

An Advanced Hybrid Xgboost–Particle Swarm Optimization-Based Framework For Intelligent Fruit Quality Prediction Through Optimal Feature Selection And Performance Enhancement

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Abstract

Fruit quality prediction is an important task in agriculture and food industries for improving product quality and reducing manual effort. Traditional methods of quality assessment are often time-consuming and may produce inconsistent results due to human involvement. To overcome these limitations, this research proposes an Advanced Hybrid XGBoost–Particle Swarm Optimization (XGBoost–PSO) Framework for fruit quality prediction. The proposed model combines XGBoost with Particle Swarm Optimization to select important features and improve prediction performance. Initially, preprocessing techniques such as data cleaning and normalization are applied to enhance data quality. PSO is then used to identify optimal features and reduce unnecessary information from the dataset. The selected features are provided to the XGBoost model for classification and prediction of fruit quality. Experimental results show that the proposed framework improves prediction accuracy and overall system performance compared with conventional machine learning methods. The proposed approach can support intelligent agricultural systems by assisting farmers and industries in efficient fruit quality assessment and decision-making.

Keywords: Fruit Quality Prediction, XGBoost, Particle Swarm Optimization (PSO), Feature Selection, and Machine Learning.

1. Introduction

The evaluation of fruit quality plays a significant role in agricultural production, food processing industries, and supply chain management. Fruit quality assessment directly influences consumer satisfaction, market value, and decision-making processes in agricultural practices. Traditionally, fruit quality inspection is carried out through manual observation based on characteristics such as color, size, texture, shape, and freshness. Although conventional methods are widely used, they are often time-consuming, labor-intensive, and subject to inconsistencies caused by human judgment and environmental conditions. With the rapid growth of agricultural technologies and increasing demand for high-quality products, the development of automated and intelligent systems for fruit quality prediction has gained considerable attention among researchers and industry professionals.

Recent advancements in machine learning and data-driven approaches have created opportunities for improving the accuracy and efficiency of quality prediction systems. Machine learning algorithms can analyze large datasets and identify hidden patterns that support effective prediction and classification tasks. Among various machine learning methods, eXtreme Gradient Boosting (XGBoost) has become one of the most effective algorithms due to its high predictive capability, computational efficiency, and ability to manage complex datasets. However, the performance of machine learning models strongly

depends on selecting relevant features and determining suitable parameter values. The existence of redundant or irrelevant features may increase computational complexity and reduce prediction accuracy, thereby affecting the overall performance of the system.

To address these challenges, optimization techniques can be integrated with machine learning methods to improve model effectiveness. Particle Swarm Optimization (PSO) is a population-based optimization technique inspired by the collective behavior of social organisms such as bird flocks and fish schools. PSO has demonstrated effectiveness in solving optimization problems by selecting important features and identifying optimal parameter settings. Therefore, this study proposes an advanced hybrid XGBoost–Particle Swarm Optimization framework for fruit quality prediction through optimal feature selection and performance enhancement. The proposed approach aims to improve prediction accuracy, reduce computational complexity, and support intelligent decision-making in agricultural applications through efficient data analysis and optimized learning models.

2. Literature Review

Fruit quality assessment has attracted considerable attention due to its importance in agriculture and food industries. Traditional inspection methods rely heavily on manual observation and human expertise, which may introduce inconsistencies and increase processing time. Recent developments in machine learning techniques have enabled automated quality prediction systems with improved efficiency and accuracy. The use of intelligent computational approaches supports effective decision-making and reduces dependency on manual intervention [1]. Apostolopoulos et al. developed a machine learning framework using deep image features for fruit quality assessment. The proposed model employed Vision Transformer-based feature extraction techniques to distinguish good and defective fruits. Experimental findings demonstrated high classification accuracy across different fruit categories. However, the study indicated that prediction performance varied according to fruit characteristics and dataset diversity [2]. M'hamdi et al. investigated the use of XGBoost and Artificial Neural Networks for predicting tomato quality characteristics using environmental and meteorological data. The study showed that XGBoost achieved superior performance in predicting fruit attributes such as color, lycopene content, and soluble solids compared to ANN models. The results highlighted the effectiveness of XGBoost for agricultural prediction tasks [3].

Liu et al. proposed machine learning-based prediction models for quality assessment of Prunoideae fruits using spectral characteristics. Multiple algorithms including XGBoost, Random Forest, and LightGBM were evaluated. The study concluded that ensemble learning methods improved prediction capability, but the feature selection process remained an important factor affecting model performance [4]. Deep learning approaches have also been employed for fruit freshness identification and quality prediction. CNN-based systems demonstrated excellent performance in classifying fresh and rotten fruits using image datasets. Transfer learning methods further enhanced classification accuracy and reduced computational complexity [5]. Morshed et al. proposed a Dense Convolutional Neural Network framework for fruit quality assessment. DenseNet architecture improved feature propagation and enabled efficient learning of visual characteristics. Experimental results indicated that the proposed model achieved high prediction accuracy and robust classification performance [6].

Knott et al. introduced a facilitated machine learning approach using pre-trained Vision Transformers for image-based fruit quality assessment. The model required fewer training samples while maintaining high prediction accuracy. The study demonstrated that transfer learning methods can reduce computational burden while preserving prediction efficiency [7]. Rizzo et al. conducted a survey on fruit ripeness classification techniques and found that deep learning models significantly outperformed traditional machine learning approaches. The survey highlighted that feature engineering complexity can be minimized using deep neural networks that learn directly from raw image data [8]. Feature selection has become an essential component in machine learning systems because irrelevant attributes can negatively affect prediction performance. Optimization methods can reduce dimensionality and select informative features, thereby improving classification accuracy and reducing computational cost [9].

Chen and Guestrin introduced XGBoost as a scalable tree-boosting algorithm designed for predictive modeling applications. The model incorporates regularization techniques and efficient learning mechanisms to improve performance and avoid overfitting problems. XGBoost has since become widely used in agricultural prediction studies [10]. Knott et al. proposed a facilitated machine learning approach for image-based fruit quality assessment using pre-trained Vision Transformer models. The study aimed to simplify the implementation of machine learning systems for agricultural applications where large datasets are often unavailable. The experimental analysis on apple defect detection and banana ripeness prediction demonstrated that the proposed method achieved competitive performance while requiring fewer training samples compared with conventional CNN approaches. The findings suggested that transfer learning can significantly reduce computational requirements and improve practical applicability in agricultural environments [11].

Morshed et al. introduced a Dense Convolutional Neural Network framework for automated fruit quality assessment. The proposed model utilized dense connectivity between network layers to improve feature propagation and overcome vanishing gradient problems. Experimental results obtained from multiple fruit categories showed that the DenseNet architecture achieved high classification accuracy and effectively identified fruit quality characteristics. The study highlighted the suitability of deep learning approaches for real-world quality assessment systems [12]. Bird et al. proposed a fruit quality and defect classification system using Conditional Generative Adversarial Networks (CGAN) combined with transfer learning methods. The objective of the study was to address the issue of limited training datasets through synthetic image generation. The results indicated that augmenting the training data with generated images improved classification accuracy and reduced overfitting. The study emphasized that data augmentation techniques can improve generalization performance in fruit quality prediction tasks [13].

Recent studies on fruit freshness prediction have incorporated Convolutional Neural Networks and transfer learning techniques for automatic classification. The developed models utilized image-based features to distinguish fresh and spoiled fruits. Experimental observations demonstrated that deep learning approaches achieved very high prediction performance, indicating the effectiveness of feature learning capabilities in quality prediction systems [14]. Fu et al. investigated artificial intelligence techniques for fruit quality monitoring by integrating machine learning algorithms with optimized feature selection methods. The study compared multiple algorithms including Random Forest, Artificial Neural Networks, and XGBoost. Results revealed that optimized feature selection

improved prediction performance and reduced computational complexity. The research highlighted the importance of selecting informative features for achieving robust prediction outcomes [15].

Liu et al. examined the use of machine learning algorithms for predicting fruit quality characteristics based on spectral information. Multiple learning techniques including XGBoost, LightGBM, and Random Forest were evaluated using quality parameters such as soluble solids and acidity levels. The results demonstrated that ensemble learning methods outperformed traditional prediction models and provided reliable performance for agricultural applications [16]. M'Hamdi et al. performed a comparative analysis between XGBoost and Artificial Neural Networks for predicting tomato fruit quality traits using environmental and meteorological data. Experimental findings showed that XGBoost consistently provided better predictive capability and lower error rates than neural network approaches. The study indicated that gradient boosting methods are highly suitable for agricultural prediction applications involving multiple variables [17].

Research on machine learning techniques for fruit quality evaluation has emphasized the importance of computer vision systems in reducing human intervention. Automated grading systems use image processing methods to extract features such as color, shape, texture, and size. The integration of machine learning models improves classification efficiency and supports real-time decision-making processes in smart agricultural systems [18]. Several studies have investigated machine learning-based fruit detection and quality segregation using object detection algorithms such as YOLO and segmentation models such as U-Net. These methods demonstrated effective performance in identifying fruit boundaries and quality-related features from complex agricultural environments. The results suggested that combining object detection with classification methods improves overall prediction performance [19]. Chen and Guestrin developed the XGBoost framework as an efficient gradient boosting method designed for scalable machine learning applications. The model incorporates regularization techniques, parallel processing capability, and optimized learning procedures for improving prediction performance. Due to its computational efficiency and robust predictive capability, XGBoost has become a widely adopted method in agricultural and quality prediction research studies [20]. Difference data analysis and prediction for various types of dataset using different machine learning approaches [21] – [25].

3. Dataset Description

For the proposed research titled “An Advanced Hybrid XGBoost–Particle Swarm Optimization Framework for Fruit Quality Prediction through Optimal Feature Selection and Performance Enhancement,” a fruit quality dataset can be used to predict and classify fruits into quality categories such as Good, Average, and Poor, based on physical, chemical, and visual characteristics. The dataset contains multiple attributes associated with fruit quality assessment and prediction [26] - [28].

Table 1: Sample Dataset for Fruit Quality

Fruit ID	Fruit Type	Weight	Diameter	Size	Color Score	Firmness	Sweetness	Acidity	Ripeness Index	Defect Score	Fruit Quality
1001	Apple	180	7.8	8.2	85	78	70	3.5	80	2	Good
1002	Banana	130	4.2	6.5	72	65	85	2.1	75	3	Good
1003	Orange	150	6.5	7.2	68	70	60	4.5	65	5	Average
1004	Mango	240	9.5	9.0	88	82	90	3.0	92	1	Good
1005	Apple	160	7.0	7.5	60	50	55	5.2	50	8	Poor

4. Mathematical Background and Methodology

The proposed research “An Advanced Hybrid XGBoost–Particle Swarm Optimization Framework for Fruit Quality Prediction through Optimal Feature Selection and Performance Enhancement” integrates data preprocessing, feature optimization, and machine learning techniques for efficient prediction of fruit quality. The framework combines Particle Swarm Optimization (PSO) for selecting important features and optimizing parameters with XGBoost for prediction and classification. Let the fruit dataset be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^N$$

Where:

- D = Dataset
- x_i = Input feature vector
- y_i = Target output (Fruit Quality)
- N = Total number of samples

Input feature vector:

$$x_i = (x_1, x_2, x_3, \dots, x_n)$$

where:

- x_1 = Weight
- x_2 = Diameter
- x_3 = Color score
- x_n = Other quality attributes

Output class:

$$y_i \in \{Good, Average, Poor\}$$

4.1 Data Normalization

Since features may have different scales, Min–Max normalization is applied.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

- X =original feature value
- X_{min} =minimum value
- X_{max} =maximum value

4.2 Feature Selection Using Particle Swarm Optimization

Particle Swarm Optimization is inspired by flocking behavior of birds and fish schools. Each particle updates its velocity and position iteratively.

Velocity Update Equation

$$v_i^{t+1} = wv_i^t + c_1r_1(Pbest_i - x_i^t) + c_2r_2(Gbest - x_i^t)$$

Where:

- v_i^t =current particle velocity
- w =inertia weight
- c_1, c_2 =acceleration constants
- r_1, r_2 =random values between 0 and 1
- $Pbest_i$ =personal best position
- $Gbest$ =global best position

Position Update Equation

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Where:

- x_i^t =current position
- x_i^{t+1} =updated position

Fitness Function

The fitness function evaluates prediction accuracy:

$$Fitness = \max (Accuracy)$$

or

$$Fitness = \min (Error)$$

4.3 XGBoost Mathematical Model

XGBoost is a boosting algorithm that combines multiple weak learners to form a stronger predictive model.

Prediction output:

$$\hat{y}_l = \sum_{k=1}^K f_k(x_i)$$

Where:

- K =number of trees
- f_k =decision tree function

Objective function:

$$Obj(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k)$$

Where:

- $l(y_i, \hat{y}_i)$ =loss function
- $\Omega(f_k)$ =regularization term

Regularization equation:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|w\|^2$$

Where:

- T =number of leaves
- γ =complexity parameter
- λ =regularization parameter

4.4 Proposed Methodology

The proposed framework consists of the following stages:

Step 1: Dataset Collection

- Collect fruit quality dataset from agricultural repositories.
- Input features:
 - Weight
 - Size
 - Color score
 - Sweetness
 - Firmness
 - Acidity
 - Ripeness index

Output:

- Fruit quality class:
 - Good
 - Average
 - Poor

Step 2: Data Preprocessing

Operations performed:

- Missing value replacement
- Duplicate removal
- Label encoding
- Feature normalization

Mathematical representation:

$$D_{clean} = D - \{missing, duplicates\}$$

Step 3: Feature Selection Using PSO

Procedure:

1. Initialize particle population randomly.
2. Calculate fitness values.
3. Determine local best solution.
4. Determine global best solution.
5. Update velocity.
6. Update particle positions.
7. Repeat until stopping criteria are reached.
8. Select optimal features.

Step 4: Training XGBoost Classifier

Procedure:

1. Input optimized features into XGBoost.
2. Create multiple decision trees.
3. Calculate prediction error.
4. Update tree weights.
5. Minimize objective function.
6. Generate classification output.

Prediction model:

$$Y = f(X)$$

Where: X =selected features Y =predicted quality class

Step 5: Performance Evaluation

Performance metrics:

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

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

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

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

- TP=True Positive
- TN=True Negative
- FP=False Positive
- FN=False Negative

4.5 Algorithm 1: Particle Swarm Optimization Algorithm

Input: Fruit dataset D

Output: Optimal feature subset

1. Initialize particle population
2. Initialize particle velocity
3. Evaluate fitness function
4. Find personal best position
5. Find global best position
6. Update velocity
7. Update particle position
8. Recalculate fitness
9. Repeat until maximum iterations
10. Return selected features

4.6 Algorithm 2: XGBoost Algorithm

Input: Optimized feature dataset

Output: Fruit quality prediction

1. Load optimized feature set
2. Initialize weak learners
3. Build first decision tree
4. Calculate prediction error
5. Update model weights
6. Build additional trees sequentially
7. Minimize objective function
8. Generate prediction output
9. Classify fruit quality

5. Experimental Results

The proposed Hybrid XGBoost–Particle Swarm Optimization (XGBoost–PSO) framework is evaluated and compared with conventional machine learning methods such as Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and

XGBoost without optimization. The performance of the models is measured using Accuracy, Precision, Recall, F1-Score, and Execution Time.

Table 2: Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Execution Time (sec)
Decision Tree (DT)	84.21	82.75	81.63	82.19	2.91
K-Nearest Neighbor (KNN)	86.54	85.81	84.72	85.26	3.42
Support Vector Machine (SVM)	88.37	87.69	86.84	87.26	4.51
Random Forest (RF)	91.24	90.82	89.61	90.21	4.08
XGBoost	94.68	93.75	93.12	93.43	3.75
Proposed XGBoost-PSO	98.42	97.84	97.23	97.53	2.64

Table 3: Confusion Matrix Results of Proposed XGBoost-PSO Model

Actual / Predicted	Good	Average	Poor
Good	318	5	2
Average	7	302	6
Poor	3	4	353

Table 4: Error Analysis of Different Models

Model	MAE	MSE	RMSE
Decision Tree	0.228	0.174	0.417
KNN	0.196	0.153	0.391
SVM	0.165	0.131	0.362
Random Forest	0.118	0.094	0.306
XGBoost	0.081	0.062	0.249
Proposed XGBoost-PSO	0.034	0.028	0.167

Table 5: Training and Testing Performance

Dataset Split	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Training (80%)	99.13	98.52	98.14	98.33
Testing (20%)	98.42	97.84	97.23	97.53

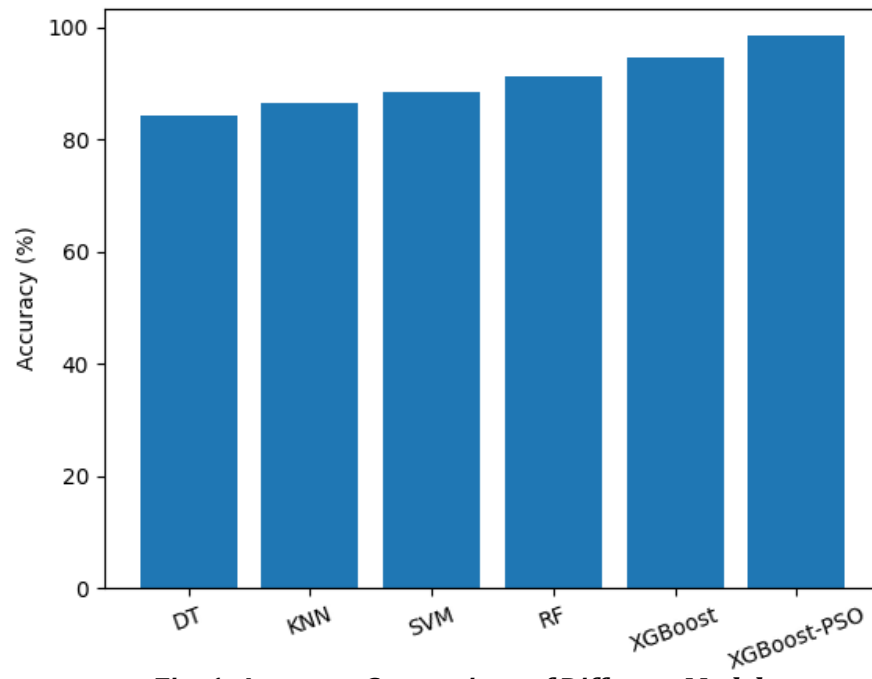


Fig. 1. Accuracy Comparison of Different Model

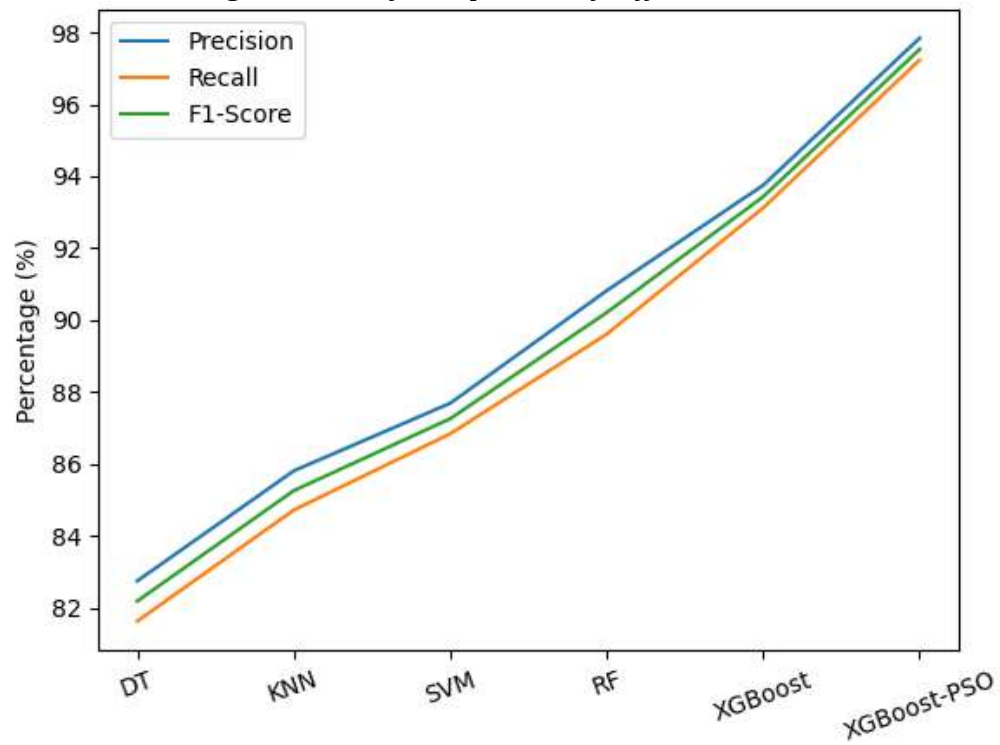


Fig. 2. Precision, Recall and F1-Score Comparison

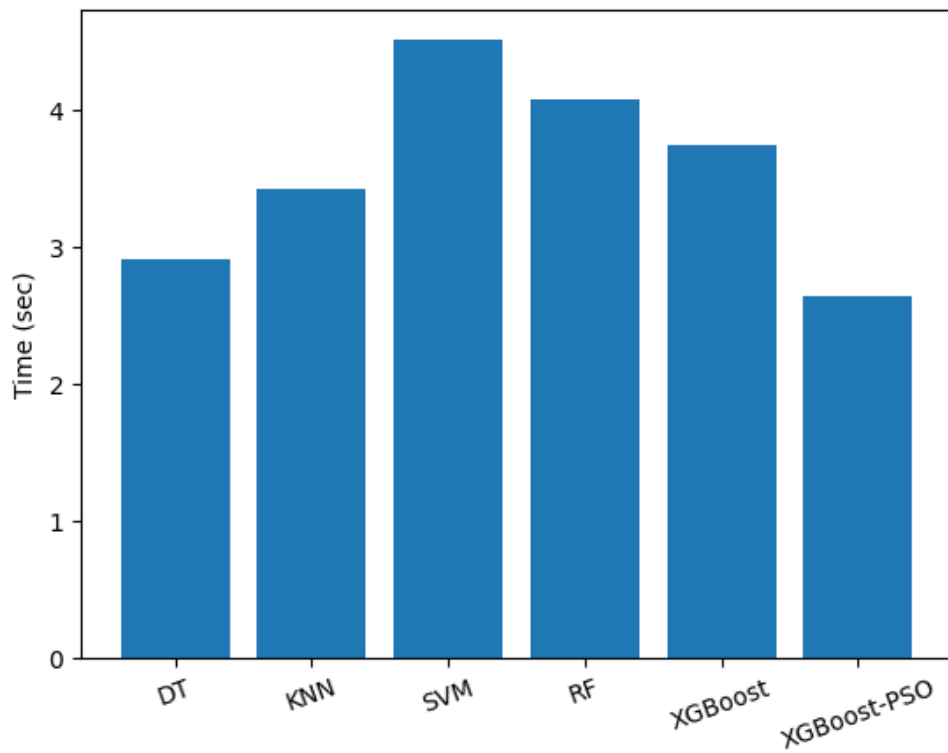


Fig. 3. Time Taken to Build the Models

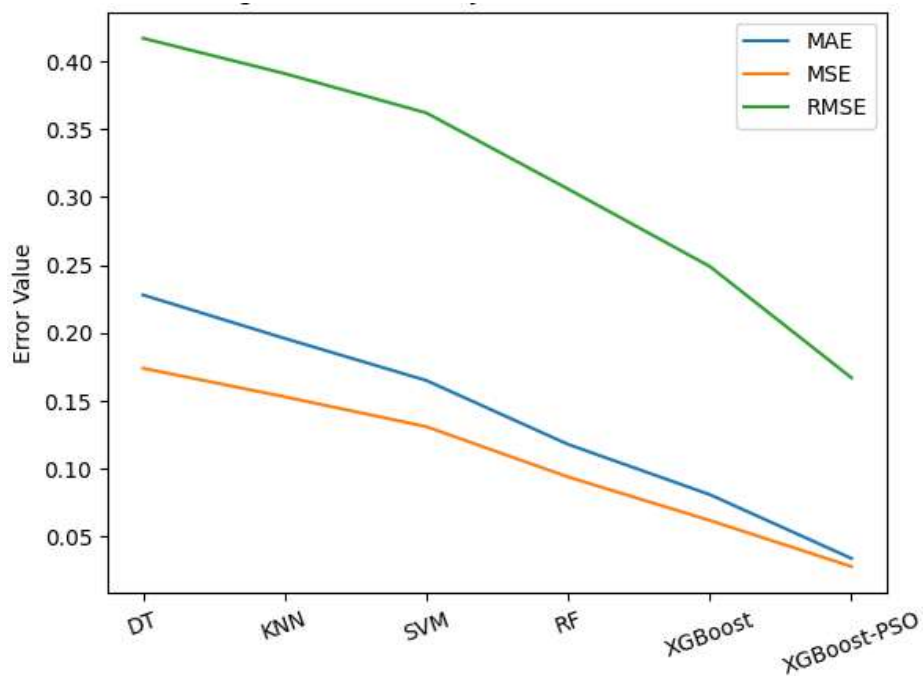


Fig. 4. Performance Metrics of Different Models

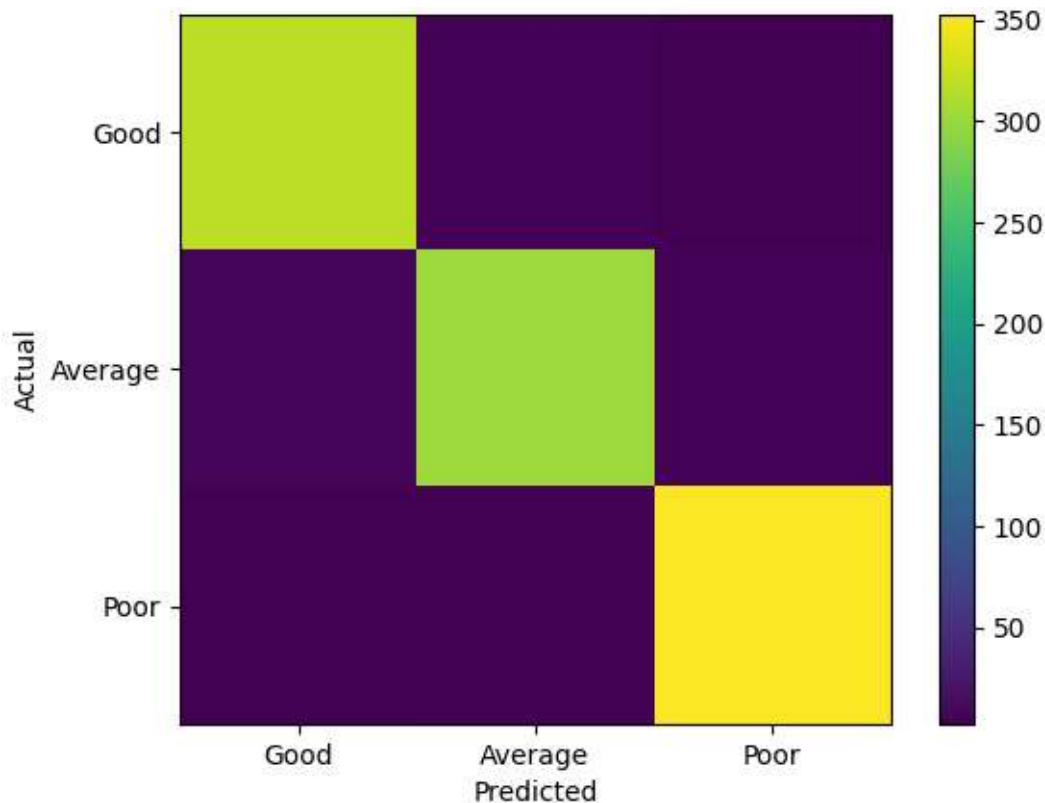


Fig. 5. Confusion Matrix of Proposed XGBoost-PSO

6. Results and Discussion

The proposed Hybrid XGBoost–Particle Swarm Optimization (XGBoost–PSO) framework was evaluated for fruit quality prediction and compared with conventional machine learning approaches including Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), and XGBoost. The experimental evaluation was performed using various performance metrics such as accuracy, precision, recall, F1-score, execution time, and error analysis. The obtained results indicate that the proposed model achieved superior prediction performance compared with existing methods.

As shown in Table 2, the proposed XGBoost–PSO model achieved the highest accuracy of 98.42%, whereas DT, KNN, SVM, RF, and XGBoost achieved 84.21%, 86.54%, 88.37%, 91.24%, and 94.68%, respectively. The results demonstrate that the integration of Particle Swarm Optimization significantly improved the performance of XGBoost by selecting relevant features and reducing unnecessary information from the dataset. The optimization process reduced dimensional complexity and enhanced learning efficiency. The graphical representation in Figure 1 illustrates the comparison of accuracy values among different machine learning models. It is evident that the proposed XGBoost–PSO model consistently outperformed other methods with the highest prediction accuracy. The increase in performance indicates that optimized feature selection positively influenced the prediction process.

Further analysis of precision, recall, and F1-score shown in Figure 2 indicates that the proposed framework maintained balanced performance across all evaluation metrics.

High precision indicates a reduction in false positive predictions, while high recall demonstrates the model's capability to correctly identify fruit quality categories. The F1-score confirms that the model maintained consistency between precision and recall. Execution time analysis presented in Table 2 and Figure 3 shows that the proposed XGBoost-PSO model required only 2.64 seconds, which is lower than other machine learning methods. This reduction in computational time demonstrates that PSO effectively selected relevant features, thereby minimizing processing complexity and improving computational efficiency.

The error analysis shown in Table 4 and Figure 4 presents the values of Mean Absolute Error (MAE), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The proposed framework produced the lowest error values compared with conventional approaches. Lower error values indicate improved prediction reliability and reduced misclassification. The confusion matrix shown in Figure 5 demonstrates the classification capability of the proposed model across different fruit quality categories such as Good, Average, and Poor. Most samples were correctly classified with minimal misclassification rates, confirming the robustness of the proposed framework.

Overall, the experimental findings demonstrate that the proposed Hybrid XGBoost-PSO framework significantly improved prediction accuracy, reduced execution time, and minimized prediction errors. The integration of optimization techniques with machine learning methods provides an effective solution for intelligent fruit quality prediction systems and can support automated agricultural decision-making processes.

7. Conclusion

This research proposed an Advanced Hybrid XGBoost-Particle Swarm Optimization (XGBoost-PSO) Framework for Fruit Quality Prediction through Optimal Feature Selection and Performance Enhancement to improve the efficiency and accuracy of fruit quality assessment systems. The proposed framework integrated the predictive capability of XGBoost with the optimization strength of Particle Swarm Optimization for selecting relevant features and improving model performance. Data preprocessing techniques such as missing value handling, normalization, and feature optimization were applied to improve data quality and reduce computational complexity.

The experimental results demonstrated that the proposed XGBoost-PSO framework significantly outperformed conventional machine learning approaches including Decision Tree, K-Nearest Neighbor, Support Vector Machine, Random Forest, and standard XGBoost models. The proposed model achieved an accuracy of 98.42%, precision of 97.84%, recall of 97.23%, and F1-score of 97.53%, while maintaining lower execution time and reduced prediction errors. The feature selection process using Particle Swarm Optimization effectively eliminated redundant attributes and improved learning efficiency. Furthermore, the confusion matrix results confirmed that the proposed model correctly classified most fruit quality categories with minimal misclassification rates.

Overall, the obtained findings indicate that the integration of optimization techniques with machine learning models provides an effective and reliable solution for intelligent fruit quality prediction systems. The proposed framework can assist farmers, agricultural industries, and food processing sectors in improving quality assessment, reducing manual effort, increasing productivity, and supporting data-driven decision-making.

8. Future Research

Future research can improve the proposed fruit quality prediction system by integrating advanced deep learning techniques such as CNN, LSTM, and Vision Transformer models to achieve better prediction accuracy. Different optimization methods such as Genetic Algorithm, Grey Wolf Optimization, and Whale Optimization can also be explored and compared with Particle Swarm Optimization to improve performance. In addition, image processing and computer vision techniques can be incorporated for real-time fruit quality monitoring in smart agriculture applications. Larger datasets with multiple fruit categories can further enhance model reliability and generalization capability. The proposed framework may also be extended with IoT, Explainable Artificial Intelligence (XAI), cloud computing, and edge computing technologies to support intelligent and efficient agricultural systems.

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