YIELD-NET FRAMEWORK: HYBRIDIZING RECURRENT NEURAL NETWORK WITH XGBOOST AND RANDOM FOREST FOR ANNUAL CROP YIELD PREDICTION

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Abstract

The agricultural sector has contributed tremendously to the development of many countries in the world, by providing food and employment. However, knowing the number of crops produced yearly has become a major challenge. This paper introduced an advanced framework known as Yield-Net which combines XGBoost, Gated Recurrent Unit (GRU) and Random Forest (RF) machine learning techniques in predicting annual crop yield from different regions. The dataset used for this experiment is the world crop yield dataset covering the period of 1990 to 2010 sourced from ourworldindata.org with 28242 instances with 7 variables. Data preprocessing steps such as handling missing entries, dealing with duplicates, data encoding and scaling were applied in order to structure the dataset in a format suitable for modelling. The preprocessed data was portioned into segments, 90% for training and 10% for Yield-Net testing. XGBoost was employed in this study for selecting important features from the crop yield data for model training while GRU extracted sequential patterns from the selected features. Random Forest predicts the amount of crop yield using the extracted features from GRU as input. The Yield-Net model was trained in 20 iterations. State-of-the-art metrics widely used in assessing the level of error and performance of regression model, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Root Square Error (R^2) were employed. The proposed Yield-Net system achieves RMSE score of 5.3, MAE result of 3.95 and $R^2 = 0.94$ outperforming baseline models developed for similar tasks. This paper contributes significantly to the ongoing research in the field of precision agriculture while laying a solid foundation for future work.

Keywords: Crop yield, Recurrent Neural Network, Annual crop Prediction, Deep Learning, XGBoost

Introduction

Agricultural productivity remains a critical factor in ensuring food security and supporting economic stability worldwide (Akbar et al. 2024). Accurate estimation of crop yields has become increasingly important for policymakers, farmers, and agribusinesses to make informed decisions regarding resource allocation, market planning, and risk management (Ahmed et al. 2023). Traditional methods of yield prediction often rely on historical trends, manual field surveys, and basic statistical models, which can be limited by inaccuracies, labor intensiveness, and delayed reporting (Ahmed et al. 2023; Akbar et al. 2024; Babatunde et al. 2024). The growing availability of large-scale agricultural datasets and advances in machine learning have opened new opportunities for developing predictive models that are more precise, scalable, and data-driven (Ahmed et al. 2023).

Recent studies in crop yield prediction (Ahmed et al. 2023; Logeshwaran et al. 2024; Huber et al. 2024; Li et al. 2024) have increasingly explored the use of deep learning models, particularly recurrent neural networks (RNNs), due to their capacity to capture temporal dependencies in sequential data such as weather patterns, soil conditions, and crop growth stages (Akbar et al. 2024). According to (Zhang et al. 2019; Urfan et al. 2024) RNN-based models have shown promising results in modeling complex non-linear relationships inherent in agricultural systems. However, challenges such as overfitting, feature redundancy, and sensitivity to noisy inputs often limit their predictive performance (Zhang et al. 2019; Bezabh et al. 2023; Babatunde et al. 2024). To address these challenges, this paper proposes hybrid approaches that combine RNNs with other machine learning techniques, offering potential improvements in both accuracy and robustness.

In this paper, a novel hybrid framework named Yield-Net is introduced, which integrates RNNs with XGBoost and Random Forest algorithms for annual crop yield prediction. The RNN serves as the primary model to capture sequential patterns in crop and environmental data. XGBoost is incorporated to enhance model performance through feature selection and gradient boosting, while Random Forest contributes additional analytical support, such as evaluating variable importance and providing complementary predictive insights. This multi-algorithm design aims to leverage the strengths of each method, addressing limitations associated with single-model approaches and enabling a more reliable prediction system.

The proposed framework is evaluated using world crop yield datasets, encompassing multiple crop types and regional variations. Performance metrics are employed to assess the predictive accuracy, stability, and computational efficiency of the hybrid model, while comparisons are made against conventional RNN-only and standalone machine learning models. The outcomes of this research are expected to provide a practical tool for precise crop yield estimation and offer insights for future studies seeking to integrate deep learning with ensemble techniques in agricultural prediction tasks.

This paper contributes the following benefits to the agricultural domain.

i. Offers a robust and accurate crop yield prediction system capable of capturing complex temporal patterns in environmental and crop data.
ii. Enhances predictive performance by hybridizing deep learning with ensemble machine learning methods, addressing limitations such as feature redundancy and sensitivity to noisy inputs.
iii. offers analytical insights into key factors influencing crop yield, enabling stakeholders to identify critical variables that impact productivity.

The subsequent sections of this paper are structured as follows: Section 2 presents a review of related literature on crop yield prediction using machine learning and deep learning techniques. Section 3 describes the materials and methods employed, including data collection, preprocessing, and the proposed hybrid model framework. Section 4 presents the experimental results, model evaluation, and comparative analysis. Section 5 provides a discussion of the findings, highlighting the implications and limitations. Finally, Section 6 concludes the paper and outlines directions for future research.

Related works

Crop yield prediction using machine learning has emerged as a field of significant interest among researchers due to its potential to improve agricultural planning, resource allocation, and food security (Ahmed et al. 2023). The growing availability of high-resolution climate data, soil properties, and satellite imagery has driven ongoing research aimed at developing models that can accurately forecast crop productivity (Darra et al. 2023; Urfan et al. 2024). Consequently, many experiments have been conducted to explore different machine learning and deep learning techniques, ranging from traditional regression models to advanced hybrid frameworks. These studies not only investigate the predictive capabilities of individual algorithms but also examine the integration of multiple methods to enhance accuracy, handle complex datasets, and capture both spatial and temporal patterns in agricultural data**.**

Khaki et al. (2020) proposed a deep learning framework combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for crop yield prediction, incorporating environmental factors and management practices. The study applied the model to forecast corn, and soybean yields across 13 U.S. Corn Belt states for 2016–2018, comparing performance with Random Forest, deep fully connected neural networks (DFNN), and LASSO. Evaluation using RMSE showed the CNN-RNN achieved 8–9% of average yield, outperforming all other methods. The model captured temporal dependencies, generalized well to untested environments, and quantified the contribution of weather, soil, and management factors to yield variability.

To improve what was done in previous studies, Gong et al. (2021) developed a greenhouse crop yield prediction model by hybridizing Temporal Convolutional Networks (TCN) and Recurrent Neural Networks (RNN) to capture temporal dependencies in environmental data. The study used multiple real greenhouse datasets for tomato cultivation and evaluated performance using RMSE. Results indicated that the hybrid TCN-RNN model outperformed traditional machine learning methods and classical deep neural networks, with historical yield information identified as the most critical factor for accurate prediction.

Sun et al. (2022) investigated the simultaneous prediction of wheat yield and grain protein content (GPC) using deep learning models and time-series proximal sensing data. They compared multiple approaches incorporating data fusion, time-series feature extraction, and multitask learning. The study evaluated RNN, LSTM, CNN, and attention-based layers within a "two-to-two" model that used two input data sources and produced two outputs. Results showed that time-series data fusion improved prediction accuracy (R^2 = 0.817 for yield, 0.809 for GPC), while the attention-based two-to-two model achieved the highest performance (R^2 = 0.833 for yield, 0.846 for GPC) (Sun et al. 2022).

Wang et al. (2024) highlighted the increasing significance of crop yield prediction within agricultural science, emphasizing its role in supporting economic planning and informing national agricultural policies. (Wang et al. 2024) noted that accurate yield forecasts allow for assessing the influence of key factors such as crop growth cycles, soil properties, and rainfall distribution on production outcomes. While traditional machine learning approaches can provide approximate yield estimates, Wang et al. (2024) observed that their predictions often deviate significantly from actual yields, limiting practical applicability. To address these shortcomings, Wang et al. (2024) systematically reviewed deep learning-based prediction methods, analyzing major models and their application to different crop types. The authors also provided insights into future research directions, advocating for the integration of advanced deep learning techniques to improve predictive accuracy and reliability in crop yield estimation.

Morales & Villalobos (2023) explored how algorithm choice, dataset size, and data partitioning affect crop yield prediction. The authors generated synthetic sunflower and wheat yield data (2001–2020) using DSSAT's OilcropSun and Ceres-Wheat models across five regions in Spain, incorporating variations in soil depth and farm management. Random Forest (RF) regularized linear models, and artificial neural networks (ANNs) were tested, with ANNs implemented in Keras and others in R. Training used older data, testing used newer data to evaluate extrapolation performance. RMSE showed Random Forest (RF) performed best (35–38%), followed by ANNs (37–141%) and linear models (64–65%), only slightly better than a baseline of average farm yield (42%).

Babatunde et al. (2024) developed a smartphone-based disease detection system for habanero plants using a modified VGG16 (MVGG16) deep transfer learning model. The study trained the model on a labeled dataset of healthy and infected habanero leaf images and evaluated it on a separate test set. Performance metrics included accuracy (98.79%), precision (97.93%), recall (98.95%), F1-score (98.44%), and AUC (98.63%). The MVGG16 model was integrated into a smartphone app, allowing users to upload leaf photos, receive diagnoses, and track historical results. Testing confirmed the system's high accuracy, demonstrating its potential to support early disease detection and improve crop yield and quality.

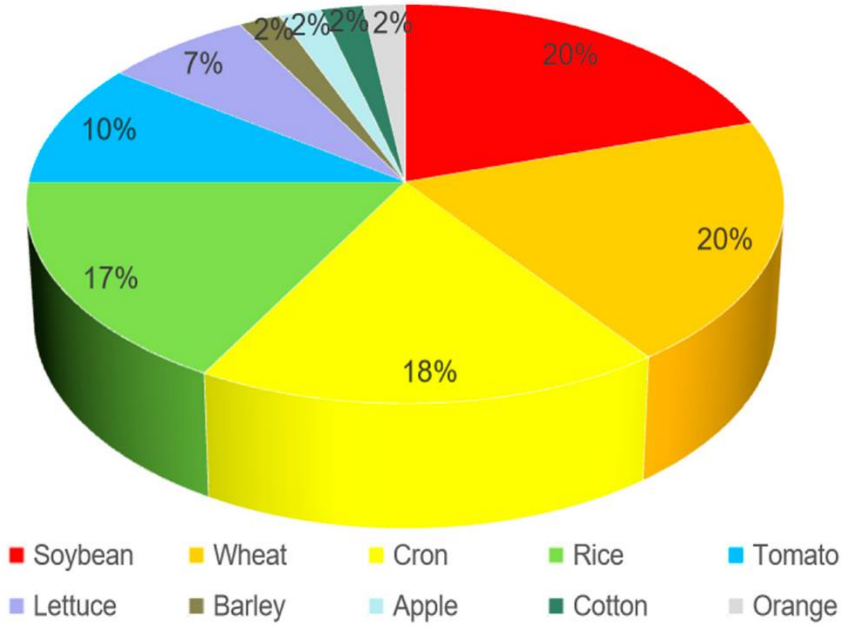
Selvanarayanan et al. (2024) proposed an RNN-IoT system for real-time soil health monitoring in coffee plantations. IoT sensors collected data on soil temperature, moisture, pH, nutrients, weather, and historical trends, transmitted via a cloud platform. RNN and GRU models were trained to predict

soil conditions and crop hazards. The system improved accuracy over conventional methods, optimized irrigation and fertilization, minimized ecological impact, and provided actionable insights through a mobile app (Selvanarayanan et al. 2024).

Ashfaq et al. (2025) developed DeepAgroNet, a three-branch deep learning framework combining CNN, RNN, and ANN to predict winter wheat yields in southern Pakistan using satellite, meteorological, and soil data (2017–2022). CNN achieved the highest performance ($R^2 = 0.77$, 98% accuracy), with all models showing <10% yield error. Benchmarking against Crop Report Services confirmed reliability, highlighting the framework's potential for precision agriculture and food security.

Li et al. (2025) developed CNNAtBiGRU, a deep learning framework combining 1D-CNN, BiGRU, and an attention mechanism to predict maize yields in Northeast China. Using vegetation indices, phenology, meteorological, soil, and mechanization data, the model achieved high accuracy ($R^2 = 0.896$, RMSE = 908.33 kg/ha) and robustness across years and extreme events. Key predictors included EVI, SIF, and Degree of Cultivation Mechanization. The framework enables 1–2 month-ahead yield forecasts without relying on future weather predictions.

predictive accuracy across diverse crop types and regions. Khaki et al. (2020) and Gong et al. (2021) demonstrated the benefits of hybrid CNN-RNN and TCN-RNN models in capturing temporal dependencies, yet their models were often limited to specific crops or datasets, restricting generalizability. Sun et al. (2022) showed that multitask learning and data fusion improved prediction of yield and grain protein content, but their approach required extensive time-series proximal sensing data, which may not always be available. Similarly, studies by Morales and Villalobos (2023) and Wang et al. (2024) highlighted limitations in extrapolation, dataset dependency, and the deviation of traditional machine learning predictions from actual yields. While smartphone-based disease detection (Babatunde et al., 2024) and IoT-driven soil monitoring systems (Selvanarayanan et al., 2024) improved specific aspects of crop management, they did not provide an integrated framework for overall yield prediction. Ashfaq et al. (2025) developed multi-branch deep learning models with promising results, yet challenges remain in harmonizing heterogeneous data sources and optimizing model performance for broader agricultural applications. Therefore, this paper proposes the Yield-Net framework, designed to address these limitations by hybridizing RNN with XGBoost and Random Forest,



Despite the significant contributions of previous studies in crop yield prediction, there remains a need for more comprehensive frameworks that can fully integrate temporal, spatial, and environmental factors while maintaining high leveraging temporal and environmental data to enhance prediction accuracy, generalizability, and practical applicability across multiple crops and regions.

Figure 1: Percentage distribution of crops in the current literature review (Wang et al. 2024)

Materials and Methods

This section describes the datasets, preprocessing techniques, and the proposed Yield-Net framework. It outlines the methodology for integrating temporal, environmental, and management data, the architecture of the hybrid RNN-XGBoost-Random Forest model, and the evaluation metrics used to assess prediction performance.

1.1 *Data collection*

The dataset used for this experiment was sourced from world crop yield production dataset obtained from [ourworldindata.org]. This dataset is also available in Kaggle [view data]. The data file comprises of five different data including: (1) pesticides data (2) rainfall data (3) temp data file (4) yield data (5) yield data file. This dataset comprises of world crop yield production from 101countries in the world from the period of 1990 to 2013. The dataset contains a total of 28242 instances with 7 variables. The variables in the dataset were (1) Area (this is the region where the crop is cultivated) (2) Item (This indicates the specific type of crop in the data) (3) Year (The calendar year the crop was cultivated) (4) Hg/Ha

yield (This variable represent the hectogram per hectare yield which means the amount of harvested crop per unit of land) (5) Average rain fall mm per year (The total annual rainfall measured in Millimeters for the geographical region and specific year) (6) Pesticides Tones (The amount of pesticides applied in tones in a given year and in specific location) (7) Average Temperature (The average annual temperature for a given region and year).

Table 1: **Data Sample Used for this experiment showing first 8 instances with 7 variables**

Area	Item	Year	Hg/Ha yield	Average Rainfall	Pesticides Tones	Avg temp
Albania	Maize	1990	36613	1485.0	121.0	16.37
Albania	Potatoes	1990	66667	1485.0	121.0	16.37
Albania	Sorghum	1990	23333	1485.0	121.0	16.37
Albania	Soybeans	1990	12500	1485.0	121.0	16.37
Albania	Wheat	1990	7000	1485.0	121.0	16.37
Albania	Maize	1991	30197	1485.0	121.0	16.37
Albania	Potatoes	1991	29068	1485.0	121.0	15.36
Albania	Rice, paddy	1991	77818	1485.0	121.0	15.36

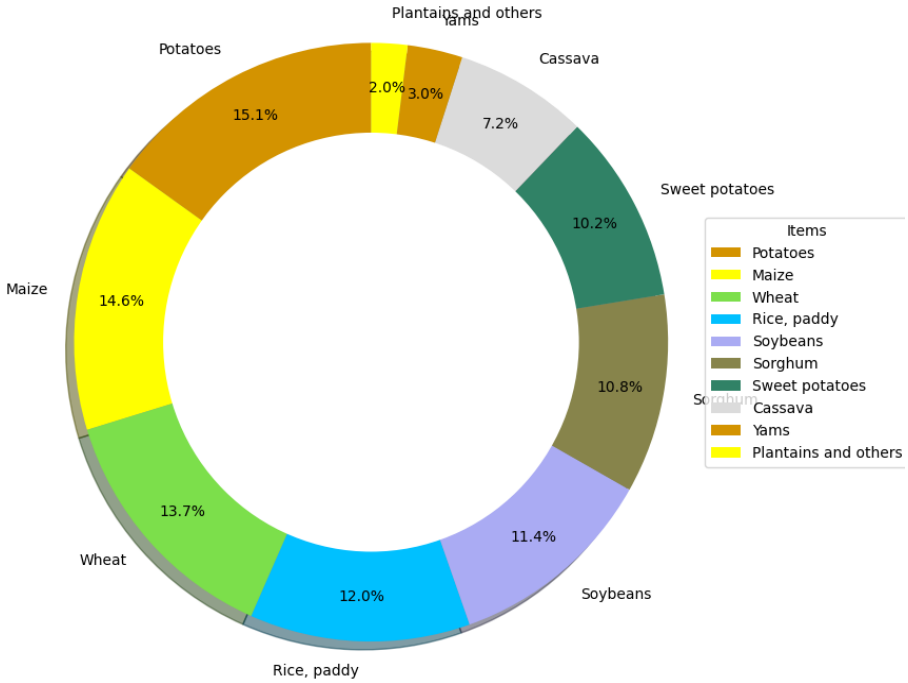


Figure 2: Percentages of crops' appearance in the sample dataset

Data Preprocessing

Data preprocessing is one of the core tasks to be performed when preparing sample datasets for training machine learning systems. This step ensures that the sample dataset is cleaned, by removing irrelevant characters, filling in missing entries etc. This step enhances model's performance while keeping only important variables for the system to be trained on. In this paper, the sample dataset undergoes severe cleaning process. These steps are discussed below:

Handling Missing Field

Machine learning algorithms are not trained with sample data whose variables contained missing entries. To handle this setback while building machine learning systems, fields with missing entries are to be filled up. In this paper, missing entries were systematically fixed to ensure the quality of the data. The overall dataset was carefully examined to check for missing entries, and a total of 109 cells were without values which cut across several variables. The mean substitution technique which replaces empty cells with the average score of the available observation was applied. This technique minimized data loss while maintaining the entire distribution of the sample data.

Handling Duplicate Entries

After handling the missing entries issue in the sample dataset. The data was also inspected to check for duplicated rows. Out of 28242 instances in the sample dataset, a total of 41 rows were detected as duplicates during the data cleaning phase. In machine learning, duplicate records often introduce redundancy, leading to model bias and also distort system performance if ignored. In this paper, the 41 duplicate records identified after the inspection were removed using python method from Panda's library known as drop duplicates. By deleting duplicate records from the dataset, this ensures that the sample data for this experiment contain unique

observations which improve the data quality and model's outcome.

3.2.3 *Data Types Conversion*

Another crucial step during the data preprocessing phases was data types conversion. The data types conversion was performed in this paper to ensure that the data is compatible with the selected machine learning techniques in this paper. Categorical variables such as Item and Area were converted into numbers (integer). Similarly, Hg/Ha yield, Average rain falls mm per year, Pesticides Tones and Avg temp were changed to integer. The data types conversion step helps in eliminating potential type mismatches and ensures that each feature was represented in the most appropriate format.

Feature Encoding

During this experiment, only two features from the sample dataset contained string values: Area and Item, which must be transformed into numerical format for compatibility with the selected algorithms which form the Yield-Net framework proposed in this paper. The **Area** variable, being ordinal type with limited distinct categories was transformed into numerical format using Label Encoder technique from scikit-learn machine learning library. Label Encoder functions by assigning unique integer values to each area category. Conversely, Item variable was encoded using one Hot Encoder technique, which creates binary fields for each category. This step was essential to transform textual data into numeric format which is readable by machine learning algorithms.

Feature Selection

We selected only the important variables which contribute significantly to crop yield detection from the seven (7) variables in the sample data. During the feature selection step, the XGBoost Algorithm (XGB) was applied to select only important variables for the proposed Yield-Net model training. The XGB technique measures the dependency between independent variables and the dependent variable (target variable). To systematically detect variables which are not relevant to the experiment, the XGB method when applied on the preprocessed dataset identified Area (country or region where crops were cultivated) and pesticide tones with low P-value scores indicating their less importance in predicting the target. After this experiment, only five (5) features (Item, Year, Hg/Ha yield, Average Rainfall and Avg temp) had high p-value scores which were selected for the experiment.

Feature Scaling

Variable scaling is another important task to be conducted when preparing dataset for training AI or machine learning framework. Feature scaling is often employed to normalize the range of numerical variables in order to ensure uniformity in the data. To scale the features in our sample dataset, Standard scaler technique was adopted. This technique normalizes selected variables by standardizing the values to have the mean of 0 and the standard deviation of 1. We adopted Standard scaler for this study because it is suitable for scaling the sample dataset preprocessed for this experiment, because machine learning algorithms such as Random Forest (RF), Gradient Boosting (GB) and many others rely on distance-based calculation and are highly sensitive to differences in feature magnitudes.

Data Partitioning

Following the data preprocessing steps in the paper, the data was further partitioned into training and test sets. The sample world crop yield dataset consisting of 28,242 instances was divided into a 90% training and 10% test set to enhance the Yield-Net model development and performance monitoring (evaluation). This data partitioning reserves 25, 418 rows of the entire dataset for training and 2, 8,24 records were set aside for model's evaluation after the training. The reason for using larger portion of the entire data for training was justified by the need to expose the proposed Yield-Net framework to huge data sample for learning complex patterns and relationships between variables, in order to enable the proposed model achieve better prediction results. Similarly, reserving smaller portion of the data (10%), allows for model evaluation after training, to measure how best the system will perform on new unseen crop yield data. This approach of dividing the sample dataset strikes a balance between maximizing the Yield-Net training efficiency while enhancing robust performance evaluation.

Yield-Net Architectural Design

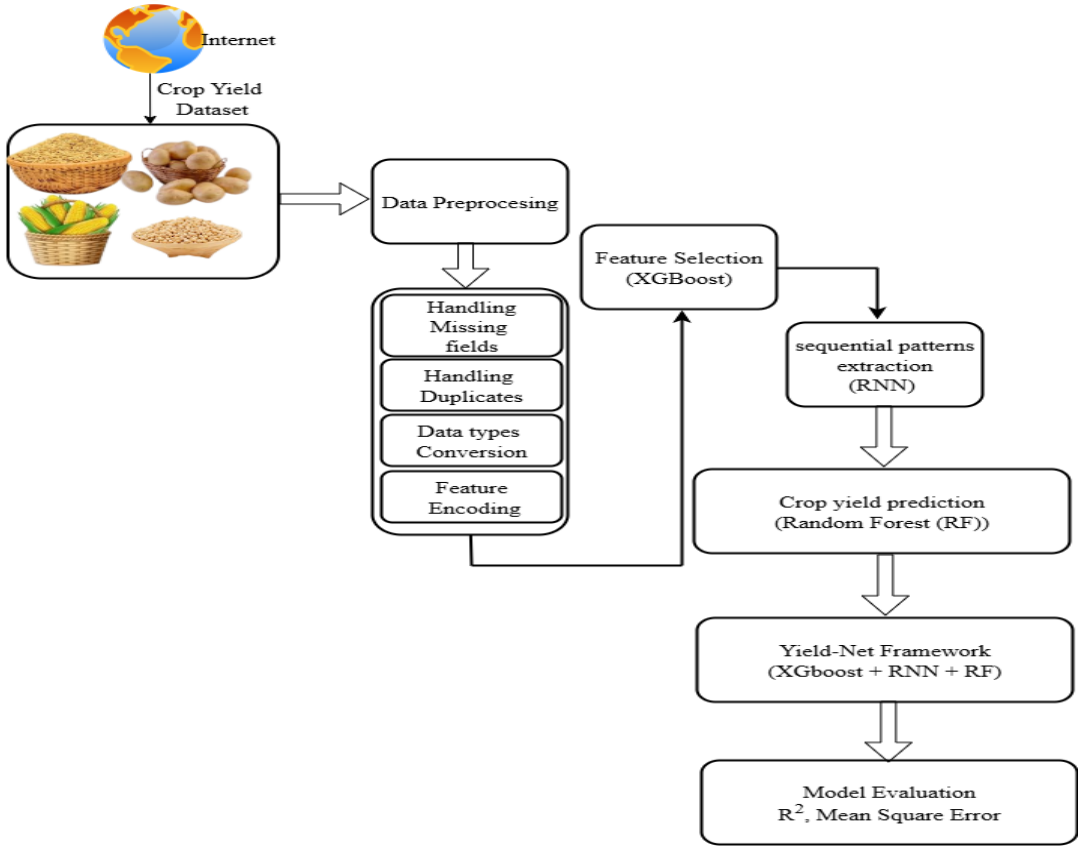


Figure 3: Architectural design of the proposed Yield-Net framework

3.8 Mathematic Model for Selected Algorithms

The proposed Yield-Net framework in this paper combines three different machine learning techniques, XGBoost, RNN (Specifically GRU model) and Random Forest (RF). In the proposed Yield-net framework, XGBoost is apply in selecting only the relevant variables for model training, GRU (Gated Recurrent Unit), type of RNN model is employed in the framework to extract sequential patterns from the processed crop yield data sample and the extracted output from the GRU serves as input to the Random Forest (RF) model which the n predict the amount of crop yield based on region and a specified year. However, the mathematic models for these algorithms are presented below:

The XGBoost model is represented mathematically as:

$$y = \sum_{i=1}^{n} l(y_i - y) + \sum_{k=1}^{k} \gamma Tk + \frac{1}{2}\lambda \sum_{j-1}^{TK} w_{kj}^2 \quad 1$$

where:

l (y_i-y) = loss function measuring different between actual and predicted values

K = number of trees

Tk = Numbers of trees in the k-th trees

w_{kj} = weight of leave j in tree k

Υ = penalty for number of leaves

λ = regularization parameter

Mathematically, GRU model is represented as:

For a given time, step *t,* input x_t and previous hidden state h_{t-1}:

$$Z_t = \partial(w_z x_t + U_z h_{t-1} + b_z) \quad 2$$

$$r_t = \partial(w_z x_t + U_r h_{t-1} + b_r) \quad 3$$

$$h_t = tanh(w_h x_t + U_r(r_t \odot h_{t-1}) b_h) \quad 4$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h_t)$$

Where:

Z_t = update gate (This gate controls how much of the paste state is kept)

r_t = reset gate (This gate controls much paste information is forgotten)

h_t = Candidate hidden state

W, U, b = weight metrics and bias terms

σ = sigmoid activation function

$\odot$ = element wise multiplication

Similarly, the mathematical equation for Random Forest model is represented as:

$$y(x) = \frac{1}{k}\sum_{k=1}^{k} fk_x \quad 5$$

y(x) = final prediction of the Random Forest *fk(x) = prediction from the k-th decision tree*
K = total number of decision trees in the forest

Yield-Net Model Development

To build the proposed Yield-Net Framework, we combined three advanced machine learning algorithms, XGBoost, GRU and Randon Forest models. To commence the development process, the dataset obtained for this experiment was uploaded to Jupyter Notebook development environment using Panda's python data manipulation library. The sample data was preprocessed and restructured in a format suitable for training machine learning system. XGBoost Method was employed to select important variables that assist the Yield-Net framework to learn the complex patterns in the crop yield data. Five key variables were identified by the XGBoost technique as essential features; however, the remaining less important variables were deleted from the data table to prevent model overfitting which often occurred when noisy data are ignored during model training. The selected features were further passed into Gated Recurrent Unit (Gated Recurrent Unit) technique which assisted in extracting sequential data from the selected features. The extracted features from the GRU algorithms were passed into Random Forest (RF) model for crop yield detection. We carefully set up the hyperparameters of the Random Forest (RF) to facilitate the optimal performance of the proposed Yield-Net framework. The number of estimators was set to 200, this ensures sufficient ensemble of trees, the maximum depth of the RF trees was left as none, this allows the tree nodes to expand fully. To avoid the proposed Yield-Net from overfitting, the minimum sample split for the RF model was set to 5 for internal nodes while the minimum sample per leaf node was initialized to 2, ensuring that every terminal node in the RF model contained a reasonable number of observations. Likewise, bootstrapping techniques were enabled. This was done to allow each tree to be trained on bootstrapped subsets of the crop yield dataset. Finally, the processed crop yield data was employed to train the Yield-Net framework. The Yield-Net framework was trained using 20 iterations. The repeated training phase helps the framework to learn and extract complex patterns from the crop yield data.

Performance Evaluation

The outcome of the proposed Yield-Net framework developed in this paper was measured using three state-of-the-art metrics widely used for assessing regression models. These metrics include; Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2 Score). To measure the Yield-Net prediction error after training, RMSE was employed. These metrics measure the prediction error magnitude by penalizing larger deviations between actual and predicted model outcomes. The mathematical equation for RMSE is given as:

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - y\hat{}_i)\,2} \quad 6$$

Where:
n = total number of observations
y_i = actual value of the i^{th} observation
$y\hat{}_i$ = predicted value of the i^{th} observation

MAE was introduced in this paper to quantify the magnitude of absolute errors made by the proposed Yield-Net framework. The MAE metric helps to provide interpretable insight on how close the Yield-Net predictions results were to the actual yield values. The mathematical model for MA 7

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{i-1}^{n} |\,y_i - y\hat{}_i|$$

Where:
n = total number of observations
y_i = actual value of the i^{th} observation
$y\hat{}_i$ = predicted value of the i^{th} observation

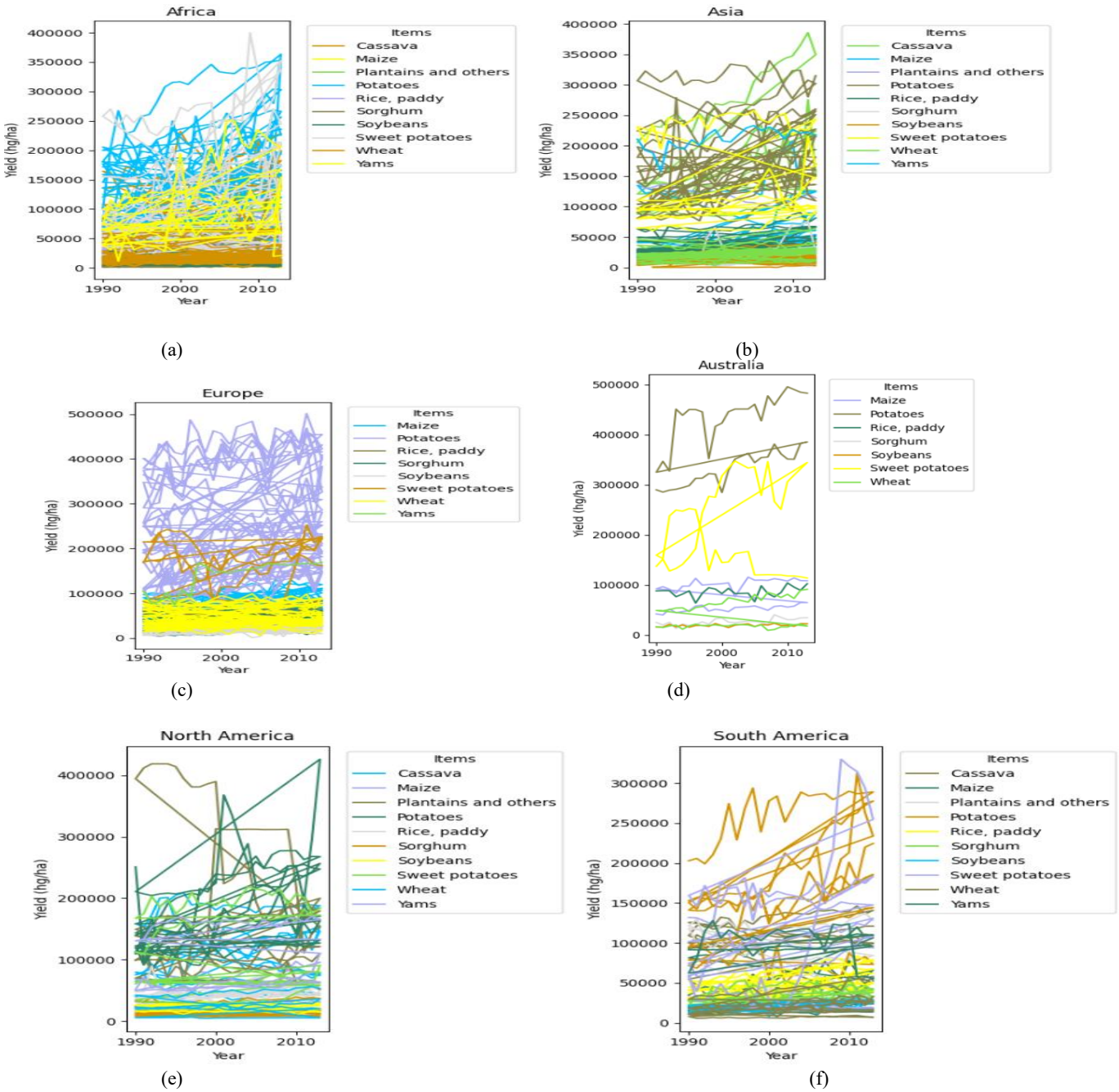
Furthermore, R^2 metric was employed to measure the proportion of variance in the crop yield outcome predicted by the proposed Yield-Net model. The mathematical formula for R^2 metrics is:

$$\mathbf{R2} = \frac{\sum_{i-1}^{n}(y_i - y\hat{}_i)2}{\sum_{i-1}^{n}(y_i - y\hat{}_i)2} \quad 8$$

Results

This section presents the experimental results of the Yield-Net framework. Results of variable analysis, model evaluation outcomes, Yield-Net training time and the results of comparing the experimental outcome of the Yield-Net model with other-state-of-the-art framework developed for similar tasks are also presented in this section using graphs, charts and tables.

Yield-Net Variable Analysis Results



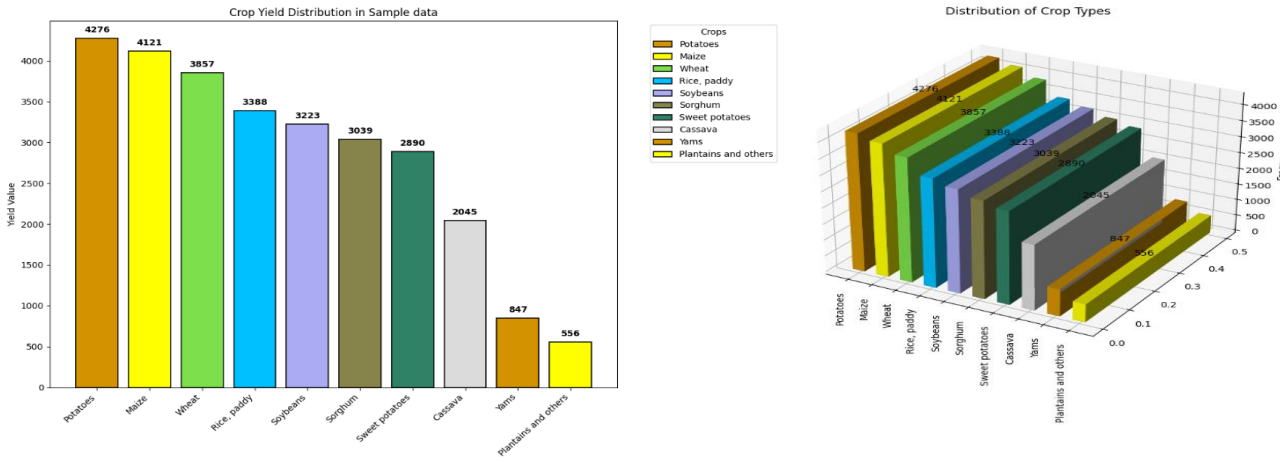
(a) (b)

(c) (d)

(e) (f)

Figure 4 (a), (b) (c), (d), (e) (f): Crop yield distribution by continent from 1990 - 2010

To derive more insight from the world crop yield dataset used for this experiment, we critically examined total crop yield by grouping all crop yield by continent from the period of 1990-2010 as shown in figures 4 (a), (b) (c), (d), (e) (f). The outcome of the analysis shows that Maize, potatoes, Rice Sorghum, Soybeans sweet potatoes, wheat, yam were cultivated across all continents while cassava, plantain were cultivated cross Africa, Asia, North America and south America.



(a) (b)

Figure 5 (a) and (b): Crop yield distribution count in sample data used for this experiment

The bar charts in figure five shows the distribution of crops by type grown across different regions, with Potatoes having the highest production yield of 4,276 followed by Maize with a yield distribution count of 4,121 and wheat having a yield distribution count of 3,857, Rice with a distribution count of 3,388, Soybeans (3,223 hg/ha), Sorghum (3,039 hg/ha), and Sweet Potatoes (2,890 hg/ha) fall within the middle range, while Cassava (2,045 hg/ha), Yams (847 hg/ha), and Plantains and others (556 hg/ha) represent the lowest yields. This distribution shows which crops were dominant in global production. This analysis reveals that Potatoes records the highest yield of 4,276 hg/ha, followed closely by Maize at 4,121 hg/ha and Wheat across all continents.

Yield-Net Experimental Result

Table1: Experimental Training Outcomes of the Proposed Yield-Net Framework on training Data samples

Iteration	RMSE	MAE	R^2 Score
1	8.42	6.11	0.871
2	7.96	5.72	0.884
3	7.53	5.39	0.892
4	7.11	5.07	0.901
5	6.83	4.92	0.907
6	6.54	4.75	0.912
7	6.28	4.58	0.918
8	6.09	4.43	0.922
9	5.91	4.31	0.926
10	5.79	4.24	0.929
11	5.65	4.16	0.931
12	5.54	4.08	0.934
13	5.48	4.01	0.936
14	5.41	3.97	0.938
15	5.34	3.92	0.940
16	5.28	3.88	0.942
17	5.21	3.83	0.944
18	5.18	3.81	0.945
19	5.14	3.78	0.946
20	5.10	3.75	0.947

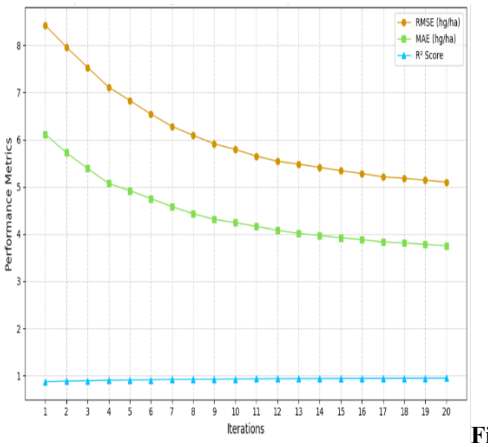


Figure 6

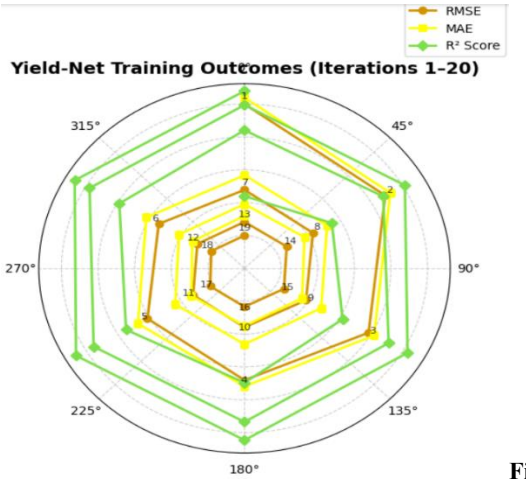


Figure 6 (b)

Figure 6 (a) (b): graphical representation of the experimental training outcomes of the proposed Yield-Net framework

The experimental outcome of the proposed Yield-Net model developed in this paper is shown in Table 1 on the training data, while figure 6 (a) and (b) visualizes the outcome using a line graph. From model training results table, it is clearly noticed that the values of the RMSE consistently decreased from 8.42 hg/ha at iteration 1 to 5.14 value at the final training step. This result shows that the Yield-Net model performance increases at each training phase. Similar decreased in training values were also observed with the MAE metric scores with a decline from 6.11 hg/ha to 3.78 hg/ha across the same training steps, which further confirms the Yield-Net ability to minimize prediction error. Conversely, the coefficient of determination, (R^2) also shows improved outcome from 0.871 in the first iteration to 0.946 in the 19th iteration, which indicate that the model explained a higher proportion of the variance in crop yield as training advanced. Figure 6, using a line graph, clearly illustrates the training outcomes of the Yield-Net model showing the downward trajectory for the RMSE and MAE metrics and the upward projection for the R^2 score. The evaluation outcomes of the Yield-Net model on the training set strongly suggest that the proposed framework effectively learned the complex patterns in the crop yield data sample used for this experiment,

Table 2: Experimental Evaluation Outcomes of the Proposed Yield-Net Framework on 10% Reserved Test Data

Metric	**Score**
RMSE	**5.32**
MAE	**3.95**
R^2 Score	**0.941**

Figure 7: Evaluation result of Yield-Net model on 10% test data

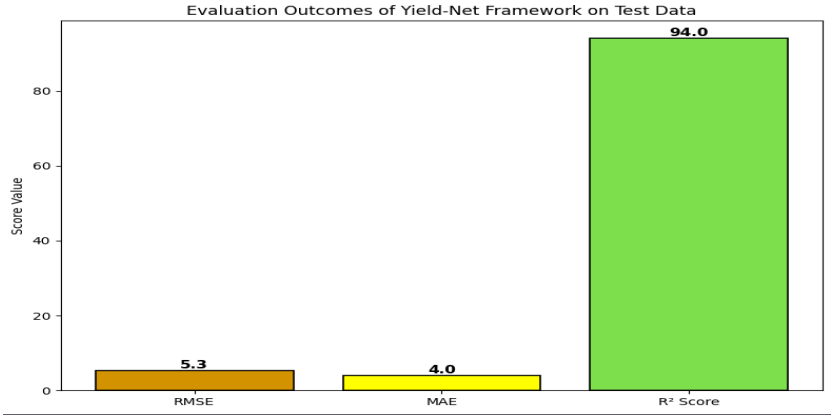


Table 2 and Figure 7 present the evaluation outcome of the proposed Yield-Net model on the 10% reserved test data. The Yield-Net framework achieves RMSE of 5.32 and the MAE of 3.95 showing very minimal performance error. At the same time, the proposed model R^2 score shows 0.941 which indicates strong predictive capability of the proposed system on the unseen data. This alignment between the Yield-Net training and test performances demonstrates lack of overfitting in the proposed system and robust model capability for crop yield prediction

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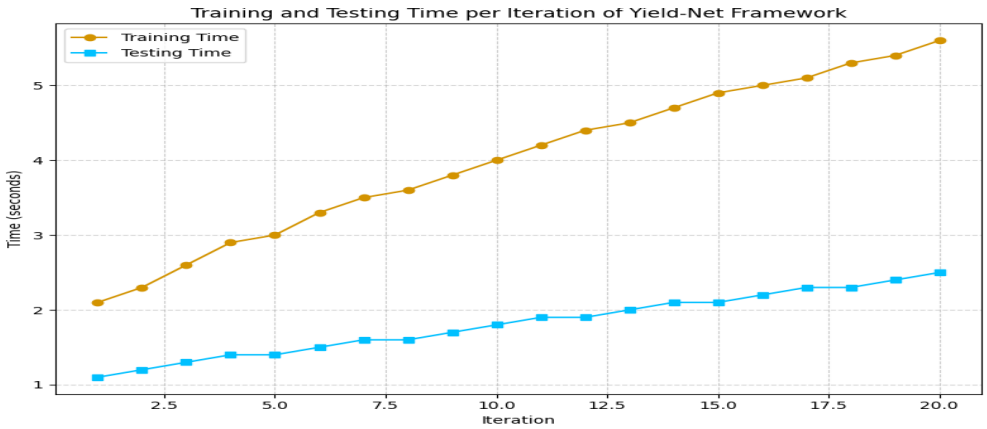


Figure 8: graphical representation of training and testing time per iteration for the proposed Yield-Net framework

The graph in figure 8 shows the relationship between the proposed Yield-Net training and testing time after 20 iterations. As clearly illustrated in figure 8, the Yield-Net training time increased gradually from each training phase. This increase in training time for each phase allows the framework to extract requires pattern from the crop yield dataset used for this experiment. Secondly, the model training time increased at each training phase as expected since the training phase involves iterative optimization, weight updates and backpropagation. The Yield-Net training and test times were stable across iterations. However, the outcome of the proposed Yield-Net model training and test times confirms that while the framework takes longer training time, it remains lightweight during testing.

4.3 Yield-Net Comparison with Baseline Models

In this section, we compare the performance of the Yield-Net framework developed in this paper for annual crop yield prediction with other baseline models to evaluate its effectiveness. The comparison mainly focuses the scores obtained in previous studies using key evaluation metrics such as RMSE, MAE and R^2. This comparison provides insights on how the proposed Yield-net outperforms previous models developed earlier for similar assignment.

Table 3: **Comparison of Yield-Net Performance with Baseline Models**

Author/ Year	Paper Title	Algorithms used	RMSE	MAE	R^2
Kuradusenge et al. (2023)	Crop Yield Prediction Using Machine Learning Models: Case of Irish Potato and Maize	Random Forest, Polynomial Regression, and Support Vector Regressor	**MAE** =510.8 and 129.9	---------	**R^2** =0.875 and 0.817
Peng et al. (2025)	Evaluation and Optimization of Prediction Models for Crop Yield in Plant Factory	Wide Neural Network (WNN)	**RMSE** = 27.15	**MAE**= 11.74	**R^2 = 0.95**
Proposed model (2025)	Yield-Net Framework: Hybridizing Recurrent Neural Network with XGBoost and Random Forest for Annual Crop Yield	XGBoost, RNN, RF	**RMSE** =5.3	**MAE** =3.95	**R^2** = 0.94

We compared the results of Yield-Net system developed in this paper with existing studies as shown in Table 3. Recent work presented by Kuradusenge et al. (2023) applies Random Forest, Polynomial Regression and Support Vector Regressor in predicting Irish Potato and Maize yield. Their studies reported MAE score of 510.8 for Potato and 129.9 MAE score for maize with R^2 score of 0.875 and 0.817. The high MAE and R^2 scores presented in this study indicates the limitations of a single traditional machine learning algorithm in extracting complex patterns in crop yield data for prediction tasks. Similarly, the performance report in a study by Peng et al. (2025) using Wide Neural Network achieves better model outcome with RMSE of 27.15, MAE score of 11.74 and R^2 result of 0.95, demonstrating that deep learning (DL) techniques are capable of achieving better results in crop yield prediction. The proposed Yield-Net framework developed in this paper which combines Gate Recurrent Unit (GRU) with XGBoost and Random Forest further improves crop yield prediction outcome, producing RMSE of 5.3, MAE score of 3.95 and R^2 result of 0.94. Compared to existing studies, the proposed Yield-Net framework implemented in this paper achieves the lowest error rate while producing a better explanatory outcome close to the WNN benchmark thereby outperforming previous baseline frameworks in predicting annual crop yield across diverse datasets.

Discussions

The main goal of this paper was to developed an advance framework for predicting annual crop yield from different regions. Three advance machine earning algorithm: Gated Recurrent Neural Network (GRU), XGBoost and Randon Forest were hybridized to form the proposed Yield-Net architecture. The world crop yield dataset recorded from the period of 1990 to 2010, which undergoes rigorous cleaning and preprocessing was used for this experiment. The hybridized Yield-Net framework was trained in 20 iterations to learn and extract complex patterns from 90% segmented training dataset. Table 1 shows the experimental results of the Yield-Net system

after 20 training phases achieving RMSE of 8.42, MAE outcome of 6.11 and R^2 score of 0.871 at the initial step and 5.10, 3.75, 0.947 at the final iteration respectively. The 10% reserved portion of the dataset which the proposed Yield-Net system was not exposed to during training, was used to evaluate the level of error in the new system when predicting annual crop yield using unseen data. The Yield-Net architecture obtained RMSE score of 5.32 and the MAE of 3.95 showing very minimal performance error. At the same time, the proposed model R^2 score shows 0.941 which indicates strong predictive capability of the proposed system on the unseen data. The Yield-Net framework when compared to baseline models developed for similar task, outperformed prior studies in terms of performance and error rate as shown in table 3 of this paper. The results of this experiment shows that the aim of this exercise has been achieved successfully and the current study offers an advance and better machine learning power framework for crop yield prediction. This paper contributes to the ongoing research in the area of precision agriculture while also laying a solid foundation for further studies.

Conclusion

This paper highlights the importance of combining advance machine learning algorithms for crop yield prediction. The dataset employed during this exercise covers crop yield production from 6 continents, Africa, Asia, Australia, Europe, North and South America thereby indicating that our proposed Yield-Net framework was trained with crop yield data that covers wide geographical locations with different temperature, rainfall and soil type. The outcome of this experiment shows that the proposed Yield-Net system is capable of predicting annual crop yield effectively with fast processing speed.

Future work

In future work, we recommend that more advance machine learning algorithms such as transformers and explainable AI should be trained with same dataset. Secondly, the dataset used for this experiment should be enhanced to include more crop types such as: Tomatoes, Yam, Beans and fruits such as Mango, Pawpaw, Orange etc. This will enable the system to learn sequential features from the newly introduced plants for effective results.

References

Akbar, F., Aribi, Y., Muhammad Usman, S., Faraj, H., Murayr, A., Alasmari, F., & Khalid, S. (2024). Automated lesion detection in cotton leaf visuals using deep learning. *PeerJ Computer Science, 10*, e2369. [view source]

Ahmed, A., Adewumi, S. E., & Victoria, Y.-P. (2023). Crop yield prediction in Nigeria using machine learning techniques: A case study of southern part of Nigeria. *UMYU Scientifica, 2*(4), 31–38. [view source]

Ashfaq, M., Khan, I., Shah, D., Ali, S., & Tahir, M. (2025). Predicting wheat yield using deep learning and multi-source environmental data. *Scientific Reports, 15*(1), 26446. [view source]

Babatunde, R. S., Babatunde, A. N., Ogundokun, R. O., Yusuf, O. K., Sadiku, P. O., & Shah, M. A. (2024). A novel smartphone application for early detection of habanero disease. *Scientific Reports, 14*(1), 1423. [view source]

Bezabh, Y. A., Salau, A. O., Abuhayi, B. M., Mussa, A. A., & Ayalew, A. M. (2023). CPD-CCNN: Classification of pepper disease using a concatenation of convolutional neural network models. *Scientific Reports, 13*(1), 15581. [view source]

Darra, N., Espejo-Garcia, B., Kasimati, A., Kriezi, O., Psomiadis, E., & Fountas, S. (2023). Can satellites predict yield? Ensemble machine learning and statistical analysis of Sentinel-2 imagery for processing tomato yield prediction. *Sensors (Basel), 23*(5), 2586. [view source]

Gong, L., Yu, M., Jiang, S., Cutsuridis, V., & Pearson, S. (2021). Deep-learning based prediction on greenhouse crop yield combined TCN and RNN. *Sensors (Basel), 21*(13), 4537. [view source]

Huber, F., Inderka, A., & Steinhage, V. (2024). Leveraging remote sensing data for yield prediction with deep transfer learning. *Sensors (Basel), 24*(3), 770. [view source]

Khaki, S., Wang, L., & Archontoulis, S. V. (2020). A CNN-RNN framework for crop yield prediction. *Frontiers in Plant Science, 10*, 1750. [view source]

Kuradusenge, M., Hitimana, E., Hanyurwimfura, D., Rukundo, P., Mtonga, K., Mukasine, A., Uwitonze, C., Ngabonziza, J., & Uwamahoro, A. (2023). Crop yield prediction using machine learning models: Case of Irish potato and maize. *Agriculture, 13*(1), 225. [view source]

Li, X., Chen, M., He, S., Xu, X., He, L., Wang, L., Gao, Y., Tang, F., Gong, T., Wang, W., Xu, M., Liu, C., Yu, L., Liu, W., & Yang, W. (2024). Estimation of soybean yield based on high-throughput phenotyping and machine learning. *Frontiers in Plant Science, 15*, 1395760. [view source]

Li, X., Lyu, Y., Zhu, B., Liu, L., & Song, K. (2025). Maize yield estimation in Northeast China's black soil region using a deep learning model with attention mechanism and remote sensing. *Scientific Reports, 15*(1), 12927. [view source]

Logeshwaran, J., Srivastava, D., Kumar, K. S., Rex, M. J., Al-Rasheed, A., Getahun, M., & Soufiene, B. O. (2024). Improving crop production using an agro-deep learning framework in precision agriculture. *BMC Bioinformatics, 25*(1), 341. [view source]

Morales, A., & Villalobos, F. J. (2023). Using machine learning for crop yield prediction in the past or the future. *Frontiers in Plant Science, 14*, 1128388. [view source]

Peng, Y., Zheng, Y., Zheng, Z., & He, Y. (2025). Evaluation and Optimization of Prediction Models for Crop Yield in Plant Factory. *Plants*, *14*(14), 2140. [view source]

Sun, Z., Li, Q., Jin, S., Song, Y., Xu, S., Wang, X., Cai, J., Zhou, Q., Ge, Y., Zhang, R., Zang, J., & Jiang, D. (2022). Simultaneous prediction of wheat yield and grain protein content using multitask deep learning from time-series proximal sensing. *Plant Phenomics, 2022*, 9757948. [view source]

Selvanarayanan, R., Rajendran, S., Algburi, S., Ibrahim Khalaf, O., & Hamam, H. (2024). Empowering coffee farming using counterfactual recommendation based RNN driven IoT integrated soil quality command system. *Scientific Reports, 14*(1), 6269. [view source]

Urfan, M., Rajput, P., Mahajan, P., Sharma, S., Hakla, H. R., Kour, V., Khajuria, B., Chowdhary, R., Lehana, P. K., Karlupia, N., Abrol, P., Tran, L. S. P., & Choudhary, S. P. (2024). The Deep Learning-Crop Platform (DL-CRoP): For species-level identification and nutrient status of agricultural crops. *Research (Washington, D.C.), 7*, 0491. [view source]

Wang, Y., Zhang, Q., Yu, F., Zhang, N., Zhang, X., Li, Y., Wang, M., & Zhang, J. (2024). Progress in Research on Deep Learning-Based Crop Yield Prediction. *Agronomy*, *14*(10), 2264. [View source]

Zhang, Z., Jin, Y., Chen, B., & Brown, P. (2019). California almond yield prediction at the orchard level with a machine learning approach. *Frontiers in Plant Science, 10*, 809. [view source]