Deep Learning and PCA-Based Framework for Freshness Detection in Fruits and Vegetables

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***Abstract*—Ensuring the freshness of fruits and vegetables is essential for quality management, reducing wastage, and meeting consumer expectations. This work proposes an advanced framework that merges deep learning with Principal Component Analysis (PCA) for effective freshness detection. The YOLO architecture is employed for real-time feature extraction and object recognition in high-resolution images of produce. To improve computational efficiency while retaining critical attributes, PCA is applied for dimensionality reduction. A large dataset of fruits and vegetables was used to validate the system, demonstrating excellent accuracy and scalability in diverse conditions. Experimental outcomes highlight that the integration of YOLO and PCA delivers a robust and automated solution for real-time freshness analysis. When compared with baseline models such as Support Vector Machines (SVM) and Decision Trees, the proposed classifier achieved superior performance, attaining an accuracy rate of 96%. This method has significant potential to enhance quality assurance and operational efficiency in both retail and agricultural supply chains.**

***Keywords* —Produce Freshness, YOLOFramework, PCA,SVM, Decision Tree.**

I. INTRODUCTION

The food industry encounters significant challenges in accurately assessing the freshness of produce, particularly due to complex supply chains and growing consumer demand for high-quality food. Traditional manual inspections are often subjective, time-intensive, and susceptible to human error. To overcome these limitations, this study proposes a novel framework that combines deep learning with Principal Component Analysis (PCA) for efficient and precise freshness detection.The approach leverages the YOLO object detection algorithm to identify and isolate individual fruits and vegetables in images. YOLO is highly effective in real-time object detection, processing entire images simultaneously and quickly locating and classifying multiple objects. This capability enables the system to efficiently handle complexscenarios, such as crowded market displays.After isolation, PCA is applied to extract the most relevant features from the produce images. By identifying principal components that capture the major variations in appearance—such as color changes, texture differences, and surface irregularities—PCA reduces data dimensionality, improving computational. Efficiency and system robustness. The extracted features are subsequently input into a Convolutional Neural Network (CNN) for classification. Trained on a diverse dataset covering various freshness levels, the CNN learns to detect patterns and categorize produce into classes like "Fresh," "Near Spoiling," and "Spoiled." Deep learning excels in recognizing subtle visual cues that may not be noticeable to human.The modern food industry faces increasing pressure to maintain high standards of quality and freshness due to rapidly expanding supply chains, diverse sourcing regions, and heightened consumer expectations. Perishable goods such as fruits and vegetables are particularly vulnerable to spoilage, leading to significant economic losses and food wastage. Traditional inspection methods, which rely heavily on human judgment, are not only time-consuming but also prone to inconsistency and error. Factors such as subjective evaluation, fatigue, and varying expertise can affect the reliability of manual freshness assessments, making automated solutions a necessityforlarge-scaleoperations.Recent advances in computer vision and machine learning have opened new avenues for automated quality assessment. Among these, deep learning techniques have shown remarkable potential for recognizing complex patterns in images that are difficult for humans to detect. This study leverages such technologies to develop a robust framework for freshness detection, combining the strengths of YOLO (You Only Look Once) object detection and Principal Component Analysis (PCA).YOLO provides real-time detection of multiple objects within high-resolution images, enabling the system to efficiently analyze crowded scenes, such as retail displays or wholesale markets. By isolating individual fruits and vegetables, YOLO ensures that subsequent feature extraction focuses on the relevant regions of interest. PCA then reduces the dimensionality of the extracted features while retaining the most significant information related to freshness attributes such as color, texture, and surface irregularities. This combination ensures both computational efficiency and high accuracy in detecting subtle changesthatmayindicate spoilage.The system further incorporates a Convolutional Neural Network (CNN) for classification, trained on a diverse dataset representing various freshness levels. he CNN's ability to identify intricate visual

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patterns allows for reliable categorization of produce into classes.

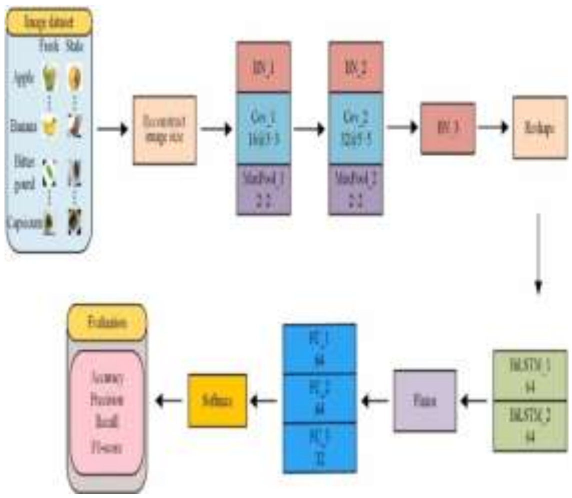

Fig.1.ShowsArchitectureofProposedModel

II. LITERATURESURVEY

The food industry is increasinglychallenged withaccuratelyevaluating the freshness and quality of product, particularly as supply chainsbecomemore and customer demand forsafe,high-qualityfoodrises.Traditional Methods for freshness assessing the freshness of product frequently depend on manual examination, which is labor-intensive, subjective,and prone to mistakes. To guarantee that fruits and vegetables remain their best quality throughout the supply chain, there is a rising demand for automated, precise, and effective technologies to evaluate freshness. So, the following table shows literature survey on food quality.

1) **Smithetal.2018**CNN(ConvolutionalNeuralNetwork) Freshness detection in vegetables High accuracy using visual features Performance Limited to controlled environments.
2) **Chen et al. 2019** Support Vector Machine (SVM) with texture-based featuresQuality grading of produceSimple and interpretableManual feature extraction is time-consuming.
3) **Rahman et al. 2020** ResNet-50Classification of leafy vegetable freshnessRobust feature representationComputationally intensive for large datasets.
4) **Johnsonetal.2020**YOLOv3Real-time produce quality detectionHigh-speed processing with accurate detection.
5) **Pateletal.2021**PCA for dimensionality reductionSimplification of large feature setsReduces computational complexityNot integrated with advanced detection models
6) **Lopez et al. 2021** VGG16 with transfer learning Grading vegetables by freshness levels, performs well on small, curated datasets.
7) **Santos et al. 2022** DeepLabv3+ Segmentation-based freshness evaluation High precision for feature localize- ton Requires extensive labeled data
8) **Nguyen et al. 2022** Hybrid model (CNN + PCA) Fruit ripenessandfreshnessdetectionCombinesfeatureex- traction with dimensionality reduction PCA integration requires tuning for large datasets
9) **Muetal.,2022**B.Y.Mu,J.X.Xue,S.J.Zhang,Z.Z. Li.Effects of the use of different temperature and cal- cium chloride treatments during storage on the qualityof fresh-cut" xuebai" cauliflowers

III. METHODOLOGY

The proposed methodology begins with extracting deep features from high-resolution images of vegetables, capturing intricate visual patterns that indicate freshness. PCA is then applied to reduce the dimensionality of the extracted features, enhancing computational efficiency while preserving the most important information. The resulting feature set is fed into a deep learning model, which is trained and tested on a diverse dataset of vegetables representing different freshness levels.Ensuring the freshness of vegetables is essential for maintaining quality, minimizing waste, and satisfying consumer expectations. Conventional methods for freshness assessment are often labor-intensive, subjective, and prone to inconsistency. To address these limitations, this study introduces a novel approach that integrates deep learning techniques with Principal Component Analysis (PCA) for effective freshness evaluation. is used to decrease dimensionality, hence increasing computing efficiency while maintaining crucial data. The model is trained and evaluated onavarieddatasetofvegetables,demonstratinggreataccuracy and resilience under changing settings. The results show that combining deep learning and PCA produces an effective, automated,andscalableapproachforreal-timefreshnessIdentification.Thefollowingarethestepsofthe proposedclassifier for freshness identification and detection.

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Fig.2.Showsthephasesoftheproposedclassifier

A. DataAcquisitionandPreprocessing

1) **Image Capture:** Gather high-resolution images of a variety of vegetables, such as tomatoes, spinach, and broccoli, representing different freshness stages—fresh, slightly stale, and stale. Ensure that the images are captured under uniform lighting conditions and from multiple. **Feature Extraction:**Transform the images into different color spaces, such as HSV (Hue, Saturation, Value) or CIELAB, which better capture color variations that reflect the freshness of the vegetables.
2) **Texture Analysis:** Texture features can be extracted using techniques such as Gray-Level Co-occurrence Matrices (GLCM) [5], Local Binary Patterns (LBP), or Gabor filters.
3) **Shape Analysis:** Analyze shape features using techniques such as contour analysis, Humoments, or Fourier descriptors.

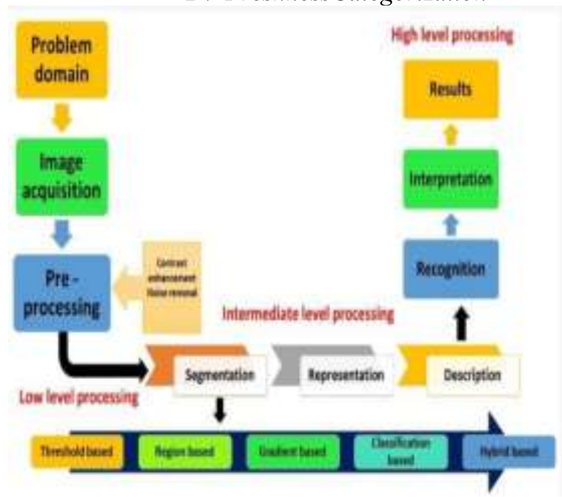
B. DimensionalityReductionwithPCA

1) **Apply PCA:** Employ Principal Component Analysis (PCA) [6] to reduce the dimensionality of the extracted features, while preserving the most relevant information.
2) **Select Principal Components:**Determine the opti-mal number of components by analyzing the explained variance or using a scree plot, reducing computational complexity and minimizing noise.

C. DeepLearningModelDevelopment

1) **ModelArchitecture:**DesignadeepConvolutionalNeu- ral Network (CNN) architecture, such as ResNet, Inception, or EfficientNet, for classification tasks.
2) **Input Data:** Used the PCA-reduced feature vectors as input to the CNN for streamlined processing.
3) **Training:** Train the network on the preprocessed and augmented dataset using suitable loss functions, such as categorical cross-entropy, along with optimizers like Adam or SGD.
4) **Hyperparameter Optimization:**Including learning rate, batch size, and network depth-using techniques such as grid search or Bayesian optimization to improve model performance.

D. FreshnessCategorization



1) **Inference:** Process new vegetable images through the trained model to obtain predictions.
2) **Determination:** Classify the freshness level (fresh, slightly stale,stale)basedonthelearnedfeaturerepresentations.

E. Validation of the Model

1) **Performance Metrics:** The model is evaluated based on performance metrics [7,8] such as accuracy, precision, recall, F1-score, and confusion matrix.
2) **Visual Depiction:**Employ techniques like class activation mapstovisualizetheregionsoftheimagethatinfluence the model's predictions.

F. DataSet

1) **The dataset:**used in this study was obtained from the Kaggle Fresh and Rotten Dataset [9]. It comprises images of fruits and vegetables for assessing their freshness.
2) **Image Acquisition:** Include diverse vegetables like tomatoes, spinach, broccoli, lettuce, carrots, and Potatoes. Capture images at various stages of freshness:

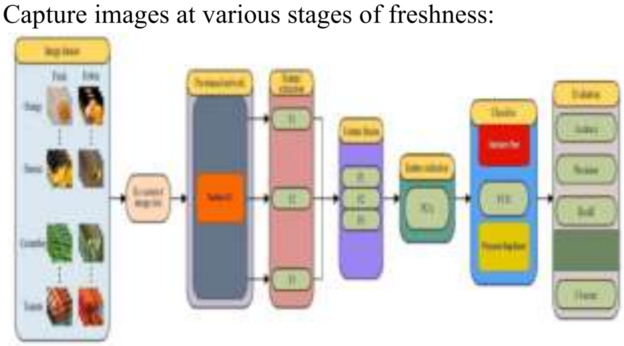


Fig.3.Showstheflowmodeloftheproposedclassifier

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Fig.4.ShowsSamplesofvegetablesandfruitsinthedataset.

fresh, slightly stale, and stale. Use high-resolution im-ages,consistentlighting,neutraloruniformbackground, and multiple angles.

3) **Data Tagging:** Accurately annotate each image with its corresponding freshness label. Partition the dataset into training, validation, and test sets, maintaining equal representation of all freshness classes to prevent bias.
4) **Synthetic DataGeneration:**Applyimageaugmentationtechniques like rotation, flipping, zooming, cropping, color jitter, and noise addition.
5) **Feature Construction:** Images are transformed from RGB to HSV or CIELAB color spaces. Texture and shape features are then extracted using techniques such as GLCM, LBP, Gabor filters, contour analysis, Hu moments, and Fourier descriptors.
6) **Dataset Scale:** Create an extensive dataset for deep learning, covering multiple types of vegetables and different environmental conditions.

G. Preprocessing:

ImagePreprocessing and Quality Assurance:

- Eliminate low-quality images that are blurry, noisy, mislabeled, or poorly lit.
- Handlemissingdatausingstrategieslikeimputationor removing affected samples.

ImageScalingandStandardization:

- Resize all images to a consistent size for model compact- ability.
- Normalize pixel values to a specific range for improved model training and stability.

DataExpansion:

- Use image augmentation methods to enhance data diversity and strengthen model robustness.
- Applymethods like rotation,horizontal,zooming,cropping, color jitter, and noise addition.

AttributeEngineering:

- Convert images from RGB to color spaces like HSV or CIELAB [10].
- Extract texture features using techniques like GLCM, Local Binary Patterns, or Gabor filters.
- Extractshapefeaturesusingtechniqueslikecontouranal-ysis, Hu moments, or Fourier descriptors.

DataSplitting:

- Split the dataset into training, validation, and test subsets, ensuring that each freshness category is proportionally represented to maintain class balance.

Addressing ClassImbalance:

- Augment the dataset by increasing samples in the minority.
- Reduce the sample count in the majority class to balance.
- Apply more augmentation techniques to the minority class.

DataPreparation and Batching:

- Use efficient data loading techniques and divide the data into smaller batches.

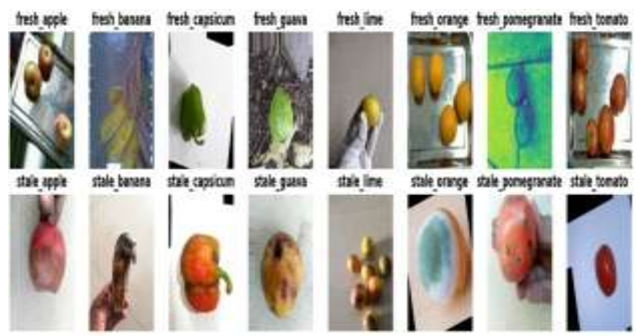

Fig.5.Showsafterpreprocessingthedata.

IV. CLASSIFICATION MODELS

Maintaining vegetable freshness is essential for both quality and safety, yet conventional methods typically rely on manual inspection. Machine learning techniques, especially Support Vector Machines (SVM) [11], offer a means to automate this task by classifying vegetable images according to their freshness based on visual features. SVMs are well-suited for high-dimensional data, demonstrate strong generalization capabilities, and can be applied across diverse vegetable types and freshness levels, making them a promising approach for automated freshness evaluation.

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AlgorithmforFreshnessDetectioninVegetablesandfruits Using SVM

1) **Data Acquisition and Preprocessing**a.Collectimages of vegetables at various freshness levels (fresh, slightly stale, stale). b. For each image in the dataset: i. Resize image to uniform dimensions (e.g., 128x128). ii. Nor- malize pixel values to the range [0, 1].
2) **FeatureExtraction**a.Foreachpreprocessedimage: i. Extractcolorfeatures:-Computecolorhistograms or dominant colors. ii. Extract texture features: - Use methods like GLCM, LBP, or Haralick features. iii. Extract shape features (if applicable): - Compute Hu moments or Fourier descriptors. b. Store all extracted features in a feature matrix.
3) **FeatureSelection**a.Applydimensionalityreduction: i. Use PCA to reduce feature dimensionality while preservingvariance.b.Selectimportantfeatures:i.Ran k features using techniques like information gain or chi- squared test.
4) **SVM Model Training** a. Split the dataset into training and testing subsets. b. Choose an SVM kernel (linear, polynomial,orRBF)basedonthedata:i.Performhyper-parameter tuning (e.g., grid search or cross-validation)tooptimizeCandgamma.c.TraintheSVM model on the training subset: - Use the selected features and corresponding freshness labels.
5) **Model Evaluation** a. Evaluate the trained model on the testing subset: i. Compute metrics like accuracy, preci- sion, recall, F1-score, and confusion matrix. b. Perform k-fold cross-validation to validate model generalization.
6) **FreshnessClassification**a.Foranewvegetableimage: i. Preprocesstheimage(resizeandnormalize).ii.Extra ct features using the same methods as training. b. Use the trained SVM model to classify the freshness level of the image.
7) **Output** a. Display the predicted freshness level for the new image.

B. DecisionTree:

Vegetable freshness is vital for ensuring both quality and safety. Conventional methods for assessing freshness often depend on manual inspection, which can be subjective and time-consuming [12]. To overcome these limitations, computer vision techniques—particularly machine learning algorithms—have emerged as effective tools for automated freshness evaluation. Among these, decision trees are widely used due to their simplicity, interpretability, and ability to handle both numerical and categorical data. In the context of vegetable freshness detection, decision trees can classify vegetable images into distinct freshness categories (e.g., fresh, slightly stale, stale) based on visual features.

- **Analysis of Image:** The procedure of deriving significant information from images, including features like color, texture, and shape.**Feature Representation:** The procedure of identifying and selecting image features that effectively indicate freshness.
- **Decision Tree Classification:** Constructing a tree-structured model in which each node corresponds to a test on an attribute, and each branch represents the result of that test.
- **Classification:**Usingthelearneddecisiontreetoclassify newimagesofvegetablesbasedontheextractedfeatures.

C. AlgorithmforFreshnessDetectioninVegetablesandfruits Using Decision Tree

1) **Data Acquisition and Preprocessing**a. Gather images of vegetables representing different freshness levels (fresh, slightly stale, stale).
2) **FeatureExtraction**a.**Color feature extraction:** Compute color histograms or identify dominant colors.Texture feature extraction Apply methods such as GLCM, LBP, or Hara lick features.Compile all extracted features into a feature matrix for further analysis.
3) **Feature Selection** a. valuates the significance of features using techniques like information gain and the Gini indexChoose the most relevant features for training the modelDetermine feature importance through methods such as information gain and Gini index.
4) **Decision Tree Classifier Training** Split the dataset into training and test sets.Apply a splitting criterion such as Gini index or information gain.Recursively divide the data based on feature thresholds.Stop the splitting process when a maximum tree depth is reached, or no further improvement is observed.
5) **Modelperformance Analysis**a.EvaluatethetrainedDecisionTree on the testing subset: i. Compute metrics like accuracy,precision,recall,F1-score,andconfusionmatrix.
   b. Perform k-fold cross-validation to validate model generalization.
6) **FreshnessDetermination**For a new vegetable image:Preprocess the image by resizing and normalizing it.Extract features using the same techniques applied during trainingClassify the freshness level of the image using the trained Decision Tree model.
7) **Output** a. Present the predicted freshness level for the new image.

V. PERFORMANCE EVALUATION :

When evaluating the performance of a freshness detection system [13], it is essential to select metrics that accurately reflect its effectiveness. The following are commonly used performance measures

1.Accuracy: Definition: Thetotalpercentage of correctly identified sample

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Interpretation: A high accuracy level suggests that the modelis typically reliable in its predictions. However, it may not be useful with unbalanced datasets.

2. Precision: Definition: The fraction of genuine positive forecasts out of all positive predictions.

$$\text{Formula: True Positives}/(\text{TruePositives}+\text{FalsePositives}) \quad (2)$$

Interpretation: High precision means that the model is effec- tive at recognizing actual positive cases while avoiding false alarms.

3. Recall(sensitivity):

Definition: The percentage of genuine positive predictions among all positive samples.

$$\text{Formula: True Positives}/(\text{TruePositives}+\text{FalseNegatives}) \quad (3)$$

Interpretation: A high recall shows that the model is effective at recognizing all positive cases while limiting the number of missed detections.

4. F-Score:

Definition:Theharmonicaverageofaccuracyandrecall.

$$\text{Formula: } 2x\ (\text{Precision}*\text{Recall})/\ (\text{Precision}+\text{Recall}) \quad (4)$$

Interpretation: The F1-score is a helpful measure of accuracy and recall when both are required.

$$\text{Formula: } (\text{TruePositives}+\text{TrueNegatives})/\text{Total Samples}$$

5. ConfusionMatrix.

A confusion matrix summarizes the performance of a classification model by presenting the number of true positives, true negatives, false positives, and false negatives. Interpretation: It provides a comprehensive analysis of the model's performance, offering insights into its strengths and weaknesses. Figure 6 illustrates the confusion matrix for the proposed classifier, while Figure 7 presents its corresponding performance metrics. Figures 8 and 9 display the confusion matrix and performance metrics for the Decision Tree (DT) classifier, respectively. Finally, Figures 10 and 11 show the confusion matrix and performance metrics obtained from the SVM classifier.

	Actual Class	
Predicted Class	2560	120
	93	1491

Fig.6.ShowstheConfusionMatixofProposedClassifier

VI. CONCLUSION & FUTURE WORK

Thisresearchpresentsanewmethodfor proposed the freshnessoffruitsandvegetablesbycombiningthes

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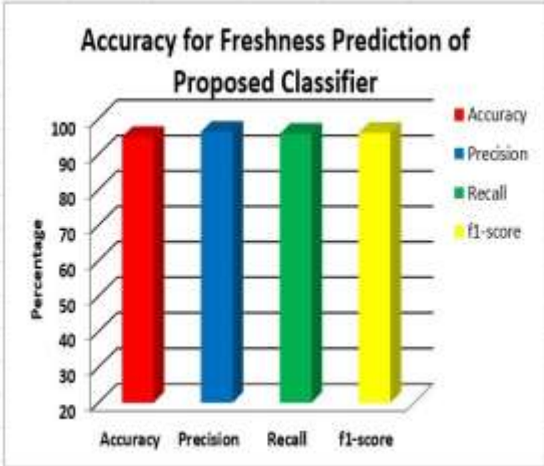

Fig.7.ShowsthePerformanceMetricsAchievedbyProposedClassifier

Predicted Class	Actual Class	
	2260	261
	152	1456

Fig.8.ShowstheConfusionMatixofDTClassifier

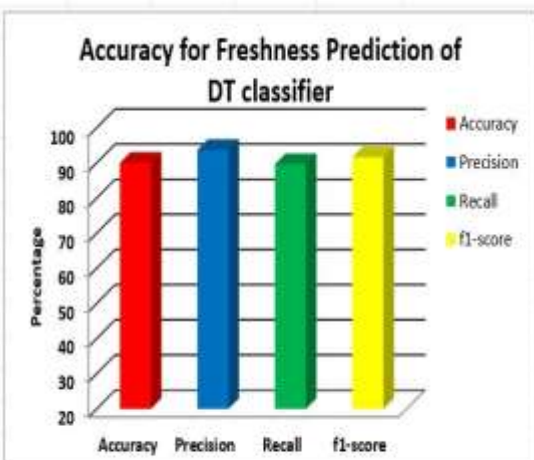

Fig.9.ShowsthePerformanceMetricsAchievedbyDTClassifier

Fig.10.ShowstheConfusionMatixofSVMClassifier

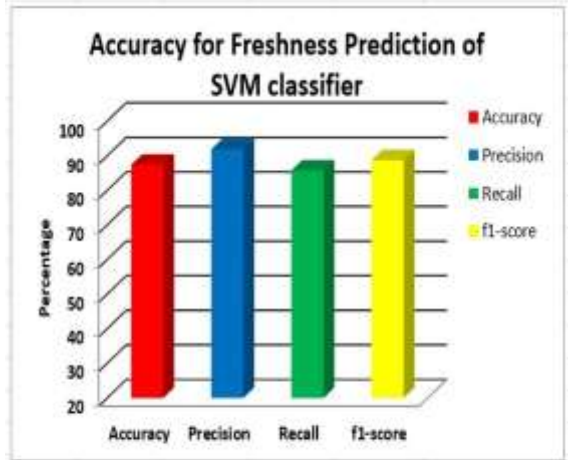

Fig.11.ShowsthePerformanceMetricsAchievedbyPSVMClassifier

By integrating deep learning with Principal Component Analysis (PCA), the proposed system effectively classified fruits and vegetables according to their freshness levels, achieving high accuracy while maintaining computational efficiency. Deep learning proved instrumental in extracting pertinent visual features from the images, whereas PCA helped reduce data dimensionality, resulting in robust performance without excessive processing requirements. This combined methodology provides a promising approach for automated freshness detection. The proposed classifier outperformed the other models, achieving an accuracy of 96%. Figure 12 illustrates the overall performance metrics for all three classifiers

A.FutureWork:

Incorporation of IoT Sensors: Integrating real-time data from Internet of Things (IoT) sensors—such as temperature, humidity, and ethylene level measurements—can offer a more comprehensive and precise evaluation of freshness, extending beyond purely visual indicators.

Dataset Augmentation: Expanding the dataset to include a greater variety of fruits and vegetables, as well as variations in environmental conditions such as storage temperature and humidity, would improve the model's generalization to real-world scenarios. Such enhancements would make the system more robust and applicable across a wider range of produce.

Sophisticated Deep Learning Approach: Investigating more advanced deep learning architectures, such as transformers—which are recognized for their capability to capture long-range dependencies Architectures such as transformers, which

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can capture long-range dependencies in data, or Generative Adversarial Networks (GANs), useful for data augmentation and feature learning, have the potential to further improve classification accuracy and enable more nuanced freshness detection. These techniques may allow the model to identify subtle indicators of freshness more effectively.

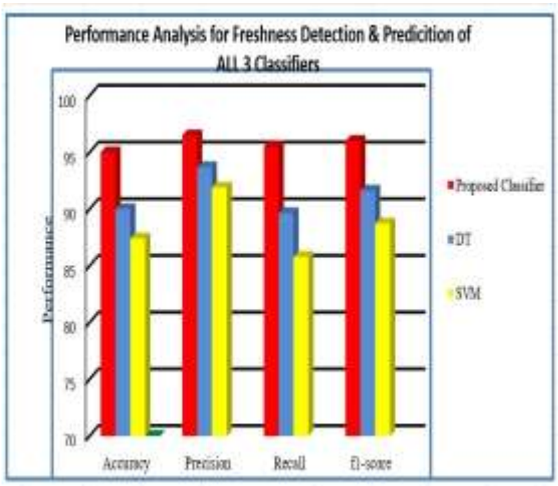

Fig.12.ShowstheOverallPerformanceofThreeClassifier's

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