^i and x_{min}^i are the maximum and minimum values of the corresponding feature.The pre-processed time-series crop yield dataset has been generated from this approach. Subsequently, both the soil image dataset and the time-series crop yield dataset are divided into training and testing subsets. The training dataset is utilized to construct the predictive model with the Q-learning technique. Following model development, the capability of the model to forecast crop yields is assessed with testing set.

3.2 Design of DeepMMRLCropYNet Model

This study uses supervised learning to solve a regression problem that represents crop yield forecasts. In order to determine the crop yield in the specific region, this supervised learning-based approach for forecasting crop yields requires appropriate crop yield data and related variables as inputs.The total rewards in Q-learning algorithm determine the learning efficacy of the agents. Together with the supervised learning techniques, it results in unstable feedback that allows the agents to modify their performance. The agents won't be able to determine which samples weren't learned efficiently because they can't access that information from the inputs.By demonstrating the significant variations in crop yield, this component compels the agent to be more effective.

Based on the input data, a yield prediction environment is formed that changes the supervised learning into a DQLprocedure. A yield forecasting game can be used to find out the environment.A set of samples is included in each game, along with specific parameter-based feature groupings and thresholds related to the crop yield. The agent performs the behaviors to obtain the rewards when it first begins playing, hence determining the crop yield values. For each adjacent anticipated value of the target, the agent is rewarded positively if it succeeds, and negatively if it fails. The agent's overall performance will be evaluated once the entire process is finished.Figure 2 displays a flow diagram of the yield prediction process based on this DeepMMRLCropYNet model using DQL algorithm.

It is challenging to differentiate and assess the crop output prediction since real reinforcement learning methods, such Q-learning, have a restricted ability to describe the states. A DeepMMCropYNet is employed for predicting agricultural productionusing crop yield, weather, and soil data, taking inspiration from the Deep Q Network (DQN) principle of analyzing vast amounts of data.

The DeepMMCropYNet model is used to frame the DQN agent in this study. To convert the DeepMMCropYNet model's output to Q-values, a linear layer is included to the model's parameters once they have been configured utilizing the weights saved in the pre-training method. The structure of the DeepMMCropYNet model is presented in [13].All training samples endure a pre-training process before the DQL training process begins. Then, the input layers of DeepMMCropYNet build final Q-values are produced by the FC layer, which is responsible for the agent's yield estimation vision.

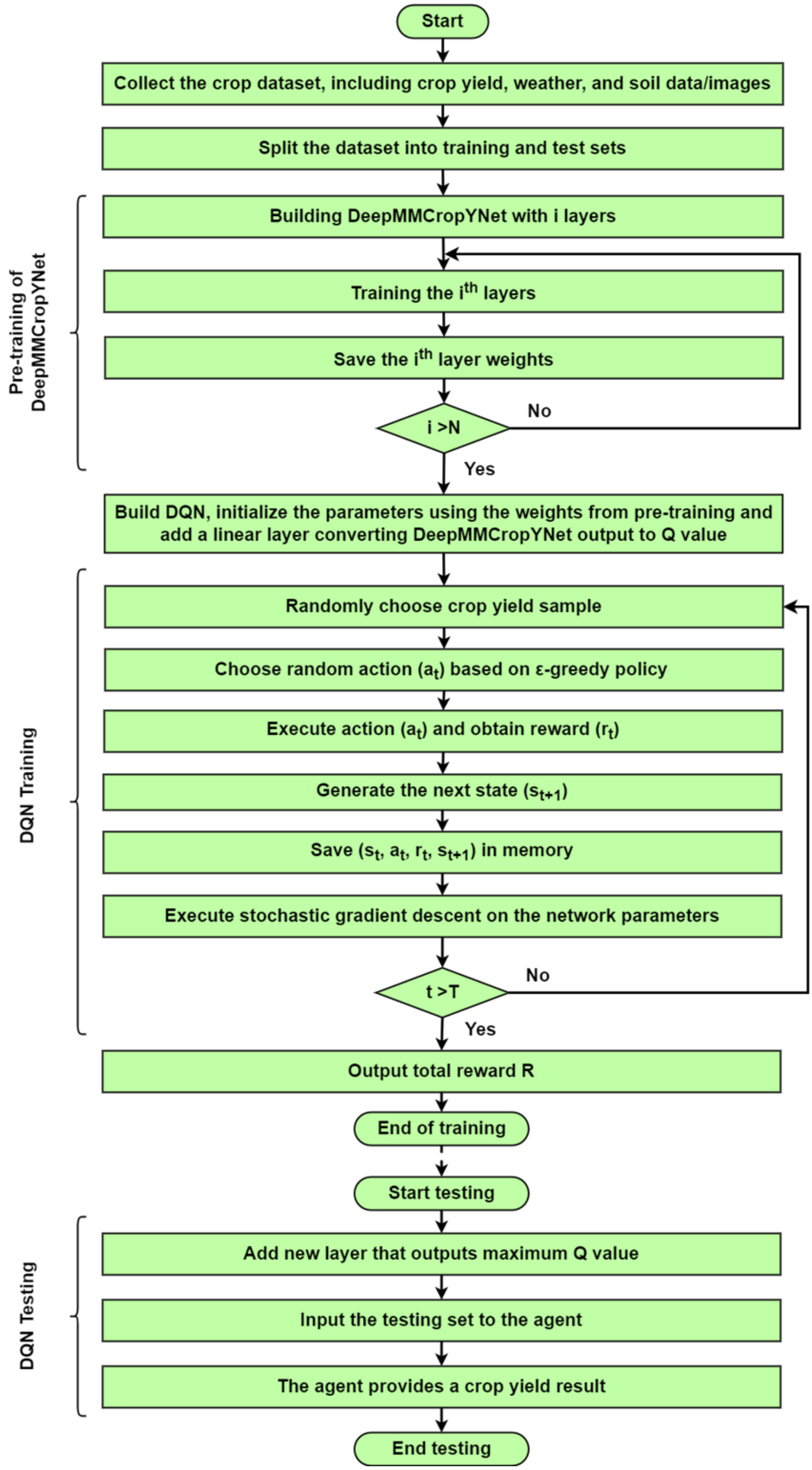


Figure 2. Flow Diagram of Crop Yield Estimation Using DeepMMRLCropYNet Model

The DQLtechnique processes a vast amount of state and action space during its training, that could potentially disrupt stability as a result of correlations in the data. To guarantee that the DQL algorithm's training process does not diverge, two modifications are performed to the Q-Learning in the DQN's training procedure. The first is experience replay, where the agent's experience is stored in replay memory (D) using the current and following timestamps' states, actions, and rewards.

Assume that the experience replay first records the agent's experience at every time step t, producing a group of distinct experience sets. An individual experience e_t at a time t is defined as $e_t = (s_t, a_t, r_t, s_{t+1})$ and the memory at t is described as $D_t = \{e_1, \dots, e_t\}$.

To help agents learn from their own mistakes, experience replay is a great tool for eliminating parameter divergence. Two, throughout the Q-learning update process, a different network is used to generate the targets.These changes can significantly increase the stability of DQL. Also, It should be mentioned that Q-learning technique usually use a Bellman equation to iteratively update the action-value function. The DeepMMCropYNet function approximator with weight θcalculating the action-value function using this method is cumbersome in practice, thus it is utilized instead. Consequently, the DQN is constructed by modifying the parameters θ_i in the i^{th} iteration in order to decrease the MSE in the Bellman equation.

There are two phase in the training process. Pre-training of the DeepMMCropYNet is the initial phase, and training the DQN agent is the second. The agent uses an ε-greedy policy to choose and carry out an action. With a probability of ε, the action is selected at random in this example, while the action representing the largest q value is selected with a probability of $1 - \varepsilon$.This study uses the stochastic gradient descent as its optimization technique, which iteratively adjusts the network weightsby the training information.Algorithm 1 presents the entire pseudocode for training theDeepMMRLCropYNet model.

Algorithm 1: Training DeepMMCropYNet model based DQN

1. **Begin**
2. Pre-training of the DeepMMCropYNet
    a. Set the replay memory capacity as N;
    b. Set the DeepMMCropYNet with θ_i;
    c. $\mathbf{for}(i = 1, I)$
    d. Train the i^{th} layer in the DeepMMCropYNet;
    e. Save the parameters of the i^{th} layer;
    f. **end for**
    g. Put the hidden layer parameters into action-value network Q as an initialization parameter, excluding the input and output layers;
    h. Set the parameters of the target action-value function Q' to match those of Q.
3. DQN agent training
    a. $\mathbf{for}(\text{event} = 1, M)$
    b. Randomly output the projected yield to create s_1;
    c. $\mathbf{for}(t = 1, T)$
    d. Choose a random action a_t with probability ε;
    e. Executea_t and get the reward r_t;
    f. Randomly produce the subsequent state s_{t+1};
    g. Protect$D$ as (s_t, a_t, r_t, s_{t+1});
    h. Execute gradient descent on $\left(r_t - Q(s_t, a_t; \theta)\right)^2$according to θ;
    i. Reset $Q' = Q$;
    j. **end for**
    k. **end for**
4. **End**

4. EXPERIMENTAL RESULTS

This section evaluates the efficiency of the DeepMMRLCropYNet model with existing models, such as 1DCNN [11], DeepCropYNet [12], DeepMMCropYNet [13], and KSTAGE [16], GTODL-CRYPM [20].

4.1 Simulation Environment

The crop yield prediction models were implemented in MATLAB 2019b. The experiments were conducted on a system with an Intel® Core™ i5-4210 CPU @ 3GHz, 4GB RAM, and a 1TB HDD running on Windows 10 64-bit. The parameter settings for training different models are given in Table 1.

Table 1. Parameter Settings

Parameters	Range

1DCNN [11], DeepCropYNet [12], DeepMMCropYNet [13], KSTAGE [16], GTODL-CRYPM [20], and Proposed DeepMMRLCropYNet	
Learning rate	0.001
Batch size	64
No. of epochs	100
Optimizer	Stochastic gradient descent
Dropout	0.5

4.2 Dataset Description

This study primarily focuses on estimating yield values for five primary crops in Tamil Nadu: groundnut, maize, moong, rice, and Urad. These agricultural yield datasets were created utilizing numerous sources. A publicly available website [21] was used to generate a custom agricultural crop yield dataset. This dataset comprises weather, yield, and soil data for the crops studied from 2016 to 2022. In addition, a Kaggle dataset [22] was used, which contains crop names, years, harvesting periods, states, farming regions, production amounts, yearly rainfall, fertilizer and pesticide use, and intended yields. Additionally, this study provides a soil image dataset. To build this dataset, the https://data.gov.in/ website was utilized to determine soil types in specific regions using geographical and agricultural datasets. The crop yield forecast was then supported by comparable soil photos obtained from Kaggle datasets.

Consequently, 1012 samples are included in the time-series dataset and soil picture collected for every crop. Taking this into account, the dataset is split into 80:20 for training and testing.

4.3 Evaluation Metrics

Cohen's Kappa: A statistical metric that assesses inter-rated consent for categorized results, while accounting for chance agreement.

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

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

In Eq. (3), 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. (4).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4)$$

MSLE:A metric that quantifies the squared logarithmic disparity between anticipated and actual results, imposing greater penalties on underestimations compared to overestimations.

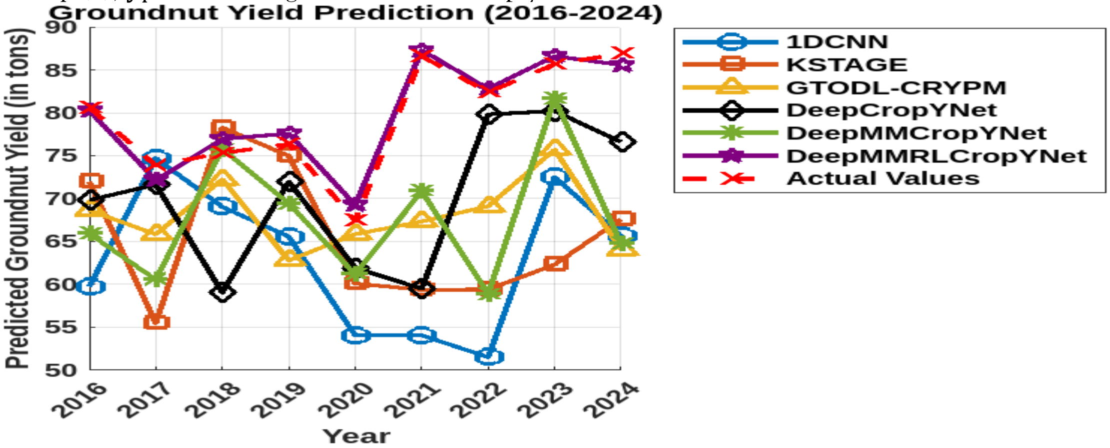
RMSE: It is the square root of the MSE, provided that a mean magnitude of losses in Eq. (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (5)$$

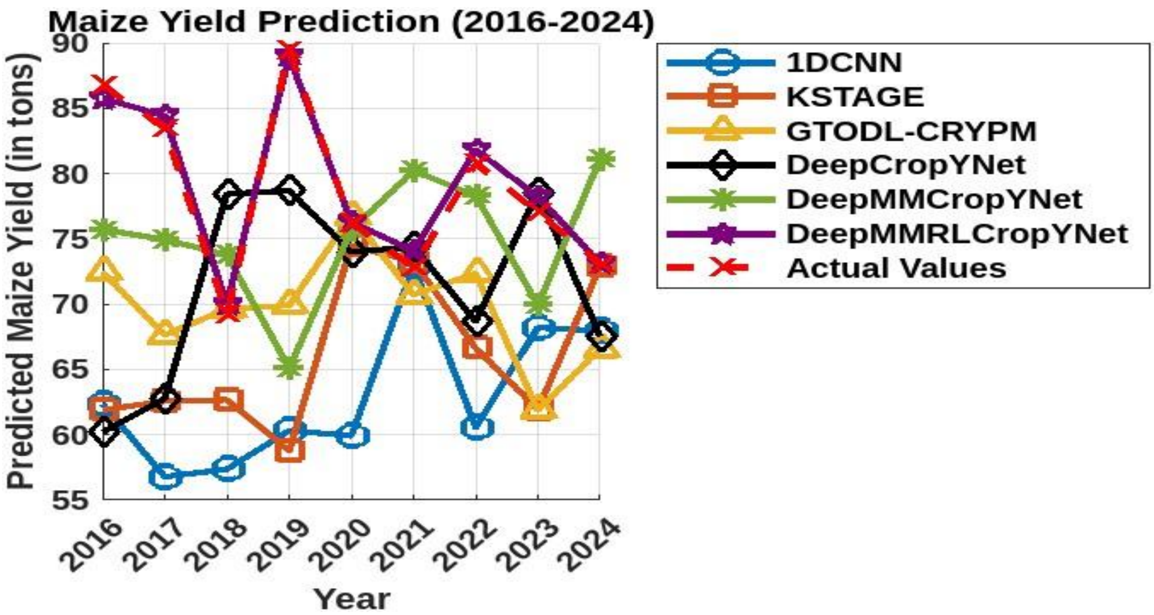
Correlation coefficient (R): It is used to assess the degree of association between predicted crop yields and actual crop yields.

$$\mathrm{R} = \sqrt{1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}} \quad (6)$$

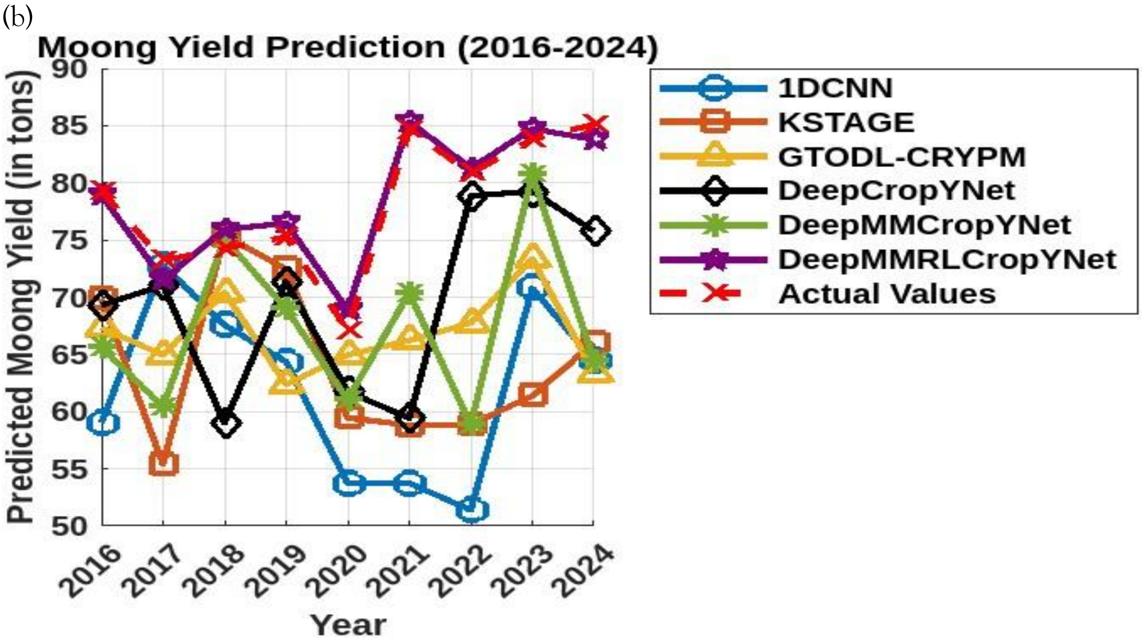
In Eq. (6), $\bar{y}_i$ is the average of the actual crop yield values.



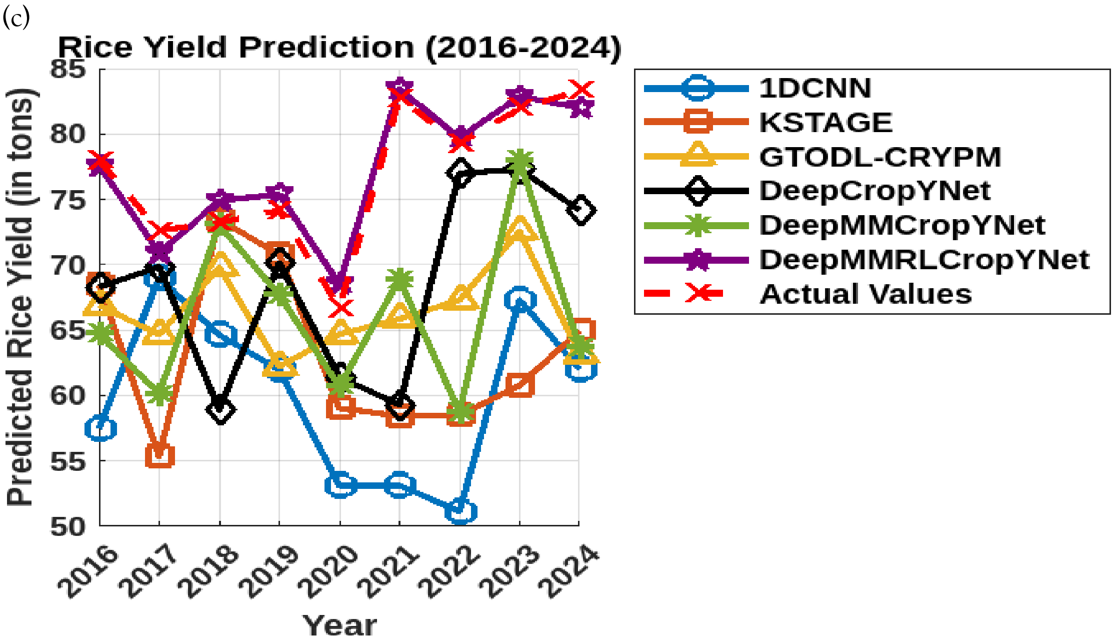
(a)


Maize Yield Prediction (2016-2024)
Predicted Maize Yield (in tons)
Year
1DCNN
KSTAGE
GTODL-CRYPM
DeepCropYNet
DeepMMCropYNet
DeepMMRLCropYNet
Actual Values

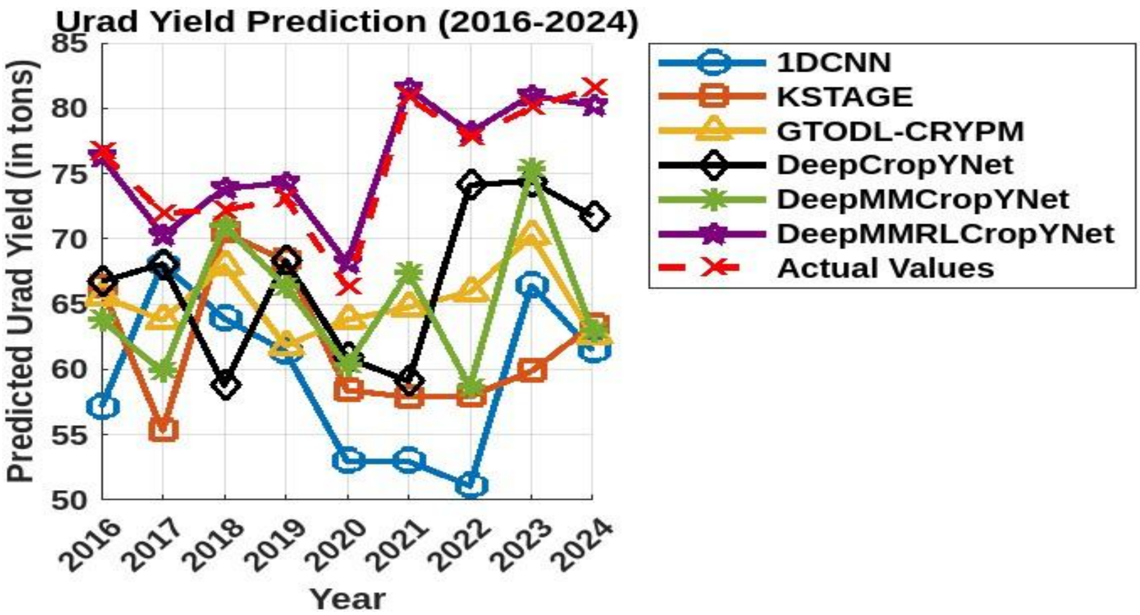
(b)


Moong Yield Prediction (2016-2024)
Predicted Moong Yield (in tons)
Year
1DCNN
KSTAGE
GTODL-CRYPM
DeepCropYNet
DeepMMCropYNet
DeepMMRLCropYNet
Actual Values

(c)


Rice Yield Prediction (2016-2024)
Predicted Rice Yield (in tons)
Year
1DCNN
KSTAGE
GTODL-CRYPM
DeepCropYNet
DeepMMCropYNet
DeepMMRLCropYNet
Actual Values

(d)



(e)

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

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

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

Groundnut Crop										
Models	Cohen's Kappa	MAE	MSE	MSLE	RMSE	R	Accuracy	Precision	Recall	F-M
1D-CNN	0.92	0.081	0.0728	0.0082	0.2705	0.8329	80.14	79.65	80.13	79.85
KSTAGE	0.9347	0.072	0.0644	0.0077	0.2548	0.8457	83.58	82.65	83.25	82.69
GTODL-CRYPM	0.9477	0.065	0.0582	0.0068	0.2369	0.8520	85.15	85.47	85.03	85.35
DeepCropYNet	0.9576	0.0513	0.0469	0.0064	0.2166	0.8617	88.38	88.26	89.24	88.35
DeepMMCropYNet	0.971	0.049	0.043	0.0052	0.2024	0.8835	91.41	91.11	91.25	91.13
DeepMMRLCropYNet	0.9891	0.038	0.03	0.0049	0.1911	0.9254	93.09	92.35	92.94	92.63
Maize Crop										
Models	Cohen's Kappa	MAE	MSE	MSLE	RMSE	R	Accuracy (%)	Precision(%)	Recall (%)	F-M (%)
1D-CNN	0.912	0.0904	0.1	0.0084	0.3151	0.8155	79.55	77.15	79.55	78.35
KSTAGE	0.9258	0.0832	0.0911	0.0076	0.301	0.8268	85.47	82.39	84.17	82.64
GTODL-CRYPM	0.9314	0.0741	0.0807	0.0068	0.2843	0.8314	88.12	88.14	86.62	87.75
DeepCropYNet	0.9421	0.0586	0.0719	0.0065	0.2681	0.8459	90.12	92.21	89.55	90.55
DeepMMCropYNet	0.963	0.0525	0.0683	0.0051	0.2576	0.8532	91.65	93.76	91.84	92.35
DeepMMRLCropYNet	0.987	0.047	0.055	0.0035	0.2354	0.8625	93.49	95.18	92.36	93.79
Moong Crop										
Models	Cohen's Kappa	MAE	MSE	MSLE	RMSE	R	Accuracy (%)	Precision(%)	Recall (%)	F-M (%)
1D-CNN	0.8902	0.0921	0.0865	0.0079	0.2911	0.8364	77.12	75.53	80.12	77.75
KSTAGE	0.9358	0.086	0.0807	0.0068	0.2743	0.8444	80.58	80.48	83.47	80.35
GTODL-CRYPM	0.9547	0.075	0.071	0.0055	0.2515	0.8563	83.63	82.48	85.39	83.55
DeepCropYNet	0.962	0.0612	0.06	0.0048	0.2449	0.8644	86.24	85.54	88.78	86.52

DeepMMCropYNet	0.9621	0.0577	0.049	0.0035	0.2381	0.8712	88.52	87.88	88.45	87.75
DeepMMRLCropYNet	0.977	0.05	0.04	0.0021	0.227	0.8827	90.15	89.75	90.01	89.85
Rice Crop										
Models	**Cohen's Kappa**	**MAE**	**MSE**	**MSLE**	**RMSE**	**R**	**Accuracy (%)**	**Precision(%)**	**Recall (%)**	**F-M (%)**
1D-CNN	0.8751	0.0894	0.089	0.0087	0.2956	0.8281	77.45	74.49	81.54	77.71
KSTAGE	0.8799	0.0826	0.08	0.0081	0.2748	0.8318	80.47	76.54	83.25	80.12
GTODL-CRYPM	0.8852	0.073	0.0676	0.0074	0.2527	0.8547	82.14	78.48	85.56	83.09
DeepCropYNet	0.8948	0.0576	0.0552	0.0062	0.2349	0.8653	84.68	82.25	88.42	85.54
DeepMMCropYNet	0.9516	0.054	0.051	0.0056	0.2296	0.8681	86.21	85.75	89.25	87.35
DeepMMRLCropYNet	0.9936	0.048	0.043	0.0047	0.221	0.8818	89.07	87.47	90.32	88.85
Urad Crop										
Models	**Cohen's Kappa**	**MAE**	**MSE**	**MSLE**	**RMSE**	**R**	**Accuracy(%)**	**Precision(%)**	**Recall (%)**	**F-M (%)**
1D-CNN	0.8698	0.1006	0.0998	0.0079	0.3172	0.8273	74.75	73.54	76.55	74.75
KSTAGE	0.8745	0.094	0.09	0.0074	0.2948	0.8347	78.15	75.25	79.57	78.43
GTODL-CRYPM	0.8802	0.083	0.081	0.0070	0.2755	0.8424	80.39	78.38	83.14	80.35
DeepCropYNet	0.8916	0.0741	0.0709	0.0068	0.2663	0.8587	82.54	80.45	85.54	82.55
DeepMMCropYNet	0.9064	0.07	0.065	0.0060	0.2552	0.862	85.12	82.36	87.89	84.65
DeepMMRLCropYNet	0.9332	0.06	0.052	0.0055	0.2351	0.876	87.56	85.42	89.21	87.25

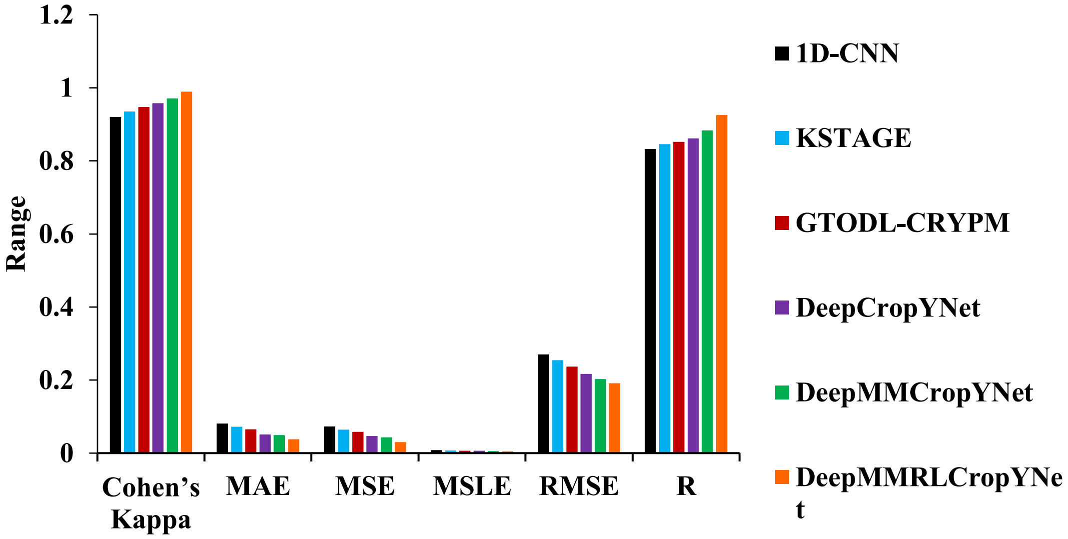


Figure. 4 Performance analysis of different yield prediction models for groundnut yield prediction

Figure 4 illustrates a performance comparison of the suggested with conventional DL methods using groundnut yield information. The MAE of DeepMMRLCropYNet is 53.1%, 47.2%, 41.5%, 25.9%, and 22.5% lower than 1D-CNN, KSTAGE, GTODL-CRYPM, DeepCropYNet, and DeepMMCropYNet, respectively. Similarly, it reduces the MSE by 58.8%, 53.4%, 48.5%, 36%, and 30.2% in comparison to the same models. In terms of RMSE, DeepMMRLCropYNet achieves a reduction of 29.4%, 24.7%, 19.8%, 11.8%, and 5.6%, respectively. Moreover, the correlation coefficient (R) is enhanced by 8.1%, 7%, 5.6%, 4.4%, and 1.9% compared to 1D-CNN, KSTAGE, GTODL-CRYPM, DeepCropYNet, and DeepMMCropYNet, respectively. These results demonstrate the superior predictive accuracy and robustness of DeepMMRLCropYNet over the existing methods.

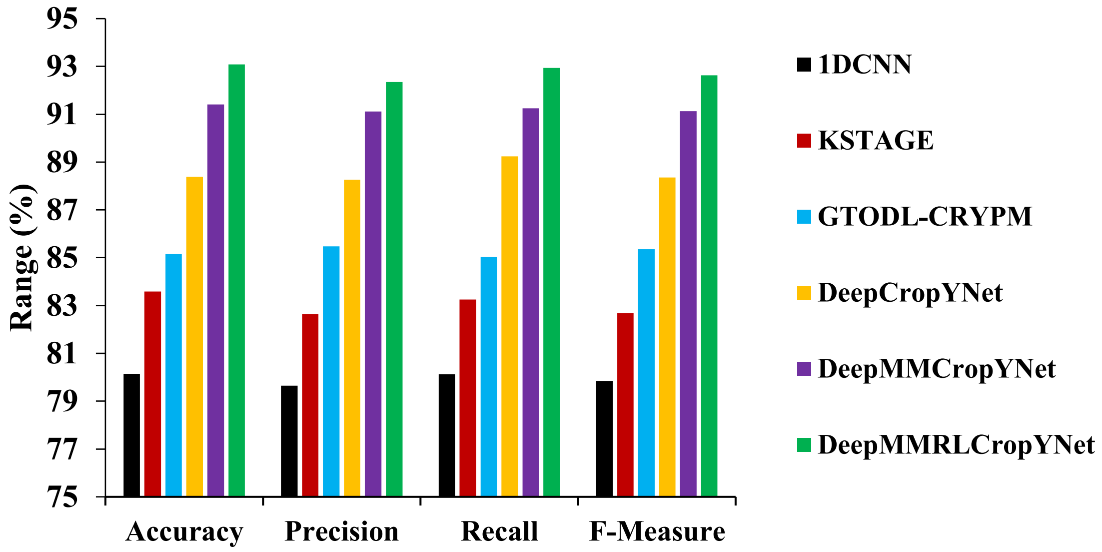


Figure. 5 Prediction efficiency of different yield prediction models for groundnut yield prediction

Figure 5 presents the classification performance comparison of the proposed DeepMMRLCropYNet model with other deep learning models using groundnut yield data. The accuracy of DeepMMRLCropYNet reaches 93.09%, which is 16.8%, 9.8%, 7.1%, 4.7%, and 1.8% higher than the existing models, respectively. In terms of precision, DeepMMRLCropYNet outperforms the above models by 15.9%, 10.5%, 6.8%, 4.6%, and 1.4%, respectively. The recall is also significantly improved, showing increases of 15.9%, 10.3%, 7.8%, 4.1%, and 1.5% compared to the same models. Furthermore, the F-measure of DeepMMRLCropYNet is 16%, 9.9%, 7.6%, 4.8%, and 1.6% higher than that of other models, respectively. These results confirm the superior classification capability and generalization strength of the proposed DeepMMRLCropYNet model.

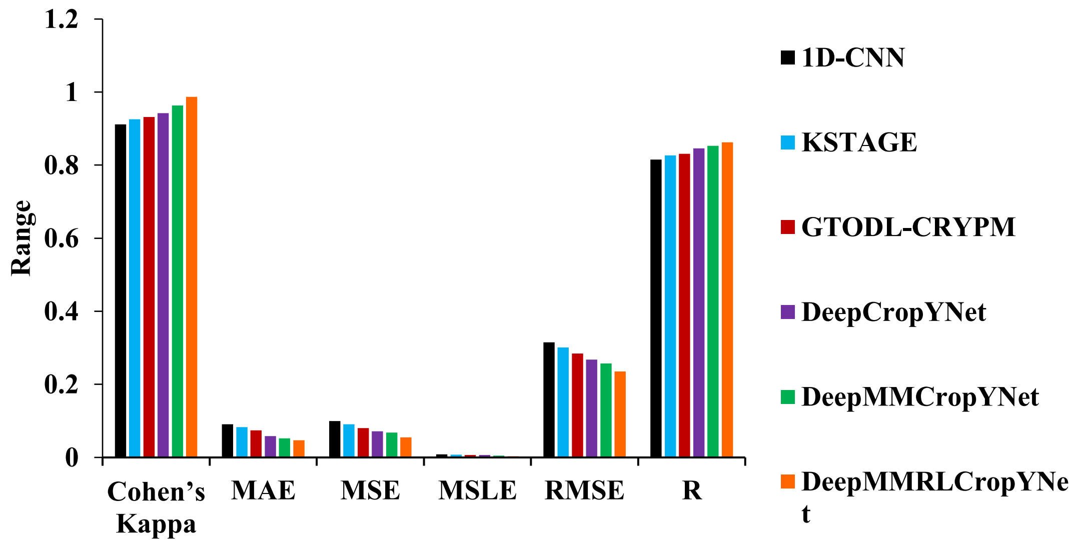


Figure. 6 Performance analysis of different yield prediction models for maize yield prediction

In Figure 6, a performance comparison of the suggested with conventional DL methods using maize yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of Cohen's Kappa, MAE, MSE, MSLE, RMSE and R, demonstrating superior performance over in maize yield prediction.

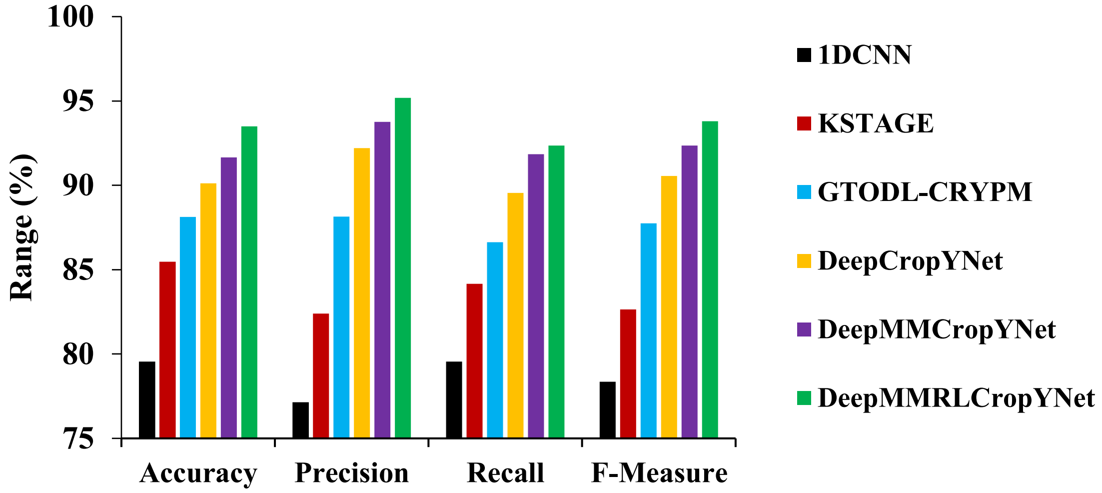


Figure. 7 Prediction efficiency of different yield prediction models for maize yield prediction

In Figure 7, a performance comparison of the suggested with conventional DL methods using maize yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of accuracy, precision, recall and f-measure, demonstrating superior performance over in maize yield prediction.

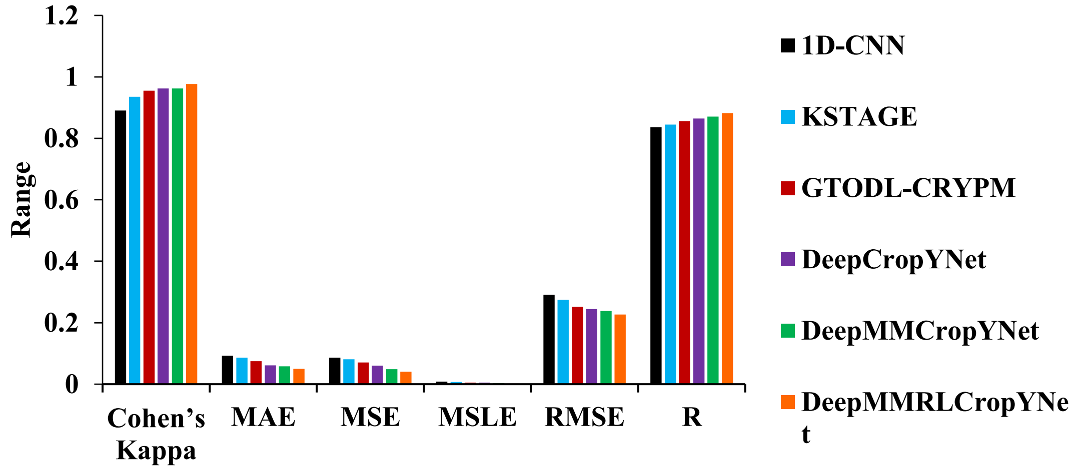


Figure. 8 Performance analysis of different yield prediction models for moong yield prediction

In Figure 8, a performance comparison of the suggested with conventional DL methods using moong yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of Cohen's Kappa, MAE, MSE, MSLE, RMSE and R, demonstrating superior performance over in moong yield prediction.

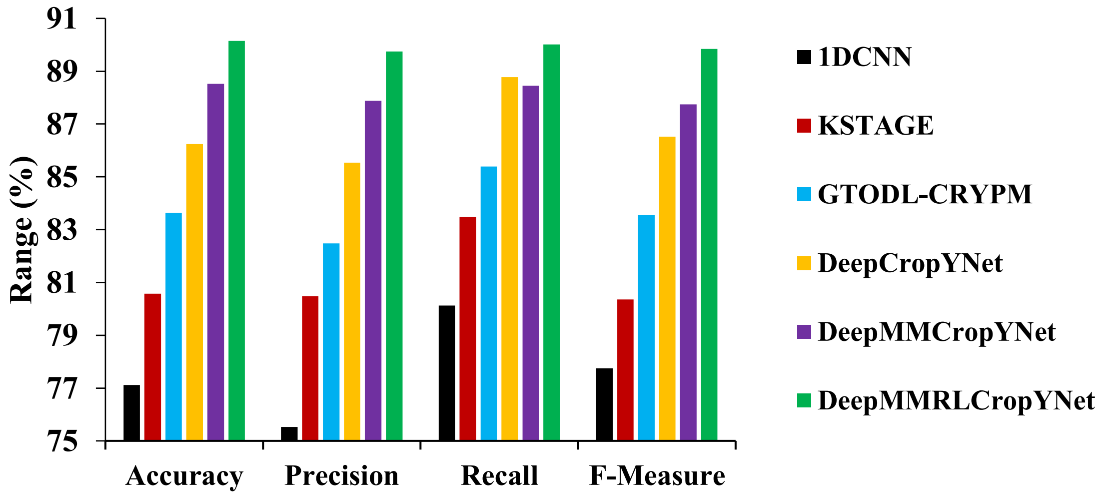


Figure. 9 Prediction efficiency of different yield prediction models for moong yield prediction

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In Figure 9, a performance comparison of the suggested with conventional DL methods using moong yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of accuracy, precision, recall and f-measure, demonstrating superior performance over in moong yield prediction.

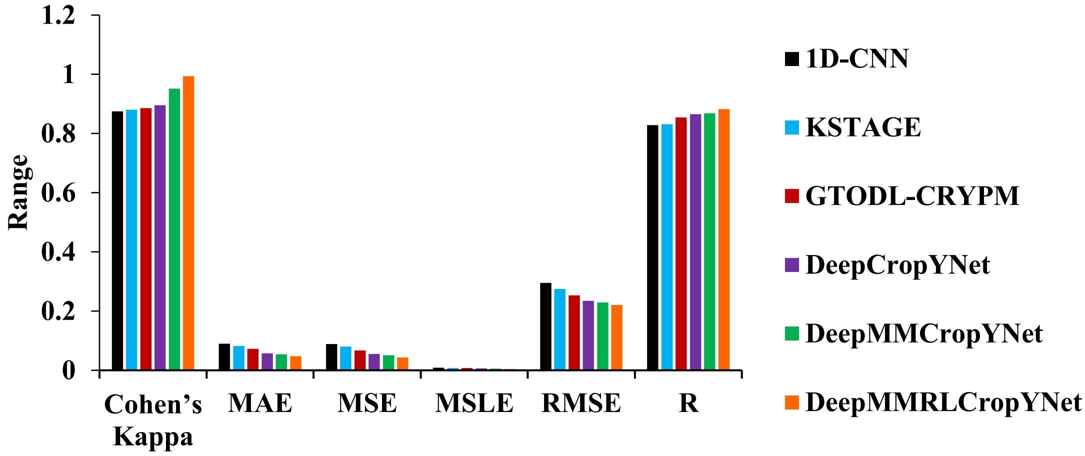

Figure. 10 Performance analysis of different yield prediction models for rice yield prediction

In Figure 10, a performance comparison of the suggested with conventional DL methods using rice yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of Cohen's Kappa, MAE, MSE, MSLE, RMSE and R, demonstrating superior performance over in rice yield prediction.

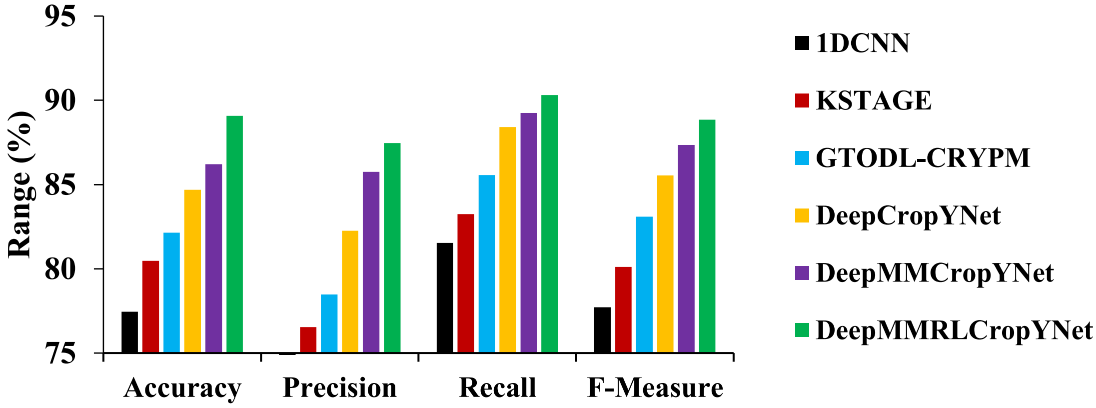

Figure. 11 Prediction efficiency of different yield prediction models for rice yield prediction

In Figure 11, a performance comparison of the suggested with conventional DL methods using rice yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of accuracy, precision, recall and f-measure, demonstrating superior performance over in rice yield prediction.

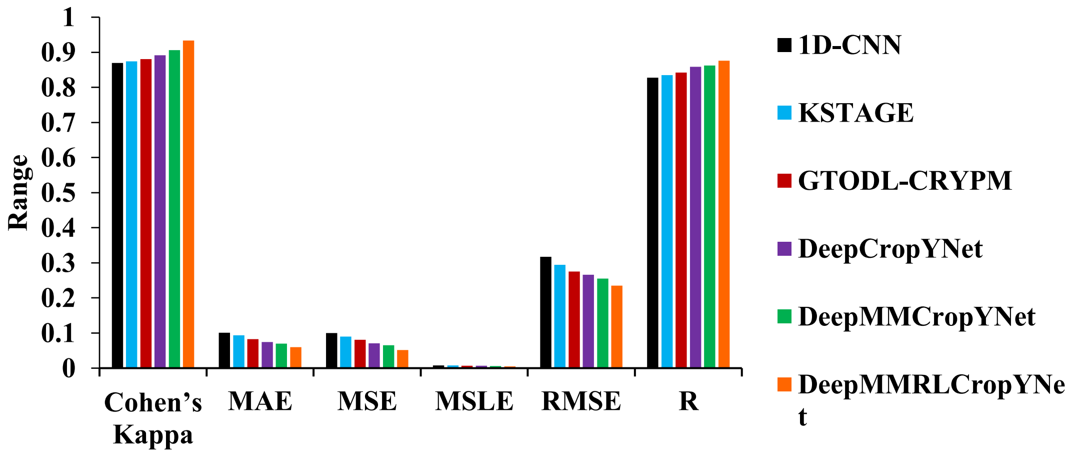

Figure. 12 Performance analysis of different yield prediction models for urad yield prediction

A performance comparison of the suggested with conventional DL methods using uradyield data is illustrated in Figure 12. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of Cohen's Kappa, MAE, MSE, MSLE, RMSE and R, demonstrating superior performance over in urad yield prediction.

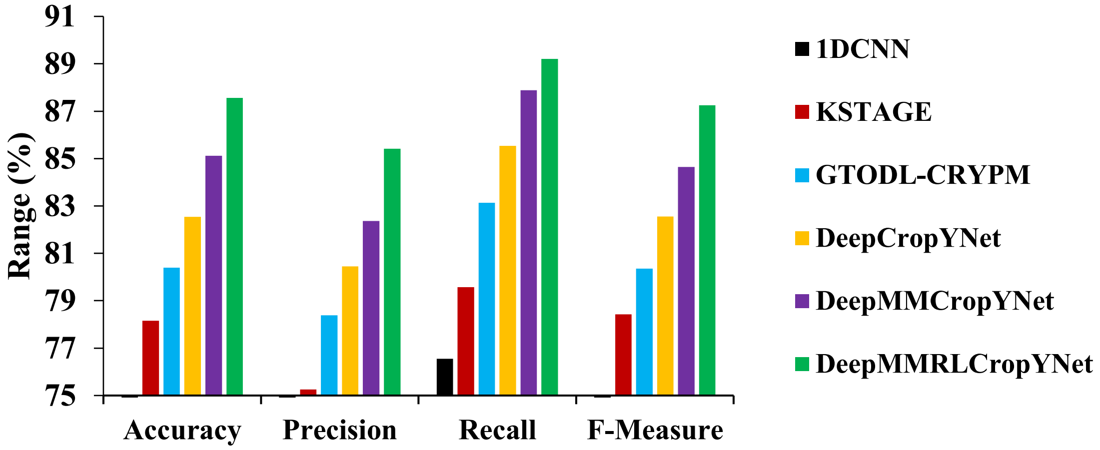

Figure. 13 Prediction efficiency of different yield prediction models for Urad yield prediction

In Figure 13, a performance comparison of the suggested with conventional DL methods using Urad yield data is portrayed. It is observed that the proposed DeepMMRLCropYNet model outperforms every other model in terms of accuracy, precision, recall and f-measure, demonstrating superior performance over in Urad yield prediction.

Tests showed that the DeepMMRLCropYNet is better at predicting groundnut yield than other models, with a Cohen's Kappa of 0.9891, 0.038 MAE, 0.03 MSE, 0.0049 MSLE, 0.1911 RMSE, and a R of 0.9254.. It has a Cohen's Kappa of 0.987, 0.047 MAE, 0.055 MSE, 0.0035 MSLE, 0.2354 RMSE, and 0.8625 R for predicting maize yield. For moong yield prediction, the model achieved a Cohen's Kappa of 0.977, 0.05 MAE, 0.04 MSE, 0.0021 MSLE, 0.227 RMSE, and a R of 0.8827. In predicting rice yield, it recorded a Cohen's Kappa of 0.9936, 0.048 MAE, 0.043 MSE, 0.0047 MSLE, 0.221 RMSE, and 0.8818 R. For Urad yield, the model attained a Cohen's Kappa of 0.9332, 0.06 MAE, 0.052 MSE, 0.0055 MSLE, 0.2351 RMSE, and a R of 0.876.For groundnut, maize, moong, rice, and Urad crops, DeepMMRLCropYNet achieved precision values of 92.35%, 95.18%, 89.75%, 87.47%, and 85.42%; recall values of 92.94%, 92.36%, 90.01%, 90.32%, and 89.21%; F-measure values of 92.63%, 93.79%, 89.85%, 88.85%, and 87.25%; and accuracy of 93.09%, 93.49%, 90.15%, 89.07%, and 87.56%, respectively

The above outcomes highlight the significance of the DeepMMRLCropYNet method in forecasting crop yields precisely compared to other models by learning the relationships between input parameters and crop yield. By combining reinforcement learning with DL, this model fine-tunes the forecasting results to ensure robustness and prediction performance.

5. CONCLUSION

This study presented the DeepMMRLCropYNet model by integrating the DeepMMCropYNet on top of the DQL algorithm to predict crop yield. First, the actual output values of the DeepMMCropYNetwere mapped into the Q values. The Q-learning agent then integrated the parametric attributes with the threshold to forecast crop yield. The agent received a unified grade for the actions executed by reducing the error and increasing the precision with the best rewarding iterations. Besides, the total rewards determined the agents' learning efficiency. Tests showed that the DeepMMRLCropYNet is better at predicting groundnut yield than other models. On the other hand, the performance of DeepMMCropYNet relies on the proper tuning of hyperparameters. So, future work will involve implementing a metaheuristic algorithm for optimizing hyperparameters to enhance crop yield prediction performance. Additionally, the focus will be on recommending the appropriate use of pesticides or fertilizers to improve yield productivity.

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