Confidence-Aware BLSTM with CDLS for Crop Recommendation and Yield Prediction

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***Abstract*—The field of agriculture continues to face challenges in terms of predicting crop yields, which is a critical factor for decision-making at international, regional, and local levels. Crop yield prediction depends on factors such as climatic conditions, soil properties, crop-specific traits and environmental influences. Therefore, selecting the most appropriate crop for maximizing crop yield plays a vital role in improving real-life farming scenarios. In this manuscript, a Class Dependent Label Smoothing-Bayesian Long Short-Term Memory (CDLS-BLSTM) approach is developed for an efficient crop recommendation and yield prediction. The CDLS regularization method is incorporated in the traditional BLSTM technique to prevent the bias and enhance both the recommendation and prediction process. The BLSTM learns distribution across LSTM weights instead of fixed weights and predicts the uncertainties in data. In pre-processing phase, the min-max normalization technique is utilized to scale data into a uniform range of 0 to 1. The developed CDLS-BLSTM acquired an accuracy of 99.78% in Crop Recommendation Dataset (CRD, 2000 samples) dataset and an accuracy of 95.32% in Crop Yield Prediction (CYP, 4000 samples) dataset when compared with conventional algorithms.**

***Keywords*—Bayesian Long Short-Term Memory (BLSTM), class dependent label smoothing, crop recommendation, crop yield prediction and min-max normalization**

I. Introduction

Agriculture is usually considered as the primary occupation among all others since it is the most vital resource of living for humans [1]. India is an agrarian country, wherein half of the workforce is involved in the agricultural occupation, which contributes almost 17%–18% of the Gross Domestic Product (GDP) [2]. Therefore, agriculture has a significant impact on the country's economy as it also contributes towards exports that involve a wide range of stakeholders [3]. Additionally, food security and safety are also very necessary, especially for a widely populated country like India [4]. The United Nations has identified Zero Hunger as one of its sustainable growth goals to ensure a reliable and sustainable future. The main objective of farming is to receive large yield within the specified time to meet the requirements of all stakeholders efficiently [5]. The crop yield prediction in the initial phase enables the farmers to make informed decisions to properly manage their finances and avoid losses [6, 7]. Crop yield prediction is a challenging task because of dependencies on several parameters [8]. The yield of any crop depends on soil attributes, environmental factors, assigned nutrients, and field management. The crop yield attribute is a dependent variable, while other parameters are either independent or interdependent attributes, which makes yield prediction a challenging task [9]. Among the inter-dependent factors, environmental parameters are highly variable but also play a significant role in determining crop yield [10]. The continuous utilization of nutrients, irrigation, and pesticides irrespective of their environmental effects and various arbitral modifications in the developing process causes lesser yield [11]. Machine Learning (ML)-based approach which is a subsection of Artificial Intelligence, concentrates on learning and providing better Crop Yield Prediction (CYP) depending on various characteristics [12]. ML-based approaches define the patterns as well as correlations from the data [13–15]. Various works have employed ML-based approaches to CYP, that includes Regression Tree (RT), Artificial Neural Network (ANN), Random Forest (RF), association rule mining, and multivariate regression [16]. Compared to these approaches, Deep Learning (DL) approaches with numerous hidden layers are more efficient in capturing non-linear relationships among response and input variables. Increasing the number of hidden layers minimizes errors in classification and regression tasks.

Gopi and Karthikeyan [17] suggested a technique for yield prediction and crop recommendation known as the

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Hybrid Moth Flame Optimization along with Machine Learning (HMFO-ML) approach. The suggested approach efficiently recommended crops and predicted the crop yield precisely. It utilized the Probabilistic Neural Network (PNN) to recommend crops and Extreme Learning Machine (ELM) approach to predict crop yield. The HMFO approach helped to maximize the prediction rate of the ELM algorithm. Gopi and Karthikeyan [18] presented a Red Fox Optimization with Ensemble Recurrent Neural Network for Crop Recommendation and Yield Prediction (RFOERNN-CRYP) approach. The algorithm employed ensemble learning and integrated three various DL approaches such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM) to obtain improved prediction performance in comparison with individual classifier algorithms. Additionally, RFO approach was implemented for hyperparameter selection of DL-based approaches for maximizing the entire performance. Talaat [19] introduced the CYP Algorithm (CYPA), utilizing Internet of Things (IoT) algorithms for precisely implementing agriculture. The simulations of crop yield comprehensively simplified the continuous effects of field variables such as nutrient deficits and water issues during respective seasons. The big data encompassed several characteristics across space and time, also supported the comprehensive meteorological analysis and evaluation of plant species traits. The introduced CYPA included factors such as weather, climate, chemical information, and agricultural yield to facilitate crop yield prediction and assisted farmers to develop efficient strategies within their country. Nagesh *et al.* [20] examined different approaches of ML and automatic agricultural yield prediction methods that depended on selecting highly relevant attributes. Grey Level Co-occurrence Matrix (GLCM) approach was utilized for attribute selection, while classification was performed by Decision Tree, AdaBoost, K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) approaches. The utilized data was simplified to compile data related to various topics that included pesticide usage, rainfall, mean temperature and crop yield. Banerjee *et al.* [21] implemented the LSTM-enabled Recurrent Neural Network (RNN) crop prediction approach with DL that mainly relied on weather. Information about the developed method's performance was acquired from Uniform Soybean Tests (UST) which were employed in North America. This implemented method offered better outcomes that led to an effective crop prediction. The existing approaches employed conventional ML-based methods to crop recommendation and crop yield prediction. The conventional ML-based approaches were developed with a particular amount of training data for predicting agricultural yields based on particular criteria. There are several limitations attributed to the gathered data by these conventional ML-based algorithms, as the data was not precise, thus resulted in lower performance.

In this article, the Class Dependent Label Smoothing-Bayesian Long Short-Term Memory (CDLS-BLSTM) model is developed to mitigate challenges in existing crop recommendation and yield prediction algorithms. Conventional algorithms often face challenges such as class imbalance sensitivity, overconfidence in predictions and lack of uncertainty estimation, and factors which are particularly significant while dealing with noisy, imbalanced and context data. To address these challenges, CDLS is introduced to dynamically adjust the target labels based on class frequency, which helps to minimize overfitting for dominant classes and enhance generalization ability on minority crops. The Bayesian LSTM model is applied for prediction process which is particularly important in the prediction of crop yield, where weather fluctuations, soil conditions and regional variations introduce high levels of uncertainty. Additionally, the sequential modeling ability of BLSTM enables it to efficiently extract temporal dependencies in historical crop data, where conventional models fail to exploit. Further, the incorporation of CDLS and BLSTM provides accurate, interpretable, generalization and robustness which are essential for practical deployment in agricultural systems. Existing ensemble and Bayesian RNN-based models majorly focuses on improving prediction accuracy or extracting uncertainty but struggles with imbalance and overconfidence problems which is inherent on agricultural dataset. Ensemble model enhance stability by multiple learners but lacks probabilistic interpretation, when Bayesian RNNs quantifies uncertainty without addressing biased label distributions. The proposed CDLS-Bayesian BLSTM integrates class-dependent label smoothing for balancing class representation with Bayesian inference for uncertainty modeling, which resulted in confidence-aware and balanced model to crop recommendation and yield prediction. The primary contributions of the manuscript are described below.

- CDLS-BLSTM approach is utilized to efficiently crop recommendation and yield prediction.
- CDLS regularization technique is incorporated in traditional BLSTM technique, which prevents the bias and helps to enhance the recommendation and prediction process.
- The BLSTM learns the distribution across LSTM weights rather than fixed weights and predicts the uncertainties in data.

This manuscript is arranged as follows: Section II provides the details of the proposed approach. Section III evaluates the proposed approach's result and compares to existing algorithms. Finally, Section IV presents a summary of the findings of the proposed approach as a conclusion.

II. Proposed Methodology

In this manuscript, a DL-based approach is developed to improve the process to crop recommendation and yield prediction effectively. Crop Recommendation Dataset (CRD) and CYP dataset are used in this article. Then, in the pre-processing phase, min-max normalization technique is utilized to scale data in a uniform range of 0 to 1. Finally, the CDLS-BLSTM algorithm is developed for crop recommendation and crop yield prediction. Fig. 1, describes the process of crop recommendation and yield prediction.

A. Dataset

Dataset used in this manuscript are Crop Recommendation and Crop Yield Prediction dataset that contain data on different crops. The dataset includes various crop samples and crop yield data. The detailed description of dataset is provided below.

1) Crop Recommendation Data (CRD)

This dataset is acquired from the Kaggle repository [22] that includes information on rainfall, fertilizer, and climate. This includes 2000 instances with several classes such as moth beans, rice, apple, coconut, orange, kidney beans, blackgram, banana, chickpea, jute, mungbean, lentils, pomegranate, mango, grapes, pigeon peas, watermelon, maize, papaya, cotton, muskmelon and coffee. This balanced class distribution and comprehensive feature representation make the dataset suitable for training, evaluation and intelligent crop recommendation systems under varying soil and climate conditions.

2) Crop Yield Prediction (CYP) dataset

In this dataset, the yield and pesticides are gathered from Food and Agriculture Organization (FAO) of the United Nations, then rainfall and mean temperature are gathered from World Data Bank [23]. Yield_df.csv is the finalized data of the process that involves data cleaning and integration of yield, rainfall, pesticides, and mean temperature. Fig. 2, represents the feature description of the Crop Yield Prediction dataset.

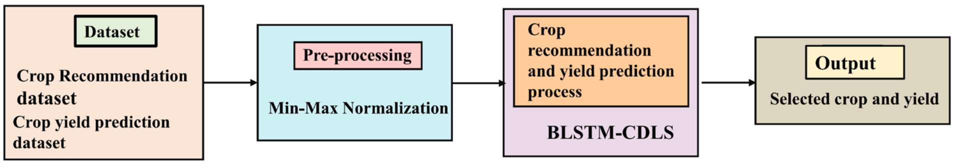

Fig. 1. Process of crop recommendation and yield prediction.

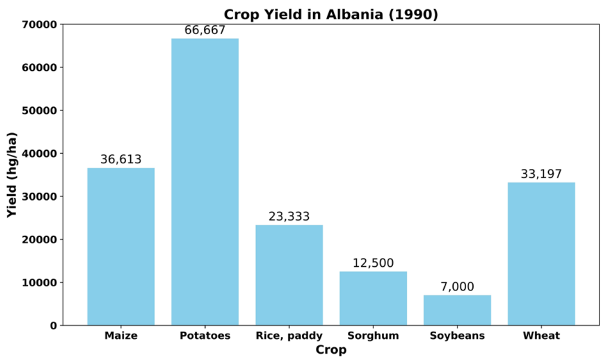

Fig. 2. Feature distribution of crop yield prediction dataset.

B. Pre-processing

The data is provided as the input for pre-processing phase to enhance the performance of the model. Here, min-max normalization technique is utilized to convert the data into numeric values between 0 and 1. This technique relies on defining large and small numerical values of each numerical attribute and transforming accordingly [24]. Mathematical expression for min-max normalization is given in Eq. (1).

$$X^* = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

C. Recommendation and Prediction using Long Short-Term Memory (LSTM)

LSTM learns and extracts the temporal correlations from the pre-processed data using an internal memory unit and a gated mechanism. LSTM mitigates the gradient vanishing issue of standard RNNs as well as avoids the issue of long-term dependencies [25, 26]. LSTM includes memory cell, input, output and forget gates and the mathematical expressions are given in Eqs. (2)–(4).

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \tag{2}$$

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

$$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \tag{4}$$

In the above Eqs. (2)–(4), i_t, f_t and o_t are input, forget and output gates. W_i, W_f and W_o represent the weights. The h_{t-1} represents the result of a memory cell and x_t represents the input. b_i, b_f and b_o represent the bias vectors. The mathematical expression for a memory cell state c_t is given in Eq. (5). In Eq. (5), W_c represents weight, c_{t-1} represents the state of a memory cell and b_c represents the bias vector. The mathematical expression to compute h_t is given as Eq. (6).

$$c_t = f_t \times c_{t-1} + i_t \times \left(tanh\left(W_c \times \left[h_{t-1,x_t}\right] + b_c\right)\right) \tag{5}$$

$$h_t = \sigma_t \times tanh(c_t) \tag{6}$$

1) Bayesian optimization

This concept represents two formats of uncertainty by Bayesian techniques. Initially, an observation noise is captured by aleatoric uncertainty. The Bayesian Optimization (BO) generates predicted distribution instead of using point estimations, such as in DNNs. Hence, it is required to represent whether the confidence level of the model's prediction was high or low. Prediction uncertainty is an integration of epistemic and aleatoric uncertainties which represents the entire uncertainty in prediction together. Fig. 3 represents the architecture of Bayesian LSTM with CDLS.

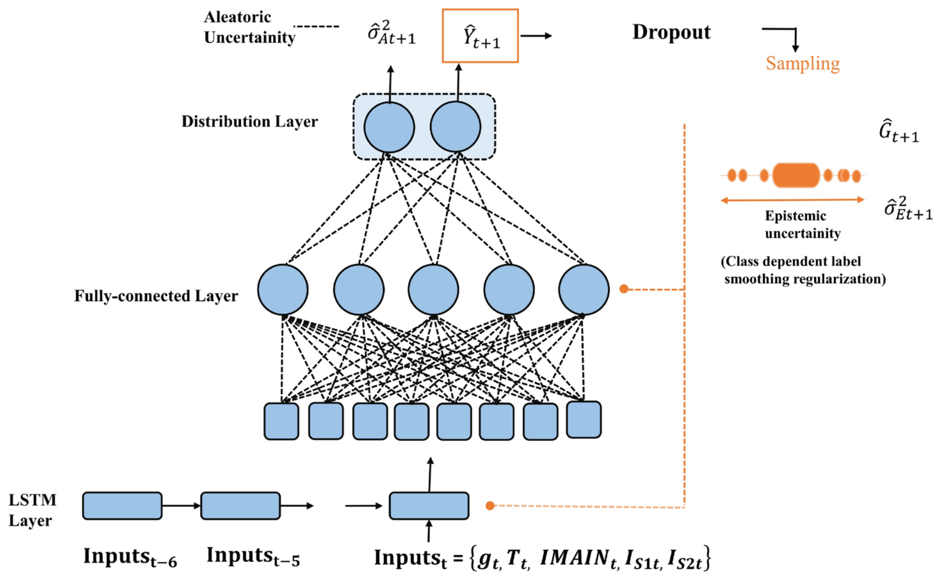

Fig. 3. Architecture of bayesian LSTM with CDLS.

The epistemic uncertainty represents the degree of ambiguity about the model parameters. The aleatoric uncertainty represents the uncertainty that arises from an input data. Additionally, high aleatoric uncertainty represents lack of essential knowledge while evaluating the results in the case of input with a fixed weight because of the inability of the method to capture unseen or latent parameters. The $p(Y|X,w)$ and $p(w)$ represent the method likelihood and past distributions, which are utilized for evaluating likelihood of the method for a parameter $w \in \Omega$ in the training set $\{X,Y\}$. Random variables are considered as method parameters. The posterior and predictive distributions are measured using Eqs. (7) and (8),

$$p(w|X,Y) = \frac{P(Y|X,w)p(w)}{P(X|Y)} \tag{7}$$

$$p(y^*|x^*,\ X,\ Y) = \int p(y^*|x^*,\ w)p(w|X,Y)dw \tag{8}$$

Basic mathematical expressions are utilized to validate random variables associated with uncertainty and to predict the distribution of outcomes for new inputs based on the training set. Because of high execution costs which are associated with integrating the entire parameter area, the uncertainty is not directly measured while executing DL-based algorithms. The mathematical expression for the output distribution is given as Eq. (9). The difference attained from the prediction distribution quantifies uncertainty of the prediction, which is further explained by utilizing the law of total difference as represented in Eq. (10). In Eq. (10), initial values are called as avoidance as per the model's parameters, and the subsequent value is inherent noise.

$$p(y^*|x^*,\ D) \approx \frac{1}{k}\sum_{k=1}^{K}\ p(y^*|x^*,\ w^K) \tag{9}$$

$$Var(y^*|x^*) = Var[E(y^*|W,x^*)] + E[Var(y^*|W,x^*)] \tag{10}$$

2) Class Dependent Label Smoothing (CDLS)

CDLS is an enhanced version of label smoothing that adjusts the confidence level of the model per class, while enabling more effective handling of class imbalance. In the recommendation process, certain crops are recommended more frequently, which causes bias in the prediction process. Though various crops have varied yield uncertainties, CDLS ensures good generalization. Mathematical expression for CDLS is given as Eq. (11). In Eq. (11), the α_c represents a class-dependent smoothing factor that is adjusted per crop, the y_{true} represents the actual label, and the u represents uniform distribution across all classes. Mathematical expression for adjusting α_c is given as Eq. (12).

$$y_{smooth} = (1-\alpha_c)\cdot y_{true} + \alpha_c \cdot u \tag{11}$$

$$\alpha_c = \frac{1}{log(1+N_c)} \tag{12}$$

In Eq. (12), the N_c represents the number of instances in class c. In proposed model, CDLS plays an essential role through dynamically adjusting the label confidence for each crop class which was depended on their occurrence frequency. Instead of employing fixed one-hot labels, CDLS redistributes a portion of confidence from dominant classes to minority one by class-dependent smoothing factor. This mechanism minimizes overfitting to frequently occurring crops and enhances model's generalization for underrepresented classes. When integrated with BLSTM, CDLS ensures that model learns balanced feature representations and leads to much stable gradient updates and enhanced convergence in training, while improving crop recommendation accuracy and yield prediction reliability. Larger smoothing is applied for rare classes, which led to low confidence in the model to prevent overfitting. The frequent classes undergo lesser smoothing, while allowing for high confidence in the model. The proposed CDLS-BLSTM model incorporates CDLS with a BLSTM network to process accurate and reliable crop recommendations and yield prediction. The CDLS algorithm dynamically adjusts the label distribution depending on class frequency, thereby minimizing bias towards majority classes and improving the generalization ability for underrepresented crops. The BLSTM extracts long-range temporal dependencies in agricultural data while including Bayesian inference to estimate predictive uncertainty. This integration allows the model to provide high accurate predictions and confidence-aware results. The below Algorithm 1 represents the process of CDLS-BLSTM for crop recommendation and yield prediction.

Algorithm 1: CDLS-BLSTM for crop recommendation and yield prediction

Input – Dataset with features and labels, Number of classes, smoothing factor, number of epochs, learning rate.
Output – Predicted crop type or yield value with uncertainty estimate.

Data pre-processing
    Normalize input features
    Split dataset to training, validation and test sets
    Apply one-hot encoding to class labels
Apply Class-Dependent Label Smoothing
For every class
    Measure class frequency f_c
    Determine smoothing factor
\varepsilon_c=\sfrac{\varepsilon}{f_c}
    Modify target label y_i using:
y_{i_{smoothed}}=\left(1-\varepsilon_c\right)\times y_i+\sfrac{\varepsilon_c}{C}
Define Bayesian LSTM architecture
    Input layer gets time-sequence features
    BLSTM layer with probabilistic weights
    Dropout or variational inference for uncertainty
    Dense output layer with:
        Softmax activation for classification
        Liner activation for regression (yield)
Model training
    For epoch = 1 to E do:
        For each batch B in training set
            Forward pass through BLSTM
            Compute loss (KL-divergence + Cross-entropy)
            Backpropagate and update weights using Adam optimizer
Inference
For every test instance x
    Run T stochastic forward passes
    Collect T predictions
    Compute mean prediction
    Estimate uncertainty = variance
Output
    Final predicted class
    Predictive uncertainty for confidence estimation

III. Experimental Analysis

The performance of the developed CDLS-LSTM model is simulated in Python 3.7 environment and system configurations are i5 processor, 8GB RAM and Windows 10 (64-bit). The considered evaluated measures to validate the performance of the CDLS-LSTM approach are accuracy, F1-Score, recall, precision, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of determination (R^2). The developed CDLS-BLSTM model is nonlinear time series model, the R^2 is utilized as auxiliary reference indicator. The primary evaluation metrics are RMSE and MAE, that reflects the prediction error for time-dependent data. Mathematical expressions of these evaluation measures are given from Eqs. (13)–(20).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

$$Recall = \frac{TP}{TP+FN} \tag{15}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{16}$$

$$R^2 = \left[\frac{\sum(o_i-\bar{o})(y_i-\bar{y})}{\sqrt{\sum(o_i-o)^2(y_i-y)^2}}\right]^2 \tag{17}$$

$$MAE = \frac{\sum_{i=1}^{N}|y_i-x_i|}{n} \tag{18}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n} \ (A-B)^2 \tag{19}$$

$$RMSE = \sqrt{MSE} \tag{20}$$

A. Quantitative Analysis

To ensure fair evaluation and prevent overfitting, CRD and CYP dataset are divided using 70:15:15 ratio for training, validation and testing. The Experiments are conducted by 5-fold stratified cross-validation, which maintains proportional class distribution across folds. Moreover, early stopping, dropout regularization and Bayesian inference layers are employed to control overfitting and capture uncertainty in predictions. The consistent outcomes across all folds shows the model’s stability and generalization ability for moderate dataset size. In Tables I–III, the performance of CDLS-BLSTM is shown for different crops like ragi, jowar and maize, respectively. These different crops are taken for evaluation from existing research [21]. In Table I, the performance of

CDLS-BLSTM is evaluated on ragi crop with different metrics of accuracy, precision, recall, F1-Score, RMSE, MAE and R^2. The developed CDLS-BLSTM acquired 94.52% accuracy, 94.12% precision, 93.77% recall, 93.94% F1-Score, 68.32 R^2, 85.17 RMSE and 29.05 MAE on ragi crop.

In Table II, the performance of CDLS-BLSTM is evaluated on jowar crop with different metrics of accuracy, precision, recall, F1-Score, RMSE, MAE and R^2. The developed CDLS-BLSTM acquired 95.73% accuracy, 95.25% precision, 95.02% recall, 95.13% F1-Score, 77.65 R^2, 93.65 RMSE and 32.89 MAE on jowar crop. The proposed CDLS-BLSTM model incorporates CDLS with a BLSTM network to process accurate and reliable crop recommendations and yield prediction. The CDLS algorithm dynamically adjusts the label distribution depending on class frequency, while minimizing bias toward majority classes and improving generalization ability of the model for underrepresented crops. The BLSTM extracts long-range temporal dependencies in agricultural data while including Bayesian inference to estimate predictive uncertainty. This integration allows the model to provide high accurate predictions and confidence-aware results.

TABLE I. PERFORMANCE OF CDLS-BLSTM ON RAGI CROP

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
MLP	91.03	90.68	90.05	90.36	83.42	92.40	39.42
RNN	91.75	91.28	90.31	90.79	81.39	90.31	37.80
LSTM	92.80	92.36	92.18	92.26	77.65	88.29	34.52
GNN	93.71	93.25	93.04	93.14	72.39	87.65	32.49
CDLS-BLSTM	94.52	94.12	93.77	93.94	68.32	85.17	29.05

TABLE II. PERFORMANCE OF CDLS-BLSTM ON JOWAR CROP

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
MLP	85.58	82.79	80.17	81.45	90.49	159.03	44.59
RNN	88.79	85.21	83.27	84.22	87.54	138.71	40.21
LSTM	90.27	88.48	86.54	87.49	84.32	102.68	39.03
GNN	92.15	90.77	89.72	90.24	79.04	97.82	36.81
CDLS-BLSTM	95.73	95.25	95.02	95.13	77.65	93.65	32.89

In Table III, performance of CDLS-BLSTM is evaluated on maize crop with different metrics of accuracy, precision, recall, F1-Score, RMSE, MAE and R^2. The developed CDLS-BLSTM acquired 96.74% accuracy, 96.18% precision, 95.83% recall, 96.00% F1-Score, 85.62 R^2, 109.52 RMSE and 35.67 MAE on maize crop. In Table IV, the performance of CDLS-BLSTM is evaluated on CRD with different metrics of accuracy, precision, recall, F1-Score, RMSE, MAE and R^2. The developed CDLS-BLSTM acquired 99.78% accuracy, 98.32% precision, 97.76% recall, 98.03% F1-Score, 95.23 R^2, 118.08 RMSE and 21.47 MAE on the CRD dataset.

TABLE III. PERFORMANCE OF CDLS-BLSTM ON MAIZE CROP

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
MLP	94.93	94.76	94.35	94.55	103.41	161.29	53.74
RNN	95.41	95.17	94.78	94.97	97.62	147.82	49.32
LSTM	95.82	95.56	95.07	95.31	93.47	135.69	44.98
GNN	96.16	96.07	95.52	95.79	89.04	117.03	39.21
CDLS-BLSTM	96.74	96.18	95.83	96.00	85.62	109.52	35.67

TABLE IV. PERFORMANCE OF CDLS-BLSTM ON CRD DATASET

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
MLP	95.03	94.83	94.21	94.51	193.75	206.77	41.38
RNN	95.73	95.46	95.17	95.31	176.92	184.76	36.72
LSTM	96.38	96.04	95.78	95.90	135.79	168.03	30.87
GNN	97.63	97.25	97.04	97.14	114.56	136.62	24.53
AgriTransformer	98.15	97.68	97.23	97.03	105.21	128.09	23.41
VITA	98.88	98.03	97.42	97.21	99.03	123.15	22.78
CDLS-BLSTM	99.78	98.32	97.76	98.03	95.23	118.08	21.47

In Table V, performance of CDLS-BLSTM is evaluated on CYP with different metrics of accuracy, precision, recall, F1-Score, RMSE, MAE and R^2. The developed CDLS-BLSTM acquired 95.32% accuracy, 94.15% precision, 93.79% recall, 93.96% F1-Score, 93.52 R^2, 98.76 RMSE and 15.90 MAE on the CYP dataset. The proposed CDLS-BLSTM model integrates CDLS with a BLSTM network to process accurate and reliable crop recommendations and yield predictions. The CDLS algorithm dynamically adjusts the label distribution depending on class frequency, thereby minimizing bias towards majority classes and improving generalization ability for underrepresented crops. The BLSTM extracts long-range temporal dependencies in agricultural data while including Bayesian inference to estimate predictive uncertainty. This integration allows the model to provide high accurate predictions and confidence-aware results.

Table VI presents the K-fold cross-validation results for the proposed CDLS-BLSTM model which is utilized for crop recommendation and yield prediction. From Table VI, model shows high performance of variance in crop yield predictions. These results validate the consistency and robustness of the model, thereby representing its effectiveness for agricultural decision-making.

TABLE V. PERFORMANCE OF CDLS-BLSTM ON CYP DATASET

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
MLP	94.33	94.05	93.87	93.95	96.72	173.47	18.40
RNN	94.79	94.37	94.05	94.20	95.93	166.32	17.95
LSTM	95.03	94.88	94.38	94.62	95.24	146.79	17.24
GNN	95.47	95.18	93.26	94.21	94.77	103.46	16.82
AgriTransformer	95.41	93.98	93.22	93.78	93.02	101.25	16.32
VITA	95.39	94.03	93.31	93.75	93.27	99.82	16.09
CDLS-BLSTM	95.32	94.15	93.79	93.96	93.52	98.76	15.90

TABLE VI. K-FOLD CROSS-VALIDATION RESULTS FOR CDLS-BLSTM MODEL ON THE CROP YIELD PREDICTION PROCESS

K-fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE	MAE	R^2 Score
K = 1	95.12	94.10	93.85	93.96	99.45	16.10	93.10
K = 2	95.46	94.28	93.91	94.09	98.92	15.87	93.42
K = 3	95.33	94.30	93.68	93.99	98.74	15.91	93.52
K = 4	95.51	94.31	93.74	94.02	98.62	15.79	93.61
K = 5	95.32	93.96	93.66	93.81	98.97	15.83	93.41
Mean	95.32	94.15	93.79	93.96	98.76	15.90	93.52
SD	0.15	0.14	0.09	0.09	0.31	0.12	0.19

The below Table VII, represents the comparative results of the proposed CDLS-BLSTM method that outperformed various uncertainty-handling models in crop yield prediction. MC-Dropout LSTM and Variational GRU determines reliable uncertainty modelling and shows less accuracy because of their limited ability to balance class distributions. Bayesian LSTM without CDLS enhances predictive stability through learning probabilistic weight distributions, while still suffering from biased label confidence across dominant crop classes. By integrating CDLS with Bayesian inference, the proposed CDLS-BLSTM obtains superior performance and less RMSE and MAE. This enhancement shows the effectiveness of CDLS in minimizing the overconfidence on frequent classes and improving generalization across imbalanced dataset. When Bayesian modeling ensures better uncertainty quantification. These mechanisms ensure the CDLS-BLSTM provides more confident, accurate and robust yield predictions under varying environmental and data uncertainty conditions.

TABLE VII. PERFORMANCE OF PROPOSED CDLS-BLSTM WITH DIFFERENT UNCERTAINTY-HANDLING MODELS

Methods	Uncertainty handling Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	RMSE	MAE
MC-Dropout LSTM	Monte Carlo sampling by dropout at inference	93.86	93.27	92.84	93.05	112.45	18.94
Variational GRU	Variational inference using probabilistic weights	94.21	93.58	93.11	93.34	105.62	17.43
Bayesian LSTM (without CDLS)	Bayesian inference with fixed label targets	94.67	93.89	93.42	93.65	101.73	16.74
Proposed CDLS-BLSTM	Class-dependent label smoothing + Bayesian uncertainty modeling	95.32	94.15	93.79	93.96	98.76	15.90

TABLE VIII. UNCERTAINTY CALIBRATION PERFORMANCE OF DIFFERENT METHODS

Methods	Prediction Interval Coverage Probability (PICP) (%)	NMPD (%)	Expected Calibration Error (ECE)	Sharpness (σ^2)
Bayesian LSTM	92.8	95	0.051	0.243
MC-Dropout LSTM	93.4	95	0.045	0.218
Proposed CDLS- BLSTM	94.7	95	0.036	0.192

TABLE IX. STATISTICAL PERFORMANCE OF PROPOSED MODEL WITH EXISTING MODELS

Methods	Accuracy (Mean ± SD)	F1-Score (Mean ± SD)	RMSE (Mean ± SD)
MLP	91.23 ± 0.48	90.75 ± 0.44	128.32 ± 3.45
RNN	92.45 ± 0.36	91.90 ± 0.29	121.16 ± 3.12
LSTM	94.12 ± 0.27	93.41 ± 0.23	108.52 ± 2.71
GNN	94.86 ± 0.31	94.02 ± 0.25	103.48 ± 2.39
Proposed CDLS-BLSTM	95.32 ± 0.21	94.15 ± 0.18	98.76 ± 1.92

The below Table VIII represents the uncertainty calibration performance of various methods by Prediction Interval Coverage Probability (PICP), Normalized Mean Prediction Deviation (NMPD), Expected Calibration Error (ECE) and Sharpness (σ^2). The proposed CDLS-BLSTM obtains high PICP, which represents the superior reliability in capturing actual target values in its predictive intervals, while maintaining consistent NMPD that shows unbiased mean deviation. Additionally, it obtains less ECE and sharpness which shows well-calibrated confidence estimates and tighter predictive intervals. These results show that including CDLS improves confidence calibration through minimizing overfitting and enhancing the label balance when Bayesian uncertainty modeling ensures precise interval estimation. The CDLS-BLSTM determines more reliable, confident and sharper uncertainty predictions while comparing with Bayesian and MC-Dropout LSTM models, makes its suitable for uncertainty-aware agricultural decision-making.

The below Table IX represents the statistical performance of different models in terms of mean accuracy, F1-Score and RMSE with its respective standard deviations. The proposed CDLS-BLSTM method outperformed the baseline models, while obtaining high accuracy and F1-Score with less RMSE which represents superior predictive accuracy, high stability and consistency across multiple runs. The CDLS-BLSTM efficiently integrates CDLS to balance label confidence and Bayesian inference for model uncertainty that resulted in better generalization and robustness. The minimized standard deviations show model's reliability and consistent convergence, thereby determining its effectiveness for precise and uncertainty-aware crop yield prediction.

TABLE X. STATISTICAL ANALYSIS AND COMPUTATIONAL ANALYSIS FOR THE PROPOSED CDLS-BLSTM MODEL

Metrics	Values
Mean accuracy	95.32%
Confidence interval	[95.14, 95.50]
Standard deviation	0.15
p-value from t-test	0.003
Training time	160 s
Inference time per instance	50 s
Memory usage	254 MB

B. Statistical and Computational Analysis

Table X represents the statistical and computational performance analysis of the proposed CDLS-BLSTM for crop recommendation and yield prediction. From Table X, the model performed well and shows its accuracy, reliability and practicality for agricultural usage. The statistical measures and computational measures such as mean accuracy, confidence interval, standard deviation, confidence interval, *p*-value, training time, inference time per instance and memory usages are analyzed. A paired t-test is performed on accuracy scores to evaluate statistical significance of CDLS-BLSTM model's improvement. The obtained *p*-values shows that the performance differences are statistically significant. This shows that the superior accuracy and minimized RMSE obtained by proposed CDLS-BLSTM model are because of random variation but resulted from efficient integration of class dependent label smoothing and Bayesian uncertainty modeling. The below Table XI represents the computational analysis of the proposed model with existing models.

TABLE XI. COMPUTATIONAL ANALYSIS OF PROPOSED METHDO USING INFERENCE AND TRAINING TIME

Methods	Inference time (s)	Training time (s)
MLP	105	258
RNN	89	227
LSTM	73	204
GNN	65	189
Proposed CDLS-BLSTM	50	160

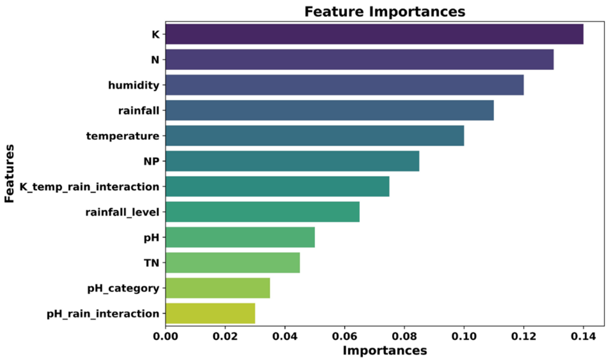

Fig. 4. Visualization of feature importance.

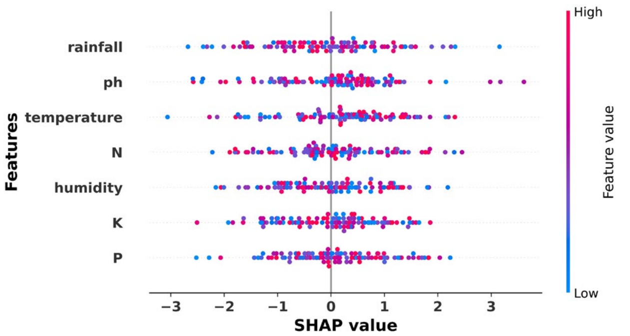

Fig. 5. Visualization SHAP interpretability.

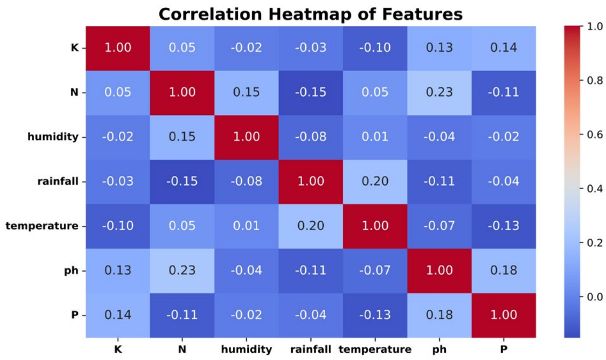

Fig. 6. Visualization of correlation heatmap.

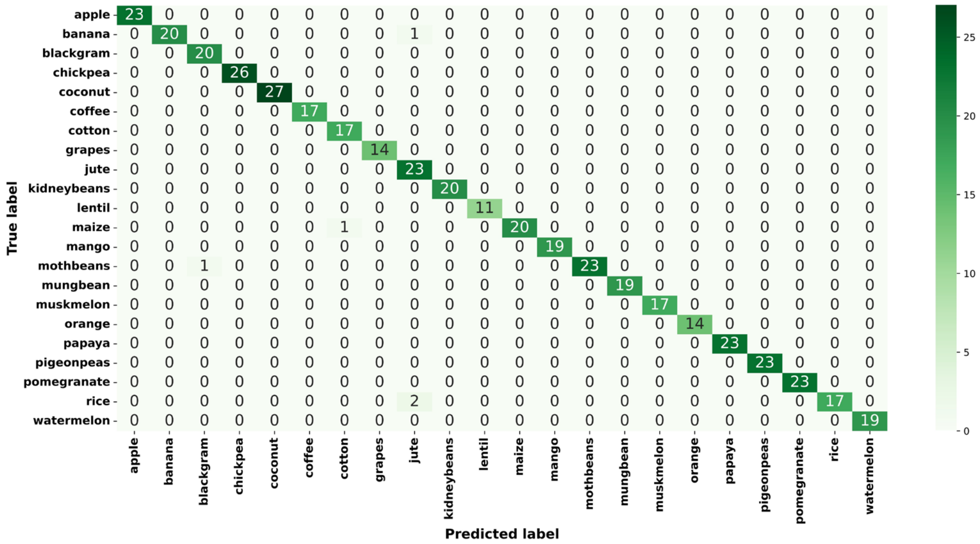

Fig. 7. Confusion matrix for proposed CDLS-BLSTM.

C. *Qualitative Analysis*

Figs. 4–7 represents the feature relevance and interdependencies that influence crop recommendation and yield prediction. The feature importance which is represented in Fig. 4 highlights the soil nutrients (N, P, K), humidity and rainfall are much influential parameters for prediction accuracy. SHAP representation represented in Fig. 5 explains individual feature contributions, where higher values of N, P and K positively affect the model output. A correlation heatmap that is represented in Fig. 6 shows strong positive correlations between nutrient variables and moderate associations between temperature, humidity and rainfall represents environmental interdependence. Finally, confusion matrix represented in Fig. 7 shows consistent feature relationships, validates integrity of dataset and robustness of proposed CDLS-BLSTM method.

D. *Comparative Analysis*

In this section, the performance of CDLS-BLSTM approach is compared with existing algorithms such as HMFO-ML [17], RFOERNN-CYRP [18], CYPA [19] and KNN GLCM [20] on CRD and CYP dataset. The developed CDLS-BLSTM acquired accuracy of 99.78% on the CRD dataset and accuracy of 95.32% on the CYP dataset when compared with existing algorithms. The proposed CDLS-BLSTM model can efficiently address the limitations of conventional crop recommendation and yield prediction algorithms, particularly in handling class imbalance, temporal dependencies and uncertainty. By incorporating CDLS, the proposed model minimizes bias towards frequently occurring classes and improves generalization ability for underrepresented crops. The Bayesian LSTM enables sequential learning while capturing predictive uncertainty that is essential in agriculture because of the noisy and variable nature of input data.

This integration causes enhanced accuracy, robustness and reliability, while making the CDLS-BLSTM more suitable and effective model for agricultural decision-making. Table XII represents the comparative analysis of the developed CDLS-BLSTM.

TABLE XII. COMPARATIVE ANALYSIS OF DEVELOPED CDLS-BLSTM

Dataset	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	R^2	RMSE	MAE
CRD	HMFO-ML [17]	99.67	96.43	96.39	96.40	98.82	NA	NA
	RFOERNN-CYRP [18]	98.45	98.51	98.45	98.46	NA	NA	NA
	Proposed CDLS-BLSTM	99.78	98.32	97.76	98.03	95.23	118.08	21.47
CYP	CYPA [19]	NA	NA	NA	NA	NA	132.01	34.79
	KNN GLCM [20]	84	88	89	86	NA	NA	NA
	Proposed CDLS-BLSTM	95.32	94.15	93.79	93.96	93.52	98.76	15.90

E. *Discussion*

The experimental outcomes of the proposed CDLS-BLSTM model determine the effective advancements in prediction accuracy and model reliability when compared with existing algorithms. The incorporation of CDLS efficiently addressed the challenges of class imbalance that were generally identified. By adjusting the label targets according to class frequency, the proposed model prevented the overconfidence in dominant crop classes and enhanced generalization across all classes which represented consistent high-performance metrics across all cross-validation folds and high reliability. The utilization of BLSTM introduced the essential advantages through quantifying uncertainty in predictions, where the input variability was high because of seasonal, regional and environmental factors. Unlike conventional LSTM models, the BLSTM model extracted temporal relationships in historical crop and weather data while providing confidence estimates, thereby enabling much informed and risk-aware decision-making. The lower RMSE and higher R^2 score showed model effectiveness in handling the continuous yield prediction process. Statistical analysis shows that the model's enhancement is statistically significant. Moreover, the model is computationally effective with reasonable training, inference time, and less memory consumption, while making it more suitable for agricultural applications. The CDLS-BLSTM model provides a robust, scalable and interpretable solution for intelligent crop recommendation and yield prediction. The CDLS-BLSTM model determine strong generalization ability which provides consistent performance across multiple validation folds with minimal variation in accuracy. The incorporation of CDLS mitigates overfitting by preventing overconfidence in dominant classes, when a Bayesian LSTM network introduced uncertainty modeling that adapted well to unseen and variable data patterns. This enables the model to maintain high prediction accuracy even on underrepresented crops and different environmental conditions, thereby confirming its robustness and adaptability for agricultural scenarios. The proposed CDLS-BLSTM model determines superior predictive accuracy, stability and confidence calibration when comparing with traditional models. Its improved performance is because of integration of class-dependent label smoothing that overcomes class imbalance through adjusting label confidence and Bayesian inference that model's uncertainty in time-dependent agricultural data. This ensures balanced generalization and robust prediction across different crops through RMSE and MAE values and statistically significant. The model act as a reliable decision- support model for farmers through enabling accurate crop selection, yield forecasting and resource optimization under varying climatic and soil conditions.

F. Discussion and Implications

This manuscript introduced a robust DL framework that directly addressed the essential challenges in agricultural prediction systems such as class imbalance, uncertainty estimation and temporal data variability. By integrating CDLS with Bayesian LSTM, the proposed model enhanced predictive accuracy and improved decision confidence. The method has significant potential for precise agriculture, while enabling smarter crop selection and more reliable yield prediction. It also supported the development of data-driven decision support systems which adapted to dynamic environmental conditions, thereby enhancing resource utilization, boosting farm productivity and promoting sustainable agricultural practices. The proposed CDLS-BLSTM model acts as a decision-support tool for farmers and policymakers through providing confidence-aware predictions for crop selection and yield estimation. Farmers utilize model's recommendation to select optimum crop varieties that are suitable for soil and climatic conditions, when quantified uncertainty supports assess risk before cultivation. Policymakers and agricultural agencies employed model for regional yield forecasting, resource allocation and developing targeted irrigation strategies that depended on reliable predictive insights.

IV. Conclusion

Selecting the appropriate crop for achieving maximum yield is a critical factor to attain maximum benefits in real-life farming scenarios. In this manuscript, the developed CDLS-BLSTM approach is implemented for efficient crop recommendation and yield prediction. The dataset utilized in this manuscript include a crop recommendation and a yield prediction dataset, each covering different crops. CDLS regularization technique is incorporated in the traditional BLSTM technique, which prevents the bias and helps to enhance the recommendation and prediction process. The BLSTM learns the distribution across LSTM weights instead of fixed weights and predicts the uncertainties in data. In the pre-processing phase, the min-max normalization technique is utilized to scale data into a uniform range of 0 to 1. The developed CDLS-BLSTM acquired accuracy of 99.78% on the CRD dataset and 95.32% on the CYP dataset when compared with conventional algorithms. Although proposed CDLS-BLSTM determines strong predictive accuracy and confidence calibration, it is limited by moderate size of dataset and absence of various regional and seasonal variations. The model's performance further validated by larger, multi-regional dataset and additional uncertainty-aware architectures such as transformer-based models. In future work, the proposed model will be improved by incorporating multi-model data like weather and satellite imagery to enhance prediction accuracy. Integrating attention mechanisms highlights the essential temporal features affecting crop yield. Moreover, employing federated learning will enable decentralized, privacy-preserving model training. By utilizing larger and more different dataset cover multiple regions and crop varieties. This enables broad model variation under various climatic and soil conditions, thereby enhancing scalability and reliability for real-world agricultural decision support.

Code Availability Statement

The source code developed for the proposed CDLS-BLSTM model will be made publicly available as open-source on GitHub within three months after the paper's publication, following completion of code optimization.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

NGR conceived the idea, designed the methodology, and prepared the initial draft of the manuscript; KGR contributed to data analysis, interpretation of results, and refinement of the research framework; RML provided critical revisions, technical guidance, and overall supervision of the work; all authors had approved the final version.

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