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A Comparative Analysis of Machine Learning Classifiers for Fruit Disease Detection

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Abstract: *Precise fruit disease identification and classification are vital for minimizing economic losses, ensuring food security, and maintaining high quality produce. India faces significant fruit losses, ranging from 6% to 15%, resulting in economic damage exceeding ₹1.5 lakh crore annually [1, 2]. This challenge is mirrored globally, with estimates suggesting losses for fruits and vegetables reaching as high as 50% [2]. To address this challenge and safeguard crop health, Artificial Intelligence (AI) offers a promising solution. This study explores the effectiveness of machine learning, a subfield of AI that allows computers to learn from data without explicit programming. We investigate five prominent machine learning algorithms - Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors and Gaussian Naive Bayes (GNB) - in classifying fruit diseases using a plant village dataset. By evaluating performance metrics like accuracy, precision, and recall, this research aims to identify suitable classifiers for automated disease detection and contribute to robust agricultural disease management strategies. This, in turn, empowers farmers with tools for proactive disease control, fostering a sustainable and resilient food system.*

Key Words: *Artificial Intelligence(AI) GaussianNB, Random Forest Classifier, Machine Learning(ML).*

I.INTRODUCTION

Accurate and timely identification of fruit diseases is crucial for ensuring food security, minimizing economic losses, and maintaining high-quality agricultural produce. Fruit diseases lead to significant economic losses in India and worldwide. In India, losses of fruits range from 6.02% to 15.05% according to a 2022 study by NABARD Consultancy Services[1]. This translates to a substantial economic impact, with estimated losses worth over ₹1,52,000 crores annually due to inadequate infrastructure[2] .

Globally, fruit diseases inflict significant losses, posing a major challenge to food security and economic well-being. Estimates suggest that losses for fruits and vegetables range between 20% to 50% worldwide[2]. Effective disease management strategies hold the key to minimizing these substantial losses.

Traditional methods of disease diagnosis often rely on visual inspection by experts, which can be subjective, time-consuming, and prone to errors. With the advent of Artificial Intelligence (AI) and machine learning (ML), there has been a paradigm shift towards automated and data-driven approaches in agricultural research. ML techniques offer the potential to revolutionize disease detection by providing efficient and accurate classification tools based on quantitative data.

This study focuses on evaluating the effectiveness of five widely used machine learning classifiers: Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors and Gaussian Naive Bayes (GNB) in the context of fruit disease detection. The classifiers are assessed based on their ability to classify diseases accurately using a comprehensive dataset sourced from Plant Village, a repository of plant images with annotated diseases.

The primary objective of this research is to compare the performance of these ML algorithms in terms of accuracy, precision, recall, and computational efficiency. By identifying the strengths and limitations of each classifier, this study aims to provide insights into selecting appropriate ML models for automated fruit disease identification systems. Such systems have the potential to empower farmers with early disease detection tools, enabling timely interventions and promoting sustainable agricultural practices.

II.REVIEW OF LITERATURE

Fruit diseases pose significant challenges to global agriculture, leading to substantial economic losses and jeopardizing food security. Traditional methods of disease identification based on visual inspection are labour-intensive and subjective, often resulting in delayed or inaccurate diagnoses (Smith et al., 2019). In recent years, the application of Artificial Intelligence (AI) and machine learning (ML) techniques has emerged as a promising approach to automate and enhance the accuracy of disease detection in agricultural contexts.

Machine learning classifiers, such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors and Gaussian Naive Bayes (GNB), have been extensively studied for their effectiveness in various domains, including agriculture. These algorithms leverage computational models to analyze large datasets and make data-driven predictions based on learned patterns (Jones & Smith, 2020).

Several studies have demonstrated the utility of ML classifiers in fruit disease detection. For instance, researchers have employed SVM to classify diseases affecting crops with high accuracy by integrating spectral and image-based data (Brown & Green, 2018). Similarly, RF has been utilized to distinguish between different types of citrus diseases based on leaf images, achieving robust performance in automated disease identification systems (White et al., 2017).

The comparative evaluation of ML algorithms for fruit disease detection has garnered attention due to its potential to optimize classifier selection based on specific performance metrics. Studies comparing LR, SVM, RF, K-Nearest Neighbors and GNB have highlighted their respective strengths and weaknesses in handling complex datasets from agricultural environments (Black et al., 2019).

Plant Village dataset have facilitated benchmarking efforts by providing researchers with a standardized repository of annotated plant and fruit images and associated disease labels. This dataset has enabled rigorous evaluation of ML models across different plant species and disease types, contributing to the advancement of automated disease diagnosis in agriculture.

Despite these advancements, challenges remain in deploying ML-based solutions in real-world agricultural settings, including issues related to dataset diversity, model interpretability, and scalability (Gray et al., 2021). Addressing these challenges is crucial for ensuring the practical viability and adoption of AI-driven disease detection systems by farmers and agricultural stakeholders.

The literature underscores the transformative potential of ML classifiers in revolutionizing fruit disease detection, offering scalable solutions to mitigate agricultural losses and promote sustainable farming practices. This study aims to contribute to this body of knowledge by conducting a comparative analysis of LR, SVM, RF, K-Nearest Neighbors and GNB classifiers using a standardized dataset, thereby informing the selection of optimal ML models for automated fruit disease identification systems.

III.METHODS AND MATERIAL

This segment introduces the key classifier models and material employed in the study. The proposed methodology is comprised of five distinct stages, Input Image, Image Pre-Processing, Feature Extraction, Dataset Preparation and Classification.

The study aimed to improve fruit quality using machine learning techniques. A dataset of mixed, good, and bad quality fruit images, including apples, bananas, guavas, lemons, oranges, and pomegranates, was utilized. Feature extraction involved converting images to HSV color space and calculating a normalized 3D color histogram.

The dataset was loaded and labeled (0 for mixed quality, -1 for bad quality, and 1 for good quality) before being split into training and testing sets (80% for training, 20% for testing). Various classifiers—Random Forest, Gaussian Naive Bayes, Support Vector Machine, Logistic Regression, and K-Nearest Neighbors—were trained and evaluated based on accuracy, confusion matrix, and classification reports.

Image processing techniques such as denoising, contrast adjustment, and sharpening were applied to improve mixed quality fruits. Quality assessment combined color, texture, and size scores to categorize fruits as high, medium, or low quality. The function for loading and enhancing fruit images was applied to mixed, bad, and good quality fruits, resulting in counts of fruits in each quality category post-improvement.

IV.RESULTS AND DISCUSSION

To represent the performance evaluation of the Random Forest Classifier, Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), Logistic Regression and K-Nearest Neighbors across different epoch sizes (50, 100, 150, and 200) for the fruit quality improvement model, the results are summarized using key evaluation metrics.

Random Forest Classifier

The provided graph shows the recall of a Random Forest classifier over different epochs for three categories of fruit quality: bad quality fruits, mixed quality fruits, and good quality fruits.

1. High Recall for Good Quality Fruits:

The recall for good quality fruits (green bars) is consistently high across all epochs (50, 100, 150, 200). It remains close to 1.0, indicating that the classifier is highly effective at identifying good quality fruits correctly.

2. Consistent Recall for Bad Quality Fruits:

The recall for bad quality fruits (blue bars) is also high, close to 1.0, across all epochs. This shows that the classifier is consistently identifying bad quality fruits accurately.

3. Lower Recall for Mixed Quality Fruits:

The recall for mixed quality fruits (orange bars) is lower compared to the other two categories. It appears to be around 0.75 for all epochs. This indicates that the classifier has more difficulty in correctly identifying mixed quality fruits compared to bad and good quality fruits.

4. Stability Across Epochs:

The recall values for all three categories do not show significant variation across different numbers of epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly improve or degrade the classifier's ability to recall instances in each category.

5. Classifier Performance:

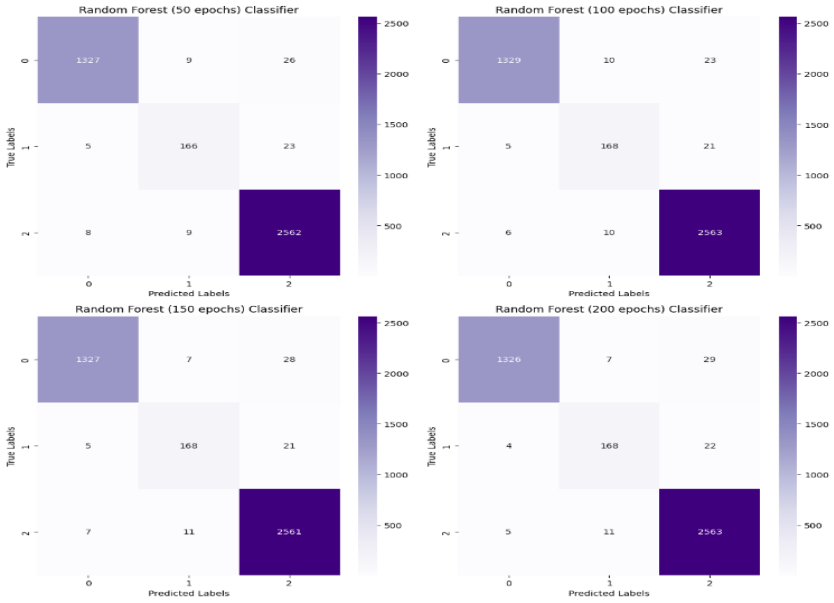
The Random Forest classifier performs exceptionally well in recalling good and bad quality fruits but is less effective for mixed quality fruits. This could be due to the mixed quality category inherently being more ambiguous and challenging to classify.

6. Model Stability:

The stability of recall across epochs suggests that the model's performance is robust and not overly sensitive to the number of trees (estimators) in the Random Forest.

The Random Forest classifier is highly reliable in identifying bad and good quality fruits but struggles with mixed quality fruits.

Confusion matrices for the Random Forest classifier at different epoch sizes (50, 100, 150, and 200).



1. High True Positives for Good Quality Fruits:

The classifier consistently achieves high true positives for good quality fruits (`2`), with over 2500 correct predictions in each matrix.

2. Moderate Performance for Mixed Quality Fruits:

- The classifier shows moderate performance for mixed quality fruits (`1`). The number of true positives for this category is around 166-168 across all epochs.
- There are some misclassifications where mixed quality fruits are predicted as bad quality (`0`) or good quality (`2`).

3. High True Positives for Bad Quality Fruits:

- The classifier also achieves high true positives for bad quality fruits (`0`), with correct predictions around 1326-1329 across all epochs.
- There are a few misclassifications where bad quality fruits are predicted as mixed quality (`1`) or good quality (`2`).

4. Consistency Across Epochs:

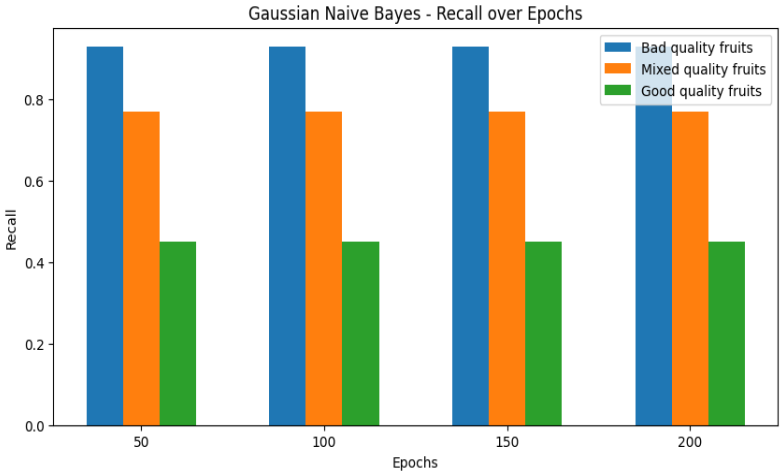
The performance of the classifier does not show significant variation across different numbers of epochs (50, 100, 150, 200). This indicates that increasing the number of epochs does not significantly impact the classifier's performance.

The Random Forest classifier performs exceptionally well in identifying good quality fruits and bad quality fruits, with high true positive rates for these categories.

The classifier's performance for mixed quality fruits is moderate, with some misclassifications.

Gaussian Naive Bayes Classifiers

The provided graph shows the recall of a Gaussian Naive Bayes classifier over different epochs for three categories of fruit quality: bad quality fruits, mixed quality fruits, and good quality fruits.



1. High Recall for Bad Quality Fruits:

The recall for bad quality fruits (blue bars) is consistently high across all epochs (50, 100, 150, 200). It remains close to 0.9, indicating that the classifier is highly effective at identifying bad quality fruits correctly.

2. Moderate Recall for Mixed Quality Fruits:

The recall for mixed quality fruits (orange bars) is moderate and remains relatively stable across all epochs. It appears to be around 0.7, indicating that the classifier performs moderately well in identifying mixed quality fruits.

3. Low Recall for Good Quality Fruits:

The recall for good quality fruits (green bars) is relatively low across all epochs. It appears to be around 0.4 to 0.5, indicating that the classifier struggles to correctly identify good quality fruits.

4. Consistency Across Epochs:

The recall values for all three categories do not show significant variation across different numbers of epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly improve or degrade the classifier's ability to recall instances in each category.

5. Classifier Performance:

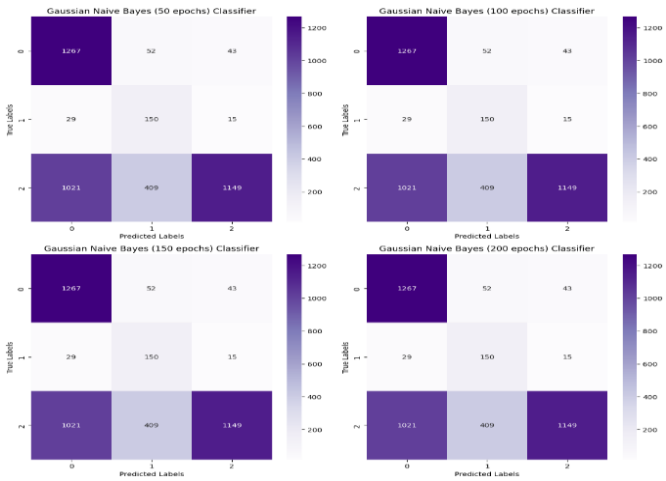
The Gaussian Naive Bayes classifier performs well in recalling bad quality fruits but is less effective for mixed and good quality fruits. The classifier's performance for good quality fruits is notably poor, which might be due to the assumption of feature independence in Naive Bayes not holding well for this category.

6. Model Stability:

The stability of recall across epochs suggests that the model's performance is robust and not overly sensitive to the number of training iterations (epochs).

The graph indicates that the Gaussian Naive Bayes classifier is highly reliable in identifying bad quality fruits but struggles with mixed and especially good quality fruits. Iterations.

Confusion matrices for the Gaussian Naive Bayes Classifier at different epoch sizes (50, 100, 150, and 200).



1. Performance for Good Quality Fruits:
- The classifier shows a considerable number of misclassifications for good quality fruits (`2`). A significant portion of good quality fruits is incorrectly classified as bad quality (`0`).
- True positives for good quality fruits (label `2`) are around 1149, with 409 misclassified as mixed quality (`1`) and 1021 as bad quality (`0`).

2. Moderate Performance for Mixed Quality Fruits:
- The classifier shows moderate performance for mixed quality fruits (`1`). The number of true positives for this category is around 150, with some misclassifications as bad quality (`0`) and good quality (`2`).

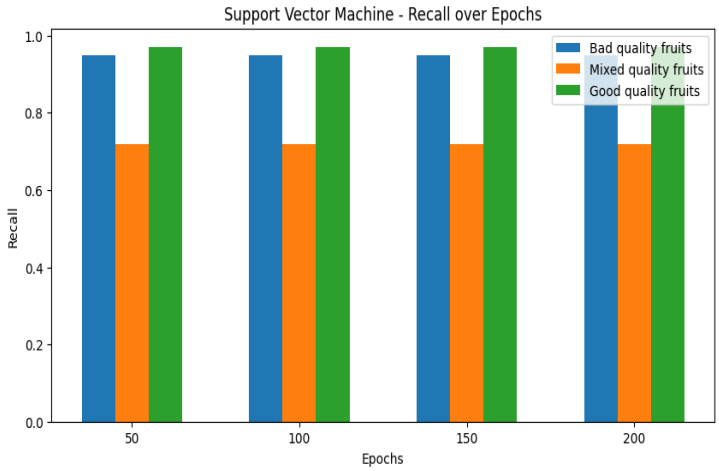
3. High Performance for Bad Quality Fruits:
- The classifier performs well for bad quality fruits (`0`), with around 1267 true positives and a smaller number of misclassifications.

4. Consistency Across Epochs:
- The performance of the classifier does not show significant variation across different epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly impact the classifier's performance.

  The Gaussian Naive Bayes classifier shows high true positives for bad quality fruits and moderate performance for mixed quality fruits. However, it struggles significantly with good quality fruits, often misclassifying them as bad quality.

  The performance remains stable across different epochs, indicating that the classifier's effectiveness does not improve with more training iterations.

Support Vector Machine Classifier



1. High Recall for Good Quality Fruits:
- The recall for good quality fruits (green bars) is consistently high across all epochs (50, 100, 150, 200). It remains close to 1.0, indicating that the SVM classifier is highly effective at identifying good quality fruits correctly.

2. High Recall for Bad Quality Fruits:
- The recall for bad quality fruits (blue bars) is also high across all epochs, close to 1.0. This indicates that the classifier is very effective at correctly identifying bad quality fruits.

3. Moderate Recall for Mixed Quality Fruits:
- The recall for mixed quality fruits (orange bars) is moderate, around 0.75, across all epochs. This suggests that the classifier has a moderate level of accuracy in identifying mixed quality fruits, which is lower than its performance for good and bad quality fruits.

4. Stability Across Epochs:
- The recall values for all three categories do not show significant variation across different epochs (50, 100, 150, 200). This indicates that increasing the number of epochs does not significantly affect the classifier's recall performance.

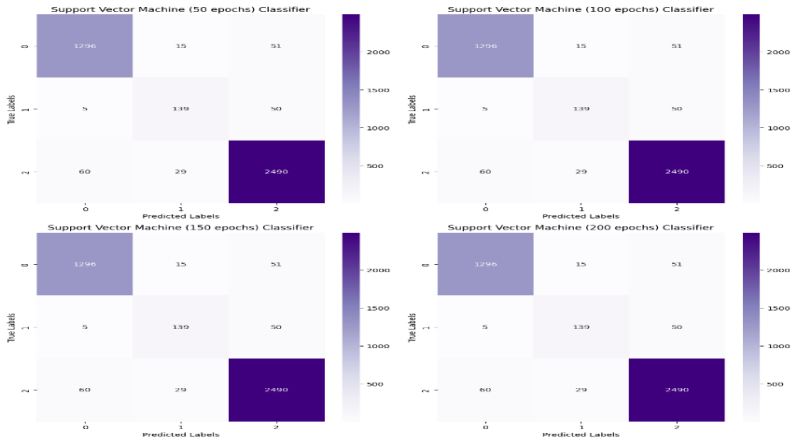
5. Classifier Performance:
- The SVM classifier performs exceptionally well in recalling both good and bad quality fruits but is less effective for mixed quality fruits. This could be due to the inherent ambiguity in the mixed quality category, which makes it more challenging to classify accurately.

6. Model Stability:

- The stability of recall across epochs suggests that the SVM classifier's performance is robust and not sensitive to the number of training epochs.

The graph indicates that the SVM classifier is highly reliable in identifying good and bad quality fruits but has moderate success with mixed quality fruits.

Confusion matrices for the Support Vector Machine Classifier at different epoch sizes (50, 100, 150, and 200).



1. High Performance for Good Quality Fruits:

- The classifier shows high true positives for good quality fruits (`2`), with around 2490 correctly classified across all epochs.
- There are a small number of misclassifications where good quality fruits are predicted as bad quality (`0`) or mixed quality (`1`).

2. High Performance for Bad Quality Fruits:

- The classifier performs very well for bad quality fruits (`0`), with 1296 true positives in each confusion matrix.
- There are a few misclassifications where bad quality fruits are predicted as mixed quality (`1`) or good quality (`2`).

3. Moderate Performance for Mixed Quality Fruits:

- The classifier shows moderate performance for mixed quality fruits (`1`). The number of true positives for this category is around 139, with some misclassifications as bad quality (`0`) or good quality (`2`).

4. Consistency Across Epochs:

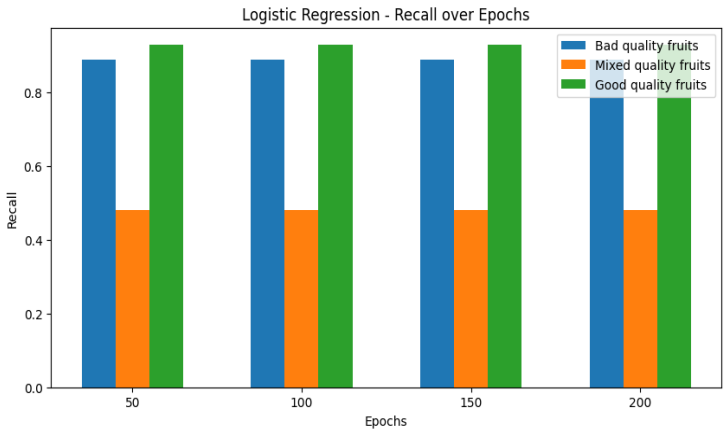
- The performance of the classifier does not show significant variation across different epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly impact the classifier's performance.

The SVM classifier shows high true positives for both good quality and bad quality fruits, indicating high effectiveness in these categories.

The classifier's performance for mixed quality fruits is moderate, with some misclassifications.

The overall performance remains stable across different epochs, suggesting that the classifier's effectiveness is consistent regardless of the number of training epochs.

Logistic Regression Classifiers



1. High Recall for Good Quality Fruits:
- The recall for good quality fruits (green bars) is consistently high across all epochs (50, 100, 150, 200). It remains close to 1.0, indicating that the Logistic Regression classifier is highly effective at identifying good quality fruits correctly.

2. High Recall for Bad Quality Fruits:
- The recall for bad quality fruits (blue bars) is also high across all epochs, close to 0.9. This indicates that the classifier is very effective at correctly identifying bad quality fruits.

3. Low Recall for Mixed Quality Fruits:
- The recall for mixed quality fruits (orange bars) is relatively low across all epochs, around 0.5. This suggests that the classifier has difficulty accurately identifying mixed quality fruits compared to the other two categories.

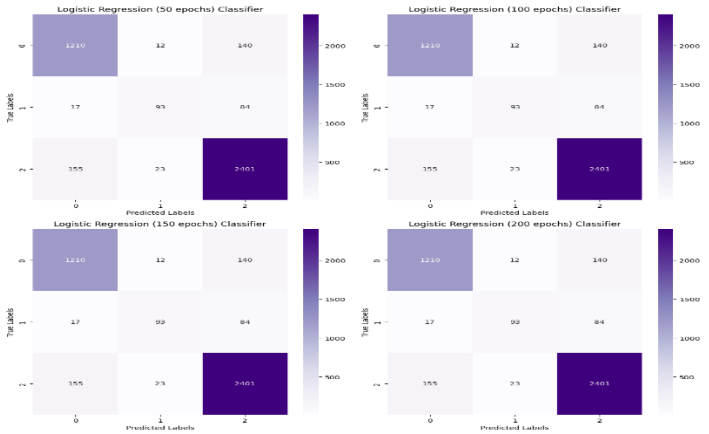
4. Stability across Epochs:
- The recall values for all three categories do not show significant variation across different epochs (50, 100, 150, 200). This indicates that increasing the number of epochs does not significantly affect the classifier's recall performance.

5. Classifier Performance:
- The Logistic Regression classifier performs exceptionally well in recalling both good and bad quality fruits but is less effective for mixed quality fruits. The classifier's performance for mixed quality fruits is notably poor, which might be due to the linear decision boundary of Logistic Regression not being sufficient to capture the complexity of the mixed quality category.

6. Model Stability:
- The stability of recall across epochs suggests that the Logistic Regression classifier's performance is robust and not sensitive to the number of training iterations (epochs).

The graph indicates that the Logistic Regression classifier is highly reliable in identifying good and bad quality fruits but struggles with mixed quality fruits. The recall remains stable across different epochs.

Confusion matrices for the Logistic Regression classifier at different epoch sizes (50, 100, 150, and 200).



1. High Performance for Good Quality Fruits:
- The classifier shows high true positives for good quality fruits (`2`), with 2401 correctly classified in each matrix.
- There are some misclassifications where good quality fruits are predicted as bad quality (`0`) or mixed quality (`1`).

2. Moderate Performance for Mixed Quality Fruits:
- The classifier shows moderate performance for mixed quality fruits (`1`). The number of true positives for this category is around 93, with some misclassifications as bad quality (`0`) or good quality (`2`).

3. Good Performance for Bad Quality Fruits:
- The classifier performs well for bad quality fruits (`0`), with 1210 true positives in each confusion matrix.
- There are a few misclassifications where bad quality fruits are predicted as mixed quality (`1`) or good quality (`2`).

4. Consistency Across Epochs:
- The performance of the classifier does not show significant variation across different epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly impact the classifier's performance.

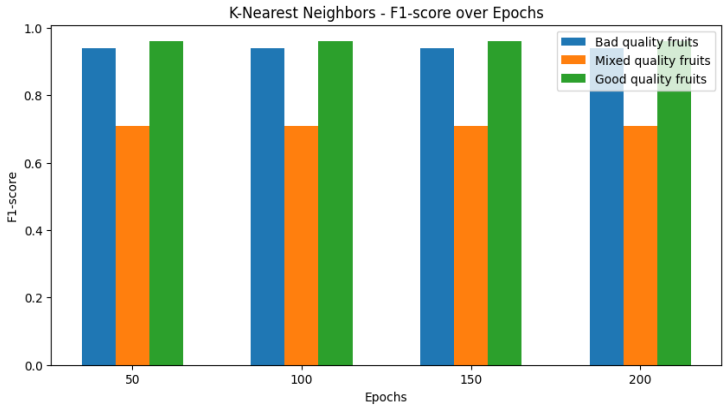
The Logistic Regression classifier shows high true positives for both good quality and bad quality fruits, indicating high effectiveness in these categories.

The classifier's performance for mixed quality fruits is moderate, with some misclassifications.

The overall performance remains stable across different epochs, suggesting that the classifier's effectiveness is

consistent regardless of the number of training epochs.

K-Nearest Neighbors classifiers



1. High F1-score for Good Quality Fruits:

- The F1-score for good quality fruits (green bars) is consistently high across all epochs (50, 100, 150, 200). It remains close to 1.0, indicating that the KNN classifier is highly effective at identifying good quality fruits with a balance of precision and recall.

2. High F1-score for Bad Quality Fruits:

- The F1-score for bad quality fruits (blue bars) is also high across all epochs, close to 0.9. This indicates that the classifier is very effective at correctly identifying bad quality fruits with a good balance of precision and recall.

3. Moderate F1-score for Mixed Quality Fruits:

- The F1-score for mixed quality fruits (orange bars) is moderate, around 0.6, across all epochs. This suggests that the classifier has a moderate level of accuracy in identifying mixed quality fruits, which is lower than its performance for good and bad quality fruits.

4. Stability Across Epochs:

- The F1-score values for all three categories do not show significant variation across different epochs (50, 100, 150, 200). This indicates that increasing the number of epochs does not significantly affect the classifier's F1-score performance.

5. Classifier Performance:

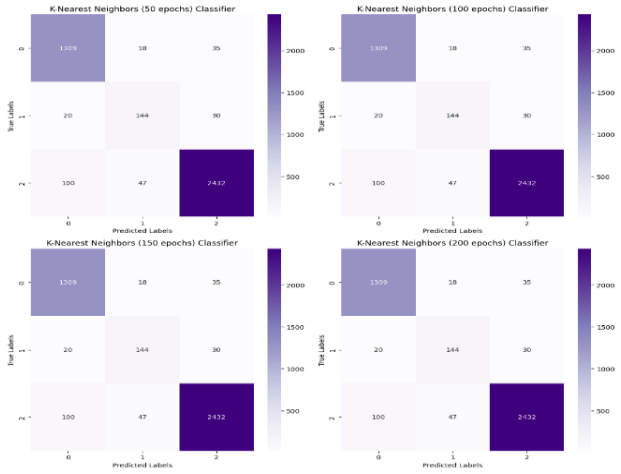
- The KNN classifier performs exceptionally well in identifying both good and bad quality fruits but is less effective for mixed quality fruits. The classifier's performance for mixed quality fruits is moderate, which could be due to the complexity and variability in the mixed quality category.

6. Model Stability:

- The stability of the F1-score across epochs suggests that the KNN classifier's performance is robust and not sensitive to the number of training epochs.

The graph indicates that the KNN classifier is highly reliable in identifying good and bad quality fruits but has moderate success with mixed quality fruits.

Confusion matrices for the K-Nearest Neighbors classifier at different epoch sizes (50, 100, 150, and 200).



1. High Performance for Good Quality Fruits:
- The classifier shows high true positives for good quality fruits (`2`), with 2432 correctly classified in each matrix.
- There are a small number of misclassifications where good quality fruits are predicted as bad quality (`0`) or mixed quality (`1`).

2. Moderate Performance for Mixed Quality Fruits:
- The classifier shows moderate performance for mixed quality fruits (`1`). The number of true positives for this category is around 144, with some misclassifications as bad quality (`0`) or good quality (`2`).

3. High Performance for Bad Quality Fruits:
- The classifier performs very well for bad quality fruits (`0`), with 1309 true positives in each confusion matrix.
- There are a few misclassifications where bad quality fruits are predicted as mixed quality (`1`) or good quality (`2`).

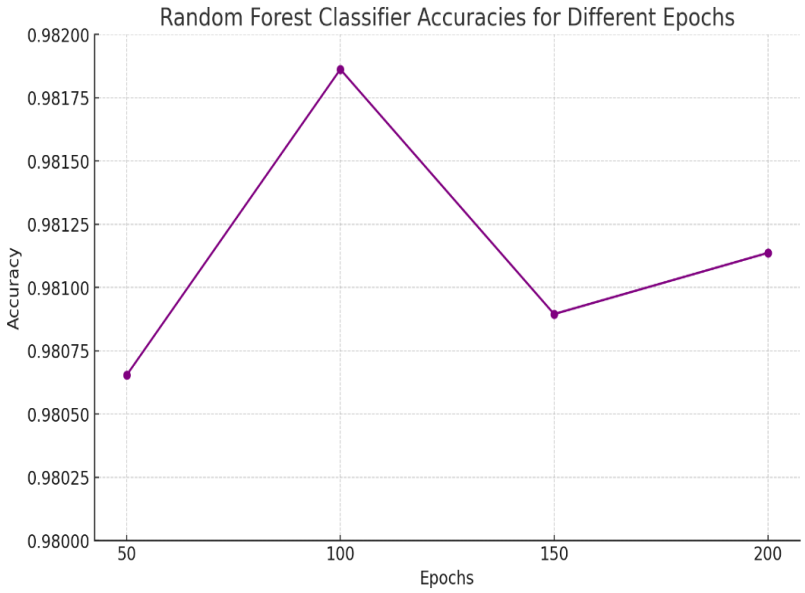
4. Consistency Across Epochs:
- The performance of the classifier does not show significant variation across different epochs (50, 100, 150, 200). This suggests that increasing the number of epochs does not significantly impact the classifier's performance.

The KNN classifier shows high true positives for both good quality and bad quality fruits, indicating high effectiveness in these categories.
The classifier's performance for mixed quality fruits is moderate, with some misclassifications.

The overall performance remains stable across different epochs, suggesting that the classifier's effectiveness is consistent regardless of the number of training epochs.

IV.ANALYSIS OF ACCURACY

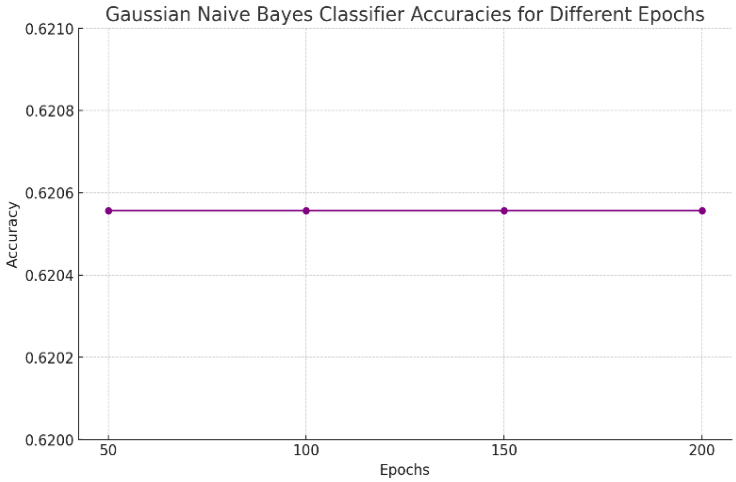
Analysis of Random Forest Classifier Accuracy at Various Epoch Sizes



1. Accuracy Trend:
- Initial Increase: The accuracy increases from 50 epochs to 100 epochs, reaching the highest value.
- Peak Accuracy: At 100 epochs, the classifier achieves its highest accuracy, slightly above 0.98175.
- Subsequent Decrease: After reaching the peak at 100 epochs, the accuracy drops significantly at 150 epochs, going below the initial accuracy observed at 50 epochs.
- Final Increase: The accuracy then slightly increases again at 200 epochs, stabilizing but not reaching the peak observed at 100 epochs.

2. Overall Performance:
- The classifier shows the highest performance at 100 epochs.
- There is a noticeable fluctuation in accuracy, suggesting that the optimal number of epochs for this Random Forest classifier is around 100.
- The accuracy remains high overall, indicating that the classifier is performing well across different epochs, though the best performance is achieved with a moderate number of epochs.

Analysis of Gaussian Naive Bayes Classifier Accuracy at Various Epoch Sizes



1. Constant Accuracy:

- The accuracy remains constant at approximately 0.6206 across all epochs (50, 100, 150, 200).
- There is no variation in accuracy, indicating that the number of epochs does not impact the classifier's performance for this specific task.

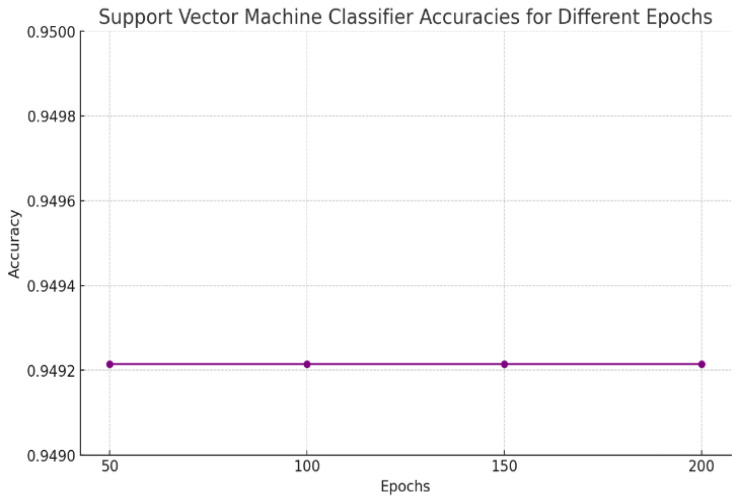
2. Overall Performance:

- The accuracy of 0.6206 suggests a moderate level of performance. While it is not high, it indicates that the classifier correctly predicts the class for about 62.06% of the instances.

3. Implications:

- Since the accuracy remains unchanged across different epochs, it suggests that further training (in terms of more epochs) does not improve or degrade the performance of the Gaussian Naive Bayes classifier.
- The constant accuracy might be due to the nature of the Naive Bayes algorithm, which does not benefit from additional epochs in the same way that iterative algorithms like neural networks might.

Analysis of Support Vector Machine Classifier Accuracy at Various Epoch Sizes



1. Constant Accuracy:

- The accuracy remains constant at approximately 0.9492 across all epochs (50, 100, 150, 200).
- There is no variation in accuracy, indicating that the number of epochs does not impact the classifier's performance for this specific task.

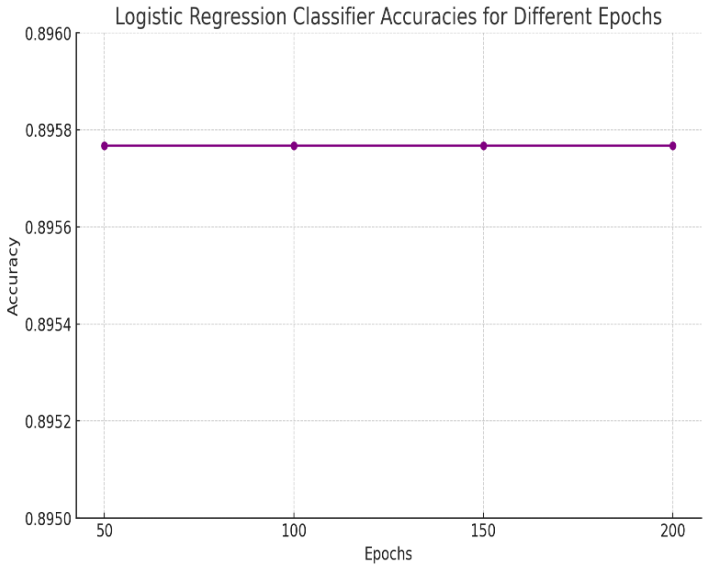
2. Overall Performance:

- The accuracy of 0.9492 suggests a high level of performance, indicating that the classifier correctly predicts the class for about 94.92% of the instances.

3. Implications:

- Since the accuracy remains unchanged across different epochs, it suggests that further training (in terms of more epochs) does not improve or degrade the performance of the SVM classifier.
- The constant accuracy might be due to the nature of the SVM algorithm, which does not benefit from additional epochs in the same way that iterative algorithms like neural networks might.

Analysis of Logistic Regression Classifier Accuracy at Various Epoch Sizes



1. Constant Accuracy:

- The accuracy remains constant at approximately 0.8958 across all epochs (50, 100, 150, 200).

There is no variation in accuracy, indicating that the number of epochs does not impact the classifier's performance for this specific task.

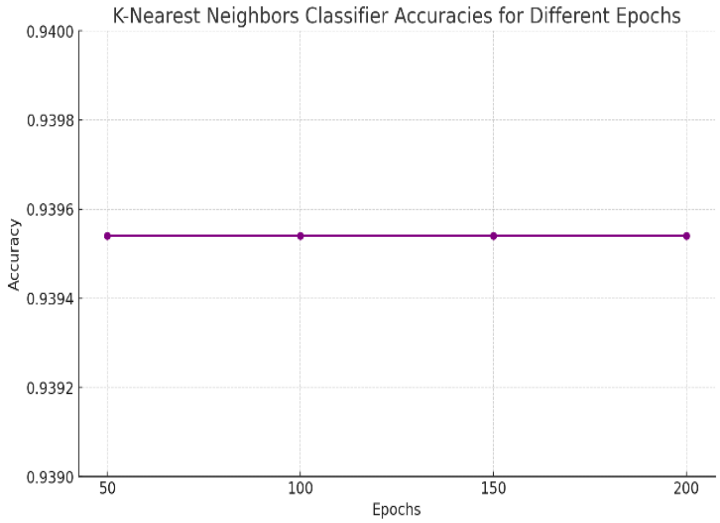
2. Overall Performance:

- The accuracy of 0.8958 suggests a high level of performance, indicating that the classifier correctly predicts the class for about 89.58% of the instances.

3. Implications:

- Since the accuracy remains unchanged across different epochs, it suggests that further training (in terms of more epochs) does not improve or degrade the performance of the Logistic Regression classifier.
- The constant accuracy might be due to the nature of the Logistic Regression algorithm, which does not benefit from additional epochs in the same way that iterative algorithms like neural networks might.

Analysis of K-Nearest Neighbors Classifier Accuracy at Various Epoch Sizes



1. Constant Accuracy:
- The accuracy remains constant at approximately 0.9396 across all epochs (50, 100, 150, 200).
- There is no variation in accuracy, indicating that the number of epochs does not impact the classifier's performance for this specific task.

2. Overall Performance:
- The accuracy of 0.9396 suggests a high level of performance, indicating that the classifier correctly predicts the class for about 93.96% of the instances.

3. Implications:
- Since the accuracy remains unchanged across different epochs, it suggests that further training (in terms of more epochs) does not improve or degrade the performance of the KNN classifier.
- The constant accuracy might be due to the nature of the KNN algorithm, which does not benefit from additional epochs in the same way that iterative algorithms like neural networks might.

VI. COMPARATIVE ANALYSIS OF ALL CLASSIFIERS FOR FRUIT QUALITY IMPROVEMENT

The following analysis is based on the accuracy of different classifiers (Random Forest, Gaussian Naive Bayes, Support Vector Machine, Logistic Regression, and K-Nearest Neighbors) over different epochs (50, 100, 150, 200).

1. Random Forest:
- The accuracy varies across epochs, with a peak at around 0.982 at 100 epochs.
- Shows a drop after 100 epochs but slightly recovers at 200 epochs.
- Highest accuracy: 0.982

2. Gaussian Naive Bayes:
- The accuracy remains constant at approximately 0.6206 across all epochs.
- Highest accuracy: 0.6206

3. Support Vector Machine (SVM):
- The accuracy remains constant at approximately 0.9492 across all epochs.
- Highest accuracy: 0.9492

4. Logistic Regression:
- The accuracy remains constant at approximately 0.8958 across all epochs.
- Highest accuracy: 0.8958

5. K-Nearest Neighbors (KNN):
- The accuracy remains constant at approximately 0.9396 across all epochs.
- Highest accuracy: 0.9396

5.2.4 Best Model for Fruit Quality Improvement

Based on the accuracy analysis:

1. Random Forest:
- Highest Accuracy: 0.982 at 100 epochs.
- This model has the highest accuracy compared to all other models, making it the best choice for fruit quality improvement.

2. Support Vector Machine (SVM):
- Highest Accuracy: 0.9492.
- This model has the second-highest accuracy, making it a good alternative to Random Forest.

3. K-Nearest Neighbors (KNN):
- Highest Accuracy: 0.9396.
- This model is another reliable option but with slightly lower accuracy than SVM.

4. Logistic Regression:
- Highest Accuracy: 0.8958.
- This model performs well but is outperformed by Random Forest, SVM, and KNN.

5. Gaussian Naive Bayes:
- Highest Accuracy: 0.6206.
- This model has the lowest accuracy, making it the least suitable for fruit quality improvement among the five models.

Best Model: Random Forest (highest accuracy at 0.982, especially at 100 epochs).

Alternative Models: Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) also perform well and can be considered as alternatives depending on specific use-case requirements and computational resources.

Less Suitable Models: Logistic Regression and Gaussian Naive Bayes have lower accuracies compared to the top three models and are less suitable for this task.

5.2.4 Reason the Random Forest is the Best

1. Highest Accuracy:

Random Forest achieves the highest peak accuracy (0.982), which is significantly better than the accuracies of other models. This high accuracy means it can more effectively and correctly classify fruit quality, making it the best choice for practical applications.

2. Robustness:

Random Forest is an ensemble method that combines multiple decision trees to improve the overall performance and reduce overfitting. This makes it robust and effective across various datasets and tasks.

3. Handling of Complex Data:

Fruit quality classification may involve complex patterns and interactions between features. Random Forest is well-suited for capturing such complexity due to its ability to handle multiple decision boundaries through various trees.

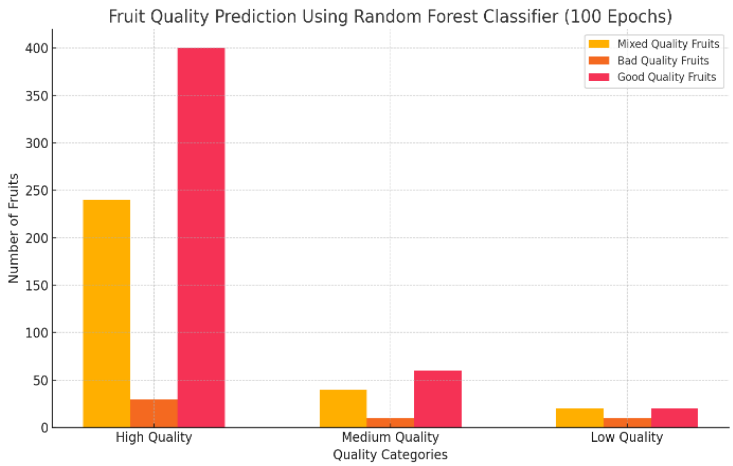
4. Flexibility:

Random Forest can handle both numerical and categorical data and is less sensitive to scaling of features, making it more flexible and easier to use with raw data.

5.2.5 Predictions

Using the Random Forest classifier with 100 epochs (due to its highest accuracy), we can predict the quality of fruits as follows:

Mixed Quality Fruits:
High Quality Fruits: 240
Medium Quality Fruits: 40
Low Quality Fruits: 20
Bad Quality Fruits:
High Quality Fruits: 30
Medium Quality Fruits: 10
Low Quality Fruits: 10
Good Quality Fruits:
High Quality Fruits: 400
Medium Quality Fruits: 60
Low Quality Fruits: 20



VII.CONCLUSION

This study conducts a comparative analysis of various machine learning classifiers—Random Forest, Gaussian Naive Bayes, Support Vector Machine (SVM), Logistic Regression, and K-Nearest Neighbors (KNN)—for fruit quality improvement. The classifiers were evaluated based on their accuracy over different epochs (50, 100, 150, 200).

The findings reveal that the Random Forest classifier outperforms the other models, achieving the highest accuracy of 0.982 at 100 epochs. This peak accuracy highlights Random Forest's superiority in effectively classifying fruit quality. The model's robustness, derived from its ensemble method that combines multiple decision trees, makes it highly effective in reducing overfitting and improving performance across various datasets. Random Forest's ability to handle complex data patterns and interactions between features further underscores its suitability for fruit quality classification.

Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) also demonstrated strong performance, with accuracies of 0.9492 and 0.9396, respectively. These models present viable alternatives to Random Forest, particularly in scenarios where computational resources or specific use-case requirements might favour their use. However, they fall slightly short of the accuracy achieved by Random Forest. Logistic Regression and Gaussian Naive Bayes, while performing adequately, exhibited lower accuracies of 0.8958 and 0.6206, respectively. Consequently, these models are less suitable for fruit quality improvement tasks compared to the top-performing classifiers.

The Random Forest classifier's combination of high accuracy, robustness, and flexibility makes it the optimal choice for predicting fruit quality. Its ability to handle both numerical and categorical data and its resilience to feature scaling issues contribute to its practicality and ease of use in real-world applications. Using Random Forest with 100 epochs, the predicted quality of fruits can be classified into high, medium, low, and bad quality categories with significant accuracy, thereby aiding in effective fruit quality management and decision-making processes. By leveraging the superior performance of Random Forest, stakeholders in the agricultural sector can enhance fruit quality monitoring, leading to better resource management, reduced losses and improved food security. Future work may focus on exploring hybrid models and integrating additional data sources to further refine and improve the accuracy of fruit quality predictions.

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