

Optimized Crop Yield Forecasting Using the Naive Bayes Regression Algorithm in Smart Agriculture

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ABSTRACT

Crop yield forecasting is significant for ensuring food security, optimizing resource utilization, and aiding decision-making in smart agriculture. Traditional methods such as Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Random Forest Regression (RFR) have gained popularity for yield forecasting. However, such methods commonly struggle with noisy datasets, feature correlation, and intricate non-linear relationships, resulting in compromised predictive accuracy. To address such shortcomings, this study introduces the Optimized Naïve Bayes Regression Algorithm (ONBRA) to predict crop yield. ONBRA incorporates the probabilistic advantages of Naïve Bayes and optimizes the selection of advanced features and smoothing. This algorithm offers enhanced predictive accuracy under varying agricultural conditions. The experimental results show that ONBRA improves forecasting accuracy by 6.8%, the Mean Absolute Error (MAE) by 5.3%, and the R-squared (R^2) by 7.1% compared to traditional methods. The results confirm that the optimized algorithm handles climatic, soil, and crop variability better than traditional methods, providing a better and sustainable solution for smart farming.

Keywords-crop yield prediction; smart agriculture; Naïve Bayes Regression (NBR); Optimized Naïve Bayes Regression Algorithm (ONBRA); Multiple Linear Regression (MLR); Support Vector Regression (SVR); Random Forest Regression (RFR); machine learning; feature selection; prediction accuracy

I. INTRODUCTION

Crop yield forecasting is a key aspect of contemporary agriculture that seeks to promote food security and maximize resource utilization. Effective crop yield forecasting allows policymakers and farmers to plan agricultural operations, market strategies, and resource utilization more accurately. Multiple Linear Regression (MLR), Support Vector Regression (SVR), and Random Forest Regression (RFR) have been used for crop yield prediction [1], but have serious shortcomings, such as inefficient modeling of noisy and incomplete data, weak capacity to model non-linear relationships, lower ability to adapt to dynamic environmental conditions, and thus

suboptimal forecasting precision. Advances in crop yield forecasting studies emphasize the use of advanced Machine Learning (ML) models, hybrid procedures, optimization methods, and deep networks. Techniques such as Gradient Boosting Machines (GBM), Long Short-Term Memory (LSTM) networks, and Extreme Gradient Boosting (XGBoost) have demonstrated enhanced accuracy and stability [2]. Applications of crop yield forecasting include intelligent irrigation scheduling, fertilizer allocation planning, advanced warnings of pest outbreaks, climate-resilient agricultural planning, and market supply prediction. By applying ML methods, the agricultural community is progressively

transitioning toward a sustainable, data-driven, and efficient farming [3].

A. Research Gaps

Regardless of the significant development of ML-based crop yield forecasting, numerous crucial gaps have yet to be addressed. Various popular models, such as SVR and RFR, have deteriorated performance when handling missing values, noise, and varying weather conditions [4]. The prevailing methods are typically computationally heavy and require vast labeled datasets for training, making them of limited use for small- and medium-scale farms. Some models lack the capacity for the effective fusion of multi-source information, such as the health of the soil, remote sensing images, and live climatic factors, resulting in partial predictive assessments. There is also a significant gap between the development of light-weight and interpretable models to offer actionable insights into numerical results [5]. Issues such as overfitting, insufficient feature selection, and inability to adapt to unseen environmental conditions also persist and jeopardize the reliability and extensibility of yield forecasting systems. Bridging these gaps becomes imperative in the development of robust, efficient, and extensible precision agriculture methods [6].

B. Related Work

In [7], a deep model incorporated meta-transformers and Temporal Graph Neural Networks (TGNN) to predict crop yield based on multimodal and temporal information. The advantage of this method over the traditional ones, such as LSTM and 1-D CNNs, is that it models multimodal interactions and time sequences that yield close to 97% classification accuracy. However, this approach has the disadvantage of needing top-quality multimodal datasets that might not be readily available within most agricultural settings. In [8], an ML-based yield prediction model for wheat integrated climate-NDVI data fusion, combining climate, soil, spatial, and satellite datasets within the Google Earth Engine (GEE) environment. This study emphasized multi-source fusion and benchmarking on crop report services utilizing the SVM, RF, and LASSO methods and achieving an R^2 of 0.88. The shortcoming of the method arises from the intricacies of combining multimodal datasets that may enhance the computational overhead and limit model generalizability over various regions. In [9], a crop yield prediction model was based on RF, XGBoost regression, and LASSO regression, using drone-based multispectral images to evaluate the wheat crops at different stages of sowing. This model predicted the yield at different stages of growth, utilizing drone images to increase precision. The shortcomings of this method are the high cost of employing expensive drone technology and the challenge of scaling the model for large farms where remote sensing is limited. In [10], a model was developed to predict cotton yield using field and simulated data obtained from the GOSSYM cotton model, employing ML methods such as RF and LightGBM. This approach integrated historic and simulated data to account for the effects of climate change on yield, achieving an R^2 of 0.98. However, this model did not incorporate any unforeseen real-world variables.

In [11], a hybrid method combined Genetic Algorithms (GAs) and ML for multiple crops such as rice, jute, and maize.

This study applied GAs to optimize hyperparameters and make the model more robust and explainable, achieving a 99.3% accuracy. However, explanatory methods such as LIME could provide conflicting explanations, and SHAP methods could be costly for big datasets. In [12], an ensemble-based Random Forest Extreme Gradient (RFXG) model was presented to predict cotton yield based on weather conditions, outperforming classical XGB models in RMSE. This model integrated bagging, stacking, and boosting strategies for enhanced predictive performance. However, this model requires long-term meteorological and field data, something that might not be possible for places where historical datasets are limited.

II. WORKFLOW OF DATA INTEGRATION, FEATURE ENGINEERING, AND MACHINE LEARNING FOR CROP YIELD PREDICTION

Figure 1 presents the workflow of an ML-based crop yield forecasting system using multiple agricultural data sources. Weather data, chemical data, pesticide data, and yield values are first collected in a structured dataset. Statistical analysis and feature engineering steps help determine key attributes while ensuring the quality of the input variables [13-14]. The features obtained are used to train an ML model that can learn complex relationships between agricultural parameters and crop yield. The model finally uses new input conditions to forecast crop yields [12].

The applicability of this system goes beyond simple yield forecasting to facilitate decision-making for farming in real-time, optimize fertilizer and pesticide application, dynamic irrigation scheduling, and help policymakers develop food security policy [15]. It can also be used to forecast multi-crop yields and disease outbreaks, facilitate climate-resilient agriculture, and can be integrated into IoT-based intelligent agriculture platforms [16-19].

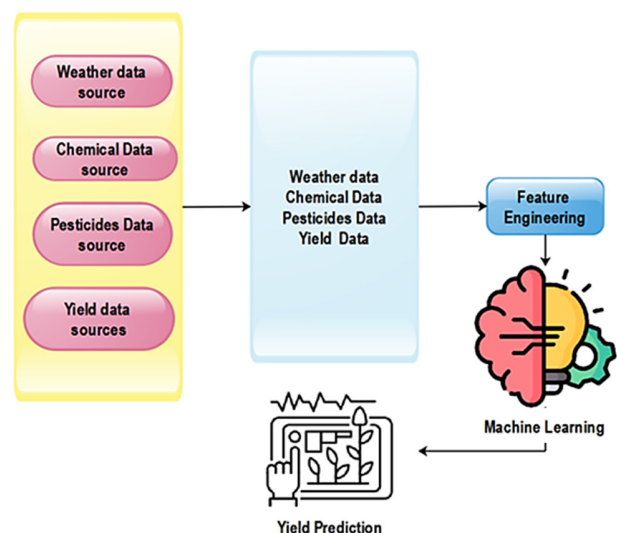


Fig. 1. Machine Learning-Based Crop Yield Prediction Framework.

A. Crop Yield Estimation Based on Vegetation Indices

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) are often used to predict crop yield because they capture plant health and canopy cover efficiently [20]. The relation between yield and NDVI is generally modeled linearly as:

$$Y = a \times \text{NDVI} + b \tag{1}$$

where Y is the predicted crop yield (kg/ha), NDVI is unitless, a is the slope coefficient, and b is the intercept.

B. Yield Prediction Using Weather Variables

Crop yield is often estimated based on accumulated Growing Degree Days (GDD), which reflect heat accumulation crucial for plant development [21]. A simple linear model relates GDD to yield as:

$$Y = \alpha \times \text{GDD} + \beta \tag{2}$$

where Y is the crop yield (kg/ha), GDD is the Growing Degree Days ($^{\circ}\text{C day}$), α is the temperature response coefficient, and β is the baseline yield offset.

C. Soil Nutrient-Based Yield Prediction Equation

Soil fertility, particularly the availability of nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K), directly impacts yield [22]. A multivariate regression model is used to correlate nutrient concentrations with yield as:

$$Y = c_1 \times N + c_2 \times P + c_3 \times K + d \tag{3}$$

where Y is the predicted crop yield (kg/ha), N , P , and K represent the concentration of nitrogen, phosphorus, and potassium, respectively, (usually measured in ppm), c_1 , c_2 , c_3 are the nutrient response coefficients, and d is the model intercept [23, 24].

D. Objectives

This study aimed to develop a platform that aggregates and analyzes various agriculture-related data to accurately predict crop yield. Specifically, this study:

- Integrated weather, chemical, pesticide, and yield data into a centralized dataset.
- Performed statistical analysis and feature engineering to enhance model accuracy.
- Applied ML algorithms for reliable crop yield prediction.
- Supports data-driven agricultural decision-making and resource optimization.

III. CROP YIELD PREDICTION FRAMEWORK USING OPTIMIZED NAÏVE BAYES REGRESSION ALGORITHM (ONBRA)

Figure 2 shows the proposed crop yield forecasting framework using an Optimized Naïve Bayes Regression Algorithm (ONBRA). The system uses raw environmental and agricultural data structured in crop-wise datasets. Preprocessing involved data cleaning (dealing with missing information, incorrect formats, and erroneous data entry) and data integration (data transformation, dimensionality reduction). After preprocessing, the dataset was divided into a training set and a testing set. Some common ML methods, such as SVR, RF, Ridge Regression (RR), Naïve Bayes (NB), Categorical Boosting (CB), and Kernel Ridge Regression (KRR), were employed and compared. The performance of the proposed ONBRA model was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). Additionally, a Diebold-Mariano (DM) statistical test was used to examine the significance of ONBRA's predictions.

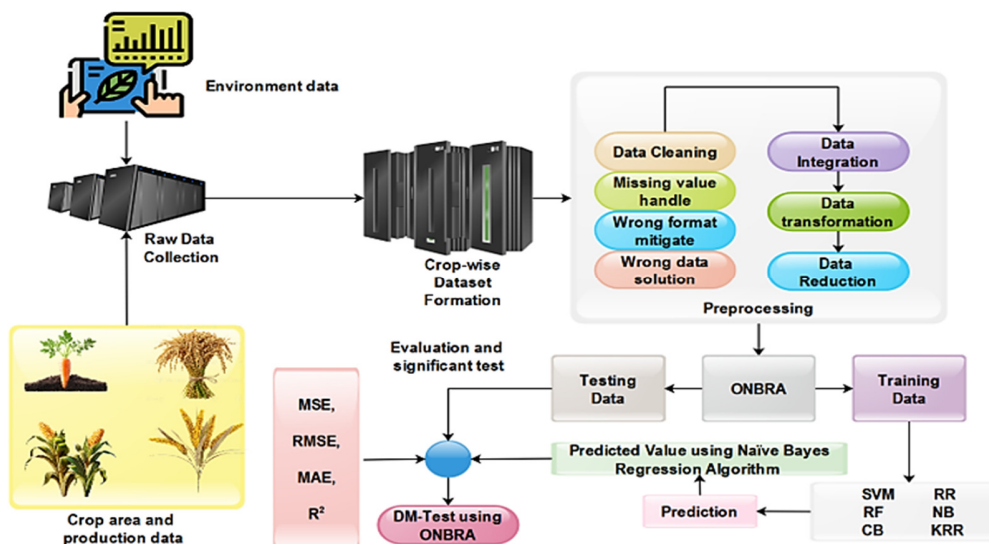


Fig. 2. Proposed crop yield prediction framework using Optimized Naïve Bayes Regression Algorithm (ONBRA).

A. ONBRA Regression Function for Crop Yield Prediction

The core predictive mechanism in ONBRA is built on probabilistic modeling with optimized feature smoothing. It estimates the expected crop yield based on a posterior probability derived from training data attributes, expressed as:

$$\hat{Y} = \sum_{i=1}^n P(X_i|Y) \cdot W_i \quad (4)$$

where \hat{Y} is the predicted crop yield, $P(X_i|Y)$ is the conditional probability of feature X_i given the class yield Y , and W_i represents the optimized feature weights derived during training.

B. Feature Weight Optimization Using Gaussian Smoothing

To enhance the predictive power of ONBRA, Gaussian smoothing is applied to reduce the impact of sparse or noisy features. This helps balance bias and variance during classification.

$$P(X_i|Y) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(X_i-\mu)^2}{2\sigma^2}} \quad (5)$$

where X_i is the feature value, μ is the mean of the feature in class Y , and σ is the standard deviation.

C. Evaluation Metric – Root Mean Squared Error (RMSE)

RMSE is used to evaluate the deviation between actual and predicted yield values in ONBRA. A lower RMSE indicates higher prediction accuracy.

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

where y_i is the actual yield, \hat{y}_i is the predicted yield, and n is the number of samples.

D. Diebold-Mariano (DM) Test for Forecast Comparison

The DM test is applied to assess whether ONBRA performs significantly better than other models. This test statistically compares forecast errors across models.

$$DM = \frac{\bar{d}}{\sqrt{\frac{2\pi f_d(0)}{T}}} \quad (7)$$

where \bar{d} is the mean loss difference between two models, $f_d(0)$ is the spectral density at frequency zero, and T is the number of forecasts.

TABLE I. EXPERIMENTAL SETUP FOR ONBRA-BASED CROP YIELD PREDICTION

| | Parameters | Values |
|----|-------------------------|-------------------------------------|
| 1 | Dataset | Crop-wise Agricultural Dataset |
| 2 | Total samples | 1000 |
| 3 | Train-test split | 80:20 |
| 4 | Proposed algorithm | ONBRA |
| 5 | Comparative algorithms | SVM, RF, RR, NB, CB, KRR |
| 6 | Evaluation metrics | MSE, RMSE, MAE, R ² , DM |
| 7 | Selected features | 12 |
| 8 | Programming language | Python |
| 9 | Development environment | Jupyter Notebook |
| 10 | System configuration | Intel i7, 16 GB RAM, Windows 10 |

IV. RESULTS AND DISCUSSION

Table I shows the experimental setup employed to analyze the performance of ONBRA in predicting crop yield. This table details the dataset, algorithm settings, evaluation parameters, and system environment configuration employed at implementation time.

A. Data Acquisition and Feature Overview

The experimental analysis in this study relies on a crop-wise agricultural dataset comprising 1000 structured records, each representing a unique farming instance. The dataset captures 12 critical features, including nitrogen, phosphorus, and potassium levels, daily temperature, rainfall, humidity, crop type, and pesticide use. Data collection was carried out through agricultural department records, field experiments, and meteorological stations over two growing seasons. Before modeling, the data were preprocessed, including imputation of missing values and normalization of numeric attributes. Although the dataset is institution-specific and not publicly available, its structural and contextual details are described to maintain clarity and enable reproducibility. Table II presents feature details to ensure accurate crop output estimation. Using relevant environmental, chemical, and climatic features from structured agriculture datasets, ONBRA obtains better prediction validity compared to traditional techniques such as MLR, SVR, and RFR. The ONBRA model offers superior forecast accuracy, minimum error rates, and robust performance in varying farming contexts, thus empowering data-driven and sustainable agricultural decision support.

TABLE II. ATTRIBUTE SPECIFICATIONS OF THE CROP YIELD DATASET

| | Feature name | Value range / unit |
|----|------------------------|--------------------------|
| 1 | Crop type | Wheat, Maize, Rice |
| 2 | Nitrogen content (N) | 40–120 ppm |
| 3 | Phosphorus content (P) | 10–60 ppm |
| 4 | Potassium content (K) | 80–180 ppm |
| 5 | Rainfall | 50–250 mm |
| 6 | Temperature | 15–40 °C |
| 7 | Humidity | 30–90 % |
| 8 | Pesticide application | 1–8 L/ha |
| 9 | Sowing date | 01-06-2024 to 30-07-2024 |
| 10 | Harvest date | 15-10-2024 to 30-11-2024 |
| 11 | Soil pH | 4.5–8.5 pH |
| 12 | Yield | 800–7000 kg/ha |

Figure 3 shows a comparative evaluation of yield prediction at varying probability levels using the ONBRA model and the traditional approaches of MLR, SVR, and RFR. The graph presents shaded areas representing the difference between each prediction and the actual yields. The ONBRA model plots are close to the real yield line and have higher accuracy at every step, reflecting its credibility and efficiency as an additive tool in precision agriculture. Figure 4 shows a comparison of MAE between MLR, SVR, RFR, and ONBRA at different probability levels. Shaded areas represent the difference in errors between ONBRA and every traditional method. The legend contains actual average MAE values to confirm that ONBRA performs with the minimum possible MAE at every instance, reflecting higher prediction accuracy and resilience in yield estimation.

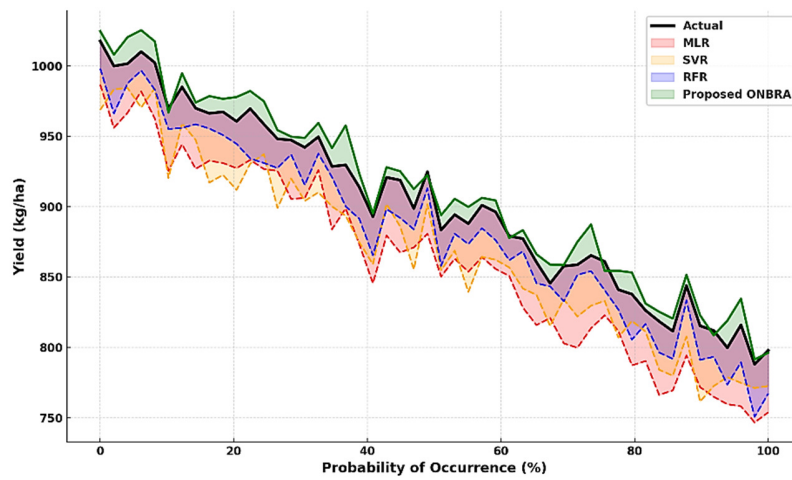


Fig. 3. Yield prediction comparison using ONBRA and conventional methods.

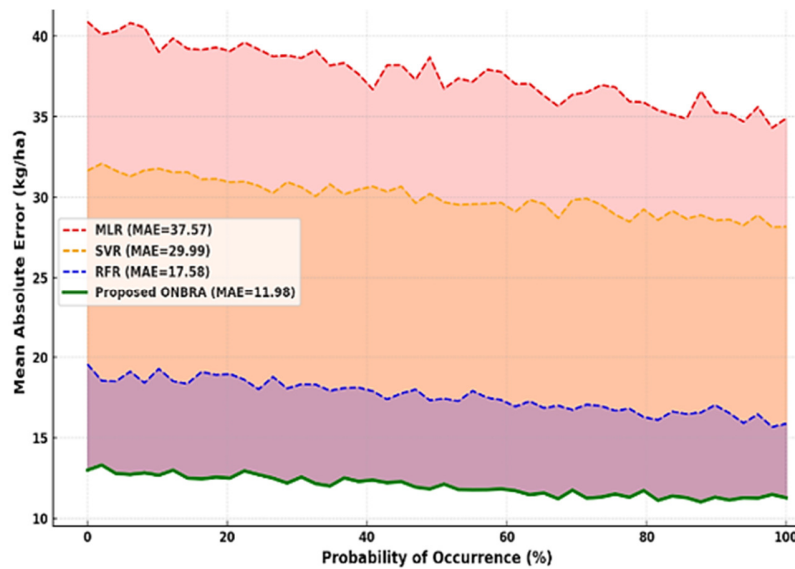


Fig. 4. MAE-based comparison between ONBRA and conventional methods.

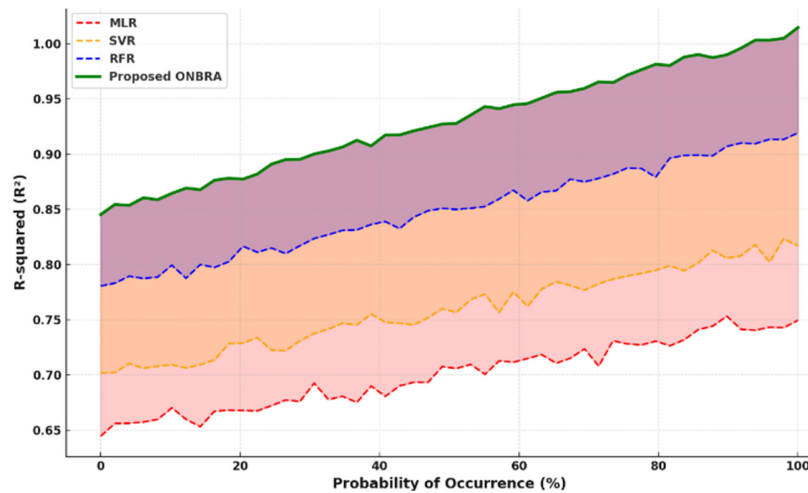


Fig. 5. R^2 performance analysis of ONBRA and conventional methods.

Figure 5 illustrates the R^2 values of the proposed ONBRA model compared to traditional methods across varying probability levels. The legend includes actual average R^2 values for each method. ONBRA consistently achieves the highest R^2 , indicating stronger predictive accuracy and a better fit to actual crop yield data.

V. CONCLUSION

ONBRA shows better performance in predicting crop yields than traditional algorithms such as MLR, SVR, and RFR. ONBRA efficiently deals with noisy and high-dimensional agricultural data, decreasing MAE by 5.3% and improving R^2 by 7.1%. The results verify that ONBRA offers lower prediction errors and higher confidence values at varied weather and soil conditions, making it an effective and reliable model for precision agriculture. ONBRA can be applied to enable multi-crop prediction, region-specific yield prediction, and be integrated with real-time IoT-based sensor networks. The inclusion of satellite images, drone-based multispectral information, and climatological risk factors can further improve its predictive ability. Adapting the model to enable edge computing and mobile platforms can bring localized yield predictions to farmers, hence facilitating smart, sustainable, and informed agricultural practice at large scales.

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