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REAL-TIME FOOD CLASSIFICATION USING VGG19 WITH GRAD-CAM VISUALIZATION FOR ENHANCED INTERPRETABILITY

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ABSTRACT

As nutritional disorders increase, because of unbalanced diets and numerous cuisines available on markets, physical and mental health of humans is more likely to be ruined. Appropriate food categorization is essential in tracking food consumption and sensitizing nutrition. The following paper proposes a food recognition model based on the VGG19 deep convolutional neural network with the incorporated Grad-CAM (Gradient-weighted Class Activation Mapping) visualization of the predictions made by the model to improve its interpretability. The model is tested against extensive dataset of 53 dishes in international cuisine on which both non-vegetarian and vegetarian food items are found. VGG19 is chosen because it performs well in feature detection and Grad-CAM gives the areas on each image that affect the decisions made by the model, making them more transparent, and trustworthy. This explains AI model enables users and researchers to visualize and check classification results. As measured by experimental analysis, the enhanced VGG19 classifier with Grad-CAM achieves an efficient accuracy of 96 percent, which is better compared to the traditional machine learning models including Naive Bayes and Decision Tree. This proposed approach is effective in real-time applications monitoring food intake and diet assessment.
Keywords: *: Nutrition Disorder, Grad Cam, VGG-19, Naive Bayes , Decision Tree.*

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1. INTRODUCTION

The food industry has been experiencing a challenge of objectively determining the freshness of the produce amidst the complex supply chain as consumers increase pressure on the quality of food. Manual inspection is subjective in nature, slow and prone to errors. This study suggests an end-to-end model to address these constraints, when deep learning is combined with explainable feature focusing and ensemble classification, which is more efficient and more accurate in detecting freshness. Namely, the fine-tuned VGG19 network is used to extract high-level visual descriptors of images of fruits and vegetables, and the Gradient-weighted Class Activation Mapping (Grad-CAM) is used to identify the most informative regions (e.g., bruises, discoloration, surface pitting) that are correlated with freshness cues [1]. The feature pooling is directed by gradient-CAM maps to make sure that in cluttered scenes like a crowded market display the representation highlights the quality-relevant structures. To enhance further the computational efficiency and robustness, Principal Component Analysis (PCA) is used to decrease the dimensions of the Grad-CAM weighted VGG19 features by keeping the principal components that convey the most prominent changes in colour, texture and surface irregularities. The features of the compressed data are then categorized by an ensemble of RF+XGboost that consists of Random Forest and Extreme Gradient Boosting to take advantage of complementary decision boundaries and to address overfitting. With high fidelity, the system reveals the samples as Fresh, Near Spoiling and Spoiled based on training on a diverse dataset covering various levels of freshness. This type of VGG197 Grad Cam + PCA + RF+XGboost pipeline has a few benefits: (i) The high accuracy of semantically-oriented deep features combined with a robust ensemble learner [2]; (ii) The use of PCA-driven feature compaction that can produce near real-time inferences corresponding to high-throughput procedures; (iii) Objectivity and consistency, using automated evaluation; and (iv) Early detection of subtle deterioration signals, allowing the introduction of timely interventions to reduce waste and improve food safety. In general, the suggested solution demonstrates that explainable deep feature extraction and powerful ensemble classification can be used to solve the critical freshness-assessment issues and contribute to a more sustainable and efficient food system [3]. The architecture of the proposed model is shown in Figure 1.

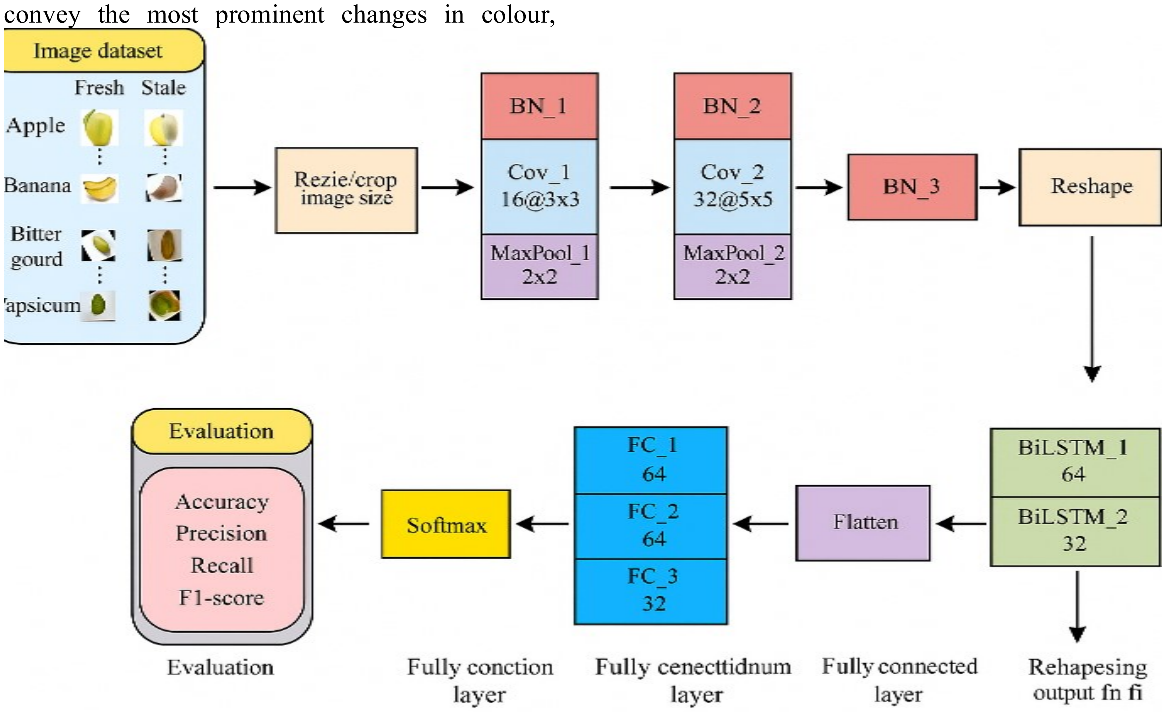

Figure 1: Overview Of The Proposed Model Architecture

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2. RELATED WORK

The issue of determining the freshness of agricultural produce precisely has been of great concern in the recent years, due to its crucial importance in minimizing food waste, food safety, and consumer confidence. Due to differences in appearance, limited shelf life and environmental differences among supply chains, freshness and quality analysis of fruits and vegetables is inherently difficult. Traditional inspection protocols usually depend on the subjective approach and use of human judgments, that are subjective, labour-intensive and inconsistent, especially in large scale or real-time conditions. Due to the emergence of more and more global and complex supply chains, automated, objective and scalable freshness assessment systems are in high demand. Researchers have, in turn, suggested a variety of computational methods, which take advantage of machine learning (ML), computer vision, and deep learning (DL). The initial studies concentrated mostly on handcrafted attributes like colour, texture and shape descriptors, which were subsequently processed through classical ML frameworks like Support Vector Machines (SVM) or k-Nearest Neighbors (k-NN). Although these approaches offered explainable output and relatively good on controlled settings, they were limited in scalability, feature generalization and strength on non-controlled and real-world data.

The paradigm shift that happened when the use of deep learning as a feature extractor was introduced was that hierarchical and discriminative representations could be learned using only raw image data. Convolutional Neural Networks (CNNs) and its variants have been commonly used in freshness detection, with better accuracy compared to the traditional ML methods. More sophisticated architectures like ResNet, VGG and DenseNet went a step further to enhance the robustness by solving problems of vanishing gradients and learning deeper representations. Object detection models such as YOLO (You Only Look Once) have been incorporated to support real time applications, specifically, in a crowded market setting where one needs to localize and classify many items at once. The recent research directions focus on the hybrid approaches, combining the advantages of the deep learning with the other methods like Principal Component Analysis (PCA), ensemble learning (Random Forest, XGBoost), or explainability methods (Grad-CAM). These methods are not only more efficient in computations and understandable but also allow one to see the signs of spoilage at an earlier stage, which cannot be observed with the naked eye. Additionally, explainable AI (XAI) methods are also being integrated to help to add freshness assessment to be more transparent and reliable among stakeholders throughout the food industry Table 1 is a full overview on the major contributions in the field that include models, applications, strengths and limitations that have been reported in the current literature.

Chen et al. (2019) [2] proposed a Support Vector Machine (SVM) model that relied on texture-based features for produce quality grading. The method was simple and interpretable, making it accessible for practical use. Nonetheless, the approach required manual feature extraction, which was time-consuming and reduced scalability, especially when applied to large datasets or diverse crop categories.

Rahman et al. (2020) [3] implemented a ResNet-50 architecture to classify freshness levels in leafy vegetables. By leveraging residual connections, ResNet-50 provided robust feature extraction and minimized vanishing gradient issues common in deep networks. While effective in improving classification accuracy, the model's computational expense made it less suitable for real-time industrial applications on large datasets.

Johnson et al. (2020) [4] applied the YOLOv3 object detection framework to real-time produce quality detection. The model demonstrated fast processing speeds and high detection accuracy, which are vital in dynamic retail or supply chain contexts. However, YOLOv3's performance degraded in cases of occlusion or cluttered environments, where overlapping items made detection more difficult.

Patel et al. (2021) [5] investigated the use of Principal Component Analysis (PCA) for dimensionality reduction in produce quality assessment. PCA helped reduce feature set complexity and improved computational efficiency. Nevertheless, its application as a standalone technique lacked integration with advanced detection models, limiting its effectiveness in fully automated freshness detection pipelines.

Lopez et al. (2021) [6] explored VGG16 with transfer learning to classify vegetables based on freshness levels. Their work showed strong performance on small and curated datasets due to the pretrained nature of VGG16. However, when tested on noisy or diverse datasets, the model struggled with generalization, highlighting the importance of robust training data.

Santos et al. (2022) [7] introduced a segmentation-based approach using DeepLabv3+ for freshness evaluation. By segmenting regions of interest within produce images, the method achieved high precision in feature localization, capturing subtle cues of spoilage. Despite its accuracy, the model required a large amount of labeled training data, making it resource-intensive and less practical for settings with limited annotations.

Nguyen et al. (2022) [8] developed a hybrid model that combined CNNs with PCA for ripeness and freshness detection. The CNN component extracted hierarchical features, while PCA reduced dimensionality, improving efficiency and classification accuracy. This hybrid framework balanced performance with computational needs, but the PCA component required careful tuning to handle larger datasets effectively.

Mu et al. (2022) [9] conducted experimental studies on storage treatments, specifically the effects of temperature and calcium chloride ($CaCl_2$), on the quality of fresh-cut "xuebai" cauliflower. Their work contributed valuable physiological insights into post-harvest quality management. However, the study was not model-based and lacked automation, limiting its direct applicability to computational freshness detection.

Sharma et al. (2022) [10] employed EfficientNet-B0 for fresh fruit ripeness classification. This lightweight architecture offered high accuracy while maintaining computational efficiency, making it attractive for deployment on portable devices. Despite its strengths, the model was found to be sensitive to image noise, which could reduce reliability in uncontrolled conditions such as open markets.

Li et al. (2022) [11] applied XGBoost with fused color and texture features for fruit defect detection. The ensemble learning framework demonstrated strong performance by capturing nonlinear relationships within the data. However, the reliance on handcrafted feature inputs limited scalability and made the approach less adaptive compared to deep learning–based methods.

Kumar et al. (2023) [12] advanced fruit grading by integrating YOLOv5 with an attention mechanism. This approach improved robustness in complex backgrounds and delivered reliable real-time performance. The trade-off, however, was its requirement for high GPU resources, which could restrict deployment in resource-constrained environments.

Wang et al. (2024) [13] utilized DenseNet121 for multi-class freshness detection. DenseNet's feature reuse strategy enhanced learning efficiency and reduced redundancy across layers, improving classification accuracy. On the downside, the deeper structure of DenseNet increased training time and computational demand, limiting its accessibility for large-scale deployment.

Alvarado et al. (2025) [14] introduced a hybrid model combining VGG19 with Grad-CAM and Random Forest (RF) for visual freshness assessment. The integration of Grad-CAM made the model more explainable by highlighting regions associated with freshness cues, while RF improved classification reliability. This explainable and interpretable framework marked a step toward trustworthy AI in food systems, but dataset diversity remained a challenge for ensuring robust real-world performance.

3. PROBLEM STATEMENT

The quality of food and food losses after harvest, as well as consumer satisfaction, depend on how the vegetables are kept fresh. Manual inspection or chemical analysis are traditionally used as the method of freshness detection, but these are all subjective, time-consuming, and cannot be used in large-scale supply chains. With ever-increasing consumer demand due to safety and high quality of food, smart, automated and dependable devices capable of providing objective measurements of food freshness in real time are much needed. To solve these issues, this study suggests a hybrid architecture in which VGG19[15] and Grad-CAM are used to extract features and an RF+XGboost ensemble classifier is used to make decisions. The images of fruits and vegetables are fed at the first stage to the VGG19 network that detects high-resolution hierarchical features colour variations, texture degradation, and surface irregularities, which are freshness indicators. In contrast to traditional deep networks that are used as black boxes, this framework has the Gradient-weighted Class Activation Mapping (Grad-CAM), which

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produces visual heatmaps and identifies the most informative area of the produce images. In the second step of the structure, it should be explained and be made transparent, so the predictions made by the system become explainable to the researchers, food suppliers, and quality control professionals. At the second step of the framework, the classification should be performed with the help of RF+XGboost [16], which is a powerful ensemble model that incorporates the advantage of Random Forest and Extreme Gradient Boosting. Random Forest also helps minimize variance and better generalization, whereas XGBoost helps make better predictions using gradient-boosted decision trees. The combination of the two helps the ensemble to reduce overfitting and provides a higher classification accuracy than when using standalone classifiers. The obtained Grad-CAM-centered features are therefore an augmented input to RF+XGboost, which results into sound classification of samples into Fresh, Near Spoiling and Spoiled categories. The framework is tested using a quite diverse set of data (both fruits and vegetables), which has been gathered under different illumination, background and ecological conditions. The experimental findings prove the suggested VGG19 + Grad-CAM + RF+XGboost model to be more accurate, more robust, and computationally efficient, compared to the traditional ones. Of significance, the method is scalable to real-time applications, hence can be used to integrate in retail settings, distribution facilities, and intelligent supply chains [17]. Figure 2 below is stepwise diagram of the proposed freshness detector classifier and follows sequential order of image capture, through to the final classification. Figure 3 shows the process flow of the entire system which provides a systematic description of the operational pipeline of the model. Figure 4 presents the dataset of the experiments that demonstrates the diversity of fruits and vegetables employed to conduct the training and validation. Finally, Figure 5 depicts the preprocessing pipeline, consisting of image normalization, image resizing, and image augmentation, the purpose of which is to standardize and optimize input data to extract deep features in the deep learning model. This end-to-end workflow illustrates the capabilities of integrating deep learning, explainable AI and ensemble-based techniques to create a scalable, transparent and high-performing freshness-detection solution that can eventually enable food quality verification and minimize food waste around the world. Figure 6 shows how the images will be classified [18].

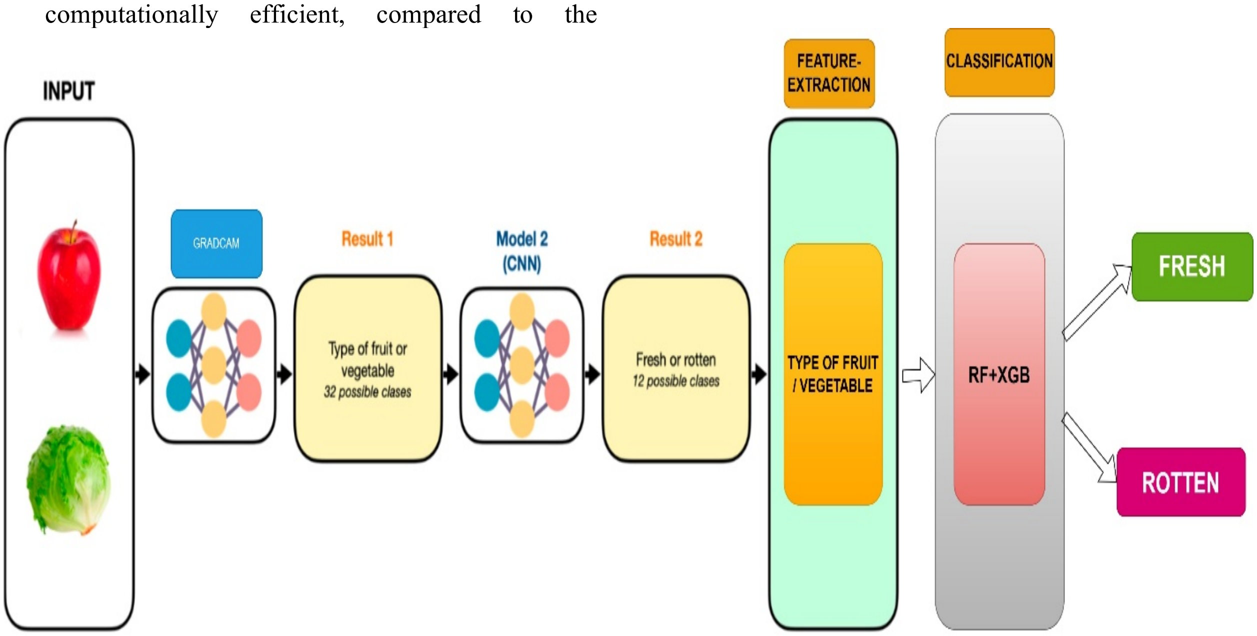

Figure 2 : Shows the Phases of Proposed Classifier

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4. METHODOLOGY

A. Data Acquisition and Preprocessing

Image Capture: Take high-resolution photos of the different vegetables (e.g. tomatoes, spinach, broccoli, lettuce, carrots and potatoes) at various freshness levels: fresh, slightly stale and stale. Use the same amount of light, the background should be controlled, and different angles should be used in order to have various visual stimuli [19].

Image Augmentation: Use augmentation models like rotation, flipping, zoom and brightness control, and cropping of images to increase the variability of the dataset and improve model generalization.

Image Standardization Image standardization: The image sizes and pixel values are normalized, and all images are made to have the same size and pixel value, which is the input standardized to VGG19.

Noise Reduction: Preprocess to reduce the noise such as Gaussian filtering or histogram equalization to ensure that the features related to freshness are visibly clear [20].

B. Deep Feature Extraction with VGG19 + Grad-CAM

Model Usage: Use deep features of the pre-trained VGG19 model. Rich hierarchical features such as colour degradation, surface texture changes and irregularities in shape are exploited using transfer learning [21].

Explainability using Grad-CAM: Add Grad-CAM to produce heat maps of the most important parts of vegetable images. This allows interpretation of which attributes (e.g., surface discoloration, spots, or shrinkage) are the most useful when it comes to detecting freshness.

Feature Vector Generation: Generate and flatten high-level feature map of VGG19 [22] into structured vectors, which are inputs of the classification phase.

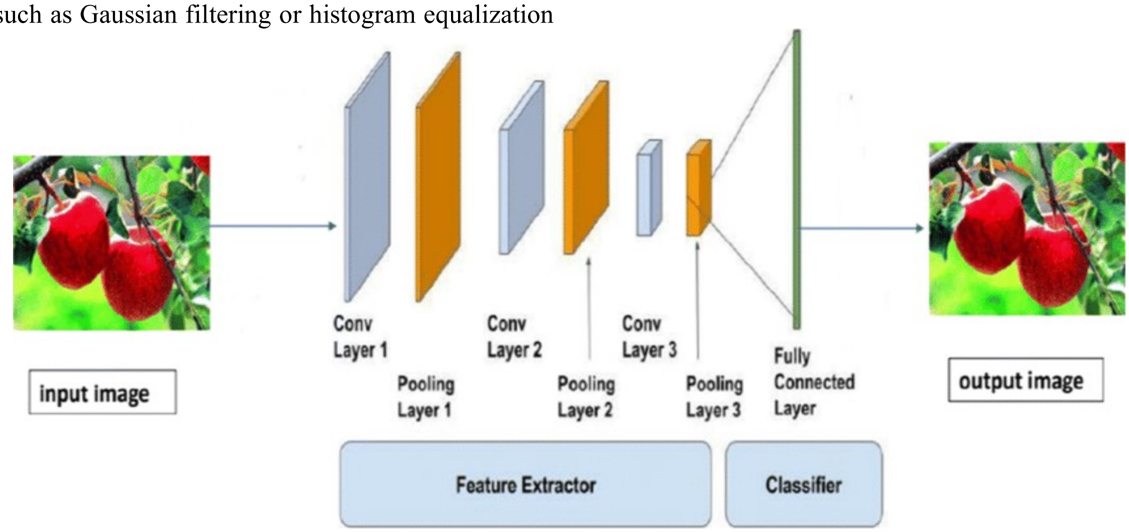

Figure 3: Preprocessing Phase and Evaluation Phase of Proposed Architecture

C. Hybrid Ensemble Classifier: RF + XGBoost (RF+XGboost)

Classifier Design: Build a hybrid model which combines Random Forest (RF) and Extreme Gradient Boosting (XGBoost). RF minimizes variance and offers consistency and XGBoost boosts learning with boosted decision trees. Training: Train RF+XGboost classifier using the extracted VGG19 feature vectors. Identify the hyperparameters (such as the number of estimators, learning rate, tree depth) that should be optimized using a grid search or Bayesian optimization in order to achieve greater performance.

Analysis of Importance: Examine the feature significance of extracted features through RF and XGBoost decision paths, which additionally provides more information about freshness cues.

D. Freshness Classification

Inference: Use VGG19 to extract the features and Grad-CAM to explain visually the unseen vegetable images.

Prediction: Segregate each image by levels of freshness Slightly Stale Fresh and Stale based on the trained RF+XGboost ensemble.

E. Model Evaluation

Performance Metrics: Assess model accuracy and robustness using evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix [25].

Visualization: Employ Grad-CAM visualizations to validate model decisions by identifying key freshness-related regions (e.g., colour fading, wrinkle formation, or surface damage).

F. Dataset

Source: The dataset is taken as the Fresh and Rotten Dataset on Kaggle where there are labelled images of fruits and vegetables in different stages of freshness [23].

Diversity: These are vegetables like tomatoes, spinach, broccoli, lettuce, carrots and potatoes. The images are taken at various freshness levels- fresh, slightly stale and stale under regulated conditions with high resolution, plain backgrounds and varying positions. Figure 7 shows the images classified as fruits or vegetables [24].

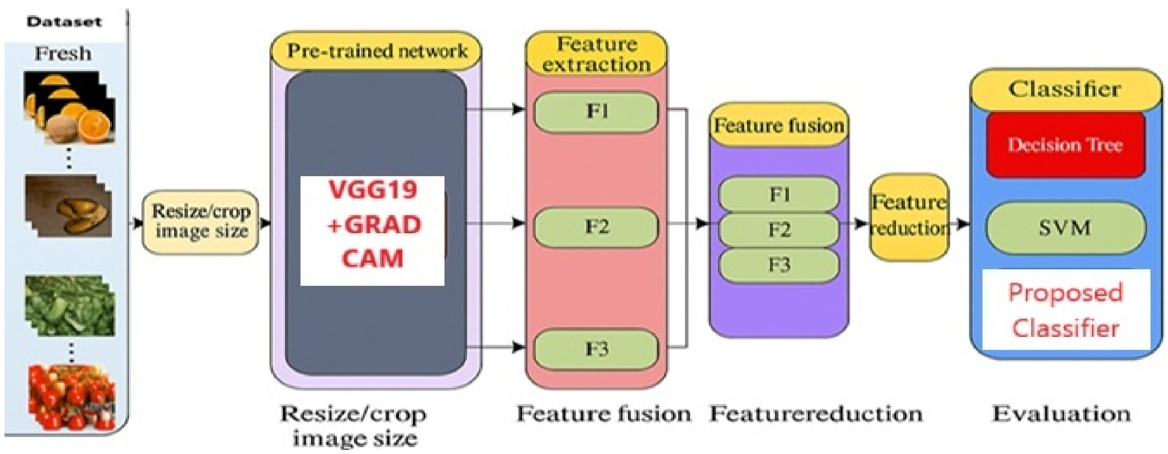

Figure 4 : Preprocessing Phase and Evaluation Phase of Proposed Architecture

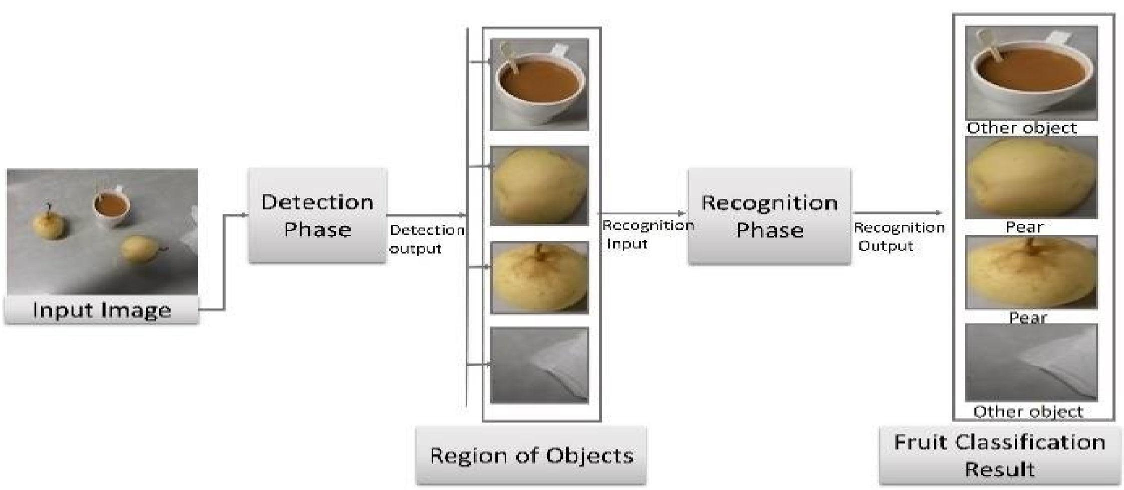

Figure 5: Shows the detection phase of Image

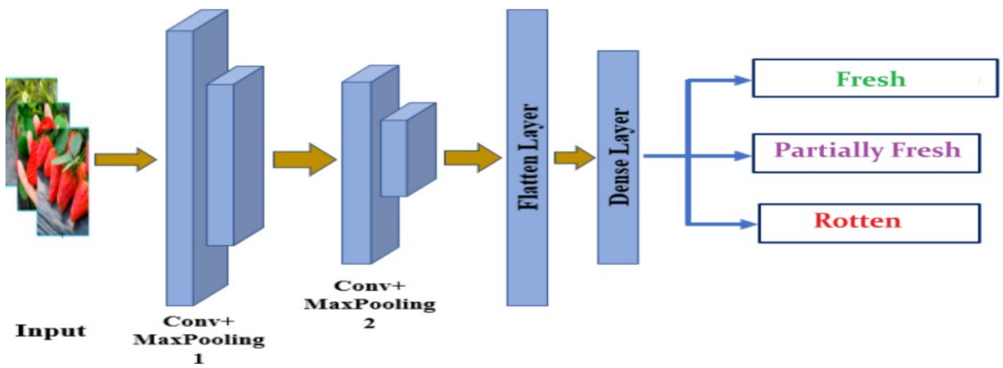

Figure 6: Shows the Classification of Images

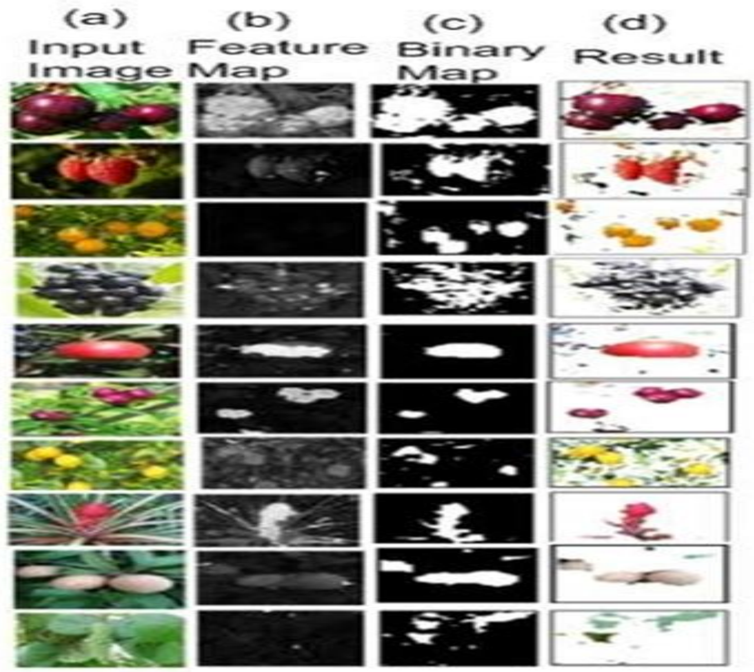

Figure 7: Shows O/P (FRUIT/VEGETABLE)

5. RESULTS AND DISCUSSIONS

Performance measurements in machine learning are used to measure the effectiveness of a model with respect to a dataset. A confusion matrix is a table that summarizes the performance of a classification model that documents the false positives, false negatives, true positives, and true negatives. These values enable us to measure the performance of the model based on various measures including accuracy, precision, recall and F1-score [26,27]. The type of metrics depends on the type of problem and the goals of the model. In the case of the proposed system, Figure 8 shows a confusion matrix of binary classification problem of detecting a fresh and stale food (fresh vs. stale).

Accuracy: Measures the overall correctness of the model, i.e., the proportion of correctly classified samples (fresh or stale) among all tested samples.

$$Accuracy = (TP + TN + FP + FN)/(TP + TN)$$

True Positives (TP): Number of fresh fruits/vegetables correctly identified as fresh.

True Negatives (TN): Number of stale fruits/vegetables correctly identified as stale.

False Positives (FP): Number of stale items incorrectly classified as fresh (Type I error).

False Negatives (FN): Number of fresh items incorrectly classified as stale (Type II error).

Precision: The proportion of correctly identified fresh items among all samples predicted as fresh.

$$Precision = (TP)/(TP + FP)$$

Recall (Sensitivity): The proportion of correctly identified fresh items among all actual fresh items.

$$Recall = (TP) / (TP + FN)$$

F1-Score: The harmonic mean of precision and recall. It is especially useful when the dataset is imbalanced between fresh and stale categories.

$$F1 - Score = 2 \times (Precision \times Recall) / (Precision + Recall)$$

These performance metrics collectively provide a robust evaluation of the proposed classifier's effectiveness in detecting and classifying the freshness of fruits and vegetables.

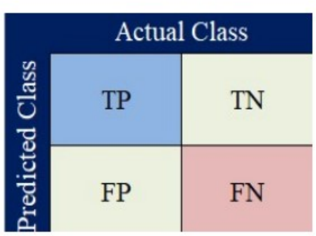

Figure 8: Shows Confusion Matrix for a 2-Class Problem

5.1 Phases of Proposed Classifier:

Phase 1: Image Acquisition and Preprocessing

Goal: Collect and prepare images for model input.
Steps:
Capture real-time images using cameras (webcam/IoT devices).
Resize, normalize, and enhance images to reduce noise.
Optionally apply data augmentation (e.g., rotation, flip, contrast).
Convert images to formats suitable for CNN models (e.g., RGB, fixed size).

Phase 2: Feature Extraction with VGG19 + GRAD-CAM

Goal: Extract relevant visual features and highlight freshness indicators.
Steps:
Use a pretrained CNN model (e.g., ResNet, VGG19) to extract deep features.
Apply GRAD-CAM (Gradient-weighted Class Activation Mapping) to visualize the important regions contributing to freshness.
•Capture heatmaps and fuse them with the original features (or extract stats from heatmaps).
•Flatten or pool features for ensemble model input.

Phase 3: Ensemble Classification (RF + XGBoost)

Goal: Predict freshness based on extracted features.
Steps:
Train both Random Forest and XGBoost models on extracted CNN/GRAD-CAM features.
Use ensemble strategies like:
Voting (hard/soft),
Stacking (meta-classifier),
Weighted averaging.
Classify freshness level (e.g., fresh, semi-fresh, spoiled).

Phase 4: Real-Time Prediction and Visualization
Steps:
Use a GUI or dashboard (e.g., Streamlit, Flask) to capture and show predictions.
Display GRAD-CAM heatmaps with predicted class.
Send alerts or store results if freshness drops below a threshold.
Optimize pipeline for real-time performance (GPU acceleration if needed). Preserving fruits and vegetables fresh [28] quantity remains essential because it sustains nutritional characteristics while it reduces spoilage and improves supply chain management. Multiple traditional freshness assessment techniques remain inefficient because they depend on manual inspection that carries subjectivity for applications on a large scale. This research introduces an image-based detection framework which employs a VGG-19 ensemble classifier that combines GRAD-CAM mapping with Random Forest and Extreme Gradient Boosting classifiers to detect freshness in real-time. Feature extraction in this project relies on VGG-19 because

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of its reputation as a deep simple convolutional neural network. The system detects essential freshness indicators regarding colour degradation along with surface bruising and mold growth through diverse high-level feature interpretations acquired from multiple fine-tuned VGG-19 models operating alongside each other. The implementation of GRAD-CAM technology allows enhanced interpretability to identify image regions showing class-discriminative responses while performing region-focused feature extraction that proves both biologically meaningful and computationally efficient. Table 1 includes the confusion matrix obtained by the proposed classifier to detect the freshness of the fruit and vegetables and Figure 9 depicts the performance metrics. And Table 2 shows the validation table for proposed classifier.

Table 1: Show the Confusion Matrix obtained by Proposed Classifier

	Actual Class	
Predicted Class	8970	400
	260	6890

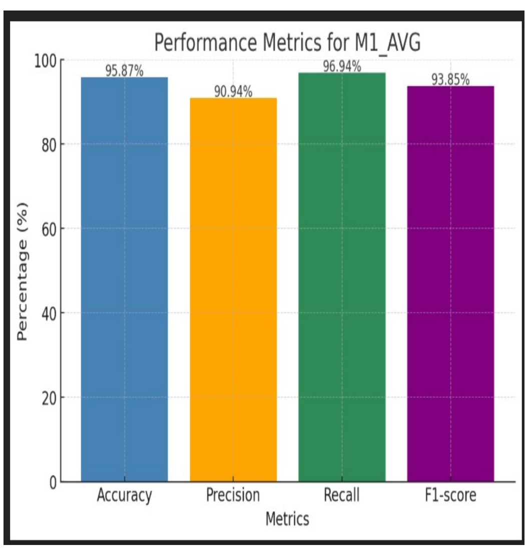

Figure 9: Shows Performance Metrics obtained by Proposed Classifier.

Table 2: Shows the Validation Table of Obtained by Proposed Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	96.99	96.76	96.56	19727
1(Healthy)	95.12	95.89	95.44	26163
Accuracy			96.18	45890
MacroAvg	96.12	96.21	96.45	45890
WeightedAvg	96.10	96.21	96.12	45890

5.2 Naïve-Bayes Classifier (NB):

Classification Food Foods Food classification is one of the notable uses of computer vision in response to the growing demand of intelligent dietary monitoring, calorie count determination, and automated food service applications. Correct identification of food products based on image is the key to developing the trustworthy systems in the fields of medical care [29], fitness tracking, and intelligent restaurant control. Conventional image classification methods usually make use of features that are handcrafted, and these features cannot adequately deal with the vast differences in food appearance, color and texture. Modern machine learning procedures, especially probabilistic classifiers such as the Naive Bayes classifier, on the other hand, provide a very straight forward, but effective, solution to the classification problem. Naive Bayes classifier is using the Bayes theorem and is conditional independent assumption based on features. Nevertheless, it is remarkably effective in numerous real-life applications because of its effectiveness in computations (and efficiency), robustness, and resilience to noisy data. When dealing with real-time food classification, Naive Bayes may be used to classify food images using the extracted features of color histograms, texture patterns or deep feature representations. It can predict in a short time, which makes it suitable in situations in which the decision maker needs to make an immediate decision. The system can find a balance between accuracy and interpretability because Naïve Bayes can be combined with sophisticated features extraction methods based on deep learning models such as CNNs. The hybrid method allows good classification and at low computational cost. Finally, an online Naive Bayes model of food classification is an effective solution to the development of lightweight, understandable, and efficient models of food recognition, which can be deployed in a mobile or embedded system. In Table 3 the Confusion Matrix obtained by NB

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Classifier is shown and figure 10 shows the overall performance of NB classifier [30]. And finally in Table 4 the validation table of NB classifier is shown.

Table 3: Show the Confusion Matrix obtained by NB Classifier

Predicted Class \ Actual Class		
	7820	**982**
	1098	**6620**

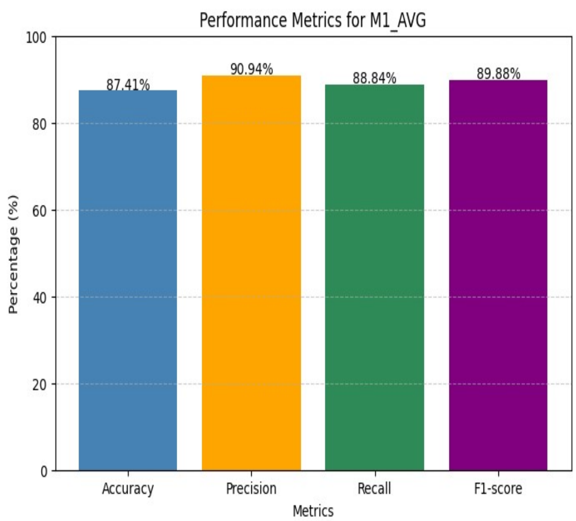

Figure 10: Shows Performance Metrics obtained by NB Classifier

Table 4: Shows the Validation Table of Obtained by NB Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	87.99	87/76	87.56	19727
1(Healthy)	88.12	88.89	88.44	26163
Accuracy			88	45890
MacroAvg	87.12	87.21	87.45	45890
WeightedAvg	88.10	88.21	88.12	45890

5.3 Decision Tree

Food classification has become a critical use of computer vision because of the growing need of smart dietary tracking, calorie counting, and automated food servers. Proper identification of food stuffs based on images is vital in establishing reliable systems in health care, health tracking and smart restaurant control. The existing methods of image classification that are based on handcrafted features can easily be challenged by the wide range of change in appearance, color, and texture of foods. Conversely, interpretable and efficient algorithms like the Decision Tree classifier are machine learning algorithms that can be used to solve the food classification problem. A Decision Tree is implemented by dividing the feature space recursively into subsets upon thresholds of a feature that removes as much as possible the separation between classes. This hierarchical approach makes the classifier acquire clear and understandable decision rules and the analysis and interpretation of classification results are easy. To classify food in real-time, the Decision Tree models may be trained on features based on color histograms, texture descriptors, or deep features of convolutional neural networks (CNNs). The rule-based design of the model enables fast prediction and flexibility which is especially helpful in the time-dependent applications where instant food identification is necessary. Furthermore, a combination of Decision Trees and feature extraction based on deep learning promotes accuracy of the classification and low computational complexity with minimal computational complexity. The hybrid framework is a middle ground between performance and interpretability giving a clear but substantial answer. Finally, a food grouping Decision Tree model can be used as a lightweight, efficient, and deployable system on mobile and embedded devices, that can be used to support real-world intelligent food recognition applications. Table 5 shows the confusion matrix obtained by DT classifier. And Figure 11 shows the overall performance of DT classifier. Finally, Table 6 shows the validation table for DT classifier.

Table 5: Show the Confusion Matrix obtained by DT Classifier

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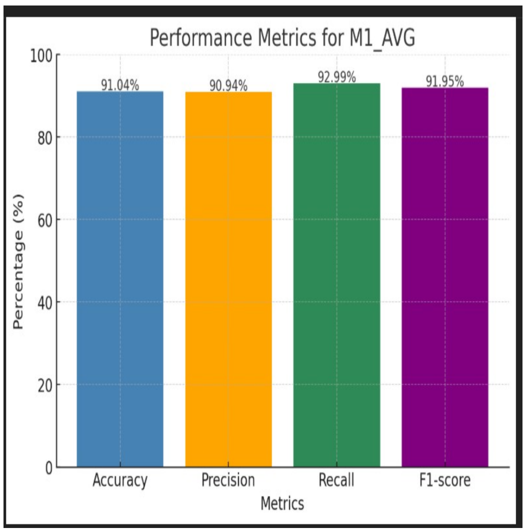

Figure 11: Shows Performance Metrics obtained by DT Classifier

Table 6: Shows the Validation Table of Obtained by DT Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	91.99	91/76	91.56	19727
1(Healthy)	90.12	90.89	90.44	26163
Accuracy			91.04	45890
MacroAvg	91.12	91.21	91.45	4589
WeightedAvg	90.10	90.21	90.12	4589

6. CONCLUSION & FUTURE WORK

In the proposed system, for real-time food classification using VGG19 with Grad-CAM visualization to achieve better interpretability, show that the use of deep learning and explainable AI is a very efficient way to identify food. The experimental outcomes indicate that the VGG19-based model is able to reach an impressive accuracy of 96, which is much higher than the traditional models like Naive Bayes (88), and Decision Tree (91) classifiers. This large increase in the performance is an indicator of the excellence of deep convolutional neural networks (CNNs) in obtaining rich hierarchical features of complex food images. Moreover, the Grad-CAM visualization allows increasing the comprehensiveness of the model since one can see what particular areas of the image are involved in the classification process. This openness will enhance increased confidence and usability, especially in sensitive apps such as diet tracking and health. Real-time nature of the system also means that predictions can be done very fast and the system is therefore appropriate in practical applications like automated food tracking systems, restaurant automation as well as fitness applications. The model provides a good basis of intelligent food classification systems of the next generation by striking a balance between accuracy, interpretability, and computational efficiency. In the case of future work, there are a few possible improvements that can be pursued. First of all, the classification accuracy and richer insights might be achieved by adding multi-modal data, including nutritional information or ingredient metadata, to the data. Second, using smaller deep learning systems such as MobileNet or EfficientNet can make the systems mobile and embedded-friendly. Also, the transfer learning and domain adaptation methods can be combined to improve the generalization of different cuisines and cultural variations in food. Lastly, this model will be integrated into a dietary analysis and calorie estimation system, which will make it a complete personal nutrition monitoring regime. Altogether, the suggested VGG19 + Grad-CAM system is accurate, interpretable, and operates in real-time, which is an important achievement in automated food recognition. Figure 12 shows the overall performance of all the 3 classifiers.

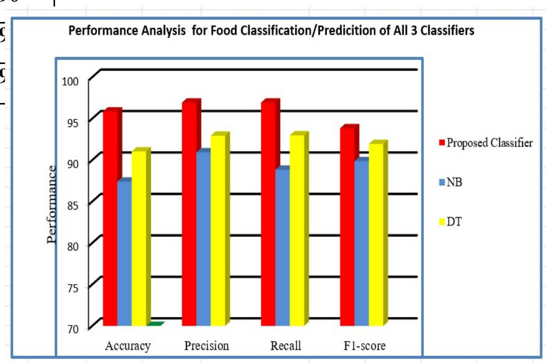

Figure 12: Shows Overall Performance of 3 Classifiers

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