



Smart Agriculture: AI-based System for Classification of Fresh, Rotten, and Formalin Fruits

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Abstract: Ensuring the freshness and safety of fruits and vegetables is critical for protecting public health, minimizing food waste, and enhancing supply chain efficiency. Traditionally, the assessment of produce quality relies on manual visual inspection, which is time-consuming, labor-intensive, and prone to errors. Recent advances in artificial intelligence have opened opportunities for automating this process, offering faster, more accurate, and scalable solutions. In this work, we propose a lightweight Convolutional Neural Network (CNN) model designed to classify fruits into three categories based on freshness: fresh, rotten, and formalin-treated. The model architecture integrates four convolutional layers with regularization techniques, enabling efficient feature extraction while maintaining low computational cost. We conducted experiments on the peer-reviewed Fruit Vision dataset, consisting of 10,154 images across 15 fruit classes. The proposed CNN achieved a test accuracy of 92.19%, with training and validation accuracies of 94.10% and 92.84%, respectively, and an F1-score of 0.93, outperforming several pretrained baseline models such as VGG16, InceptionV3, and MobileNetV2. These results demonstrate the feasibility of applying deep learning for automated fruit quality inspection. Our approach offers a reliable and efficient framework that can contribute to enhanced food safety, reduced waste, and more intelligent supply chain management.

Keywords: Fruit Freshness Detection; CNN; Image Classification; Deep Learning; Smart Agriculture; Food Safety; Formalin Detection.

I. INTRODUCTION

Agriculture is critical to maintaining global food consumption and economic growth, with fruits acting as one of the most important sources of food and income. The quality and freshness of fruits and vegetables are essential factors for consumers' health [1], economy, and sustainable food systems [2]. However, crop losses due to fruit rotting remain a significant issue, particularly in developing nations with limited storage and transportation facilities. Rotten fruits not only lower market value, but they also affect customer trust and food safety. In a traditional setting, the assessment of fruit quality depends on manual labour that is generally difficult, inefficient, and not suited for large-scale. As a result, integrating automated categorisation systems with modern technology has become increasingly crucial to boost agricultural output, ensure quality control, and reduce food waste.

In response to the global shift towards smart agriculture and digital supply chains [3], there is a growing demand for reliable automated fruit inspection systems. According to Forbes

(2020), food loss and waste are significant global issues, with reports estimating that over a third of all food produced—roughly 1.3 billion metric tons every year—is either wasted or lost. Among food types, fruits and vegetables are wasted the most, especially in developing countries, where losses can reach 60%. Inefficiencies exist across the supply chain due to bad harvesting techniques, lack of refrigerated storage, inadequate transport, and poor packaging. In many low-income countries, perishables are transported via poorly refrigerated trucks, only to be mistreated before reaching the market, increasing the likelihood of spoilage [4]. Consequently, the food loss represents a lost opportunity to sell or consume the food, especially for smallholder farmers, as well as a loss of nutrients for food insecurity, nutrition, and the environment. In South and Southeast Asia, almost half of fruits and vegetables are discarded or lost before retailing at the grocery store, and in Sub-Saharan Africa, postharvest losses can exceed 35% for crops such as tomatoes or mangoes [5]. Furthermore, wasteful activities result in environmental harm as wasted food emits unnecessary greenhouse gases and wastes resources. Solving these inefficiencies through technological

advances and changing supply chain practices and procedures requires automated quality assessment to help reduce loss of fruits and vegetables. Recent advancements in deep learning [6], and specifically Convolutional Neural Networks (CNN), have dramatically improved the performance of image-based classification challenges in many domains, including agriculture. CNNs can learn visual features [7] from raw images and reduce or eliminate the reliance on feature engineering by humans. Earlier investigations have indicated that CNNs have the potential to detect fruit ripeness and identify fruit diseases or spoilage; however, limited work has focused on simultaneously detecting formalin contamination alongside freshness and rotten categorisation [8]. Formalin is a chemical preservative used to extend shelf life of fruits. Formalin is detectable through visuals such as the fruit surface texture changes or color alterations, using computer vision. The main aim of this study is to develop and evaluate a classification model based on CNNs that can categorize fruits across multiple food categories including apples, bananas, mangoes, grapes, and oranges as fresh, rotten, and formalin mixture [9]. We aimed to establish the reliability of using a lightweight CNN model in a real-world quality inspection context. The work adds to the expanding literature of AI-driven solutions for agriculture and uses a new dataset containing chemically treated products for improved generalization.

The main contributions of this paper are:

1. Explored a peer-reviewed dataset consisting of 15 fruit classes categorized by freshness (fresh, rotten, and formalinized) and applied extensive data augmentation techniques to enhance robustness.
2. Proposed a CNN model with four convolutional layers and regularization strategies, designed to effectively capture freshness-related features from a large-scale dataset, achieving the highest classification accuracy with strong generalization across metrics.
3. Benchmarked performance against pre-trained baseline models, including MobileNetV2, InceptionV3, and VGG16, demonstrating superior accuracy and efficiency of the proposed architecture.

The remaining sections of this paper are structured as follows: Section II provides the literature review, Section III offers details on the methodology, Section IV discusses the experimental results, and Section V concludes with implications and future work.

II. LITERATURE REVIEW

Preserving the quality and freshness of fruits and vegetables is an essential issue within agriculture, food supply chain, and the health of people. As demand for precise and faster food inspection increases, researchers and developers are applying artificial intelligence and computer vision to simplify the automation of spoilage or contamination detection. Some researchers have begun exploring dilution rates of deep learning, specifically Convolutional Neural Networks, to assess the freshness of fruits and vegetables by analysing pictures. Considerable progress has been made in the last few years through deep learning focused on fruit

quality detection. This section synthesizes current research on fruit quality detection with deep and transfer learning techniques. It is essential to assess the quality of fruits for supply chain efficiency. We can achieve that with classification and quality assessment for a variety of fruits, using Convolutional Neural Networks. [3].

YOLO and VGG16 [10] have been used to detect fruit freshness and quality control. A CNN-based model [11] The CNN-Ensemble model was developed to detect damaged fruits and achieved high accuracy. Pretrained models [12] CNN, MobileNet, Inception, Xception, DenseNet121, ResNet, EfficientNet, RegNetx, NASNetLarge were used to detect spoiled fruits to minimize health issues caused by rotten fruits. Where ResNet achieved 99.30% accuracy, CNN achieved 98.35%. For evaluating the fruit quality with the help of its shape and colour, UNet and En-UNet models [13] were developed, achieving 99% accuracy. A combination of the GLCM feature extraction with CNN [14] was used to detect fruit quality. Researchers used a Kaggle dataset consisting of images of apples, bananas, and oranges and achieved nearly 85% accuracy. It is also possible to assess the fruit quality using Transfer Learning techniques. CNN, ResNet50, VGG16 and InceptionV3 also used to automate [15] fruit quality detection. Transfer learning [16] has been widely explored for detecting the freshness of apple fruit. Researchers used ResNet, GoogleNet, AlexNet, VGG, MobileNetV2 and InceptionV3. Reaching the high accuracy of 98% on the original dataset and 97% on the augmented dataset of fresh, semi-fresh, and rotten apple images.

To identify fruit quality across different conditions, a deep CNN [17] used for accurate fruit classification and quality estimation across varied conditions using apples, bananas, and oranges, an image dataset of fresh and rotten fruit. VGG16 and YOLOv5 [18] achieved 94.58% test accuracy with VGG16. It classifies freshness into three classes: fresh, medium, and rotten for waste reduction. To increase the fruit detection efficiency across long supply chains [19] ResNet50 and MobileNetV2 trained on FruitNet and FreshandRotten datasets. MobileNetV2 had 96.99% accuracy and 97.01% F1-Score. For enhanced fruit quality detection [20], ResNet50 and Gaussian filtering were used. These models outperformed prior methods. Multi-task deep learning [21] used to detect fruit freshness and classify fruit type. To extract deep features and temporal relationships for enhanced detection [22] CNN and BiLSTM combination was used. For maintaining quality in the supply chain using sensor-integrated deep learning [23] used GhostNet, MobileNetV2, ShuffleNet, Xception. They used a dataset of Okra, green vegetables, cucumbers, plums, and jujubes. MobileNetV2 achieved the best results of 96.06%, 91.12%, and 93.86% for three freshness levels. CNN have also been applicable in automated classification [24] of sound and rotten cranberries.

To maintain fruit and vegetable quality across supply chains [25], CNN has been used on a varied dataset of Apple, Orange, Banana, Grape and Bitter Gourd. For reducing the household food waste by using Deep Learning for fruits and vegetables spoilage detection, researchers applied MobileNetV2, VGG19 and EfficientNetV2S [26] pretrained models on Kaggle 'Fresh and Rotten' dataset, and EfficientNetV2S achieved 97.61% accuracy and 97.59% F1-Score. This review shows that CNN is being widely used in

fruit supply chains for quality assessment. Additionally, it can help reduce waste within households. And most importantly, prevent the diseases caused by rotten fruit and vegetables.

III. RESEARCH METHODOLOGY

This section presents a thorough account of the methodology used in the study, describing the design and operation of the entire fruit classification system. The system is divided into six main steps: dataset collection, model specification, data preprocessing, model training, model validation, and testing and assessment. Each step was designed to provide correct, reliable, and generalizable classification results.

In addressing the problem of detecting fruit freshness, a deep-learning-based approach was chosen because it can effectively learn and extract hierarchical features from image data. A specifically designed Convolutional Neural Network architecture was created for this purpose. CNNs are optimized for image classification problems, which often require distinguishing subtle, visual differences like color loss, texture decay, or chemical effects, such as formalin treatment. The proposed architecture consisted of four convolutional layers, followed by dense layers with dropout for regularization, to facilitate the extraction of

discriminative spatial features from input images. The model was trained, validated, and evaluated against an extensive and well-organized image dataset, represented by 15 classes. The classes are structured based on fruit types: apple, banana, mango, grape, orange and each kind is associated with a quality condition: fresh, rotten, or formalin. The image dataset consisted of 10,154 images, partitioned into training (70%), validation (15%), and test (15%) sets to facilitate unbiased performance evaluation. Before train the model, the images were resized, normalized, and augmented. Augmentation included transformations such as rotation, shifting, and flipping to increase dataset diversity and reduce overfitting. The training process involved multiple iterations of optimization processes using a categorical cross-entropy loss and the Adam optimizer. Throughout the training process, the training and validation tasks were intersected to assess how the model generalized with respect to the validation data. Following the training process and validation assessment, the model was evaluated using the test data.

Figure 1 shows the methodology from raw data acquisition to the final evaluation. Each component and the relationships between the elements of the proposed framework are included.

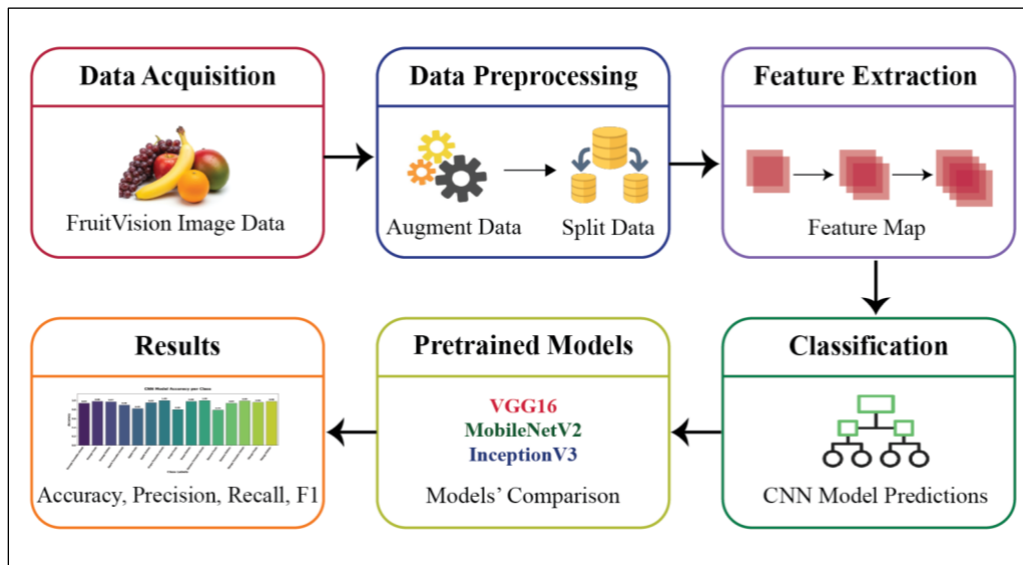


Figure 1. Proposed methodology for the classification and detection of three categories of fruits

A. Data Acquisition and Preprocessing

The dataset used in this experiment is a peer-reviewed benchmark dataset called FruitVision [27]. That has been made publicly available for free on Mendeley Data, both augmented and original. For this study, we used the original dataset without data augmentations to ensure the model's performance is based on image variability from real-world data, rather than artificially developed transformations. The dataset comprises 10,154 labelled images, well-distributed across the training, validation, and testing portions, with 70% allocated for training, 15% for validation, and 15% for testing. This allocation enables a well-balanced and rigorous model-

building process. These images are organized in 15 classes, formed by five fruit types: apple, banana, orange, mango, and grape; the fruit is also classified based on quality conditions that are fresh, rotten, and formalin; as given in Table I. Data was collected from real environmental conditions in Sylhet, Bangladesh. A sample of the data is shown in Figure 2 to illustrate the variety of fruit types and fresh conditions used in this study.



Figure 2. Fresh, Rotten and Formalin Fruit Samples from FruitVision Dataset.

TABLE I. FRUITVISION DATASET DESCRIPTION

Class Labels	FruitVision Dataset Description			
	Actual Images	Training Samples	Validation Samples	Testing Samples
Orange Formalin-mixed	647	453	97	97
Orange Fresh	753	527	113	113
Orange Rotten	656	459	98	98
Apple Formalin-mixed	643	450	96	96
Apple Fresh	765	536	115	115
Apple Rotten	630	441	95	95
Grape Formalin-mixed	610	427	92	92
Grape Fresh	770	539	116	116
Grape Rotten	630	441	95	95
Banana Formalin-mixed	660	462	99	99
Banana Fresh	749	524	112	112
Banana Rotten	632	442	95	95
Mango Formalin-mixed	616	431	92	92

Class Labels	FruitVision Dataset Description			
	Actual Images	Training Samples	Validation Samples	Testing Samples
Mango Fresh	763	534	115	115
Mango Rotten	630	441	95	95
Total Images	10,154	7,267	1,531	1,531

B. Feature Extraction and Classification

As our task is to classify fruits based on their freshness level. It is a multiclass image classification task. We used Convolutional Neural Network for classifying the images. CNN is best suited architecture for this purpose. It can learn the complex features of fruits from the images; like shape, texture and color. No manual feature extraction is required. Also, the literature review showed an excellent performance of CNNs in fruit quality detection and classification problems. The training and evaluation part includes data pre-processing, model architecture building, model training, validation, testing and evaluation [28].

To set up the dataset for training, the images were read from their respective class folders, converted from BGR to RGB format, resized to a standard shape of 128×128 pixels, and normalised to have pixel values in the range of 0 to 1. As these are closeup images quality loss is minimal with resizing. Each image had been labelled by fruit type and freshness condition for a single class. All classes of images were valid image types of JPG, PNG, JPEG. The prepared images were stored in lists with their class labels for convenience in loading for model training. Data augmentation was performed on the training images with random rotations, shifts, shearing, zooms, and horizontal flips at the training time using ImageDataGenerator in Keras (TensorFlow). Data augmentation can improve generalization and decrease model overfitting or underfitting chances during model training.

Model Architecture: The proposed Convolutional Neural Network was developed using sequential architecture. The model contained four convolutional layers, with filter sizes of 32, 64, 128 and 256, and was following by the max-pooling layer, added to decrease the spatial dimensions. The convolutional layers all use 3×3 kernels/filters with ReLU activation functions and the same padding. Once the features were extracted, we flattened the output, and followed with the dense layer of 512 units and the dropout layer of 0.5 to prevent overfitting. Our output layer used softmax to classify the input to the labelled classes. The model used an Adam optimizer and a categorical cross-entropy loss function, since this was a multi-class classification problem. Architecture is shown in Figure 3.

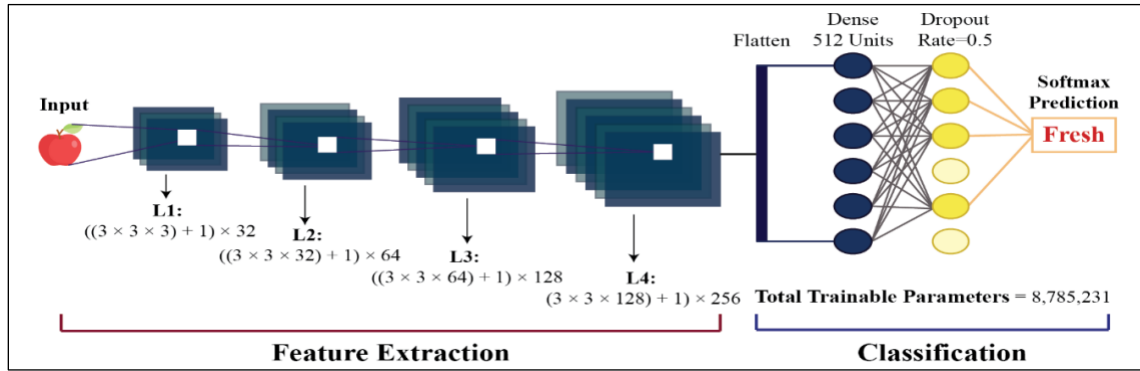


Figure 3. CNN architecture used for our model training

1) *Model Training*: The model was trained in over 50 epochs using mini-batches of 32. The model utilised an augmented training dataset through the use of a data generator. Validation performance was checked after each epoch as a way to monitor performance, loss, and accuracy.

2) *Validation*: We used a different validation set to assess the performance of the model at the end of each training epoch. This way, we could track the model's ability to generalise to unseen data and identify potential training issues that led to overfitting or underfitting. Validation accuracy and loss were recorded during the training process, allowing us to determine how to assess and tune the model.

3) *Testing and Evaluation*: After training, the model was evaluated on a test set to indicate final performance. Classification performance metrics included accuracy, precision, recall, and F1-score, calculated for each class individually using a classification report. A confusion matrix was also generated to visualise how correct and incorrect predictions were dispersed across all classes. In this study, multiple evaluation metrics were used to quantitatively evaluate the performance of the CNN model on fruit quality classification.

C. Pre-trained Models

We used three baseline pretrained models for classification of fruit condition, including VGG16, InceptionV3 and MobileNetV2. These models were trained using transfer learning. Here are the details:

1) *VGG16*: A conventional convolutional neural network architecture that the Visual Geometry Group at Oxford developed. The architecture of VGG16 consists of 16 layers with stacked small 3x3 convolutional filters that reach deep into the discovery of complex image features. While VGG16 is relatively less complex and uniform, it has proven to perform well on large image classification tasks and has become a common standard or baseline in transfer learning. In addition, VGG16 is computationally heavier than more current architectures. It gave 85.36% validation accuracy on our dataset with 10 epochs.

2) *InceptionV3*: Introduces a more sophisticated architecture based on inception modules that use multiple convolutional filter sizes in parallel to capture diverse spatial features efficiently. This model employs factorised convolutions and aggressive dimension reduction to enhance computational efficiency while maintaining robust classification performance. It is popular for its balance of accuracy and computational cost on large datasets. It achieved 82.21% validation accuracy on our dataset after 10 epochs.

3) *MobileNetV2*: MobileNetV2 is built especially for mobile and embedded vision applications that limit computational resources and power. MobileNetV2 uses depth-wise separable convolutions and an inverted residual structure with linear bottlenecks that reduce the model size and complexity. MobileNet signal a highly efficient type of model that allows for fast inference and considerably less memory footprint in comparison to pre-existing models, especially when working in resource-constricted environments. It had 89.63% validation accuracy.

D. Performance and Evaluation Measures

Overall classification performance [29] was computed in terms of accuracy, or the percentage of correctly predicted samples to total predictions:

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

To estimate the precision of the model at classifying unique classes, the precision metric was used, which is defined as the number of correctly predicted positive observations divided by the total predicted positives:

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

Recall, or sensitivity, was also calculated to determine how effectively the model captured all instances relevant to a class:

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

To help balance precision and recall, the F1-score was included as a harmonic mean of both:

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

IV. RESULTS

Table II presents the comparative results of the pre-trained models in comparison to the CNN. MobileNetV2 showed the best results out of the pretrained models, as the accuracy of training reached 88.46% and the accuracy of validation 89.63% in 10 epochs. This shows that not only did MobileNetV2 learn the features well, but also generalized on unseen data, which validates its appropriateness for classification with limited computing resources.

The VGG16, however, recorded the least performance with training accuracy of 79.65 and validation accuracy of 85.36. The relatively high difference between its training and validation outcomes suggests a low learning ability to discriminate more complex and nuanced aspects of fresh fruit, likely due to its older structure and relatively shallow depth. Although VGG16 exhibited consistent convergence, its performance was consistently lower than that of the other models, which proves its inefficiency in comparison to newer architectures. The InceptionV3 achieved an average training accuracy of 83.04% and a validation accuracy of 82.21%. InceptionV3 performed worse than MobileNetV2 despite its deeper architecture and inception modules that aim to extract multi-scale features. This means that there is a possibility of overfitting or lack of fitting of its complex architecture to the dataset with lower validation accuracy. In the comparison of these pretrained models and the proposed one, a decisive advantage is identified by the results. Not only did the CNN meet the MobileNetV2 performance but it also beat it as it had an accuracy of more than 90% on validation. Notably, this was done with a relatively lightweight structure dedicated entirely to fruit freshness classification as it highlights how task-specific model design competes with generic pretrained networks.

To conclude, MobileNetV2 was the best baseline model, but the proposed achieved better results in terms of accuracy and generalization, proving its suitability to perform automated fruit quality inspection. This analogy shows the necessity of creating tailored architectures, which perform a contrast between depth, regularization, and feature extraction specific to domains instead of using off-the-shelf pre-trained models only.

TABLE II. PRETRAINED AND PROPOSED CNN MODELS RESULTS

Pretrained Model	Pretrained Models Comparison with our Model	
	Train Accuracy	Validation Accuracy
VGG16	79.65%	85.36%
InceptionV3	83.04%	82.21%
MobileNetV2	88.46%	89.63%
CNN Model	94.10%	92.84%

Figure 4 illustrates that the model comparison, in terms of accuracy, reveals the performance gap between VGG16, InceptionV3, and MobileNetV2.

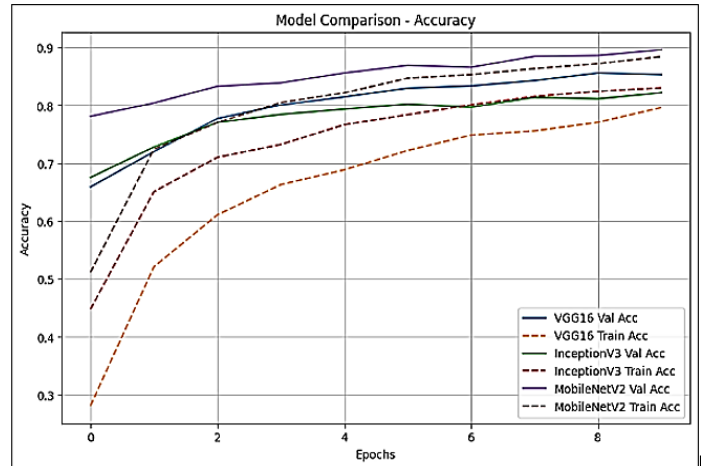


Figure 4. Pretrained models (VGG16, InceptionV3 and MobileNetV2) learning curves comparison

In general, MobileNetV2 performed better than other architecture models, as it achieved the highest validation accuracy of almost 90 per cent after just a few epochs, compared to the different architectures. This indicates its effectiveness and broad generalisation power in the fruit classification task. InceptionV3 also exhibited competitive performance, with both training and validation accuracy steadily rising and converging at levels above 80%, indicating a good balance between learning capacity and generalisation. By comparison, however, during training, VGG16 performed relatively poorly with lower accuracy, although it slightly performs better on the validation set, indicating its capability in representing complex features, unlike in modernised architectures. The strong and especially the validation accuracy performance of MobileNetV2 indicates that deeper models are more attractive because they are both lighter and very accurate in large-scale multi-class classification on fruit freshness.

The proposed CNN model was evaluated using a test set of 1,523 images, with standard classification metrics applied extensively. The final test accuracy for the model was reported at 92.19%, which represents strong results and shows good generalization and prediction capability on unseen data. The training and validation accuracies were 94.10% and 92.84% respectively. The model retained a balance between fitting the training data and generalising well without being overfit.

The evaluation of the class-level metrics consistently exhibited high precision, recall, and F1-score metrics across all fruit qualities. For example, class Orange_Formalin-mixed had a precision of 0.98, a recall of 0.94, and an F1-score of 0.96, signifying identifying the class with virtually no misclassification. Additionally, classes Banana_Formalin-mixed and Banana_Fresh also had similar metrics that were relatively balanced with respect to the trade-offs in precision and recall metrics and respective F1-scores of 0.89, indicating consistently accurate classification. Shown in Figure 5.

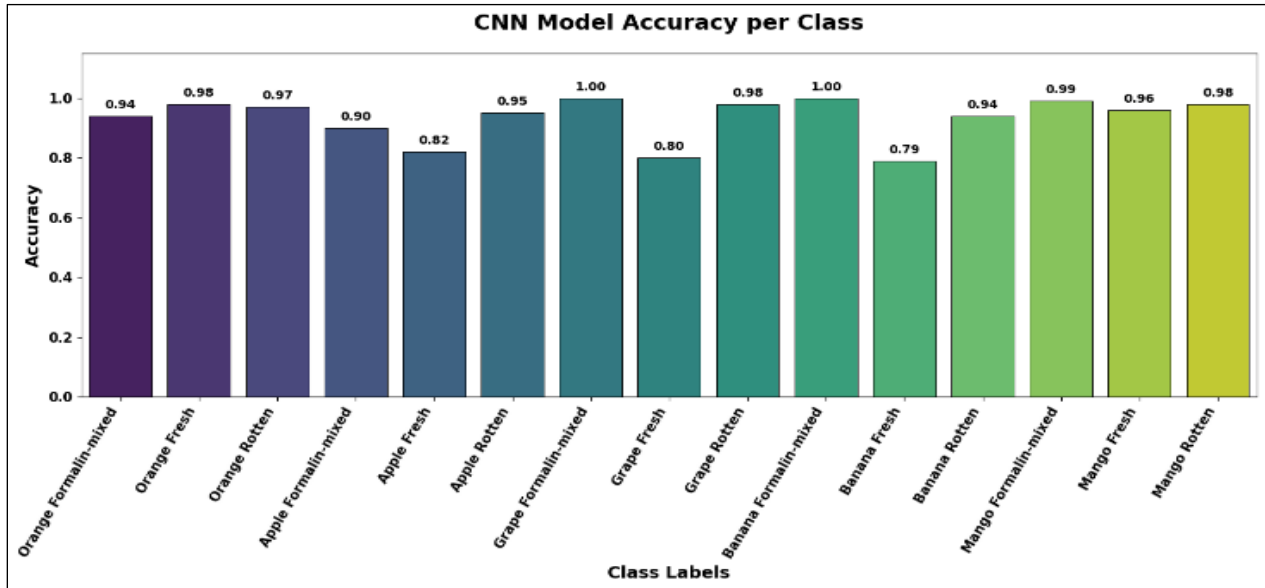


Figure 5. Class-wise accuracy of the CNN model.

The full class-wise performance metrics, precision, recall, and F1-score are located in Table III.

TABLE III. CNN MODEL PERFORMANCE ON EACH CLASS

Class Labels	Model Performance on Each Class			
	Precision	Recall	F1-Score	Support
Orange Formalin-mixed	0.98	0.94	0.96	97
Orange Fresh	0.94	0.98	0.96	113
Orange Rotten	0.93	0.97	0.95	98
Apple Formalin-mixed	0.89	0.90	0.89	96
Apple Fresh	0.91	0.82	0.86	114
Apple Rotten	0.87	0.95	0.91	95
Grape Formalin-mixed	0.85	1.00	0.92	92
Grape Fresh	0.99	0.80	0.88	115
Grape Rotten	0.93	0.98	0.95	95
Banana Formalin-mixed	0.80	1.00	0.89	99
Banana Fresh	1.00	0.79	0.89	112
Banana Rotten	0.99	0.94	0.96	95
Mango Formalin-mixed	0.95	0.99	0.97	93
Mango Fresh	1.00	0.96	0.98	114
Mango Rotten	0.94	0.98	0.96	95

The confusion matrix in Figure 6 offers an in-depth look at the model’s classification performance across fifteen fruit-condition classes. Each diagonal entry demonstrates a

high classification accuracy, as a majority of samples can be correctly predicted in their respective classes. Specifically, Orange_Formalin-mixed, Orange_Fresh, Grape_Formalin-mixed, and Banana_Formalin-mixed exhibited high true-positive counts, signifying solid model performance. Overall, misclassifications occur in limited capacity and only between classes that possess strong visual similarities. For example, there is a reasonable amount of confusion between Apple_Fresh and Apple_Formalin-mixed and some confusion with Banana_Fresh and Banana_Rotten, which the non-zero off-diagonal entries in those pairs of classes can identify. There were also a small number of misclassifications between Mango_Fresh and Mango_Formalin-mixed. As a whole, the confusion matrix supports the model’s strong abilities to differentiate subtle differences of quality and treatment conditions in fruits, indicating its capabilities in fine-grain multi-class classification. And Figure 7 shows the model’s learning curve over epochs. We also monitored the loss, precision and recall over time, Figure 8 shows all these metrics results.

Table IV shows the overall results of our CNN model.

TABLE IV. CNN MODEL OVERALL PERFORMANCE

Model	Overall Model Performance		
	Training Accuracy	Validation Accuracy	Test Accuracy
CNN	94.10%	92.84%	92.19%

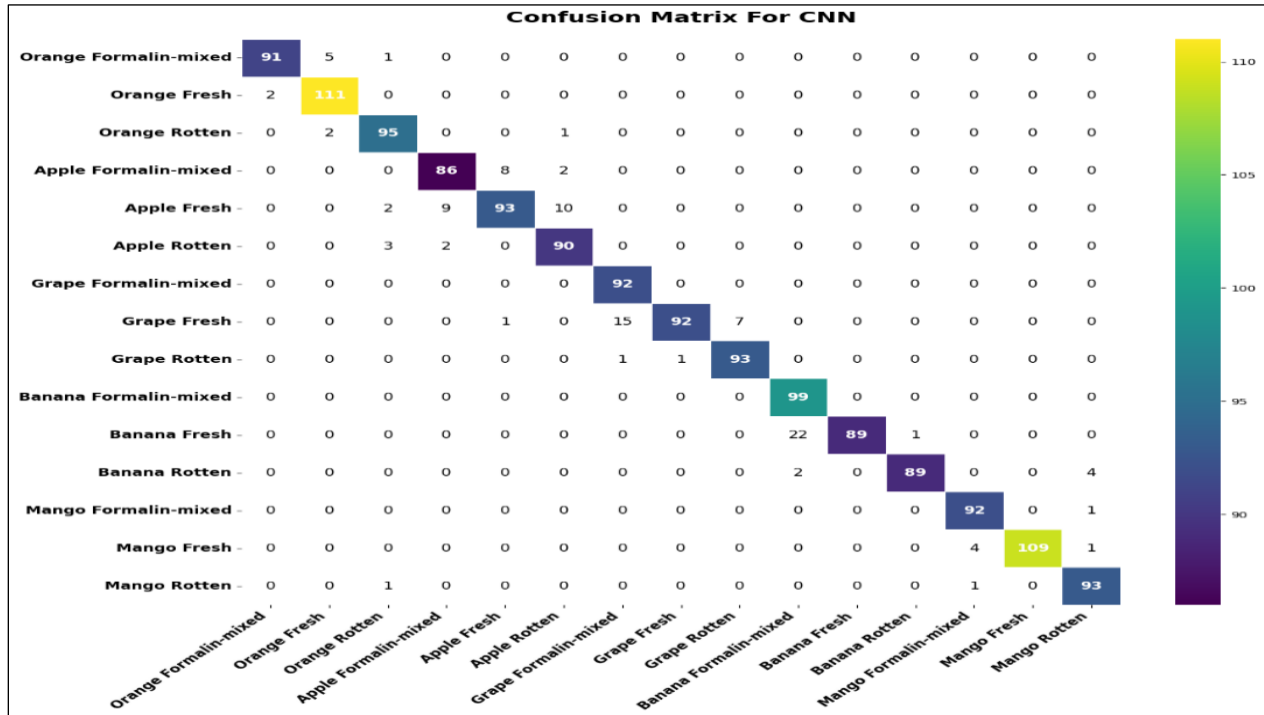


Figure 6. Confusion matrix for our CNN model’s predictions

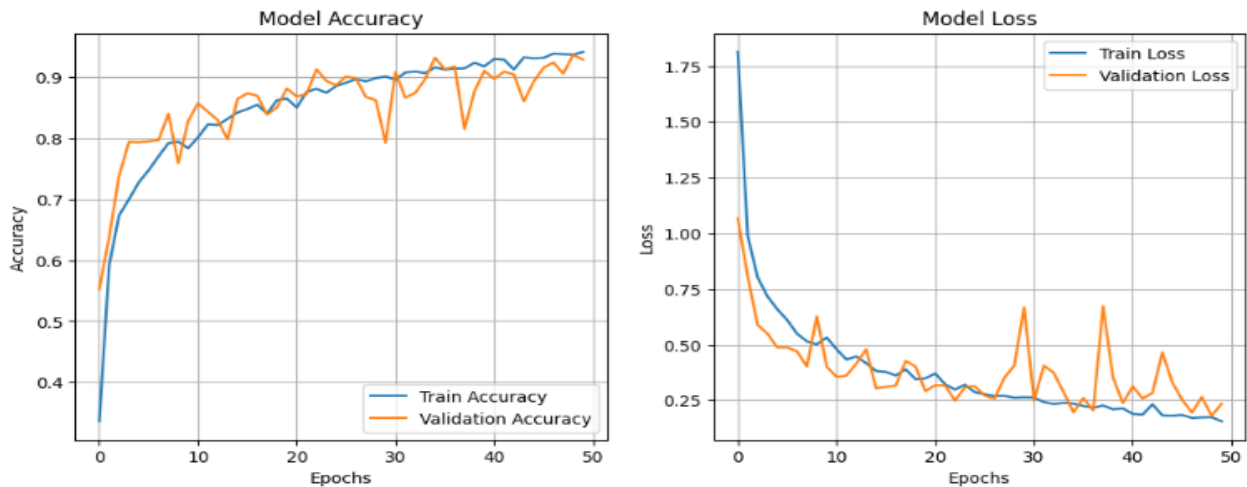


Figure 7. Learning curves (training + validation accuracy and loss) for Proposed CNN Model

The CNN model proposed shows sound learning nature in various assessment measures as shown in Figure 8. The accuracy curve increased consistently across epochs, and training and validation accuracy converged at a level above 90% which is an indication that the model generalizes well to unseen data. Likewise, the loss curves show a monotonously decreased line, and the validation loss reflects the same trend as the training one closely indicating that the overfitting was minimal as a result of employed regularization and augmentation procedures. Metrics indicating how well the model has performed, precision and recall, also justify the

strength of the model: precision consistently increases to about 0.93, and recall to about 0.90, as shown in Figure 8, indicating the model can consistently show positive instances correctly among 15 fruit classes. The similarity between training and the validation curves of the four metrics demonstrates the stability and reliability of the proposed CNN, and it is appropriate to use it in real-life practice in automated fruit quality evaluation and food safety supervision. Figure 9 shows comparison of proposed and pretrained models: VGG16, InceptionV3 and MobileNetV2.

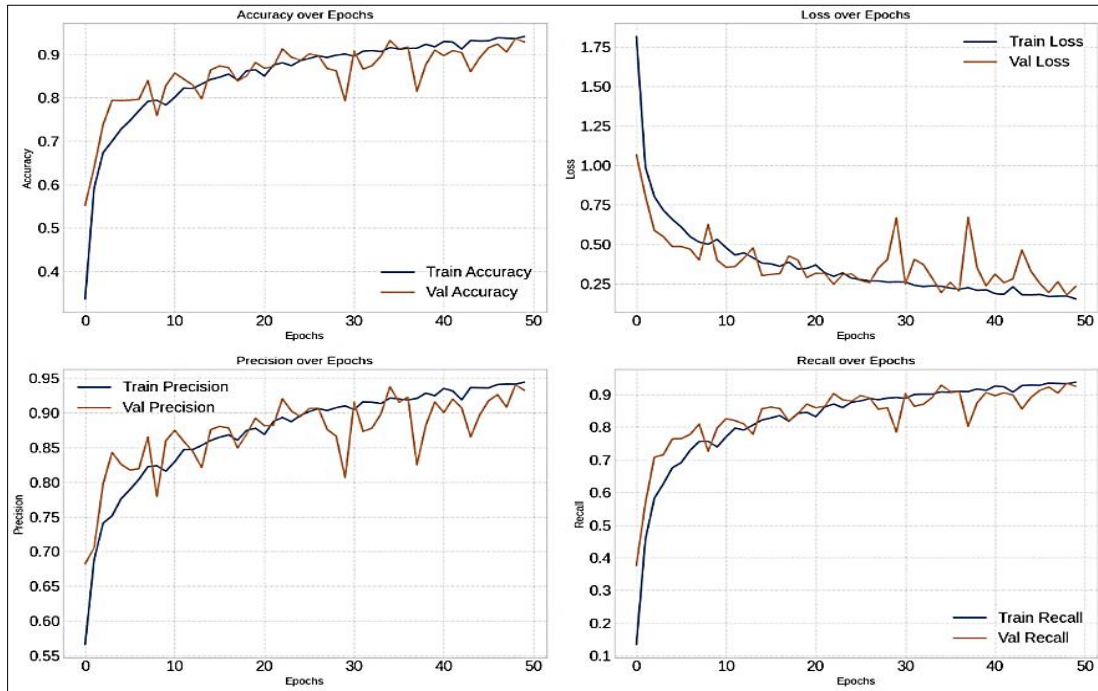


Figure 8. Learning curves for accuracy, loss, precision and recall for the proposed CNN Model

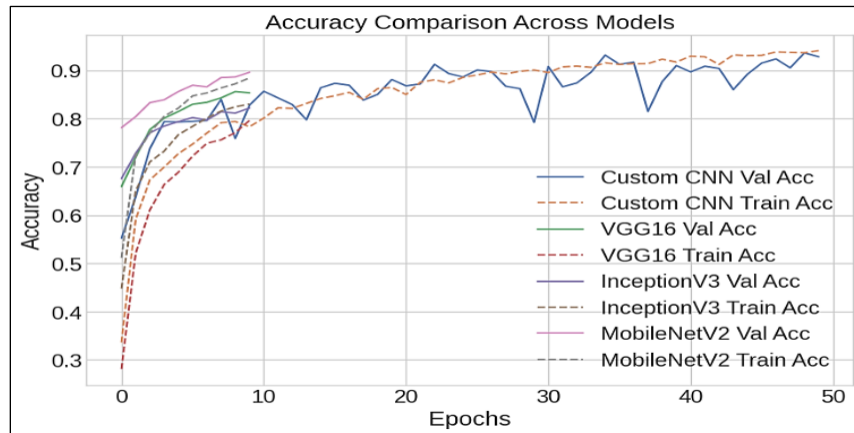


Figure 9. Pretrained models' learning curves comparison with the proposed CNN

To further validate the effectiveness of the proposed CNN model, a small selection of prediction outputs was visualized which showed the actual and predicted class labels for each fruit image. These visual samples are essential for reviewing how well the model performs in a realistic or practical domain. The results reported in Figure 10 show that the model is capable of recognizing and classifying the various fruit types: apples, bananas, grapes, mangoes, and orange into the required freshness levels. For each sample

there is a prediction from the model, where green annotations denote the correct prediction and red denotes incorrect. This complements the quantitative measures of accuracy and can provide a visual indication of the model's robustness and guarantees an acceptable level of precision across all 15 classes. This increases confidence in the model's suitability for practical deployment to perform real-time fruit quality inspections.

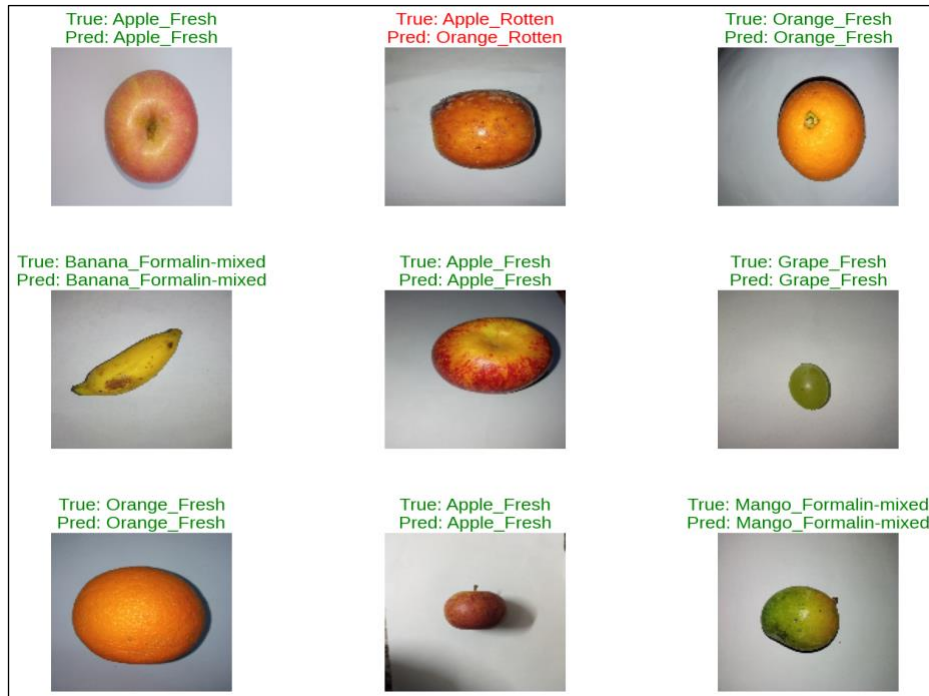


Figure 10. A sample from CNN model's rotten, fresh and formalin predictions.

V. CONCLUSION

In this study, we presented a custom CNN model for the classification of fruits into 15 categories of freshness, rotten and formalinized condition, and this paper showed how deep learning could be used to inspect food quality. The proposed model was also demonstrated to perform better in terms of several evaluation measures compared to pre-trained models like VGG16, InceptionV3, and MobileNetV2, with this model achieving a validation accuracy of over 90%. Although MobileNetV2 was the most competitive pretrained structure in terms of validation accuracy (89.63%) it did not provide as much robustness and generalization as the task-specific CNN architecture, emphasizing the benefits of task-specific model design. The results prove the effectiveness and safety of deep learning that may become a stable solution in automatic checks of fruit quality in the supply chain. There are some limitations in this study, however. The dataset, although it was not that diverse and it may not be entirely able to reproduce lighting conditions, background and fruit conditions in the real world. Additionally, the experiments did not extend to other modalities, such as spectral or chemical data, which would have been more informative in detecting freshness. To contribute to future work, it is suggested that the dataset should be extended to cover a broader range of environments, then recent results should be fused using multimodal data fusion, and finally, the model should be deployed in actual real-time embedded systems like mobile phones to increase scalability and applicability to real-world scenarios of agricultural and food supply chain settings.

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