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A Hybrid Deep Learning and Machine Learning Framework for Food Reshness and Spoilage Detection using Mobilenetv2 and Image Segmentation

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Abstract

Identifying food degradation has pinpoint the precise areas impacted by become essential for maintaining supply chain quality, reducing waste, and ensuring food safety. Traditional freshness assessment techniques are primarily based on manual inspection, which is often inaccurate, time consuming, and unreliable. The automated food freshness assessment approach proposed in this paper integrates deep learning– based feature extraction, machine learning classification, and image segmentation techniques. The proposed method determines food quality using a logistic regression classifier and extracts high-level visual features through a pre-trained convolutional neural network (CNN). In addition, a spoilage analysis module employs pixel-level evaluation to identify affected regions and estimate the severity level. Experimental results indicate that the system is suitable for real- time automated food monitoring applications, as it effectively visualizes spoiled areas while achieving high classification accuracy.

Keywords : Food Freshness Detection, Deep Learning, MobileNet Feature Extraction, Logistic Regression, Image Segmentation, Computer Vision.

1 Introduction

Assessing food quality is essential for maintaining supply chain efficiency, lowering post-harvest losses, and guaranteeing food safety. In example, microbial activity, storage problems, and environmental factors make highly perishable goods—like fruits, vegetables, and fish—more vulnerable to quick deterioration. Large-scale food waste throughout the supply chain, serious health hazards, and substantial financial loss result from improper freshness monitoring in certain food categories. Food freshness is traditionally assessed by manual inspection techniques carried out by human specialists. These methods rely on tactile inspection, smell, and visual observation. However, manual evaluation relies heavily on human experience and is subjective, unreliable, and time-consuming. Moreover, it is unable to degradation or precisely measure the degree of spoiling. Automated techniques for evaluating the quality of food have drawn more attention as a result of the quick development of computer vision and artificial intelligence. Since image-based analysis is quick, easy, and affordable, it has become a viable method for determining the freshness of food. Machine learning algorithms can reliably differentiate between fresh and spoilt food items by examining visual characteristics like colour changes, texture differences, and surface flaws. An automated food freshness prediction system that combines machine learning classification, deep learning feature extraction, and picture segmentation approaches is shown in this research. In order to provide a more thorough knowledge of the degree of spoiling, the

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suggested system will not only identify food products as fresh or spoilt, but it will also graphically show the damaged areas. A pre- trained convolutional neural network is used as a feature extractor in the suggested system to extract high-level visual representations from food photos. Transfer learning reduces computing complexity and training time by utilising prior knowledge from large-scale image datasets. To accurately estimate the food item's freshness status, a logistic regression classifier is used to process the retrieved characteristics. A spoiling segmentation module is included to improve the system's usefulness. This module analyses the food photos at the pixel level to find areas that have degraded. The technology visibly highlights impacted areas and identifies them using color-based segmentation and image processing algorithms, allowing users to comprehend the extent and presence of spoiling. This system can be used in supply chain monitoring applications, retail food inspection, smart kitchens, and automated quality control. The suggested solution is implemented as a web-based application that enables users to upload food images and receive real-time predictions along with visual spoilage analysis. This system can be used in supply chain monitoring applications, retail food inspection, smart kitchens, and automated quality control. The suggested solution is implemented as a web-based application that enables users to upload food images and receive real-time predictions along with visual spoilage.

1.1 Research problems

Detecting food spoilage is still a significant problem in contemporary food supply chains, particularly for highly perishable goods like fruits, vegetables, and fish. Due to microbial development, exposure to the environment, and inappropriate storage conditions, several food categories experience quick physical and chemical changes. Therefore, preserving food safety, lowering financial losses, and minimising waste all depend on precise and prompt rotting detection. The substantial reliance on manual inspection techniques is one of the main issues with food freshness evaluation. Conventional assessment depends on human judgement based on texture, smell, and visual appearance. Because the findings of such approaches vary based on the evaluator's experience and perception, they are intrinsically subjective and frequently inconsistent. Furthermore, manual inspection takes a lot of time and is inappropriate in large-scale industrial settings. The absence of automated methods that can detect whether food is spoilt as well as the degree and location of degradation is another serious problem. Numerous automated methods currently in use just concentrate on classification, offering a binary choice like "fresh" or "spoilt." They do not, however, provide interpretability on the areas of the food item that are impacted and the degree of spoiling. In picture-based food analysis, variations in illumination, background noise, and image quality also pose difficulties. Reduced prediction accuracy can result from images taken from real-world settings differing greatly from training datasets. Furthermore, creating fully supervised deep learning models is challenging due of the scarcity of labelled spoiling datasets. The lack of automated techniques to identify whether food is spoilt and the extent and location of deterioration is another significant issue. Current automated approaches focus only on classification, providing a binary option such as "fresh" or "spoilt." However, they do not offer interpretability on the affected areas and level of deteriorating of the food item. Changes in lighting, background noise, and image quality are further challenges in picture-based food analysis. Images from realworld environments that differ significantly from training datasets may lead to decreased prediction accuracy. Furthermore, because labelled spoiling datasets are scarce, developing fully supervised deep learning models is difficult.

1.2 Research Contributions

A complete and automated method for predicting food freshness and analysing spoilage using computer vision and machine learning approaches is presented in this study. Here is a summary of this work's main contributions.The study first suggests a hybrid method that combines conventional machine learning classification with deep learning feature extraction. High-level visual features are extracted from food photos using a pre- trained convolutional neural network, which improves classification performance while requiring less training data.In order to estimate the freshness of food, the system also presents an effective classification model based on logistic regression. With its great accuracy, our lightweight classifier guarantees faster calculation and allows for realtime prediction. Third, a new spoilage segmentation module is created to improve the system's interpretability. The suggested method pinpoints the precise

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areas impacted by spoiling, in contrast to traditional classification techniques that merely offer a freshness mark. This enables consumers to see the patterns of food item deterioration graphically.Fourth, to increase prediction reliability, the system uses image preparation methods such colour improvement, lighting normalisation, and background removal. These preprocessing procedures increase the resilience of the model and lessen the effect of environmental changes. Fifth, the study shows how the suggested method might be put into practice as a web-based application. The technology is appropriate for real-world use since it allows users to upload pictures of fruits, vegetables, and fish and receive instant freshness predictions along with visual spoiling analysis. Lastly, experimental findings confirm that the suggested framework achieves high classification accuracy and efficient spoiling visualisation, indicating its potential for use in supply chain management, automated quality control systems, smart food monitoring, and retail inspection.

2 Literature Survey

Numerous studies have explored the problem of food freshness detection using image processing and machine learning techniques. Early research primarily focused on traditional image processing methods such as colour analysis, texture feature extraction, and threshold-based segmentation techniques. These approaches were effective in controlled laboratory environments but showed limitations when applied to real-world scenarios with varying lighting conditions and complex backgrounds [1]. One of the initial studies utilized digital image processing techniques to evaluate the quality of fruits and vegetables by extracting features such as colour intensity, texture patterns, and surface defects [2]. Although this method achieved reasonable classification accuracy, it relied heavily on manually engineered features, which reduced robustness under diverse environmental conditions. As machine learning developed, researchers started incorporating supervised classification algorithms for evaluating food quality. Based on retrieved visual data, fresh and spoilt food samples were classified using Support Vector Machines (SVM), k-Nearest Neighbours (k- NN), and Random Forest classifiers [3]. Although these strategies enhanced prediction performance, they were still reliant on manually developed feature extraction techniques. The emergence of deep learning significantly enhanced food quality detection systems. Convolutional Neural Networks (CNNs) enabled automatic feature extraction from raw images, eliminating the need for manual feature engineering [4]. Pre-trained deep learning models such as VGG16, ResNet, and MobileNet have been successfully applied for fruit and vegetable classification tasks, achieving higher accuracy compared to traditional techniques [5]. Recent research has also used transfer learning to minimise computing complexity and increase generalisation performance on restricted datasets [6]. Furthermore, picture segmentation algorithms have been used to discover and emphasise spoilt regions based on colour and texture differences, making classification findings more visually interpretable [7]. Collectively, these studies demonstrate that deep learning–based feature extraction combined with machine learning classification offers improved accuracy, robustness, and adaptability for real-world food freshness detection systems. Materials (Dataset Description)

This study's dataset was gathered from Kaggle's publicly accessible sources. The collection includes pictures of several food categories, such as fruits, vegetables, and fish, taken in a variety of settings with diverse lighting, backgrounds, and orientations. Based on freshness criteria, the dataset is divided into two main classes: Images of food products in good condition with their natural colour, smooth texture, and lack of obvious decomposition are included in the Fresh Category. Spoilt Category: Contains pictures of food products that show deterioration symptoms such discolouration, fungus development, bruising, surface damage, and unusual texture. To enable supervised learning, the photos are kept in an organised folder style, with distinct folders for each class. With over 60,000 photos overall, the dataset offers enough variety for training and testing the suggested method. The resolution and backdrop complexity of each image differ, which strengthens the model's resilience in practical situations. To meet the input specifications of the convolutional neural network used for feature extraction, all photos were scaled to a fixed dimension of

224×224 pixels prior to training. Preprocessing methods like feature scaling, contrast normalisation, and background removal were used to improve model performance. By taking these actions, the influence of environmental fluctuations was reduced and consistent input quality was guaranteed. The use of a large and diverse dataset enabled the system to learn significant visual patterns related to food freshness and spoilage, thereby improving classification accuracy and generalization capability.

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Category	**Fresh Images**	**Spoiled Images**	**Total**
Fruits	17000	15700	32700
Vegetables	15000	13300	28300
Fish	802	760	1502
Total	32802	29760	62562

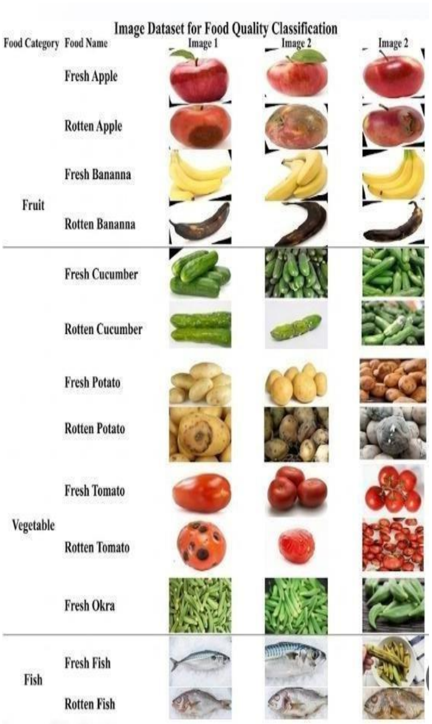

Figure 1 shows some photos from the dataset of fresh and rotten food items from several categories, including fruits, vegetables, and fish, which were utilised to train and test the proposed food freshness identification system.

3 Proposed Methodology

The three main steps of the suggested approach are spoilage segmentation, feature extraction and classification, and picture preprocessing. An organised pipeline serves as an illustration of the complete workflow.

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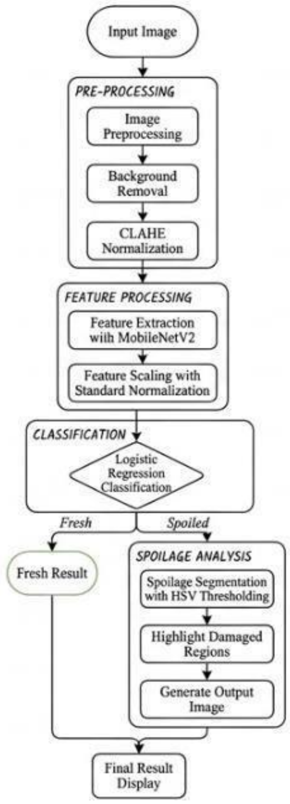

Fig.2: Proposed Methodology for food freshness detection using image preprocessing, MobileNetV2 feature extraction, logistic regression classification, and HSV-based spoilage segmentation.

3.1 Image Preprocessing

Preprocessing is done on input images prior to feature extraction in order to increase prediction accuracy. Normalisation of illumination and background removal are part of the preprocessing step. Greyscale thresholding is used to separate the food area from the background in order to remove the background. By reducing noise, this stage keeps irrelevant pixels from influencing the categorisation outcomes. It uses Contrast Limited Adaptive Histogram Equalisation (CLAHE) to normalise the lighting. This approach minimises illumination variability and improves image contrast**.**

3.2 Feature Extraction Using CNN

To extract high-level visual information from food photos, a pre-trained MobileNetV2 convolutional neural network is employed. The network creates a feature vector by removing the last classification layer and using global average pooling. The following is a representation of the feature extraction process:

$$F = CNN\ (I)\ \mathrm{F{=}CNN(I)}$$

where I is the input picture, F is the extracted feature vector. A feature vector of size 1280 is used to represent each image, capturing key visual elements like texture, colour distribution, and structural patterns.

3.2.1 Models Used in CNN-Based Feature Extraction Phase

In this stage, high-level visual features are extracted from food photos using MobileNetV2, a pre-trained deep convolutional neural network. For real-time computer vision applications, MobileNetV2 offers a lightweight and effective deep learning architecture. The model is appropriate for real-time food freshness monitoring systems since it strikes a fair compromise between computational economy and feature representation quality. After initialising the pre-trained network with ImageNet weights, the final classification layer is removed. By adding a global average pooling layer to the final convolutional output, the model is utilised as a feature extractor rather than for direct classification. The most significant visual aspects of the input image are represented by a fixed-length feature vector created by this technique from the spatial feature maps.

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Thefeature extractionprocessis mathematically expressed as:
$F = CNN(I)$

where:
- **I** represents the input food image
- **CNN** represents the MobileNetV2 feature extraction model
- **F** represents the extracted feature vector

A 1280-dimensional feature vector that captures key visual characteristics of each image includes:
- Patterns of texture
- Distribution of colours
- Information about structures
- Surface imperfections

The machine learning classifier then uses these extracted properties to forecast freshness.

3.2.2 Architecture of MobileNetV2

Multiple convolutional blocks made with depthwise separable convolutions and inverted residual connections make up MobileNetV2. The architecture consists of multiple bottleneck residual blocks after an initial standard convolution layer.

Three major levels are present in each bottleneck block:
- More channels are added via the expansion layer.
- The Depthwise Convolution Layer filters space.
- Dimensionality is decreased by the projection layer.
- This design maintains great accuracy while drastically reducing computing complexity.

The final convolutional output is processed using global average pooling to generate a fixed-size feature vector.

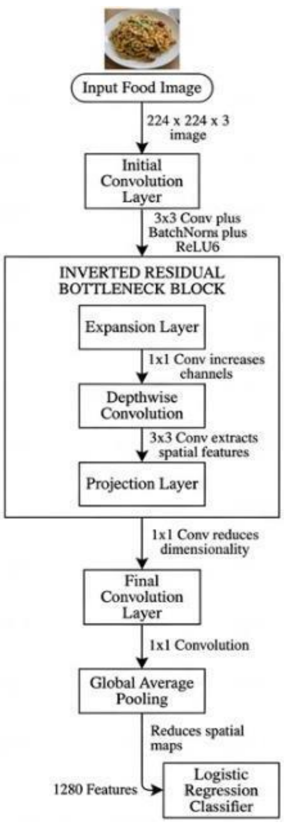

Fig 3: shows the MobileNetV2-based feature extraction architecture utilised in the proposed food freshness detection system.

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3.3 Classification Using Logistic Regression

A logistic regression classifier is trained to categorize food images into fresh or spoiled classes. The logistic regression prediction function is expressed as:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(w^T x + b)}}$$

Where,
w= weight vector
b= bias term
x= input feature vector
The classifier outputs the probability
of spoilage along with a confidence score.

3.4 Spoilage Segmentation

To identify affected regions, image segmentation is performed using color-based thresholding in the HSV color space. Spoiled regions typically exhibit darker or brownish color patterns.

The spoilage mask is generated as:

$$M(x, y) = \begin{cases} 1 & \text{if pixel intensity falls within spoilage range} \\ 0 & \text{otherwise} \end{cases}$$

The segmented mask is overlaid on the original image to visually highlight damaged areas.

4 System Architecture

The suggested system architecture is made up of several linked modules that operate in order.Through a web-based interface, users upload photographs to the image capture module, which starts the process. The preprocessing module receives the uploaded images once they have been saved on the server.High-level feature representations are produced by the feature extraction module using a CNN that has already been trained. The categorisation module then receives these scaled features.The food's freshness or spoilage is predicted by the classification module, which also gives a confidence score. The segmentation module is turned on if spoiling is found. Damaged areas of the image are identified and highlighted by the segmentation module. Ultimately, the outcomes are presented via an online interfacethat includes the visual spoiling analysis, prediction label, and confidence rating.

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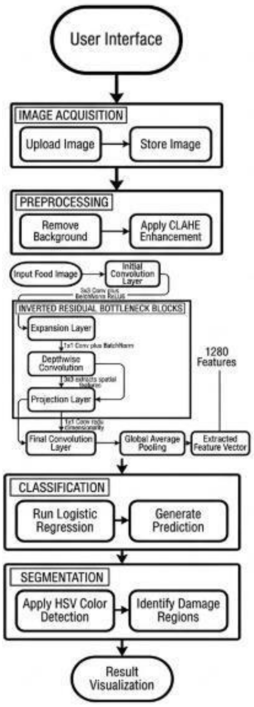

Fig 4 : shows how the proposed system architecture combines image preprocessing, MobileNetV2 feature extraction, logistic regression classification, and HSV-based segmentation to detect food freshness and visualise spoilt parts.

5 Comparative Analysis with Other Deep Learning Models

Other deep learning architectures like VGG16 and ResNet50 are frequently employed in image classification applications, even though the suggested system uses MobileNetV2 for feature extraction and Logistic Regression for classification. The choice of the suggested model is supported by a comparative analysis.

Model	Trainable parameters	Total parameters	Training Strategy	Computati - onal cost	Suitability for Small Dataset	Validation Accuracy
MobileNet V2 +Logistic Regression (Proposed)	1281	3.5M (Frozen)	Transfer Learning (Feature Extraction)	Low	High	94.36%
VGG16 (FineTuned)	~15M+	~138M	Full CNN Training	Very High	Low (Overfitting Risk)	~90–93%
ResNet50 (FineTuned)	~25M	~25M	Full CNN Training	High	Moderate	~92–94%

Figure 5: The comparison table demonstrates that the proposed MobileNetV2 with Logistic Regression model outperforms the VGG16 and ResNet50 models in terms of accuracy, computational cost, and number of trainable parameters.

6 Results and Discussion

Using a dataset of pictures of fruits, vegetables, and fish divided into fresh and spoilt categories, the suggested approach was assessed. The dataset contained thousands of photos taken in different settings.The hybrid method of deep learning feature extraction and logistic regression classification produced good prediction accuracy, according to experimental results. When separating spoilt food from fresh food, the model performed consistently.Because the preprocessing procedures lessened the effects of background noise and lighting fluctuations,the classification accuracy was

Fig 6: illustrates the web-based interface developed for uploading food images and predicting their freshness using the proposed model.

much increased. Using a CNN that had already been trained lowered computational complexity without sacrificing feature representation**.** In addition to correctly identifying damaged areas, the spoilage segmentation module offered concise visual descriptions of rotting patterns. Comparing this visualisation feature to more conventional classification-only approaches, the system's interpretability is improved. Additionally, the system showed quick processing speed, which qualifies it for real- time applications like smart retail inspection and food quality monitoring.

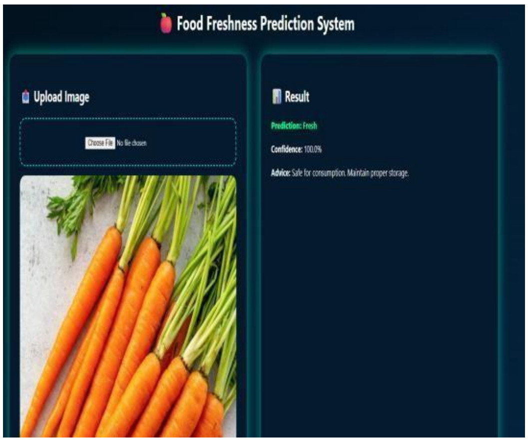

Fig 7 : The system predicts the uploaded food image as fresh and displays the classification result with confidence level.

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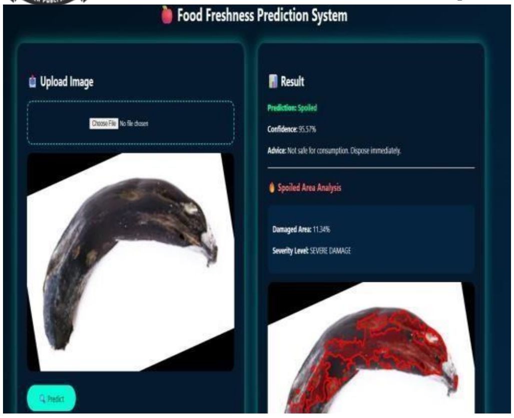

Figure 8 : shows the detection of a spoilt food image, with the system highlighting the damaged portions and indicating the extent of spoilage.

6.1 Classification Performance

Using a train–test split technique, the effectiveness of the suggested food freshness detection system was assessed. Features taken from the previously trained MobileNetV2 network were used to build a logistic regression classifier.The recovered deep features successfully capture visual qualities associated with food freshness and rotting, as evidenced by the model's 94.36% validation accuracy.The high accuracy shows how well standard machine learning categorisation works when combined with deep learning- based feature extraction. The training process's balanced class weighting significantly lessened bias between spoilt and fresh samples.

6.2 Spoilage Segmentation Results

Apart from classification, the method highlights impacted areas by performing spoilage segmentation. The segmentation module used morphological operations and colour thresholding based on HSV to successfully identify damaged areas.The visual results enable improved interpretability and help consumers comprehend the degree of food deterioration by clearly showing spoilt areas.

6.3 System Performance Analysis

The suggested system offers a number of benefits:

- 94.36 percent classification accuracy
- The capacity to make predictions in real time
- A clear representation of the areas that are spoilt
- The lightweight CNN backbone results in low computational costs.

These findings show that the system is appropriate for real-world food quality monitoring applications.

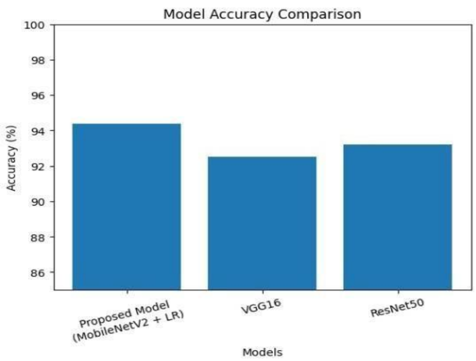

Figure 9 : compares the accuracy of the proposed model to various current models.

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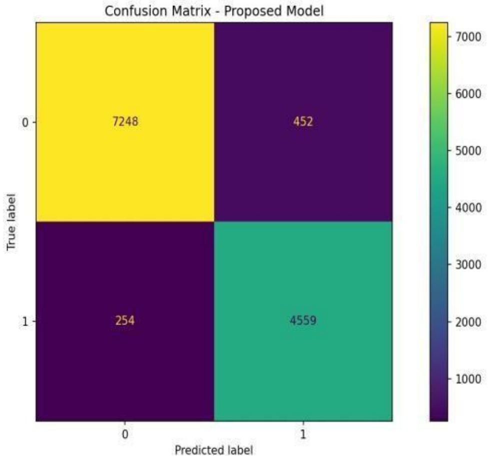

Fig 10 : illustrates the confusion matrix of the proposed model for fresh and spoiled food classification.

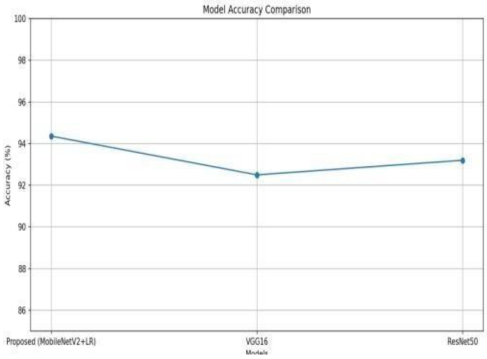

Fig 11: illustrates the comparison of accuracy between the proposed model and other existing models.

7 Conclusion and Future Work

An automated food freshness detection system that combines machine learning classification, deep learning feature extraction, and picture segmentation techniques was described in this study. Food products are efficiently divided into fresh and spoilt categories by the system, which also graphically indicates areas that are damaged. High accuracy was achieved with less computing power thanks to the hybrid strategy that combined a logistic regression classifier with a pre-trained convolutional neural network. Through the identification of impacted regions in food photos, the spoilage segmentation module improved system interpretability.The created web application shows that it is feasible to implement the system in real-world situations including supply chain monitoring, food quality inspection, and smart retail settings. Future research can concentrate on enhancing segmentation accuracy with sophisticated deep learning models like Mask R-CNN and U-Net. Multi-class freshness grading, real- time video-based monitoring, and integration with Internet of Things-based smart storage systems can all be investigated further.

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