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FruVeg_MultiNet: A hybrid deep learning-enabled IoT system for fresh fruit and vegetable identification with web interface and customized blind glasses for visually impaired individuals

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ABSTRACT

The automatic identification of fresh vegetables and fruits is imperative to streamline agricultural processes, ensuring rapid and accurate assessment of produce quality, reducing economic pressure, and addressing societal needs, particularly for visually impaired individuals. This research presents a pioneering approach for fresh fruit and vegetable identification through IoT and a hybrid deep learning model, combining EfficientNetB7 and ResNet50 architectures. The proposed hybrid model demonstrates remarkable accuracy, achieving 99.92% and 95.93% precision on dataset1 and dataset2, respectively. The study encompasses a comprehensive evaluation of four initial models: EfficientNetB7, VGG16, ResNet50, and VGG19. The hybrid model, which combines the best of these, performed better than the others. In addition to its high accuracy, the system achieved an average response time of 1.201 s, highlighting its efficiency in processing and decision-making. Considering these challenges in the agricultural industry, the research extends to fruit and vegetable classification, offering applications in self-service fruit or vegetable purchasing, production lines, and smart agriculture. Additionally, the societal impact is considered, with the development of technology aiding the visually impaired in assessing produce freshness. Furthermore, we developed a useful web application that categorizes fruits and vegetables and links to a detailed database offering important information about the recognized produce.

1. Introduction

The accurate identification and classification of fresh fruits and vegetables play a pivotal role in ensuring the production of high-quality raw materials for the global market and the health sector. Accurate classification and gradation of fruit and vegetable freshness is critical for the agricultural industry, especially in delivering the highest-quality produce to consumers. Numerous illness outbreaks can be traced back to unhealthy fruits and vegetables [1]. The significance of fruit safety in the context of the global economy further underscores the importance of developing advanced technologies [2,3] to address challenges in the agricultural sector. There is growing economic pressure on the agricultural industry [4,5] with an increasing prevalence of infections affecting fruits and vegetables. Manual sorting of various types of fruits to assess freshness is time-consuming and prone to errors. Automatic classification approaches, such as the hybrid deep learning model proposed in this research, offer a promising solution to expedite the assessment of fruit and vegetable quality.

Automated fruit categorization and recognition face challenges [6] in effectively detecting diverse varieties of fruits and vegetables. The task is inherently complex due to the range of images characterized by variations in color [7], shape [8], the proximity of the stem, and the flexibility of malformation. In response to these challenges, numerous conventional and convolutional preprocessing methods have been devised to enhance the robustness and accuracy of the recognition process. This technology is integral to self-service fruit or vegetable purchasing in developed country supermarkets, minimizes human errors in production lines, and enhances production efficiency in smart agriculture.

Notably, our research considers the broader societal impact, including addressing the needs of blind and visually impaired (BVI) individuals. To empower BVI individuals in their daily lives, we explore

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the correlation between biochemical transformations in spoiling fruits or vegetables and changes in physical conditions [9] and visual features. Leveraging this knowledge, we aim to facilitate the development of technology that enables BVI individuals to assess the freshness of fruits and vegetables independently.

In this research, we present a groundbreaking approach where we leverage the power of EfficientNetB7 and ResNet50 models to create a robust hybrid model. Through comprehensive experimentation with two distinct datasets, we compared the performance of four initial models — EfficientNetB7, VGG16, ResNet50, and VGG19. The results revealed that the hybrid model, combining EfficientNetB7 and ResNet50, outperformed the others in terms of accuracy and efficiency. Furthermore, we integrate IoT technology with the proposed deep learning model to develop a system for BVI.

Moreover, as a practical implementation of our research findings, we have developed a web application that utilizes the hybrid deep learning model. This application not only classifies fruits and vegetables but also integrates a comprehensive database providing valuable information about the identified produce. Such technological advancements hold the potential to revolutionize the agricultural industry, ensuring the delivery of high-quality fresh produce to consumers while addressing broader societal needs. The research makes several key contributions to the field of fresh fruit and vegetables:

- Proposing and implementing a novel hybrid deep learning model that combines the strengths of EfficientNetB7 and ResNet50 architectures for superior accuracy and efficiency in fresh produce identification.
- Evaluating and comparing the efficiency of four initial models – EfficientNetB7, VGG16, ResNet50, and VGG19 – to establish the superiority of the proposed hybrid model in fresh produce classification.
- Developing an IoT system for blind and visually impaired (BVI) individuals by integrating the proposed deep learning model.
- Implementing the research findings into a practical web application that not only classifies fruits and vegetables but also integrates a comprehensive database providing valuable information about the identified produce, offering a user-friendly interface for diverse stakeholders.

The paper is divided into the following sections: Section 2 discusses the related work on automatic fruits and vegetables classification. The materials and methods are discussed in Section 3. Section 4 provides the experimental setup and results. Finally, Section 5 concludes with future directions.

2. Related works

In this section, we review the existing literature related to fresh fruit and vegetable identification, with a focus on approaches utilizing deep learning techniques and their applicability to agriculture [10–12], blind individuals [13], and the food industry [14–16]. We explore the evolution of research in this domain, highlighting key advancements, challenges, and opportunities for further innovation. Additionally, we discuss relevant studies addressing accessibility issues for visually impaired individuals and advancements in food quality assessment technologies within the industry. Through this comprehensive review, we aim to contextualize our research within the broader landscape of fresh produce identification and underscore its significance in addressing critical needs across diverse user groups.

Traditionally, fresh fruit and vegetable identification relied on manual inspection by human experts, which was time-consuming and prone to errors. Early attempts to automate this process involved simplistic image processing techniques, which often struggled with variations in fruit and vegetable appearance and environmental conditions [17]. However, with the advent of deep learning [18–22], significant progress has been made in developing more robust and accurate identification systems.

Dhiman et al. [23] highlight the importance of detecting citrus fruit diseases for quality fruit production. The study proposes a method involving dataset preprocessing, selective search, and a deep neural network (DNN) model trained with transfer learning using VGGNet. Results demonstrate high accuracy in detecting different severity levels, validating the approach's effectiveness for citrus fruit disease detection. They achieved 97%, and 96% accuracy in detecting healthy and unhealthy fruits, respectively.

The study [24] utilizes a dataset of 26,149 images of 40 different fruits, split into training and test sets. It introduces TL-MobileNetV2, a modified version of MobileNetV2 with a customized head, achieving 99% accuracy and outperforming other models like AlexNet, VGG16, InceptionV3, and ResNet. Transfer learning and dropout techniques are credited for the model's success, reducing overfitting and yielding high precision, recall, and F1-score of 99%.

The research [25] aimed to improve the grading accuracy and marketability of hawthorn fruit by employing deep learning (DL) models. Three categories of hawthorn (unripe, ripe, and overripe) were classified using images captured under controlled illumination. Data augmentation techniques were applied to enhance DL performance. Inception-V3 outperformed other classifiers with a validation accuracy of 100%, highlighting the effectiveness of CNN and image processing techniques in optimizing hawthorn fruit grading and reducing waste.

The paper [26] presents an experimental approach to detect external defects using deep learning, utilizing a large dataset of nearly 44,000 images. Deep residual neural network (ResNet) classifiers were trained, showing that fine-tuning outperformed feature extraction. The best model achieved a 94.6% average precision on the test set, with a recall of 86.6% and a precision of 91.7%. The study attributes the classifier's success to an optimal distribution within the healthy class and highlights the potential of deep learning in defect detection across various food products.

The study [27] presents a novel approach to monitor vegetable freshness using a fluorescent sensor array and deep convolutional neural network (DCNN). By detecting volatile organic compounds (VOCs) emitted during spoilage, the system accurately classifies the freshness of yardlong beans, spinach, and sweet corn in real-time. The ResNet50 DCNN model achieves an impressive overall accuracy of 96.21% for freshness classification, demonstrating the platform's potential for widespread application in food safety and waste reduction efforts.

The research [28] addresses the challenge of differentiating between conventional and organic vegetables, proposing a portable multispectral sensor system as a solution. Traditional spectroscopic methods are costly and time-consuming, prompting the development of a low-cost system utilizing visible, ultraviolet, and near-infrared spectra. This study analyzes tomato, brinjal, and green chili samples using random forest and neural network models, yielding 92% and 89% accuracy rates, respectively. Further improvements through a two-stage mechanism lead to 100% accuracy in distinguishing between organic and conventional vegetables. The findings are accessible through an IoT application module, facilitating easy access to detected adulterants.

The authors of [29] examine different types of rapid food testing methods, including those for quality, nutrition, adulteration, and harmful substances, assessing their performance and practicality. Additionally, it explores the principles and implementation of food traceability systems and their impact on food safety. The study also discusses personalized dietary guidance tailored to specific groups, considering recent developments and prospects for smartphone applications in the food industry.

The study [30] discusses the importance of automatically classifying fruit and vegetable freshness in the food industry due to its impact on consumer health, purchasing decisions, and market prices. It introduces a deep-learning system based on an improved YOLOv4 model for

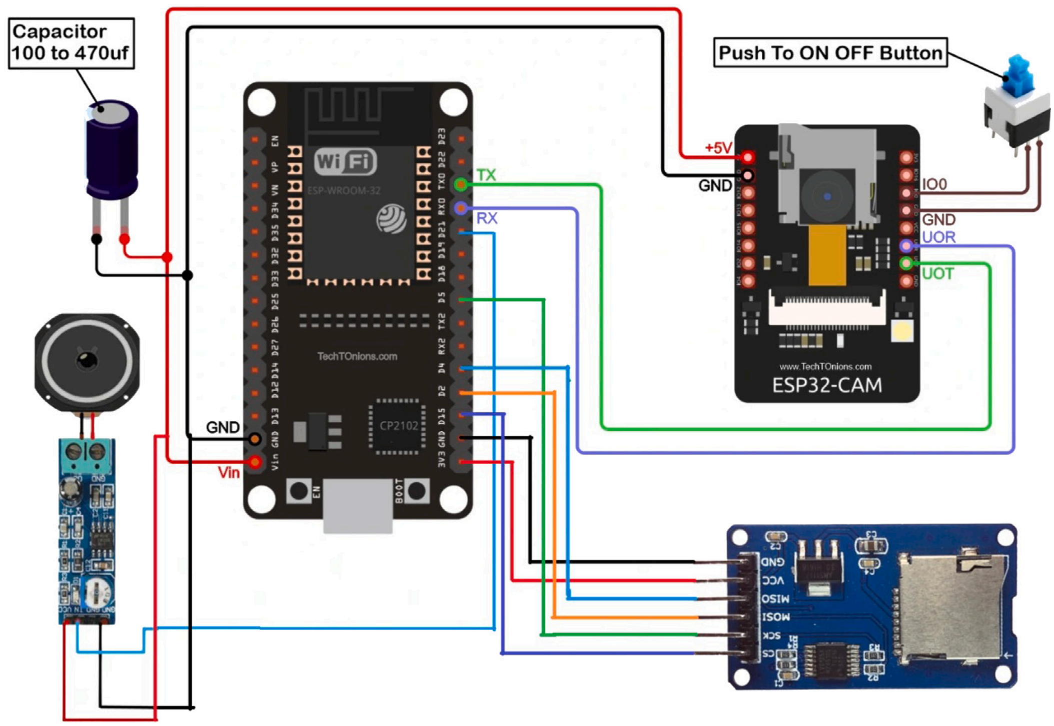

Fig. 1. Circuit Diagram of the Proposed System.

multiclass categorization of fruits and vegetables into fresh or rotten categories. The system involves dataset creation, data augmentation, and performance evaluation, with the model's backbone enhanced using the Mish activation function. Experimental results show superior performance compared to previous YOLO models, suggesting potential for real-time classification systems and aiding visually impaired individuals in food selection.

The literature on fresh fruit and vegetable identification underscores the transformative potential of deep learning approaches in addressing critical needs within the food industry, agriculture, and the blind community [31,32]. By leveraging hybrid deep learning models and innovative technologies like IoT, researchers can continue to advance the field, paving the way for more accurate, efficient, and accessible identification systems.

3. Methods and materials

This section provides an overview of the methods and materials used in the study, covering IoT devices, sensors, data transmission and analysis techniques, machine learning model design and implementation, and the proposed framework. The hardware utilized includes NodeMCU, webcam ESP32, SD Card Module, SD Card, and Speaker.

3.1. IoT devices and sensors

In this investigation, an ESP32 camera (referenced as 3.1.2), an SD card module (referred to as 3.1.3), and a NodeMCU (denoted as 3.1.1) were employed. The circuit diagram is depicted in Fig. 1, while Table 1 details the configurations and specifications of the components within the proposed IoT system.

3.1.1. NodeMCU

NodeMCU, a central component in our research, functions as a fundamental hardware element. This device, built upon the ESP8266 Wi-Fi module, facilitates smooth connectivity and communication among diverse devices within our Internet of Things (IoT) framework. With features such as 11 GPIO (General Purpose Input/Output) pins, analog-to-digital converters, and programmable interfaces, NodeMCU offers versatility for various IoT applications. We harness its capabilities to establish a robust framework, seamlessly integrating NodeMCU with sensors and data transmission modules. This integration enables the efficient wireless collection and transfer of data using the SMQTT protocol. This collaborative setup significantly enhances the overall performance of our hybrid deep learning model, ensuring real-time interaction and precise identification of fresh vegetables and fruits.

3.1.2. Webcam ESP32

The Webcam ESP32, built on the ESP32 platform, plays a crucial role in capturing visual data essential for the identification process. This device facilitates high-quality image acquisition with advanced features and compatibility, ensuring detailed and accurate visual information for our hybrid deep learning model. The ESP32 CAM is essentially an ESP32 variant that lacks a CP2102 chip but is instead equipped with a 2MP OV2640 camera module and an SD Card Reader on the board's underside. Notably, the camera module is switchable, allowing for an upgrade from 2MP to 5MP or higher. This version employs the ESP-32S WIFI module [33], featuring built-in 32Mbit of Flash and 512 KB of internal plus external 4M PSRAM. With 9 IO ports, a default baud rate of 115,200 bps, and a five-volt tolerance, it accommodates external 5 V charger setups, but caution is required as a voltage exceeding 5 V can damage the module. Its integration within our IoT framework facilitates seamless communication and collaboration with other devices, contributing to the real-time data acquisition and analysis required for the precise identification of fresh vegetables and fruits.

3.1.3. SD card module

The SD card module is essential to the storage and management of data. This module, which is integrated into our IoT framework, offers a smooth interface for reading and writing data to SD cards. This makes it easier to save important identification-related data efficiently. The SD

Table 1
Configurations and specifications of the proposed IoT system components.

Components	Specifications
NodeMCU	ESP8266 Wi-Fi module-based development board with open-source firmware. It includes a USB interface, a voltage regulator for reliable power, 11 digital I/O pins, a pin for analog input, and a UART communication interface. Able to run on the Arduino IDE.
Webcam ESP32	Features an OV2640 2MP camera module, a built-in 32 Mbit of Flash, and 512 KB Internal plus external 4M PSRAM. It can be upgraded from 2MP to 5MP or Higher.
SD Card Module	4.5–5.5 V power supply, 3.3 V regulator circuit board. Control Interface: GND, VCC, MISO, MOSI, SCK, CS.

Table 2
The details of the proposed Hybrid Deep Learning Model.

Layer (type)	Output Shape	Parameter	Connected to
input_layer (InputLayer)	(None, 150,150,3)	0	–
efficientnetb7 (Functional)	(None, 5, 5, 2550)	64,097,687	input_layer[0][0]
resnet50 (Functional)	(None, 5, 5, 2048)	23,587,712	input_layer[0][0]
global_average_pooling2d (Global)	(None, 2550)	0	efficientnetb7[0][0]
global_average_pooling2d_2 (Global)	(None, 2048)	0	resnet50[0][0]
concatenate (Concatenate)	(None, 4608)	0	global_average_pooling2d[0][0] global_average_pooling2d_1[0][0]
dropout (Dropout)	(None, 4608)	0	concatenate[0][0]
batch_normalization (BatchNormalization)	(None, 4608)	18,432	dropout[0][0]
dense (Dense)	(None, 256)	1,179,904	batch_normalization[0][0]
dropout_1 (Dropout)	(None, 256)	0	dense[0][0]
dense_1 (Dense)	(None, 20)	5140	dropout_1[0][0]
Total params: 88,888,875 (339.08 MB)			
Trainable params: 88,515,812 (337.66 MB)			
Non-trainable params: 373,063 (1.42 MB)			

card module provides dependable and easily available storage while our hybrid deep learning model processes and analyses images sensed from the camera and device. By adding to the overall robustness of our system, this component helps to identify fresh fruits and vegetables more accurately through real-time data handling and analysis.

3.2. Data transmission using SMQTT protocol

In our proposed system, seamless and efficient data transmission is facilitated through the utilization of the SMQTT (Secure Message Queuing Telemetry Transport) protocol. The process begins with the ESP32 camera capturing an image of the fruit or vegetable, which is then transferred to the cloud server. Subsequently, a pre-trained model deployed on the cloud server undertakes the crucial task of identifying whether the captured produce is fresh or rotten. Once the identification process is complete, the server sends a signal back to the system, specifying the freshness status. The transmission of this vital signal is accomplished using the SMQTT protocol, a secure and lightweight messaging protocol designed for IoT applications. The protocol ensures reliable communication between devices over constrained networks, making it an ideal choice for our system. Upon receiving the signal, the system interprets the information and triggers an appropriate response. In this case, the predefined voice signal, indicating whether the fruit or vegetable is fresh or rotten, is sent to the blind glass through the integrated speaker. This robust data transmission mechanism not only enhances the real-time interaction within the system but also ensures that individuals using the blind glass receive prompt and accurate information about the freshness status of the produce, contributing to a more accessible and inclusive user experience.

3.3. Machine learning methods

This section explains the machine learning algorithms incorporated into the analysis pipeline for image processing and insight generation. In our research, we used EfficientNetB7 and ResNet50 models to propose the hybrid model for fresh fruit and vegetable identification.

3.3.1. EfficientNetB7

EfficientNetB7, a pivotal element in our analysis pipeline, stands out as a cutting-edge convolutional neural network architecture meticulously crafted for optimal model efficiency. Tailored to attain remarkable accuracy with fewer parameters, EfficientNetB7 successfully navigates the delicate balance between computational efficiency and model performance. Derived from concepts initially introduced in MobileNet [34], EfficientNet variants incorporate a variable set of blocks. Notably, EfficientNet introduces the Swish activation function, akin to ReLU and LeakyReLU, harnessing some of their performance advantages. A distinguishing feature lies in EfficientNet's innovative scaling method, generating seven distinct models denoted from B0 to B7. Progressively increasing attributes such as model width, depth, resolution, and complexity from B0 to B7 culminate in heightened accuracy [35]. In our research, EfficientNetB7 plays a pivotal role within the hybrid model, actively contributing to the accurate identification of fresh fruits and vegetables by adeptly extracting intricate features from input images. Its demonstrated superior accuracy, combined with enhanced computational capabilities, underscores its significance in our study.

3.3.2. ResNet50

ResNet50, a cornerstone of our analysis framework, represents a revolutionary convolutional neural network architecture that has significantly impacted the field of deep learning. Introduced by Microsoft Research, ResNet50 is a variant of the ResNet (Residual Network) family, renowned for its ability to overcome the vanishing gradient problem in intense networks. The key innovation lies in the introduction of residual blocks, allowing the direct flow of information through skip connections, thereby mitigating degradation issues encountered in training bottomless models [21]. It is specifically designed for image classification tasks, and its architecture consists of 50 layers, including convolutional, pooling, and fully connected layers. The usage of skip connections enables the training of deep networks with unprecedented depth, contributing to enhanced feature extraction and representation capabilities. In our study, ResNet50 assumes a pivotal role within the hybrid model, leveraging its deep architecture to capture intricate features vital for the accurate identification of fresh fruits and vegetables. Its proven success in various computer vision tasks, combined with its robustness in handling deep neural networks, underscores its significance in contributing to the overall efficacy of our research.

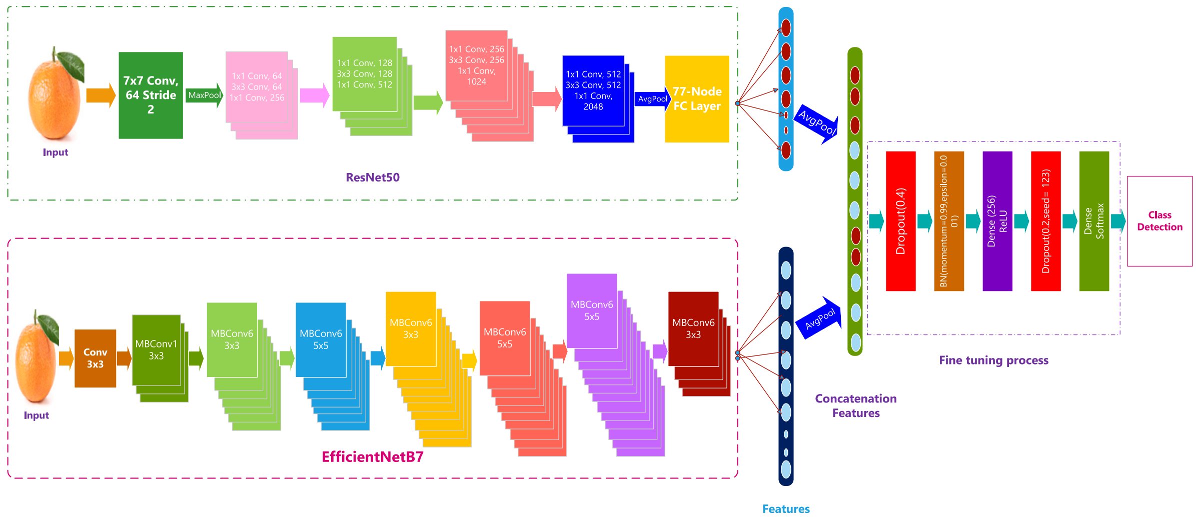

Fig. 2. Proposed Hybrid Deep Learning Model.

3.3.3. Hybrid deep learning model

Our proposed hybrid deep learning model seamlessly integrates the strengths of EfficientNetB7 and ResNet50 architectures, forming a robust and versatile framework for the identification of fresh fruits and vegetables. EfficientNetB7, renowned for its efficiency-optimized design and novel scaling method, collaborates with ResNet50, a revolutionary architecture with skip connections, to create a model that excels in both computational efficiency and deep feature extraction. The integration of these two architectures leverages their respective advantages, resulting in a model capable of accurately classifying produce based on intricate visual features. Both base models are configured with the input image shape and set to exclude the top layer. The outputs of these base models are concatenated along the last axis. Following this, a dropout layer with a rate of 0.4 is applied to mitigate overfitting. Subsequently, a batch normalization layer with momentum of 0.99 and epsilon of 0.001 is employed to enhance model stability. After that, The concatenated outputs are fed into a dense layer with 256 units and a ReLU activation function. Another dropout layer with a rate of 0.2 and a seed of 123 is introduced to further regularize the model. Finally, a dense layer with classes and softmax activation function is applied to obtain the model's predictions. This architecture combines features from both EfficientNetB7 and ResNet50, enhancing the model's capacity to identify fresh and rotten fruits or vegetables in the proposed system.

Fig. 2 illustrates the hybrid model and the utilization of interconnected tiers in a distinct and comprehensive manner, integrating various transfer learning approaches to identify fresh fruits and vegetables classes. The characteristic extraction process involves employing pre-trained models, each utilizing GlobalAveragePooling2D to flatten layers into a vector by calculating the average value for each input channel. Given a 2D input tensor X of shape(batch size, height, width, channels), the GlobalAveragePooling2D operation calculates the average value (1) along the height and width dimensions for each channel:

$$GbAvPool2D(X) = \frac{1}{height * width} \sum_{i=1}^{height} \sum_{j=1}^{width} X[:, i, j, :] \tag{1}$$

This operation essentially computes the average activation for each channel across all spatial locations, resulting in a reduced spatial dimension while retaining the channel information. The output is a tensor of shape(batch size, channels), representing the global average-pooled features for each channel.

These distinct vectors are combined into a single vector through the concatenate layer. Subsequently, five layers fine-tune the combined features for classification, employing ReLu and SoftMax activation functions. Two dropout layers are implemented, with the first discarding a significant portion of samples during training and the subsequent dropout tier retaining fewer samples to address overfitting. This approach significantly expedites the training phase. Additionally, a critical batch normalization layer is incorporated, swiftly normalizing data to accelerate training and mitigate vulnerability during system startup. The density tier, a fully connected layer, processes input data, producing the final result that calculates probabilities based on the expected class length. The SoftMax activation function discerns relevant attributes associated with the predicted class, yielding result values between 0 and 1, determining neuron firing probabilities. The SoftMax activation function (2) and ReLu activation function (3) can be defined:

$$softmax(z)_j = \frac{exp(z_j)}{\sum_{k=1}^{l} exp(x_k)} \tag{2}$$

$$f(x) = max(0, x) \tag{3}$$

The outcomes of combining various deep learning techniques and interconnected layers are presented in Table 2.

3.4. Proposed framework

Our proposed system integrates cutting-edge technologies to enhance accessibility and provide valuable insights. The framework comprises two primary modules: real-time identification with blind glasses integration and web application functionality. In this module, the ESP32 camera embedded in the blind glass captures images of fruits or vegetables. These images are then transmitted to a cloud server, where a pre-trained hybrid deep learning model determines whether the produce is fresh or rotten. Upon identification, the system sends a signal back to the blind glass, triggering the integrated speaker to play a predefined voice message corresponding to the freshness status (e.g., "fresh" or "rotten"). The entire data transmission is executed using the SMQTT protocol, ensuring secure and efficient communication. Simultaneously, our system offers a user-friendly web application that is accessible to users for fruit and vegetable analysis. Users can input images into the web application to check the freshness status, leveraging the same pre-trained hybrid model. Upon identification, the system provides valuable information about the recognized produce, including scientific names and health benefits. This information is stored in a dedicated database server, ensuring a comprehensive repository of insights. This proposed framework not only enhances accessibility for individuals with visual impairments through blind glass integration but also provides a convenient and informative interface via the web application, catering to a broader user base. The synergy between real-time identification, deep learning capabilities, and database integration establishes a comprehensive solution for fresh fruit and vegetable analysis. The proposed framework is illustrated in Fig. 3.

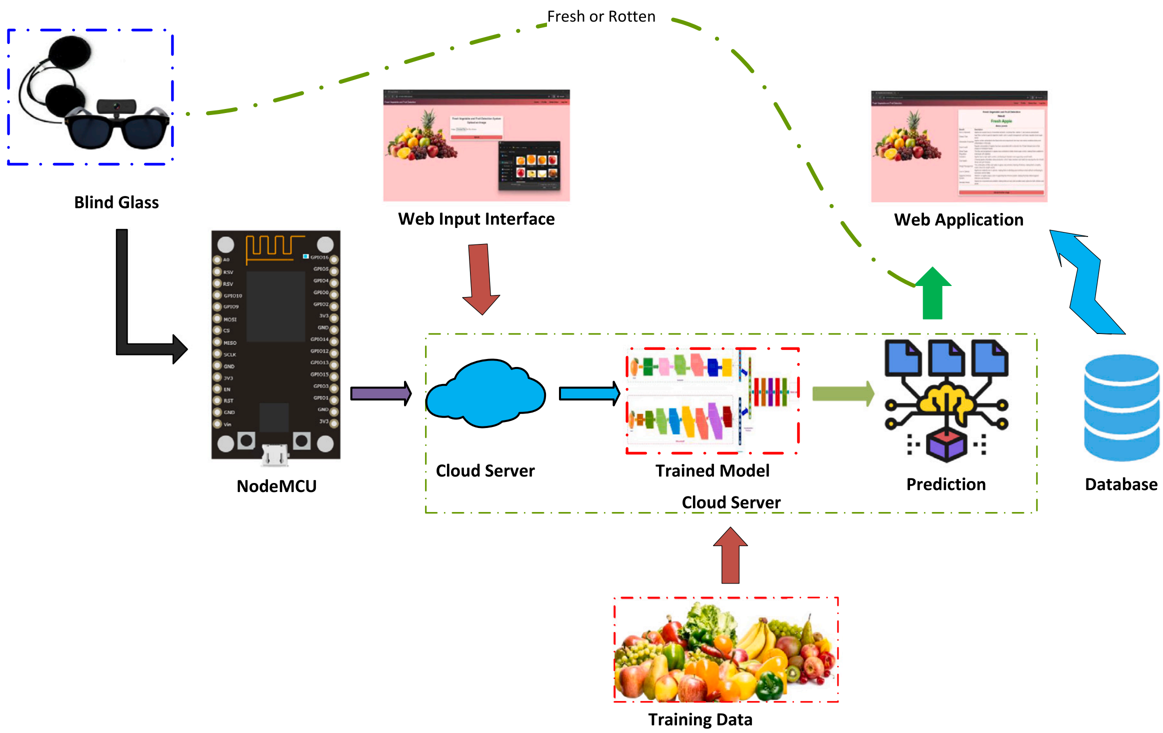

Fig. 3. Proposed Framework of A Hybrid Deep Learning-Enabled IoT System for Fresh Fruit and Vegetable Identification.

4. Experimental results

This section delves into the experimental outcomes, covering data collection and processing techniques. The exploration provides insights into the performance and efficacy of our hybrid deep learning model integrated with IoT technologies for identifying fresh fruits and vegetables. Through meticulous experimentation, we assess real-world applicability and robustness, offering a glimpse into the system's capacity to distinguish freshness statuses accurately. The results showcase the potential impact of our innovative approach on agricultural practices and food quality assessment.

4.1. Experimental setup

Our experiments were conducted using a robust hardware configuration centered around the AMD EPYC 7B12 dual-core processor, operating at a clock speed of up to 2300 MHz, and equipped with 32 GB of RAM. This robust computational infrastructure served as the foundation for our rigorous evaluation of various machine learning techniques. The experimentation and analysis were carried out using the versatile Jupyter Notebook environment. We developed a system to gather diverse image data utilizing an esp32 cam, SD card module, SD card, and NodeMCU. Critical deployment considerations encompass strategic camera placement for capturing images in diverse dimensions, positioning node controllers (NodeMCU) in proximity to sensors, ensuring power supply through batteries, establishing reliable communication networks (LoRaWAN), implementing both local and centralized data storage solutions, crafting user-friendly interfaces, and addressing scalability requirements. After that, the gathered data is transmitted to a remote cloud using the NodeMCU device and the SMQTT protocol.

4.2. Data collection and pre-processing

In this study, our dataset comprised images of fresh and rotten fruits and vegetables, sourced from Kaggle [36,37], with a total distribution of 11,215 training samples, 2403 validation samples, and 2404 test samples across 14 distinct classes. The classes encompass both fresh and rotten variations, including fruits such as apples, oranges, bananas, and vegetables like potatoes, bitter gourds, capsicums, and tomatoes. The potato dataset was collected from [38] and online. A comprehensive pre-processing approach was implemented to augment data quality. Data filtering involved the removal of duplicate images and the exclusion of poor-quality data, characterized by low resolution or diminutive size. Furthermore, all images underwent resizing to a uniform dimension of 150×150 pixels. The pre-processing pipeline aimed to standardize the dataset, ensuring consistency and enhancing the overall quality of input data. Throughout our experiments, a batch size of 64 and a three-channel configuration were employed for training purposes. These pre-processing steps collectively contribute to the reliability and uniformity of the dataset, laying a solid foundation for the subsequent training and evaluation of our hybrid deep learning model for fresh fruit and vegetable identification. Table 3 represents the dataset in detail.

Additionally, we also used another dataset [30] to evaluate the efficiency of our proposed deep learning model. This dataset encompasses a diverse range of items, divided into four categories: fresh fruits (including banana, apple, orange, mango, and strawberry), rotten fruits (featuring corresponding decayed versions), fresh vegetables (comprising potato, cucumber, carrot, tomato, and bell pepper), and rotten vegetables (encompassing their deteriorated states). The dataset is organized into two folders: "Fruits" with 5997 images across 10 classes and "Vegetables" with 6003 images spanning the same 10 classes. This dataset variation broadens the scope of our evaluation, allowing us to assess the proposed model's effectiveness across a wider array of fresh and deteriorated produce, contributing to a more comprehensive understanding of its performance in diverse scenarios. Fig. 4 represents the sample images of the fruit and vegetable dataset1 [36] and dataset2 [30] with multiple objects and various backgrounds.

4.3. Model evaluation metrics

In this section, we systematically assess the performance and efficacy of our proposed hybrid deep learning model for fresh fruit

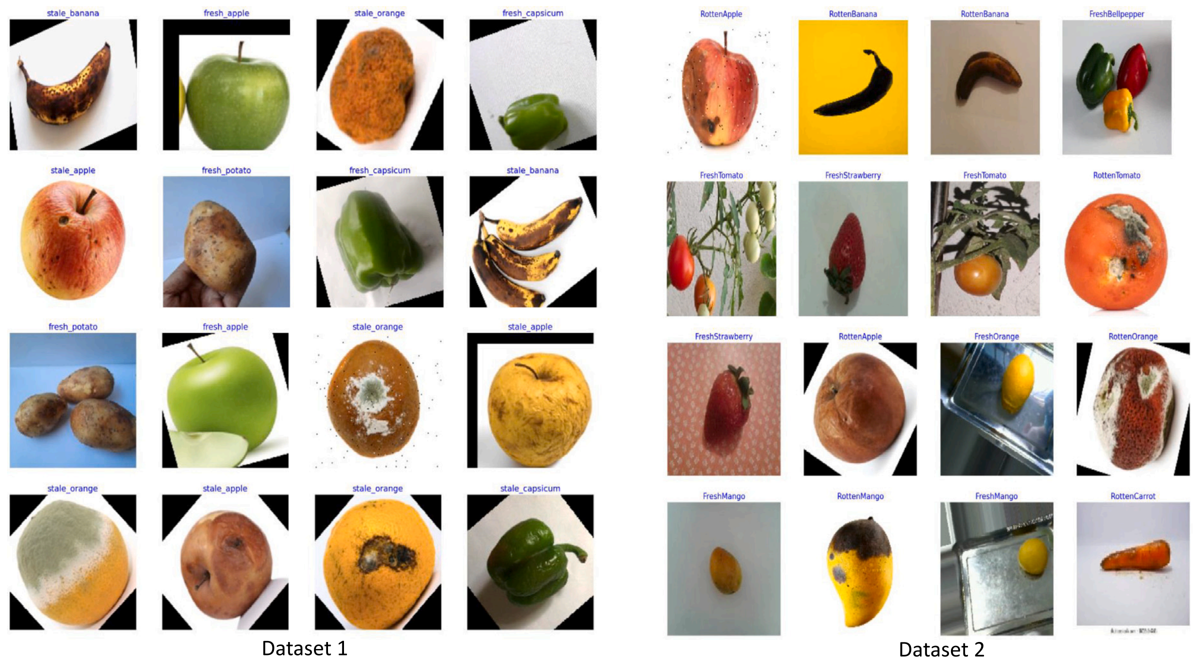

Fig. 4. Images from the fruit and vegetable dataset 1 [36,37] and dataset 2 [30] showcasing multiple objects against diverse backgrounds.

Table 3
Dataset Description.

apple		orange		banana		potato		bitter gourd		capsicum		tomato	
fresh	rotten	fresh	rotten	fresh	rotten	fresh	rotten	fresh	rotten	fresh	rotten	fresh	rotten
1692	2342	1466	1595	1582	1467	975	365	327	357	990	901	991	982

and vegetable identification. The evaluation is conducted through a comprehensive set of matrices designed to gauge the model's accuracy (Eq. (4)), precision (Eq. (5)), recall (6), and F1 score (Eq. (7)). Additionally, the system assessment is evaluated by the average Response time (Eq. (8)). These matrices serve as quantitative benchmarks, providing valuable insights into the model's ability to distinguish between fresh and rotten produce. Through meticulous analysis, we aim to not only validate the model's proficiency but also gain a nuanced understanding of its strengths and potential areas for improvement. The results obtained from these evaluation matrices form a crucial aspect of validating the real-world applicability and reliability of our proposed system, contributing to the advancement of intelligent agricultural technologies.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{4}$$

$$Precision = \frac{(TP)}{(TP + FP)} \tag{5}$$

$$Recall = \frac{(TP)}{(TP + FN)} \tag{6}$$

$$F1 - Score = \frac{(2 * Precision * Recall)}{(Precision + Recall)} \tag{7}$$

$$Average Responsetime = U + I + S \tag{8}$$

where U is the average image Upload Time, I is the average Identification time, and S is the average decision-sending time to the users.

4.4. Results analysis

In this section, we delve into a detailed analysis of the results obtained from the experimental evaluation of our applied models and proposed hybrid deep learning-enabled IoT system for fresh fruit and vegetable identification. The objective is to interpret and scrutinize the outcomes derived from the model's performance across various metrics and scenarios. Through a systematic examination of the results, we aim to uncover insights into the model's efficacy, accuracy, and robustness in distinguishing between fresh and rotten produce. The comprehensive analysis presented in this section provides a deeper understanding of the model's performance using various evaluation metrics, including accuracy, precision, recall, F1-score, confusion matrices, ROC curve, etc.

Fig. 5 illustrates the performance metrics, including accuracy, precision, F1-score, and recall, of several applied models: ResNet50, VGG16, VGG19, EfficientNetB7, and the proposed hybrid model combining EfficientNetB7 and ResNet50. Each model's corresponding metric values are displayed for comparison. Notably, the proposed hybrid model demonstrates exceptional performance across all metrics, achieving remarkably high accuracy, precision, F1-score, and recall of 99.92%. In comparison, other individual models, such as EfficientNetB7 (98.96% of accuracy) and ResNet50 ((98.54% of accuracy), also exhibit commendable performance, albeit slightly lower than the hybrid model. VGG16 and VGG19 also demonstrate strong performance but lower than others.

Fig. 6 presents the confusion matrices of the applied models, offering insights into their performance in accurately classifying fresh and rotten fruits and vegetables. The proposed hybrid model exhibits exceptional performance, misclassifying fresh potatoes only twice while correctly identifying all other images. Conversely, ResNet50 demonstrates errors in classifying several items, including misidentifications of rotten tomatoes, rotten potatoes, stale oranges, rotten capsicums, fresh bananas, and apples. Similarly, EfficientNetB7 shows misclassifications of fresh oranges, apples, bananas, potatoes, capsicums, among others. VGG16 and VGG19 exhibit more widespread errors, incorrectly identifying various types of fruits and vegetables across the board. These findings underscore the superiority of the proposed hybrid model

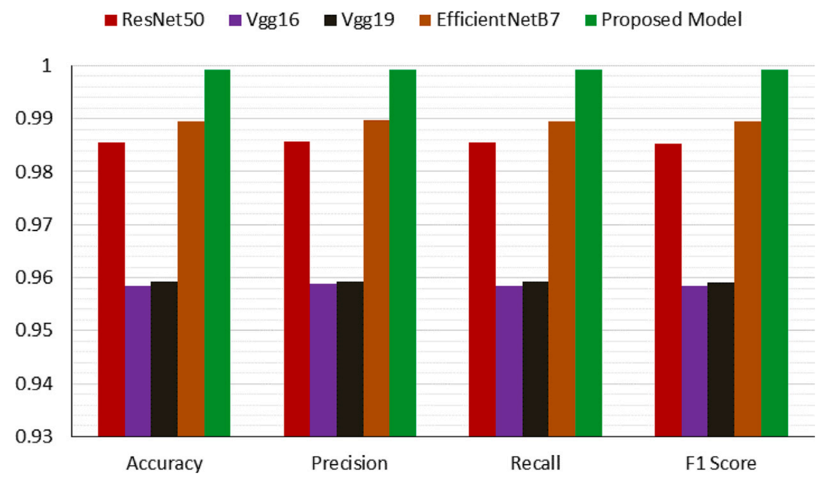

Fig. 5. Comparisons of the applied models' evaluation metrics.

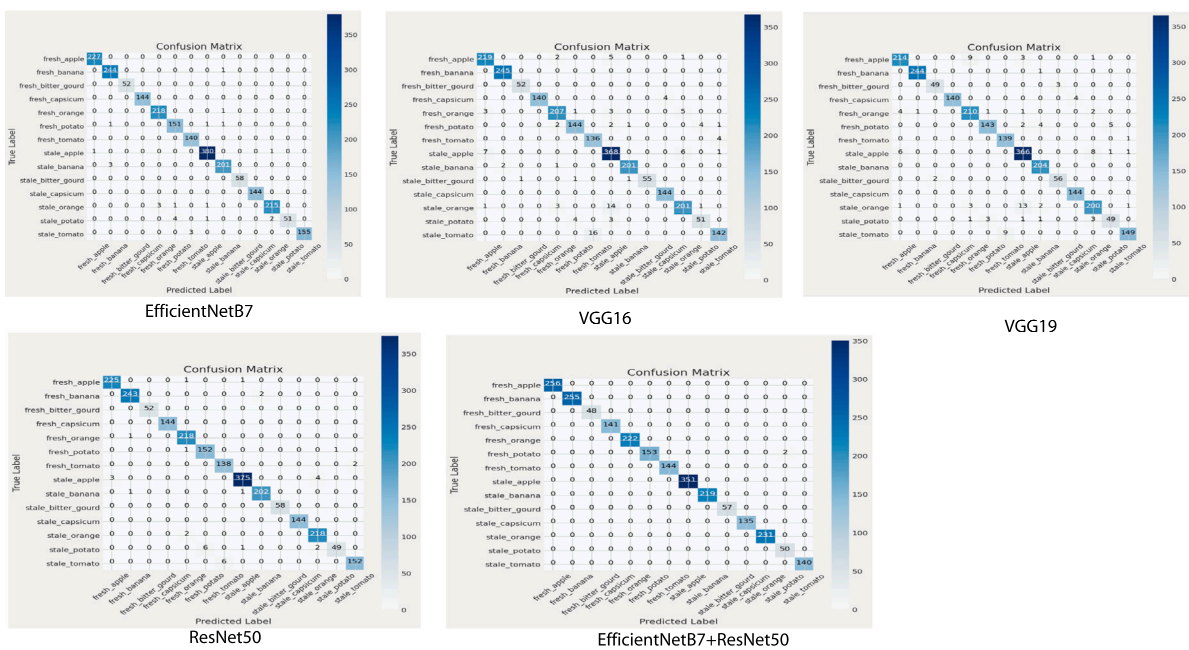

Fig. 6. Confusion Matrix of different models.

in accurately identifying fresh produce, highlighting its potential for improving agricultural practices and food quality assessment.

Additionally, the performance graph depicts the accuracy and loss of the applied models over five epochs presented in Fig. 7. Initially, all models show a rapid increase in accuracy and a decrease in loss, indicating effective learning and model convergence. As training progresses, the accuracy continues to improve steadily while the loss gradually decreases, demonstrating the models' ability to classify better and minimize errors. However, subtle differences emerge between the models: the proposed hybrid model consistently exhibits the highest accuracy and lowest loss, indicating superior performance compared to individual models. Conversely, VGG16, VGG19, and Resnet50 show little bit of fluctuations or plateauing in accuracy and loss, suggesting potential challenges or limitations in training. Overall, the graph provides valuable insights into the learning dynamics and performance trends of the applied models over the course of five epochs.

The Table 4 presents evaluation metrics for the proposed hybrid model using dataset1 [36–38]. It assesses the model's performance in classifying various classes of fruits and vegetables into fresh and stale categories. The evaluation metrics include precision, recall, and

Table 4
Classification Report for the proposed model performance using the dataset [36–38].

Class	precision	recall	f1-score	Support
fresh_apple	1.0000	1.0000	1.0000	256
fresh_banana	1.0000	1.0000	1.0000	255
fresh_bitter_gourd	1.0000	1.0000	1.0000	48
fresh_capsicum	1.0000	1.0000	1.0000	141
fresh_orange	1.0000	1.0000	1.0000	222
fresh_potato	1.0000	0.9871	0.9935	155
fresh_tomato	1.0000	1.0000	1.0000	144
stale_apple	1.0000	1.0000	1.0000	351
stale_banana	1.0000	1.0000	1.0000	219
stale_bitter_gourd	1.0000	1.0000	1.0000	57
stale_capsicum	1.0000	1.0000	1.0000	135
stale_orange	1.0000	1.0000	1.0000	231
stale_potato	0.9615	1.0000	0.9804	50
stale_tomato	1.0000	1.0000	1.0000	140
accuracy			0.9992	2404
macro avg	0.9973	0.9991	0.9981	2404
weighted avg	0.9992	0.9992	0.9992	2404

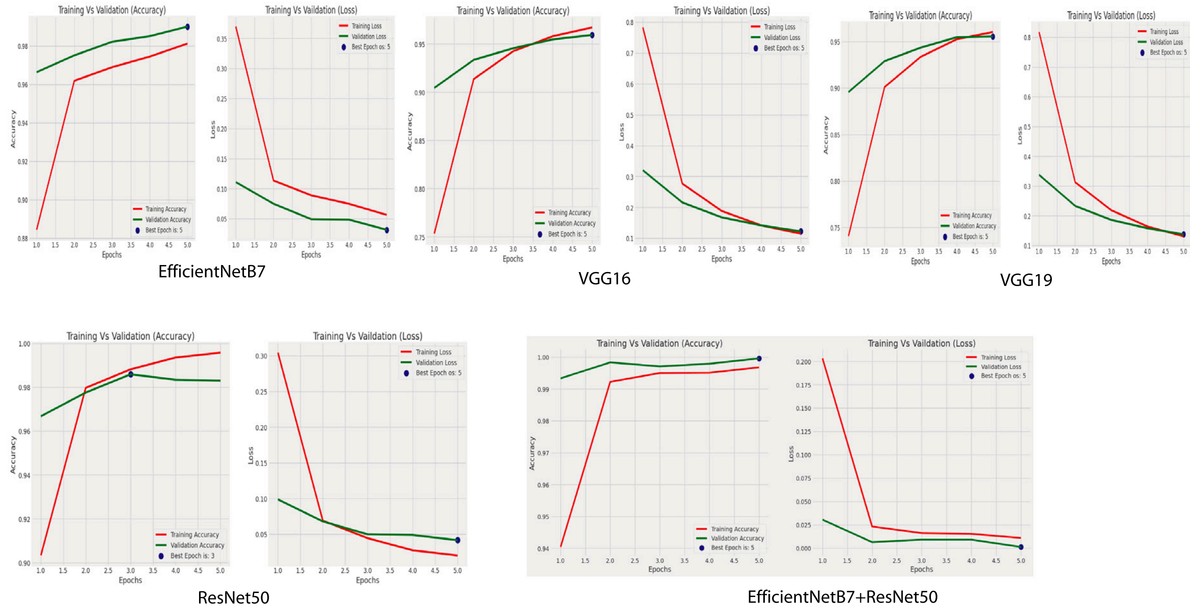

Fig. 7. Performance graph of the applied models in terms of accuracy and loss.

F1-score for each class. For “fresh_apple”, the precision, recall, and F1-score are all 1.0000, indicating perfect classification. Similar perfect scores are achieved for other classes such as “fresh_banana”, ”fresh_orange”, and "stale_orange”. However, for "fresh_potato”, while the precision and F1-score are 1.0000, the recall is slightly lower at 0.9871. In contrast, “stale_potato” has a lower precision of 0.9615, possibly indicating some misclassification. The overall accuracy of the model is reported as 0.9992, indicating high performance across all classes. The macro and weighted averages for precision, recall, and F1-score further validate the model’s effectiveness in classifying fresh and stale produce accurately.

In addition to the primary dataset, we also evaluated the efficiency of our proposed model using an additional dataset [30]. Our model achieved an impressive overall accuracy, precision, recall, and F1-score of 95.94%, underscoring its robustness and effectiveness in identifying fresh fruits and vegetables across diverse datasets. This validation of performance on a separate dataset highlights the generalizability and reliability of our proposed model, demonstrating its capability to deliver accurate results consistently across varied input sources.

Table 5 provides a comprehensive overview of each class’s precision, recall, and F1-score metrics, serving as an indicator of the model’s performance across various fruit and vegetable categories. The results demonstrate the model’s robust performance across most classes, with precision values ranging from 0.88 to 1.00, recall values ranging from 0.81 to 1.00, and F1 scores ranging from 0.85 to 1.00. These scores consistently exceed 0.90, underscoring the model’s effectiveness in accurately identifying fresh and rotten produce. However, the model exhibits comparatively lower performance in classifying specific categories such as Rotten Bell Pepper, rotten carrot, and rotten potato. Notably, the dataset comprises 20 classes of fruits and vegetables, with the table providing insights into the average accuracy (0.9594), weighted average precision (0.9594), recall (0.9594), and F1-score (0.9590) of the model across all classes.

The ROC curve figures in Fig. 8 for dataset1 [37] and dataset2 [30] of our proposed hybrid deep learning model depict the model’s performance in distinguishing between fresh and rotten fruits and vegetables across multiple classes. In dataset1, the ROC curve area is 1.0 for all 14 classes, indicating perfect classification performance. This suggests that the model achieves optimal sensitivity and specificity across all categories, effectively discriminating between fresh and rotten produce without any errors.

Table 5
Classification Report for the proposed model performance using the dataset [30].

Class	precision	recall	f1-score	Support
FreshApple	0.9881	0.9765	0.9822	85
FreshBanana	0.9912	0.9912	0.9912	114
FreshBellpepper	0.9036	0.9259	0.9146	81
FreshCarrot	0.9444	0.9808	0.9623	104
FreshCucumber	0.9608	0.9899	0.9751	99
FreshMango	0.9804	0.9804	0.9804	102
FreshOrange	0.9778	0.9888	0.9832	89
FreshPotato	0.9759	0.9759	0.9759	83
FreshStrawberry	1.0000	0.9773	0.9885	88
FreshTomato	0.9551	0.9884	0.9714	86
RottenApple	0.9195	0.9639	0.9412	83
RottenBanana	1.0000	1.0000	1.0000	88
RottenBellpepper	0.9125	0.8111	0.8588	90
RottenCarrot	0.9286	0.8553	0.8904	76
RottenCucumber	0.9571	0.9178	0.9371	73
RottenMango	0.9798	0.9700	0.9749	100
RottenOrange	0.9802	0.9706	0.9754	102
RottenPotato	0.8861	0.9091	0.8974	77
RottenStrawberry	0.9432	1.0000	0.9708	83
RottenTomato	0.9684	0.9684	0.9684	95
accuracy			0.9594’	1798
macro avg	0.9576	0.9571	0.9570	1798
weighted avg	0.9594	0.9594	0.9590	1798

Conversely, for dataset2, the ROC curve areas vary across different classes. Notably, fresh apple (class 1), fresh cucumber (class 5), fresh banana (class 2), fresh orange (class 7), fresh mango (class 6), and rotten banana (class 12) exhibit high ROC curve areas of 0.98, 0.97, 0.96, 0.95, 1.00, and 0.94, respectively. These values indicate excellent classification performance for these specific classes. The ROC curve areas for the remaining classes fall between 0.96 and 0.97, suggesting strong discrimination capabilities across most of the categories.

Overall, the ROC curve figures illustrate the model’s ability to accurately classify fresh and rotten fruits and vegetables across different datasets. The high ROC curve areas signify the model’s effectiveness in distinguishing between various produce items, highlighting its potential for reliable agricultural practices and food quality assessment.

Table 6 presents a comparative performance analysis of various Deep Learning approaches utilized in recent literature for identifying

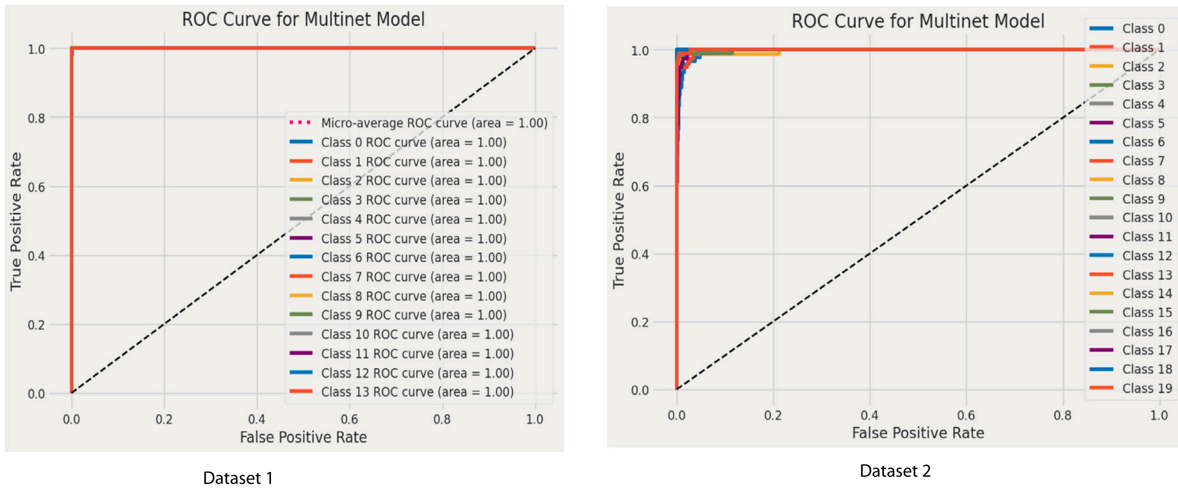

Fig. 8. ROC curves of the proposed deep learning model learned using [30,37] dataset.

Table 6
A comparative performance analysis of Deep Learning approaches used in the recent literature to identify fresh fruit and vegetable.

Ref	Year	Dataset	Sensors used	Methodology	Performance
[39]	2023	Kaggle dataset	No	DCCN+AlexNet	Accuracy: 99.8%
[40]	2024	Kaggle dataset	No	GoogLeNet, DenseNet-201 and ResNeXt-101	Accuracy: 96.98%
[41]	2023	Kaggle dataset	No	CNN,MobileNetV2	Accuracy: 99.69%
[13]	2022	Own data	Yes	CNN, VGG	Accuracy: 95%(CNN), 82%(VGG)
[42]	2021	OpenCV, Kaggle	No	Deep learning approach	Accuracy: 97.5%
[20]	2023	Kaggle	No	LSTM	Accuracy: 85%
[22]	2023	Fruits-360	No	DenseNet-201	Accuracy: 99.87%
[25]	2023	Own dataset	No	Inception-V3	Accuracy: 100%
[27]	2024	Own dataset	Yes	ResNet50	Accuracy: 96.21%
[30]	2022	Kaggle dataset	Yes	YOLOv4	Accuracy: 73.5% (fruit)and 72.6%(vegetable)
Proposed Model	2024	Kaggle+Online collected dataset	Yes	EfficientNetB7+ResNet50	Accuracy: 99.92%, 95.93%

fresh fruits and vegetables. Notably, [25] achieved an impressive accuracy of 100%, albeit with a relatively small dataset size of only 600 images. In contrast, the proposed model demonstrates superior efficiency, which integrates a hybrid approach using EfficientNetB7+ResNet50 and incorporates a web application platform and IoT technology. It achieved significantly higher accuracies for both datasets, surpassing all other models listed in the table. It achieved an accuracy of 99.92% for dataset1 and 95.93% for dataset2, showcasing its robust performance in accurately identifying fresh fruit and vegetables. Moreover, the integration of a web application platform and IoT technology enhances accessibility and usability, making it a more comprehensive and practical solution for real-world applications. Overall, the proposed model stands out as the most efficient solution, offering superior accuracy and usability compared to existing models in the literature.

Through meticulous experimentation and analysis, we demonstrated the model's superior accuracy and efficacy in accurately distinguishing between fresh and rotten produce across diverse datasets. The evaluation metrics, including accuracy, precision, recall, and F1-score, highlighted the robustness and reliability of our model, showcasing its potential for practical applications in agricultural practices and food quality assessment. Furthermore, the examination of confusion matrices and ROC curve areas provided valuable insights into the model's classification capabilities across different classes, reaffirming its effectiveness in real-world scenarios. Overall, these results validate the effectiveness of the implemented ML-IoT-enabled system for individuals with visual impairments and underscore the potential of the proposed model in aiding decision-making processes within the food industry and smart agriculture.

4.5. IoT-ML enabled fresh food detection platform

Our innovative IoT-ML Enabled Fresh Food Detection Platform represents a cutting-edge solution catering to a diverse range of users, including industry stakeholders, individuals, and those with visual impairments. This multifaceted system combines a web application interface with IoT technology, empowering users to accurately identify the freshness of fruits and vegetables in real-time.

Pictures from the web application shown in Fig. 9 are processed through an efficient pipeline. Users upload an image, which is sent to the back-end for pre-processing, including resizing, normalization, and, if necessary, augmentation. The pre-processed image is then passed through the hybrid deep learning model (EfficientNetB7 and ResNet50) for feature extraction and classification into categories such as fresh or rotten. These processes will be performed on the server. The model's output is interpreted, and the results, along with confidence scores, are displayed on the web application. The system integrates front-end and back-end components via APIs, enabling seamless image processing, result delivery, and optional logging for future reference, ensuring a robust and user-friendly platform.

Our platform offers a streamlined solution for quality control and assurance for industry players in the agricultural and food sectors. By leveraging deep learning algorithms and IoT sensors, businesses can efficiently assess the freshness of their produce, ensuring adherence to quality standards and minimizing waste. The platform's robust performance and scalability make it an invaluable tool for optimizing production processes and enhancing overall efficiency.

Individual consumers can also benefit from our platform's capabilities through its user-friendly web application interface. Whether shopping for groceries or selecting fresh produce for personal consumption, users can rely on the system to provide accurate assessments of fruit and vegetable freshness. This empowers individuals to make informed decisions as well as the benefits of that vegetable or fruit when purchasing the items, ultimately leading to improved satisfaction and quality of life. A notable feature of our system is its accessibility for individuals with visual impairments. Through the integration of IoT

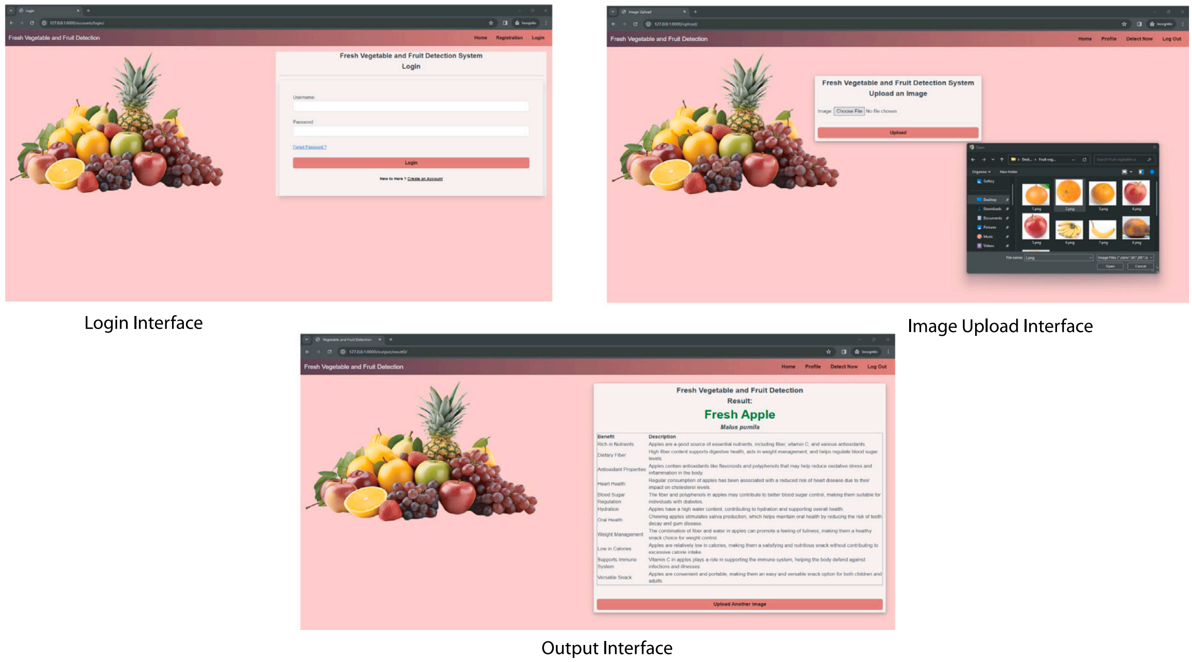

Fig. 9. Fresh fruit and vegetable identification platform hosted in the server.

sensors and audio feedback mechanisms, the system enables blind and visually impaired users to assess the freshness of fruits and vegetables independently. Our platform promotes inclusivity and autonomy by providing auditory cues and real-time information, empowering individuals with disabilities to participate more fully in daily activities such as grocery shopping. Furthermore, we conducted additional testing of our developed system using a private dataset to assess its robustness and generalizability. The system demonstrated an impressive accuracy of 97.5%, showcasing its reliability in diverse scenarios. In addition to its high accuracy, the system achieved an average response time of 1.201 s, highlighting its efficiency in processing and decision-making. These results emphasize the model's capability to handle real-world data effectively and its potential for deployment in time-sensitive applications, ensuring both precision and speed in practical environments.

Our platform represents a versatile and inclusive solution for fresh food identification. By harnessing the power of machine learning and IoT technology, we aim to revolutionize the way fruits and vegetables are assessed for freshness, catering to the needs of both industry stakeholders and individual consumers. Additionally, our commitment to accessibility ensures that all users, including those with visual impairments, can benefit from the platform's capabilities, thereby fostering greater independence and inclusion in daily life.

5. Discussion and future research

In this section, we delve into the implications of our findings, discuss the limitations of our study, and propose avenues for future research in the field of fresh fruit and vegetable identification using IoT and machine learning technologies.

Our research demonstrates the effectiveness of the proposed system in accurately identifying fresh fruits and vegetables and catering to diverse user needs, including industry stakeholders, individual consumers, and individuals with visual impairments. The platform's high accuracy, real-time assessments, and accessibility features hold significant implications for enhancing food quality assessment, optimizing production processes, and promoting inclusivity in food selection. Our proposed hybrid model shows better results as it often outperforms standalone pre-trained models because it leverages the strengths of multiple architectures to address specific limitations of individual models and optimally balances computational efficiency and prediction accuracy.

Despite the promising results, our study is not without limitations. One limitation is the reliance on limited datasets, which may not fully capture the variability and complexity of real-world scenarios. Additionally, the performance of the proposed platform may vary in different environmental conditions or with varying qualities of input images. Moreover, while efforts were made to enhance accessibility for individuals with visual impairments, further usability and interface design improvements may be necessary to meet their needs fully. Several future research avenues can be explored to address these limitations and further advance the field. Firstly, expanding the dataset size and diversity can improve the robustness and generalizability of the model. Additionally, exploring novel sensor technologies and data fusion techniques can enhance the accuracy and reliability of freshness assessments. Furthermore, integrating user feedback and iterative testing can help refine the platform's accessibility features, ensuring a seamless experience for individuals with visual impairments. Moreover, investigating the integration of blockchain technology for traceability and authentication purposes could enhance transparency and trust in the food supply chain.

In conclusion, our study opens up exciting possibilities for future research in the domain of fresh fruit and vegetable identification using IoT and machine learning. By addressing the identified limitations and exploring new avenues, researchers can continue to innovate and develop solutions that positively impact food quality assessment and accessibility for all individuals.

6. Conclusion

Our study presents a novel approach to fresh fruit and vegetable identification leveraging IoT technology and a hybrid deep learning model. By utilizing an ESP32 webcam for image capture and the SMQTT protocol for data transmission to the cloud, we established a seamless framework for real-time assessment of produce freshness. Our hybrid model, integrating EfficientNetB7 and ResNet50 architectures, demonstrated remarkable accuracy, achieving 99.92% and 95.93% accuracy rates for dataset1 and dataset2, respectively.

These findings underscore the potential of our IoT-DL-enabled system to revolutionize food quality assessment processes, benefiting both industry stakeholders and individual consumers. The high accuracy rates and low latency, 1.201 s, of our model highlight its effectiveness in accurately distinguishing between fresh and rotten produce, facilitating informed decision making and improving food safety standards.

Nevertheless, further research can explore avenues for enhancing the scalability and robustness of the proposed system, such as integrating additional sensors for environmental monitoring and expanding the dataset to encompass a broader range of produce varieties. Additionally, efforts to optimize the platform's accessibility features for individuals with visual impairments can contribute to fostering inclusivity and empowering diverse user groups in food selection and quality assessment tasks.

In summary, our study contributes to the advancement of fresh fruit and vegetable identification technologies, offering a promising solution for addressing food quality and safety challenges in the agricultural industry and beyond. As we continue to innovate and refine our approach, we anticipate broader applications and impactful outcomes in ensuring the availability of high-quality fresh produce for consumers worldwide.

Code availability

The code supporting the findings of this study is available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Khondokar Oliullah: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Md. Reazul Islam:** Visualization, Validation, Software. **Jahirul Islam Babar:** Writing – review & editing, Visualization, Formal analysis. **M.A. Nur Quraishi:** Writing – original draft, Visualization, Formal analysis. **Md. Mahbubur Rahman:** Writing – review & editing, Validation, Software, Methodology. **Md. Mahbub-Or-Rashid:** Writing – review & editing, Supervision, Formal analysis. **T.M. Amir-Ul-Haque Bhuiyan:** Writing – review & editing, Supervision, Software, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The datasets used during the current study are publicly available here:

1. https://10.17632/5m38z6jthb.1
2. https://www.kaggle.com/datasets/raghavrpotdar/fresh-and-stale-images-of-fruits-and-vegetables
3. https://www.kaggle.com/datasets/swoyam2609/fresh-and-stale-classification.

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