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CropNet-XAI: An Explainable 1D-CNN Framework for Transparent Crop Yield Prediction

Abdullah Al Mahmud Joy*, Md. Faizer Islam†, Md. Sunzid Islam‡, Shakil Ahmed§, Mirza Niaz Morshed¶, Humayra Ahmed‖
Department of Computer Science and Engineering
Bangladesh University of Business and Technology, Dhaka, Bangladesh
abdullahalmahmudjoy39@gmail.com*, faizarislam@gmail.com†, ebnajobaersunzid@gmail.com‡, shakilahmed191191@gmail.com§, niazmorshed4222@gmail.com¶, humayraahmed833@gmail.com‖

***Abstract*—One predictor of food security and sustainable agriculture is crop yields. Nevertheless, despite their accuracy, traditional machine learning techniques frequently lack transparency, which restricts their uptake by non-expert stakeholders. This paper presents XAI-Yield, an interpretable deep learning framework that combines a one-dimensional convolutional neural network (1D-CNN, also known as CropNet) with Explainable Artificial Intelligence (XAI) processes (SHAP, LIME). For performance comparison, several models were benchmarked, including deep CNN architectures (VGG16 and VGG19), RF, DT, XGBoost, and SVM. CropNet outperformed conventional machine learning techniques by up to 18.2%, achieving the highest test accuracy of 93.46%. The strongest positive yield predictors were *Fertilizer_Used_True* (0.2074) and *Rainfall_mm* (0.1946), while *Irrigation_Used_True* (-0.1649) had the opposite effect.XAI Yield connects data-driven modeling with real-world agricultural decision-making by combining high predictive accuracy with transparent interpretability to provide farmers and policymakers with actionable insights.**

Keywords: CropNet, Crop yield prediction, Explainable AI, 1D-CNN, SHAP, LIME, Agricultural analytics

I. Introduction

Agriculture is essential to preserving economic stability and guaranteeing global food security in developing nations like Bangladesh, where crop productivity directly affects livelihoods[1]. For efficient agricultural planning, resource allocation, and well-informed policy formulation, accurate crop yield forecasts are essential[2].However, it is frequently challenging to capture complex nonlinear relationships between environmental, soil, and management variables using traditional statistical methods[3].

Fine predictive power in agriculture has been demonstrated by recent developments in deep learning (DL) and machine learning (ML). Notwithstanding their achievements, these models' ambiguity restricts their interpretability and erodes confidence between farmers and decision-makers. This study suggests the interpretable CropNet crop yield forecasting framework as a solution to this problem[4], which integrates interpretable artificial intelligence (XAI) techniques using a one-dimensional convolutional neural network (1D-CNN), particularly SHapley Additive exPlanations (SHAP) and Local Interpretable Model Agnostic Explanations (LIME).

The suggested CropNet-XAI framework aims to attain both high predictive accuracy and model clarity by calculating the contribution of each feature to model prediction. Clarity analysis, model development, data pre-processing, and performance evaluation were all part of the systematic methodology employed in this study.

To sum up, this study had three primary objectives.

- Developing a high-performance crop yield prediction using a deep learning model.
- Enhancing interpretability for both local and global interpretation through the use of SHAP and LIME analysis.
- The practical acuity offered by this research supports data-driven and sustainable agricultural decision-making.

By achieving these objectives, CropNet-XAI increases the trust and adoption of AI in agricultural systems by reducing the gap between predictive performance and utility.

This paper is formatted as follows: Section II Crop yield backdrop study. Our data set, preprocessing procedures, and model architectures are all covered in Section III. Quantitative results, confusion matrices, and SHAPE and LIME visualizations are shown in Section IV. Section V concludes by going over the implications, restrictions, and potential avenues for further research.

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II. Related Works

Because of their potential to boost particular agricultural practices and enhance food security, crop yield forecasting and agricultural decision support systems have garnered a lot of attention. In recent years, numerous studies have used DL and ML models to forecast crop productivity based on management, soil, and environmental boundaries.

Mohan et al. [5] introduced an AI–XAI-integrated precision agriculture framework, resulting in an R^2 of 0.92, exhibiting that the pooling of deep learning and interpretability increases predictive confidence and precision. Similarly, Badshah et al. [6] linked several ML models using hyperparameter tuning and K-fold validation, where the Support Vector Regressor (SVR) outperformed the others with 99.9% accuracy. Malashin et al. [7] proposed a deep neural network optimized by genetic algorithms,resulting in an R^2 of 0.92, confirming the strong generalization ability of optimized DNN architectures.

Shams et al. [8] survey explainable crop recommendation method, achieving a minimum MSE of 0.94 and an MAE of 0.98, further strengthening the value of XAI in agricultural decision-making. Abekoon et al. [9] applied SHAP and LIME to soil nutrient prediction, reaching an R^2 of 0.97, demonstrating the efficacy of interpretable ML in soil management. Chandra et al. [10] used XAI for soil fertility analysis, achieving 97.02% accuracy, while Hasan [11] demonstrated an XAI-CROP model that achieved high accuracy with an R^2 of 0.94 and low error metrics, establishing the growing relevance of XAI in agricultural analysis. As regards disease classification, Nigar et al. [12] proposed an explainable deep learning system that accurately identified 38 plant diseases with 99.69% accuracy, further demonstrating the potency of XAI in plant science. In parallel, Kumar et al. [13] achieved $R^2 = 0.90$ by combining SVM and ensemble learning on multispectral UAV data, which reflects the advantage of ensemble methods in yield prediction.

Recent advancements have focused on architectural optimization and interpretability. Jovanovic et al. [14] evaluated metaheuristic-tuned weight-agnostic neural networks, achieving an MAE of 0.0177 and R^2 of 0.88, demonstrating efficient lightweight models for forecasting. Talaat [15] applied IoT-driven yield prediction models, where tree-based regressors like DecisionTreeRegressor and RandomForestRegressor achieved scores up to 0.99, validating the robustness of ensemble methods. Gupta et al. [16] also highlighted SVM (94%) as the best-performing model among traditional ML algorithms, followed by KNN and Random Forest. Hybrid and simulation-based frameworks have also been proposed. Elbasi et al. [17] reported 99.59% accuracy using Bayes Net algorithms, while BanuPriya et al. [18] achieved $R^2 = 0.88$ through Random Forest Regression. Kuradusenge et al. [19] reported $R^2 = 0.875$ for potato and 0.817 for maize using Random Forest, and Shuaibu et al. [20] found Decision Tree Regressor to perform best with 72% accuracy. Oikonomidis et al. [21] created a CNN-DNN hybrid model, achieving $R^2 = 0.87$ and RMSE = 0.266, illustrating the potential of deep hybrid architectures in agricultural forecasting.

Most current models prioritize accuracy over interpretability, which restricts their usefulness in agriculture despite tremendous advancements. Instead of being used in full predictive frameworks, current XAI methods, like LIME and SHAP, are frequently applied in isolation. To achieve high predictive accuracy and transparent, interpretable insights for sustainable crop management, this study suggests XAI-Yield, a unified framework that combines a lightweight 1D-CNN (CropNet) with dual explainability techniques (SHAP and LIME).

III. Methodology

A. Methodology Architecture

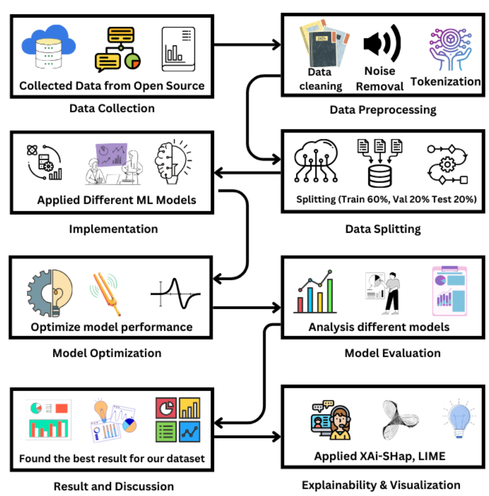

Fig. 1. Workflow of the speculated forecast for crop yield framework

The complete process (Fig. 1) of the suggested XAI-Yield framework. Information was acquired. From openly accessible sources and previously processed us-cleaning, noise reduction, and tokenization. Following creating subsets of the dataset for validation, testing, and training, the model was put into practice, refined, and assessed to ascertain which model performed the best. Lastly, result visualisation and explainability were accomplished through the use of the SHAP and LIME methodologies.

B. Dataset Analysis

The dataset used in this investigation comprised one million records pertaining to various crop types and their corresponding yield results. It was created to facilitate classification-based crop yield prediction by Samuel Oti Attakorah was derived from the open-access Kaggle dataset [22]. Environmental and management factors affecting agricultural productivity were captured in each record. Region, crop category, soil type, annual precipitation, average temperature, fertilizer type, irrigation method, weather conditions, and days to harvest after planting were among the important characteristics. The dataset is ideal for creating and assessing machine learning models in the fields of precision agriculture and yield classification because of the dependent variable `Is_High_Yield` (0 = low yield, 1 = high yield).

C. Data Preprocessing

To guarantee data quality, consistency, and suitability for deep learning, a thorough preprocessing pipeline was put in place. In order to handle missing values, the mode for categorical features and the median for numerical features were imputed. Outliers were detected and removed using the Interquartile Range (IQR) method with the standard $1.5 \times \mathrm{IQR}$ threshold to prevent distortion of model learning.

All categorical variables (*Region*, *Soil_Type*, *Crop*, and *Weather_Condition*) were transformed using one-hot encoding, whereas binary variables (*Fertilizer_Used* and *Irrigation_Used*) were encoded as 0/1. Numerical features, including annual rainfall (mm), average temperature (°C), and days to harvest, were adjusted using min–max scaling to fit the range [0, 1] to ensure equal feature contribution and faster convergence during training.

As well, to increase computational efficiency, low-variance and highly correlated superfluous features were eliminated using correlation analysis and variance thresholding.

D. Model Selection

DT, RF, LR, XGBoost, SVM, VGG16, VGG19, and the suggested CropNet (1D-CNN) were the eight models that were assessed for crop yield prediction. Similar data partitioning was applied to each model's training and validation to guarantee equity. Whereas traditional ML models act as baselines for deep learning, VGG architectures offer references. With its ability to capture nonlinear feature interrelation, CropNet performed better overall than the other models. Hyperparameters were optimized using a grid search to produce reliable and consistent results.

CropNet Architecture: A convolutional neural network with one dimension (1D-CNN) designed specifically for tabular feature data is called *CropNet* (Fig. 2). To extract local feature patterns and capture nonlinear dependencies, the architecture consists of two successive Rectified Linear Unit (ReLU) activation functions used in *Conv1D* layers. To mitigate overfitting and reduce spatial dimensionality, each convolutional layer is followed by a *MaxPooling1D* layer. The flat convolutional output is then layered using fully connected (*Dense*) layers to combine the learned renderings. To differentiate between crops with high and low yields, a single output neuron with a sigmoid activation function produces a probability score that resembles the binary classification result (`Is_High_Yield`).

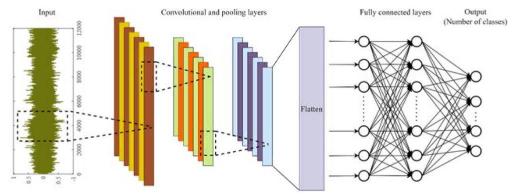

Fig. 2. CropNet (1D-CNN) Diagram [23]

E. Explainability

By elucidating how input features impact prophecy, XAI improves the interpretability of machine learning models. By bridging the gap between interpretability and accuracy, it aids users in comprehending the reasoning behind the model. This study uses two model-agnostic XAI methods, such as SHAP and LIME, to clarify how local and global traits contribute to crop yield prediction.

The effects of local and global features were interpreted using SHAP. The main factors influencing yield prediction were *Fertilizer_Used_True*, *Rainfall_mm*, and *_True*. While sufficient fertilizer and rainfall boosted the yield, excessive irrigation had the opposite effect.

By examining the effects of minor modifications to the input features on individual yield predictions, LIME was used to provide a local interpretability. This demonstrated that rainfall and fertilizer use had the greatest effects on particular samples, supporting the validity of the behavior of the local model.

IV. Results Analysis

To assess the effectiveness of the suggested model, a comparison between deep learning architectures and conventional machine learning algorithms was carried out. The deep learning baselines included VGG16, VGG19, and the lightweight CropNet model, while the classical models included XGBoost, SVM, LR, RF, and Decision Tree. All models were trained in order to guarantee an equitable comparison, verified, and tested on the same dataset under the same circumstances. The metrics that were reported included F1-score, recall, accuracy, and precision for the binary classification of crop yield (high vs. low).

TABLE I
THE MODELS' COMPARATIVE PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1-Score
CropNet	**93.46**	**93.50**	**93.40**	**93.40**
VGG19	92.98	93.00	92.90	92.90
VGG16	91.77	91.70	91.80	91.70
LR	80.30	80.00	80.00	80.00
Decision Tree	75.85	76.00	75.80	75.90
Random Forest	75.24	75.00	75.00	75.00
SVM	74.59	74.50	74.60	74.50
XGBoost	74.24	74.00	74.00	74.00

Performance metrics calculated on a held-out test set that was not seen at all during model training and validation are presented in Table I. CropNet demonstrated strong generalization ability with the highest test accuracy of 93.46%, as well as superior precision, recall, and F1-score.

TABLE II
DETAILED RESULTS OF 5-VALIDATION OF FOLDS (IN %)

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
CropNet	95.09	95.04	95.04	95.03	95.03

The training data was also subjected to 5-fold stratified cross-validation in order to evaluate the stability of the model. Table II presents the results, which consistently demonstrate average accuracies above 95% for all folds. When the model is exposed to several overlapping subsets of the training data, these values represent validation performance.

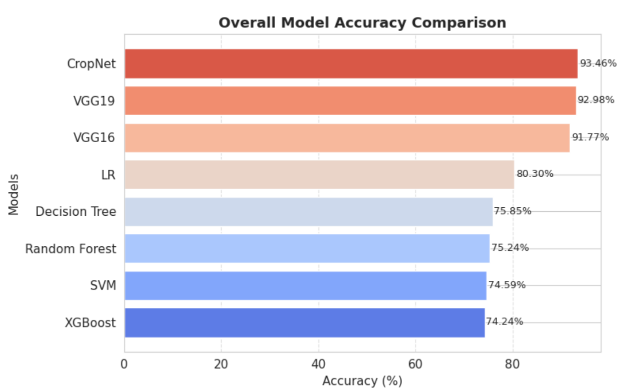

Fig. 3. Comparative analysis of all assessed models' classification accuracy, demonstrating the suggested CropNet model's superior capacity for generalization.

The superior performance of CropNet (Fig. 3) can be attributed to its 1D convolutional layers, which effectively capture spatial and nonlinear relationships among tabular numerical and categorical features, allowing it to learn feature interactions that classical models may overlook. In contrast, traditional ML models (Fig. 4) exhibited lower performance, likely because of their limited ability to model complex nonlinear dependencies.

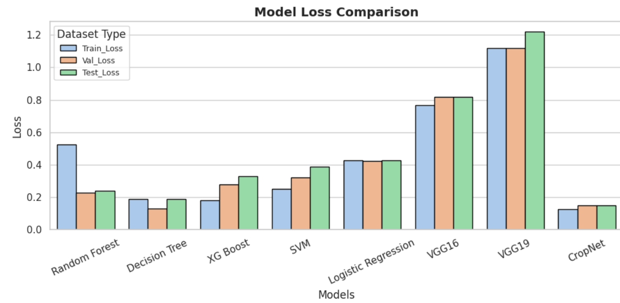

Fig. 4. Deep learning model training and validation loss curves that show reduced overfitting in CropNet and stable convergence behavior.

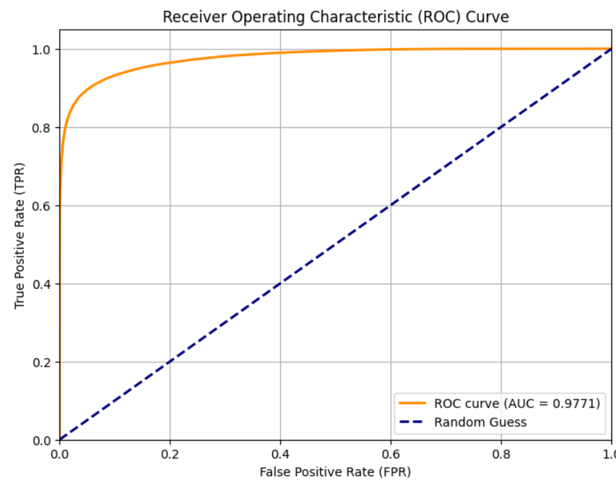

Fig. 5. The CropNet model's ROC on the test set achieved an AUC of 0.9771, indicating exceptional discriminative performance.

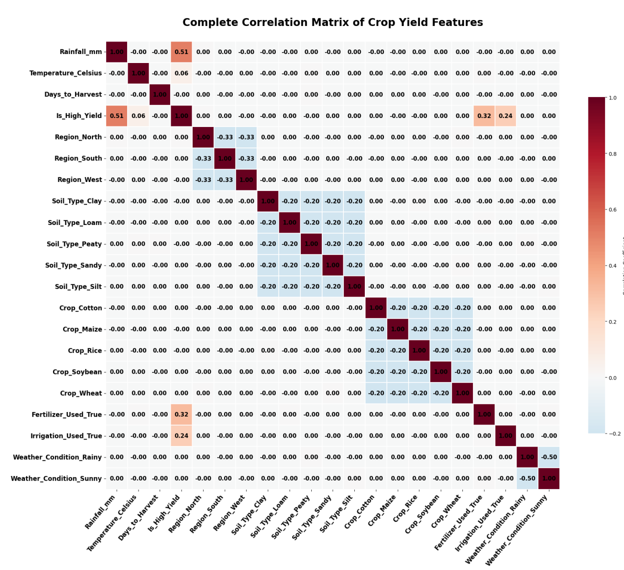

Fig. 6. The crop yield dataset's feature correlation heatmap illustrates the connections between soil, environmental, and management-related characteristics.

With an AUC of 0.9771 at the ROC curve, CropNet demonstrates excellent classification performance (Fig. 5). The crop-yield dataset's important relationships are highlighted in the feature-correlation heatmap (Fig. 6).

The SHAP summary plot (Fig. 7) quantifies the global ranking of input features based on their total contribution to CropNet's interpretation of crop yield prediction. *Rainfall_mm* exhibited the highest positive contribution with a mean SHAP value of **+0.1946**, followed closely by *Fertilizer_Used_True* (**+0.2074**). Conversely, *Irrigation_Used_True* had a negative contribution (**–0.1649**), indicating that excessive irrigation reduces yield performance. *Temperature_Celsius* showed a moderate positive influence (**+0.1023**), while soil type and regional features had minor contributions (less than 0.05). These findings reveal that climatic and management-related parameters primarily govern the predictive behavior of the model.

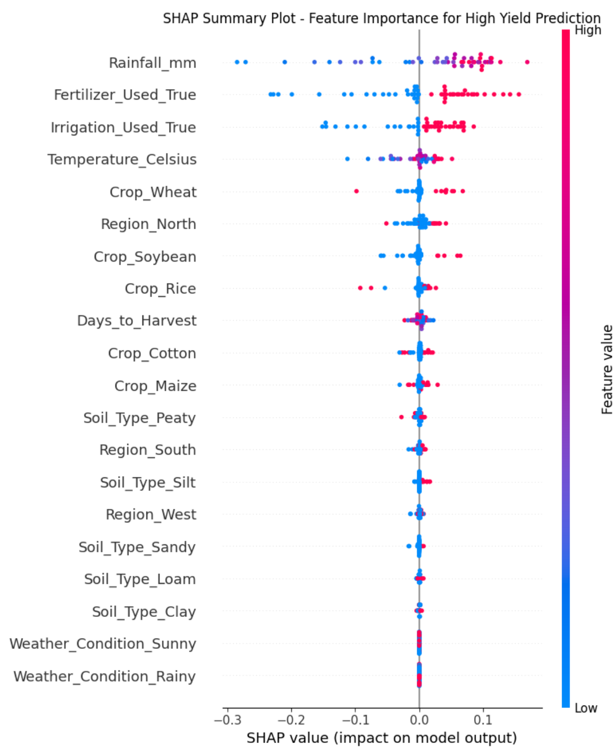

Fig. 7. Global feature importance, which shows the relative contribution of each feature to crop yield prediction throughout the dataset, is derived from SHAP analysis.

The LIME visualization (Fig. 8) provided local interpretability for a representative instance (**ID 197805**, True: 1, Predicted: 1). The instance achieved a high-yield prediction primarily due to *Fertilizer_Used_True* = 1.0 and *Rainfall_mm* $>$ 0.5, which increased the prediction probability by approximately **+0.21** and **+0.19**, respectively. In contrast, *Irrigation_Used_True* = 0.0 decreased the output by **–0.15**. Other attributes, such as *Temperature_Celsius*, *Soil_Type_Clay*, and *Region_South*, contributed marginal positive effects (less than +0.05). Overall, favorable rainfall, sufficient fertilization, and optimal environmental conditions led to a confident high-yield classification, validating both global and local interpretability of the proposed XAI-Yield model.

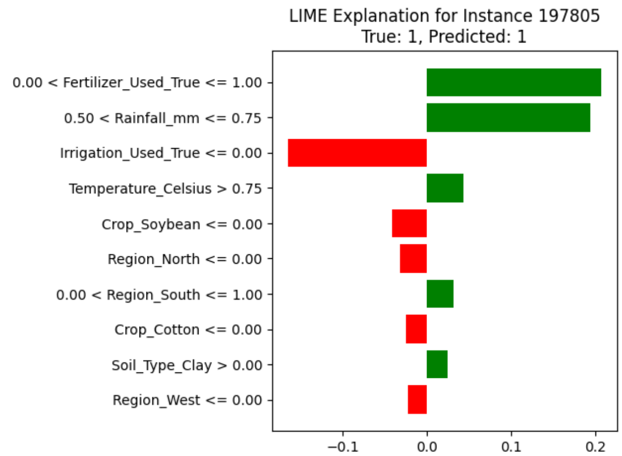

Fig. 8. Using LIME, a representative test instance's local explanation shows how each feature contributes to a high-yield prediction.

V. Conclusion & Future Directions

The given paper introduces a novel single-dimensional convolutional neural network (1D-CNN) CropNet-based classification system of crop yields. The proposed model is better than the conventional ML and transfer learning models, which have the capacity to effectively exploit the complicated nonlinear relations between environmental and agronomic factors. Besides the combination of SHAP and LIME, the model provided global and local interpretability, which presupposes that the strongest predictors of soil moisture are rainfall and use of fertilizers. These observations provide valuable guidance to applications in precision agriculture in addition to enhancing the transparency of the model.

Future studies will focus on expanding the dataset to encompass a wider range of crop varieties, soil types, and geographical areas. Real-time, data-driven forecasting will be made possible by the combination of satellite imagery and Internet of Things-based environmental data. Additionally, investigating hybrid or ensemble architectures may enhance the models' generalizability and resilience in various agricultural contexts.Finally, making CropNet a web or mobile application could democratize access to AI-powered prediction tools, enabling farmers and policymakers to make well-informed decisions that promote regionally sustainable food production.

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