A Long Short-Term Memory Guided Conditional Dynamic Variational Auto-Encoder for Crop Yield Prediction and Crop Type Classification

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ABSTRACT

Agriculture plays a significant role in India's economy and directly impacts food security, which faces the difficulties of population growth and rising food demand. The analysis of environmental factors and soil properties data to predict key determinants is difficult due to variability in weather conditions and soil quality, which affects the yield of Jowar and Ragi crops. This research proposes a Long Short-Term Memory (LSTM)-guided Conditional Dynamic Variational Auto-Encoder (LSTM-CDVAE) for crop yield prediction and classification. Using LSTM's ability to obtain temporal patterns and CDVAE's generative modeling capability, this approach provides better feature representation, thereby enhancing generalization for various crop conditions. In this study, two crop datasets, All Crops (Dataset 1) and Filtered Crops (Dataset 2), were considered and preprocessed using a standard scaler and label encoding. The standard scaler normalizes numerical features to uniform scales, while label encoding converts categorical values into numerical representations, thus preserving the integrity of various classes. The Synthetic Minority Oversampling Technique (SMOTE) is applied to balance data by oversampling minority classes. The LSTM-CDVAE achieves 99.85% accuracy and 0.0015 MSE for Dataset 1, which is better than the Weight-Tuned Deep Convolutional Neural Network (WTDCNN).

Keywords-crop type classification; crop yield prediction; feature representation; label encoding; standard scaler

I. INTRODUCTION

The ability to accurately predict crop yields enables beneficial agricultural decisions for farmers, industry members, and government officials through optimized farming methods [1]. Remote Sensing (RS) technologies provide quick and affordable data acquisition solutions that work through non-contact methods for target assessment [2], and are often used to monitor crop conditions [3]. Regional-scale agricultural monitoring for crop assessment serves vital functions in developing policies and improving food security and forecasting, while supporting global trade analysis, especially under conditions of climate change [4, 5]. The assessment of crop yield predictions at regional or administrative levels, along with their associated uncertainties, is fundamental to improving food security [6]. The world's largest food producer status gives China a fundamental role in food resource requirements worldwide [7].

Crop yield is an essential goal of agriculture, but it is primarily dependent on essential climatic elements, including rainfall, temperature, and humidity, and soil characteristics such as pH and type [8]. Soil nutrients and groundwater levels have decreased rapidly due to continued population growth [9]. According to [10], the prediction of crop yield represents a complicated issue for precision agriculture. Agricultural productivity has faced negative impacts due to climate change and unforeseen severe weather patterns in recent years, despite overall yield improvements [11]. Machine Learning (ML) models are superior to traditional regression models because they provide a more profound informational value to agricultural data [12]. ML algorithms examine extensive datasets to discover patterns that help generate predictions from relationships between multiple influencing variables [13, 14]. ML-based models require optimal data during training because it fundamentally determines the prediction accuracy and quality of crop yields [15]. The application of ML methods has expanded rapidly in agroculture, as Artificial Neural Networks (ANNs) show better capabilities for crop protection and classification tasks [16-18]. Data science operates under dominant Deep Learning (DL) algorithms that provide forecasting abilities in financial and economic time series applications [19]. The integration of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models has also yielded encouraging results in the estimation of country-level soybean crop yields from remote sensing data [20, 21]. In evaluating model performance, Spatial Cross-Validation (SCV) is superior to Random Cross-Validation (RCV), since SCV provides a better measure of predictive accuracy on unseen spatial data [22, 23].

The analysis of data in environmental factors and soil properties to predict key determinants is difficult due to variability in weather conditions and soil quality, which affects the yield of Jowar and Ragi crops. Therefore, to reduce the variability associated with crop yield, this study investigated efficient classification methods to categorize crop yield into distinct classes, such as low, medium, and high, based on weather conditions and soil quality, improving overall crop management.

Various DL and ML algorithms have been used in previous research for crop yield prediction. In [24], a crop yield prediction method used DL and dimensionality reduction for Indian regional crops. Preprocessing was applied to Indian regional crop datasets by performing data cleaning and normalization. Then, dimensionality reduction was performed using Squared Exponential Kernel-based Principal Component Analysis (SEKPCA). Finally, crop yield prediction was performed based on WTDCNN, which offered a higher crop yield accuracy. However, this model struggled to capture the impact of extreme temperature on both crops and the effect of irritation and moisture on grain maize. In [25], the prediction of agricultural yields was based on Random Forest (RF). The main goal was to predict crop yield using parameters such as crop, rainfall, area, production, and meteorological conditions, providing better insight into long-term variability. The RF algorithm was applied to minimize yield losses. The accuracy of the model increased in crop prediction when remote sensing data was combined with statistical data from the districts. However, this approach did not fully capture localized soil variations and microclimates, which affected the accuracy of the model in specific regions.

In [26], a One-Dimensional CNN and LSTM (1D CNN-LSTM) multi-head attention with multiplication skip connection was proposed for accurate crop yield prediction. The main goal was to predict two commonly cultivated Indian crops, rice and wheat, selected because of their crucial contribution to the agricultural landscape of the country. However, localized soil fertility and climate variations decrease the efficiency of crops in specific regions. In [27], an optimized Discrete Deep Belief Network with Visual Geometry Group (VGG) Network was proposed for crop yield prediction, optimized with Tweak Chick Swarm Optimization (TCSO). However, the optimization approach struggled due to unpredictable changes in weather conditions, leading to inefficient crop predictions.

In [28], a hybrid feature selection and an optimized ML method were proposed for crop yield prediction. After data normalization, K-means clustering was applied with a Correlation-Based Filter (CFS) to reduce data dimensionality. Then, a hybrid feature selection method used Fisher score and Mutual Information Gain with Recursive feature elimination (FMIG-RFE). Lastly, the Improved Crayfish Optimization Algorithm (ICOA) was used to fine-tune the hyperparameters of the Support Vector Regressor (SVR), achieving better prediction accuracy with the help of the FMIG-RFE model. However, data inaccuracies led to inefficiencies. Specifically, the model showed limited performance when measuring crop responses to extreme temperatures and soil conditions under irrigation. The predictive system did not provide good results when handling specific regional soil differences, as climate conditions and soil qualities make crops produce less efficiently. Weather changes made optimization systems ineffective, yielding incorrect predictions. This model had two major problems in simplifying large data inputs and producing incorrect results.

The contributions of this study are as follows:

- Using an innovative model architecture, this research develops LSTM-CDVAE to predict crop yields and classify them precisely. The integration of LSTM and CDVAE provides better feature extraction and makes the model perform well in varied crop environments.
- The Synthetic Minority Oversampling Technique (SMOTE) is used to resolve dataset imbalances. This method achieves better results in model training because it increases minority class samples, which helps the model predict effectively in the agricultural field.
- Applies data preprocessing methods, such as standard scalar and label encoding. Standard scaling transforms numerical values to one uniform range, while label encoding turns categorical fields into numbers, thereby preserving the integrity of various classes.
- The proposed LSTM-CDVAE model demonstrates its effectiveness on two datasets, All Crops (Dataset 1) [29] and Filtered Crops (Dataset 2) [30], reaching accuracies of 99.85% for Dataset 1 and 98.99% for Dataset 2. The proposed model achieves better results than baseline models in predicting and classifying crop yields.

II. PROPOSED METHODOLOGY

This study developed an LSTM-guided Conditional Dynamic Variational Auto-Encoder (LSTM-CDVAE) architecture for crop yield prediction and classification. Two datasets were considered, preprocessed using standard scalar and label encoding. The standard scaler was used to ensure that all numerical features were on an equivalent scale. Label encoding was used to transform categorical values into numerical ones while preserving their different classes. Then, SMOTE was applied for balancing data through oversampling minority classes. Crop yield prediction and classification were performed with the help of LSTM-CDVAE. Figure 1 shows the workflow of the proposed approach.

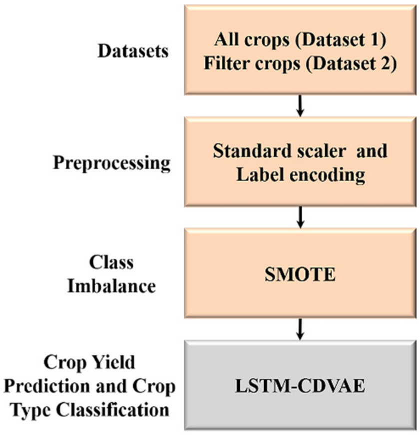


Fig. 1. Workflow of the proposed LSTM-CDVAE model for crop yield prediction and classification.

A. *Datasets*

1) *All Crops (Dataset 1)*

This dataset includes agricultural data from multiple crops grown across different states in India from 1997 to 2020 [29]. It contains essential features for crop yield prediction, such as states, crop types, cropping seasons, crop years, areas under cultivation, production quantities, calculated yields, annual rainfall, fertilizer usage, and pesticide usage. Figure 2 shows the crop distribution.

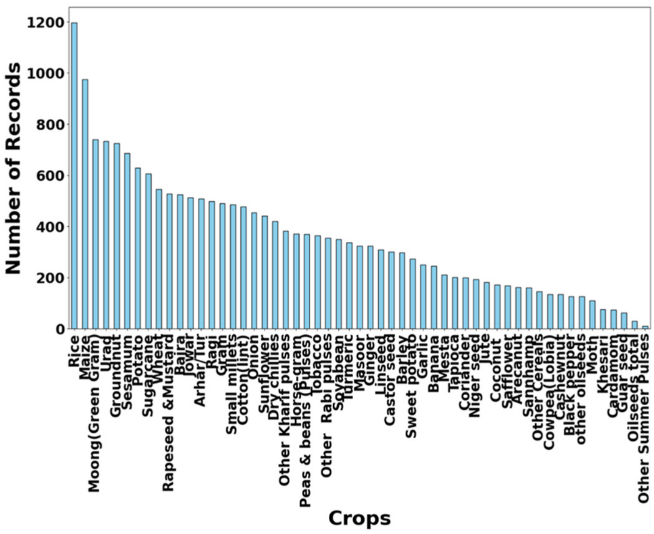


Fig. 2. Crop class distribution in Dataset 1.

2) *Filter Crops (Dataset 2)*

Three crops, such as Maize, Jowar, and Ragi, were considered as seasonal crops in this research. According to the government website of Karnataka [30], Paddy (rice) and Wheat are cultivated in larger areas compared to Maize, Jowar, and Ragi. However, Paddy (rice) is widely researched due to its prominence, while Wheat is cultivated in smaller regions of Karnataka. Thus, this study focused on Maize, Jowar, and Ragi crops. Figure 3 shows the crop distribution in this dataset.

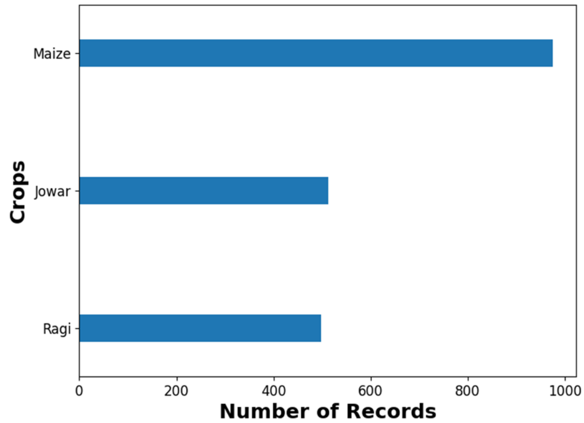


Fig. 3. Crop class distribution in Dataset 2.

B. *Preprocessing*

The standard scaler transforms the data to a mean and standard deviation of 0 and 1, respectively. For a given dataset, features such as Area, Production, Annual_Rainfall, Fertilizer, Pesticide, and Yield vary in scale, which impacts the model performance. The standard scaler is used to ensure that all numerical features are on an equivalent scale. This preprocessing is also called z-score, and its formula is :

$$x' = \frac{x-\mu}{\sigma} \quad (1)$$

where x' is the new value, x is the actual value, and μ and σ are the mean and standard deviation, respectively.

Label encoding was used to convert categorical values into numerical values while preserving their different classes. In the given dataset, the Crop, Season, and State columns have categorical values that need to be transformed into numerical values for effective processing. Label encoding allocates every unique class as a numerical value. For example, five unique crops are encoded as 0, 1, 2, 3, and 4.

C. *Class Imbalance*

SMOTE is a data sampling technique developed to address the class imbalance issue through the oversampling of minority classes. It utilizes a linear interpolation-based method to produce new instances for minority classes at random distances from K-Nearest Neighbors (KNNs). This technique contains four main steps. Initially, it chooses a random minority sample a from the original data. Then, it estimates the Euclidean distance of selected samples in feature space and discovers the KNNs. In the following step, SMOTE chooses a random sample b from the KNNs of a. Lastly, it produces a synthetic sample among these two samples a and b through:

$$\dot{a} = a + rand(0,1)|a - b| \tag{2}$$

This oversampling strategy provides equivalent synthetic samples to actual data in an efficient and simpler method, as it generates synthetic samples in the feature space of actual data without the need for a training stage. The key parameter of SMOTE is the number of selected KNNs.

D. Prediction and Classification

LSTM is a type of Recurrent Neural Network (RNN) that learns long-time dependencies. LSTM contains three gates, responsible for regulating information and transferring it to the next layer. The forget value determines whether it recollects or discards information based on its value. If the value is zero, all information is forgotten; else, all information is retained. The input gate manages the addition of new information to the next cell state and operates in two parts. The initial part is the sigmoid layer that controls the stored output value in the cell state. The second part is the tanh layer, which creates new feature vector values stored in a cell state. The output gates release information about the updated cell state. By this gate structure, statistics are performed selectively and managed by updating and holding historical data when updating the cell state. LSTM contains past historical data and analyzes the present unknown patterns based on its learning patterns, making future predictions accordingly.

The forget gate layer f_t is managed by the $sigmoid$ function based on the previous moment output (3). The input gate layer i_t utilizes $sigmoid$ to define which value is to be updated (4). The hyperbolic tangent layer (tanh) provides new candidate values to obtain updated values (5). The above two gates are the process of removing unwanted information and including new information (6). The last step is to define the output gate layer o_t, using sigmoid to obtain the initial output (7). Then, tanh is used to scale the values between -1 and 1, multiplied by the sigmoid output to attain the model output (8).

$$f_t = \sigma\left(w_f[h_{t-1}, x_t] + b_f\right) \tag{3}$$

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \tag{4}$$

$$\widetilde{C}_t = tanh(w_C[h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C}_t \tag{6}$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \times tanh(C_t) \tag{8}$$

where w_f, w_i and w_o are the weight matrices of forget, input, and output gates, respectively, b_f, b_i and b_o are the bias matrices of forget, input, and output gates, respectively, σ is the sigmoid activation function, x_t is a current input at time t, h_{t-1} and C_{t-1} are hidden and cell states from the previous time step, respectively, $\widetilde{C}_t$ is a candidate cell state, C_t is an updated cell state at time t, and h_t is an updated hidden state at time t.

CDVAE produces content by using the input label description. The starting point of data preparation involves converting multi-phase batch process data into a phase class label named c_α . LSTM networks keep valuable past information available for future inputs. The CDVAE model uses an LSTM to let it detect dynamic two-dimensional data features better. In this model, the input sequence $\underline{x}_k^i$ and label c_α serve as the input data. The CDVAE encoder includes both a mean encoder and a variance encoder. The decoder combines the obtained c_α and $\underline{z}_k^i$ values to produce the estimated output $\underline{x}_k^i$. The CDVAE model uses a specific measure to evaluate data quality in its loss function as:

$$loss_{CDVAE} = E_{z_k^i \sim q\left(z_k^i | \underline{x}_k^i, c_\alpha\right)} log\left[p\left(\underline{x}_k^i | z_k^i, c_\alpha\right)\right] - D_{KL}\left[q\left(\underline{x}_k^i, c_\alpha\right) || p(z_k^i, c_\alpha)\right] \tag{9}$$

The first part of (9) stands for residual reconstruction error, whereas the second part depicts the KL divergence from the latent space. The reconstruction loss is given by Mean Squared Error (MSE) to measure the difference between the input sequence and the reconstruction sequence $\underline{\hat{x}}_k^i$. This aims to penalize the $\underline{\hat{x}}_k^i$ to approximate the input sequence $\underline{x}_k^i$. KL encourages the latent variable z_k^i distribution to standard normal values $N(0,1)$.

Algorithm 1 describes the proposed method.

Algorithm 1: Proposed LSTM–CDVAE method
Input: Dataset D
Output: Predicted crop types, metrics
Initialize $(L, E, B, z, h, \eta, \alpha, \beta, \gamma cls, p,$
    $best\_val\_acc = 0, patience\_counter = 0)$
Preprocess (D):
    Split → Train, Val, Test
    Encode categorical
    Normalize numeric
    Build sequences of length L
    Apply SMOTE on Train
$BuildModel()$:
    Encoder: $LSTM \rightarrow (\mu, log\sigma^2)$
    $z \leftarrow \mu + \varepsilon * exp(0.5 * log\sigma^2), \varepsilon \sim N(0,1)$
    Decoder $(z|y) \rightarrow X'$
    Classifier $(z) \rightarrow \hat{y}$
For $epoch = 1\ to\ E$ do
    For each batch (Xb, yb) do
        $(\mu, log\sigma^2) \leftarrow Encoder(Xb)$
        $z \leftarrow Reparameterize(\mu, log\sigma^2)$
        $Xb' \leftarrow Decoder(z|yb)$
        $\hat{y}b \leftarrow Classifier(z)$
        $Ltotal \leftarrow \alpha * MSE(Xb, Xb') + \beta * KL(\mu, \sigma^2) +$
        $\gamma cls * CE(yb, \hat{y}b)$
        Update weights
    End For
    $val\_acc \leftarrow Evaluate(Val)$
    If $val\_acc \leq best\_val\_acc$ then
        $patience\_counter + +$
        If $patience\_counter \geq p$ then Break
        End If
    Else
        $best\_val\_acc \leftarrow val\_acc$

```
        patience_counter ← 0
    End If
End For
Predict on Test
Return results
```

Table I shows the LSTM parameters and their ranges.

TABLE I. LSTM PARAMETERS AND RANGES

Parameters	Ranges
Optimizer	Adam
Learning rate	0.001
Activation function	SoftMax
Loss	Mean squared error
Maximum epochs	100
Batch size	32

III. RESULT ANALYSIS

The proposed LSTM-CDVAE was developed in Python 3.10.12 on Windows 10 OS, an i5 processor, and 8 GB of RAM. The accuracy, recall, F1-score, precision, MSE, Root MSE (RMSE), and Mean Absolute Error (MAE) metrics were considered for both datasets. In crop yield, two categories of performance metrics are required for prediction and classification. Prediction metrics such as MSE, RMSE, and MAE are considered to estimate how closely the model predicts the continuous yield values between different years. The classification metrics (accuracy, precision, recall, and F1-score) are used to evaluate how effectively the model differentiates crop types and yield levels into classes such as low, medium, and high. This dual evaluation ensures that the model is evaluated both for its ability to forecast numerical yield trends and its efficiency in correct categorical classifications.

Metrics were calculated for different DL, encoders, and class imbalance methods to show the effectiveness of the proposed LSTM-CDVAE. The mathematical expressions for these metrics are given in (10-16), where TP, FP, TN, and FN denote true positives, false positives, true negatives, and false negatives, respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (11)$$

$$F1-score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (12)$$

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

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_{di})^2 \quad (14)$$

$$RMSE = \sqrt{MSE} \quad (15)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - y_{di}| \quad (16)$$

Table II displays the performance of different DL methods on both datasets. The LSTM-CDVAE achieved 99.85% accuracy, recall, F1-score, and precision, as well as MSE of 0.0015, RMSE of 0.029, and MAE of 0.0014 for Dataset 1. Similarly, it achieved an accuracy of 98.88%, and recall, F1-score, and precision 98%, along with MSE of 0.0075, RMSE of 0.086, and MAE of 0.0075, for Dataset 2. These results are better than the baseline models because LSTM effectively captures temporal dependencies such as rainfall and fertilizer variations across years, while CSVAE provides high feature representations, thereby reducing prediction error.

Table III displays the performance of different encoders on both datasets. CDVAE achieved 99.85% accuracy, recall, F1-score, and precision, along with MSE of 0.0015, RMSE of 0.029, and MAE of 0.0014 for Dataset 1. Similarly, it achieved an accuracy of 98.88%, recall, F1-score, and precision of 98.00%, along with MSE of 0.0075, RMSE of 0.086, and MAE of 0.0075 for Dataset 2. Compared to other encoders, CDVAE achieved better performance, as its generative modeling learns better hidden structural relationships in data, thereby reducing the reconstruction loss and enhancing the classification accuracy.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT DL METHODS ON BOTH DATASETS

Datasets	Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)	MSE	RMSE	MAE
Dataset 1	RNN	97.92	97.92	97.92	97.36	0.9903	0.995	0.990
	GRU	98.14	98.14	98.14	98.28	0.0086	0.092	0.008
	LSTM	98.54	98.52	98.54	98.52	0.0048	0.069	0.004
	LSTM-CDVAE	99.85	99.85	99.85	99.85	0.0015	0.039	0.0014
Dataset 2	RNN	95.47	96.70	95.47	97.10	0.090	0.313	0.097
	GRU	97.14	96.10	97.14	95.80	0.052	0.220	0.052
	LSTM	97.77	97.90	97.77	97.90	0.021	0.150	0.022
	LSTM-CDVAE	98.99	98.00	98.00	98.00	0.0075	0.086	0.0075

TABLE III. PERFORMANCE COMPARISON OF DIFFERENT ENCODERS ON BOTH DATASETS

Datasets	Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)	MSE	RMSE	MAE
Dataset 1	DE	97.00	96.85	96.87	96.90	0.0150	0.122	0.0145
	SAE	98.30	98.15	98.17	98.20	0.0105	0.102	0.01
	VAE	98.50	98.35	98.37	98.40	0.0098	0.099	0.0092
	CDVAE	99.85	99.85	99.85	99.85	0.0015	0.039	0.0014
Dataset 2	DE	96.50	96.30	96.35	96.40	0.0185	0.136	0.0178
	SAE	97.50	97.30	97.35	97.40	0.0135	0.116	0.0129
	VAE	97.80	97.60	97.65	97.70	0.0128	0.113	0.0122
	CDVAE	98.99	98.00	98.00	98.00	0.0075	0.086	0.0075

TABLE IV. PERFORMANCE COMPARISON OF DIFFERENT CLASS IMBALANCE METHODS ON BOTH DATASETS

Datasets	Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)	MSE	RMSE	MAE
Dataset 1	Random undersampling	97.50	97.30	97.35	97.40	0.0125	0.111	0.0120
	ADASYN	98.20	98.00	98.05	98.10	0.0098	0.099	0.0092
	SMOTE	99.85	99.85	99.85	99.85	0.0015	0.039	0.0014
Dataset 2	Random undersampling	98.20	98.00	98.05	98.10	0.0098	0.099	0.0092
	ADASYN	97.50	97.30	97.35	97.40	0.0128	0.113	0.0122
	SMOTE	98.99	98.00	98.00	98.00	0.0075	0.086	0.0075

Table IV displays the performance of different class imbalance methods on both datasets. Using SMOTE achieved 99.85% accuracy, recall, F1-score, and precision, as well as MSE of 0.0015, RMSE of 0.029, and MAE of 0.0014 for Dataset 1, and 98.88% accuracy, 98% recall, F1-score, and precision, along with MSE of 0.0075, RMSE of 0.086, and MAE of 0.0075 for Dataset 2. When handling class imbalance, SMOTE enables the model to learn equally from minority and majority classes, thereby leading to reduced bias, higher accuracy, and lower error values across the dataset.

Table V displays the performance of K-fold cross-validation, evaluating the model's robustness by dividing the dataset into K subsets for training and validation. The results show that increasing K improves generalization till the optimal value of 5 for both datasets, where the model achieves better accuracy of 99.85% for Dataset 1 and 98.99% for Dataset 2. With smaller folds, such as K=2 and 3, accuracy is lower due to less training data in every iteration, while larger folds, such as K=7, increase variability and reduce stability. These results indicate that K=5 provides the optimal trade-off between training size and validation reliability. This consistent performance across different folds ensures that the proposed LSTM-CDVAE is not overfitting and generalizes well on unseen data.

TABLE V. PERFORMANCE COMPARISON OF K-FOLD CROSS-VALIDATION ON BOTH DATASETS

Datasets	K-values	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
Dataset 1	2	96.83	96.42	96.61	96.77
	3	98.27	98.14	98.21	98.33
	5	99.85	99.87	99.86	99.84
	7	98.36	98.21	98.31	98.29
Dataset 2	2	95.62	95.13	95.27	95.41
	3	97.18	96.92	96.99	97.08
	5	98.99	98.04	98.11	98.07
	7	97.46	97.18	97.25	97.33

Figure 4 presents training and validation accuracy curves for Dataset 1 and Dataset 2 during 100 epochs. The model shows quick accuracy improvement until stabilization in the very first epochs. In Dataset 1, it achieved a training accuracy of approximately 0.995, but the validation accuracy slightly exceeds it, which indicates robust generalization abilities. Training the model in Dataset 2 achieved both accuracy values near 1.00, indicating effective model training without significant overfitting problems. The adjustment patterns of early epochs cause validation accuracy to fluctuate before stabilization occurs. The model demonstrates outstanding results because it learns effectively while sustaining excellent generalization power.

(a)

(b)

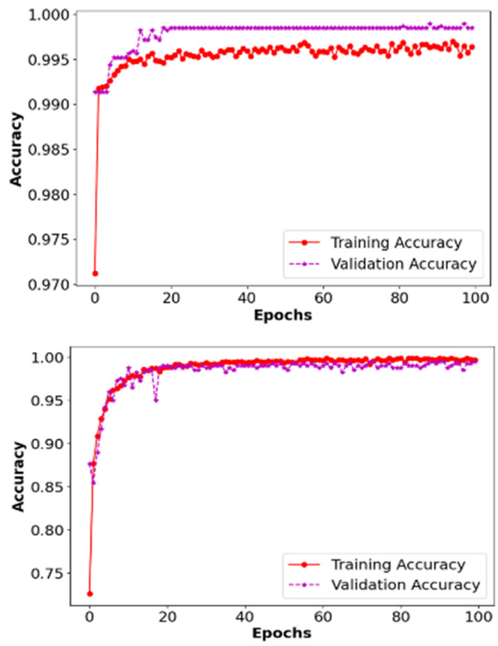
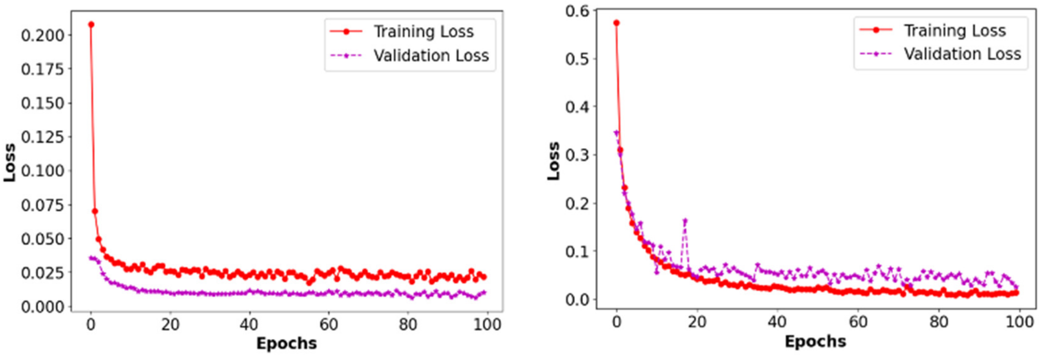


Fig. 4. Training and validation accuracy curves for (a) Dataset 1 and (b) Dataset 2.

Figure 5 presents training and validation loss results through 100 epochs for Dataset 1 and Dataset 2. Rapid learning occurs early in both cases and converges over time, causing the loss to stabilize. The loss values for Dataset 1 show a stable and low level for training and validation, which indicates that the model has successfully generalized. The training and validation loss curves in Dataset 2 achieved low values while showing higher initial fluctuations of validation loss, which indicates minor instability. The model optimization results show effective fitting because training loss tracks validation loss without significant differences.

Figure 6 shows how the model performed for Dataset 1 in predicting crop yield outputs. A solid red line shows real yield results. The predicted results appear as a dashed purple line marked with crosses. The model successfully follows real-world data trends because it identifies the proper underlying trends. Although there are minor differences in the estimates, certain locations show reliable results with slight overfitting. Figure 7 shows the predicted and actual values for Dataset 2. The solid blue line shows actual values with circles, while the dashed red line uses crosses to display the prediction results. The model shows reliable predictions because the actual output closely matches the predicted values. The model shows reliable performance, as it tracks the yield changes effectively, although sometimes it has small estimation errors.



(a) (b)

Fig. 5. Training and validation loss curves for (a) Dataset 1 and (b) Dataset 2.

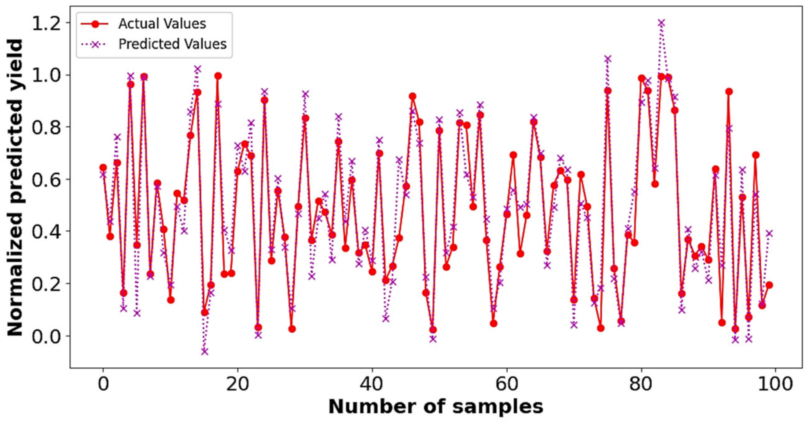


Fig. 6. Actual vs predicted values for Dataset 1.

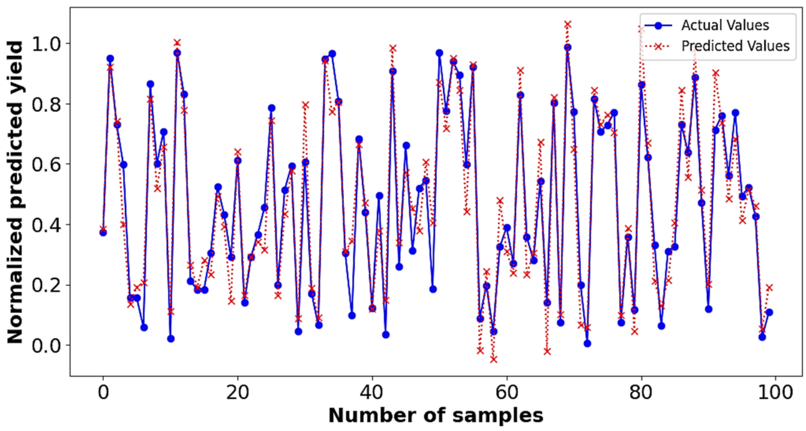


Fig. 7. Actual vs predicted values for Dataset 2.

TABLE VI. COMPARATIVE ANALYSIS FOR DATASET 1

Methods	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)	MSE	RMSE	MAE
WTDCNN [24]	98.96	99.03	98.87	98.67	0.034	0.219	NA
RF [25]	98.96	NA	NA	NA	NA	2.45	1.97
CNN-LSTM multi-head attention with multiplication skip connection [26]	98	NA	NA	NA	NA	0.017	0.009
LSTM-CDVAE	99.85	99.85	99.85	99.85	0.0015	0.039	0.0014

A. Comparative Analysis

Table VI shows a comparison of the proposed LSTM-CDVAE for Dataset 1 with WTDCNN [24], RF [25], and CNN-LSTM multi-head attention with multiplication skip connection [26]. NA denotes that the values are not available in the corresponding study.

B. Discussion

The proposed LSTM-CDVAE is effective in crop yield prediction and classification due to effectively combining LSTM and CDVAE. Standard scaling and label encoding methods were used to prepare the data so that each value receives the same attention by the model. SMOTE successfully treats unequal data samples to help the model perform better. Dataset 1 includes agricultural data from multiple crops grown across different states in India from 1997 to 2020, consisting of features such as states, crop types, cropping seasons, crop years, areas under cultivation, production quantities, calculated yields, annual rainfall, fertilizer usage, and pesticide usage. Dataset 2 focuses on crops such as Maize, Jowar, and Ragi, providing a detailed analysis of seasonal crops. LSTM captures time-based dependencies, such as how rainfall and fertilizer usage influence crop yield across different years. CDVAE produces higher internal feature representations, improving prediction and classification accuracy. The proposed model utilizes both temporal patterns and hidden structural relationships in the agricultural data. The results demonstrate that LSTM-CDVAE achieved better performance compared to baseline models such as RNN, GRU, and CNN-LSTM, with 99.85% accuracy for Dataset 1 and 98.99% for Dataset 2, along with very low error values. The model consistently followed actual yield trends, demonstrating better generalization ability and avoiding overfitting, as shown in the training-validation curves and actual vs predicted comparisons. These results demonstrate that the model effectively predicts yield levels and classifies crop types, thereby making it suitable for agricultural decision-making.

IV. CONCLUSION

Early and accurate predictions of crop yield are important for labor planning, market pricing, and transport and harvest organization. Accurate crop yield forecasts can be used to determine the best strategies for agricultural management and food supply protection. This study presented the LSTM-CDVAE model to forecast crop yields and classify different types of crops. Using these two models together allows LSTM to capture time series patterns while CDVAE generates better representations to improve prediction. Standard scaling and label encoding normalization with SMOTE data oversampling lead to better classification results during preprocessing. The experiments show that LSTM-CDVAE surpasses conventional DL models, including RNN, GRU, and CNN-LSTM, with better accuracy, 99.85% for Dataset 1 and 98.99% for Dataset 2. These results indicate that the proposed model works well when analyzing farm data of any complexity. This model can deliver accurate crop yield predictions that can help farmers and the industry make better decisions about sustainable farming. In the future, various encoder methods can be applied to further enhance the prediction and classification performance.

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