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# Fruit Quality Prediction using Deep Learning Strategies for Agriculture

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**Abstract:** In agricultural farming, defective fruits are the primary cause of global financial disasters. It has an impact on the reliability as well as the quality of the fruits. After harvest, quality inspection necessitates a lot of time and labour-intensive expertise. As a result, saving time and labour during harvest is made possible by automatically detecting fruit quality. With machine learning and image processing techniques, numerous algorithms have been developed to identify and classify fruit quality. A system incorporating Convolutional Neural Networks (CNN) and transfer learning methods have been created to advance the fruit categorization process. Two models are proposed to estimate fruit freshness. One customized CNN architecture is suggested by adjusting the network's parameters to fit the dataset. The second method uses the pre-trained VGG model and the transfer learning approach to determine the fruit's freshness. The suggested models can distinguish fresh and rotten fruit based on the input images. This study used 70 different kinds of fruit, including apples, bananas, oranges, and more. CNN collect features from input images of fruit, and then CNNs with specific categories are used to classify the input images. Because of the model's tailored design, when applied to a Kaggle dataset, the suggested model achieves a 99.39% accuracy on the training data and a 99.99% accuracy on the validation data. The model correctly classified 99.41% of the data. Transfer learning resulted in a 97.65% increase in classification accuracy, a 99.05% increase in training accuracy, and a 99.99% increase in validation accuracy. The results showed that the suggested model could distinguish between fresh and rotten fruit and applicable real-time farming applications.

**Keywords:** Fruit quality prediction, disease identification, CNN, Transfer learning, VGG16.

## 1. Introduction

The economies of several nations around the world are strongly dependent on agriculture. Producing and transporting fresh fruits and vegetables to stores and markets makes up a substantial portion of the agricultural sector. Various cutting-edge technologies have been created and are currently being used in this business due to the rising demand for adequate food production and timely and secure market supply. It has been demonstrated that technologies like Internet of Things (IoT)-based smart farming can increase fruit and vegetable production quality. Furthermore, adopting intelligent logistics by medium and large-scale firms has decreased the time needed to sort, package, and deliver goods to the market. The use of new technologies by farmers or small-scale agricultural businesses hasn't been very well documented.

The overall higher cost and the need to obtain specific skills are two main obstacles to the adoption of these technologies by them. Therefore, there is a growing need to create cost-effective and user-friendly solutions for these businesses and farmers so that they may better use new technology. The fresh fruit supply chain includes many steps, but one of the most crucial is the grading and sorting process, which is the focus of this research. It is one of the main criteria in evaluating fruits because the fruit's outside looks indicate its freshness and serve as its selling value. Grading and selecting fruits based on external appearance and freshness is still time-consuming and challenging at the level of small-scale enterprises. The trained personnel who perform the manual quality control rely heavily on them to examine the fruits' exteriors and determine how to grade them.

Automating fruit grading and sorting is crucial for addressing classification inconsistencies. It also aids in reducing the time and effort required for fruit packaging, pricing, and transport to markets or vendors. For this reason, companies on a tighter budget may consider an intelligent fruit grading system that is relatively inexpensive. India is a rural country with diverse climatic and geophysical circumstances ideal for producing various plant yields, including fruits and vegetables. Vegetables and fruits account for 90% of the nation's overall horticulture production. Regarding horticulture, which includes fruits and vegetables, India was the world's second-biggest production. It is also the first in the world the production of many other crops, such as okra, potatoes, papaya, bananas, and mangoes.

According to the final appraisal in 2020–2021, horticulture production has significantly expanded over the past two decades. Fig. 1 presents a statistical overview of the million metric tonnes of production from 2008 through 2021 (the predicted value for 2022 is shown). The production rate is rising steadily yearly, and it is possible that, based on the population, it will even be exponential in the future.

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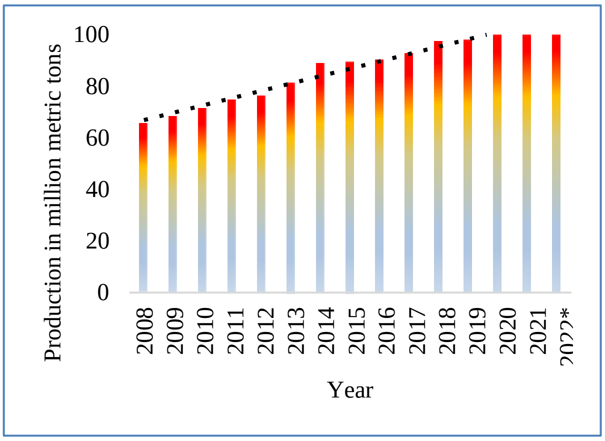


**Fig. 1.** Production in a million tons in India from 2008-2022 (Source: Statista)

Recently, efforts have been made to automate the categorization problem for fruits based on their freshness using computer vision and machine learning (ML) approaches [6, 7, 8]. However, most of these investigations have graded data using traditional feature extraction and machine learning techniques. The authors of [9] utilized the Global Color Histogram and Complete Local Binary Patterns to identify apples using colour, texture, and form feature descriptors. The gathered features were utilized singly and in combination to train and test machine learning methods, with a 95.9% accuracy rate. Apples were rated by the authors of [10] using supervised and unsupervised learning techniques. An artificial neural network (ANN) based architecture was suggested in a recent study on banana ripeness measurement [11]. The accuracy of SVM, naive Bayes, KNN, decision trees, and discriminant analysis was 97.75% compared to the ANN model. The ML models perform well but rely significantly on human, time-consuming, fruit-specific feature extraction. In addition, small data sets have been employed for training and testing these algorithms, which may lead to erroneous conclusions. Another way to address these issues is to create a system for categorizing and ranking fruits using deep learning methods. In contrast to conventional approaches, deep learning-based models may automatically extract the required features. The authors in [12] created an apple grading system with 90% accuracy using a pre-trained Inceptionv3 deep learning model. This system uses transfer learning to grade 150 self-collected apples. Deep learning was used to find apple lesions [13].

The Cycle-Consistent Adversarial Network performed lesion detection in apple images. The authors train and test CNNs for bruised apple detection using 3-D surface meshes [14]. The research established a predictive model with an accuracy of 97.67%. Cavendish bananas that have been harvested have been classified using deep learning [15]. The model was trained on four classes with 1116 photos using a self-designed CNN. Test data accuracy was 90%. Deep learning-based papaya ripeness classification was proposed. This study utilized various models for 300 self-collected photos, and the VGG19 model achieved 100% accuracy on 30 test samples [16]. These studies show deep learning's success in classifying and evaluating fruits. Most of these models were developed and tested with limited data. This meant they were as accurate as possible, typically within a 90% to 100% range. Most studies use preexisting image databases or expensive vision equipment to capture real-time images.

This research presented how deep learning models were utilized to develop an intelligent and autonomous fruit inspection system. We have used and analyzed various types of deep learning to build a robust platform for real-world testing in the field. In Section 2, we offer the relevant research and current methodologies for identifying the fruit quality that various studies have put forth. Section 3 addresses research gaps and constraints, whereas Section 4 elaborates on proposed methods. In Section 5, we report the results of our analysis using transfer learning and a customized CNN. In Section 6, future directions and conclusions are drawn in Section 7.

## 2. Related works

The field of ML combines elements of both computer science and statistics. Different from statistics, the primary goal of computer science is to create automated systems that can handle complex tasks. The efficiency and practicability of data processing algorithms and the resulting performance metrics are fundamental to ML paradigms. Machine learning utilizes a similar approach to learning as people do by drawing on past examples. ML systems use various human learning processes to identify patterns and formulate answers. Five categories of ML exist supervised, unsupervised, reinforcement learning, semi-supervised learning, and active learning. The five processes of image acquisition, preprocessing, image segmentation, feature extraction, and classification make up the traditional technique for determining fruit quality, as shown in Fig. 2.

Image filtering and polishing improve results. Scaling, noise removal, and enhancement are preprocessing steps. Image segmentation can divide an electronic image into parts after preprocessing. The primary goal is to separate the foreground from the background so that the quality can be objectively assessed. Image analysis and classifiers are less efficient when they are segmented incorrectly. Features are estimated after segmentation. Categorizing extracted features allows input to be recognized. Vectors define object shape. The extraction of attributes improves recognition. These elements aid in the evaluation and analysis of food quality. Color, texture, and morphology assess fruit and vegetable defects and maturity. By simulating human reasoning, classification assists humans in making accurate, timely decisions. Image processing can categorize products based on colour, size, shape, and texture. A classification algorithm uses a training set to determine an unusual instance. KNN, SVM, ANN, and deep learning are used in food quality evaluation [17].

It's not uncommon these days to use an image processing algorithm to determine the quality level of a fruit. Disease, flaws, and contamination are all factors in determining a fruit's quality level. Sorting is required after harvesting. Hand-grading papers are inefficient and inaccurate. It is critical to the transition to a more automated system that is both faster and more efficient. With the help of AI, we can automatically sort and grade fruit with high accuracy.

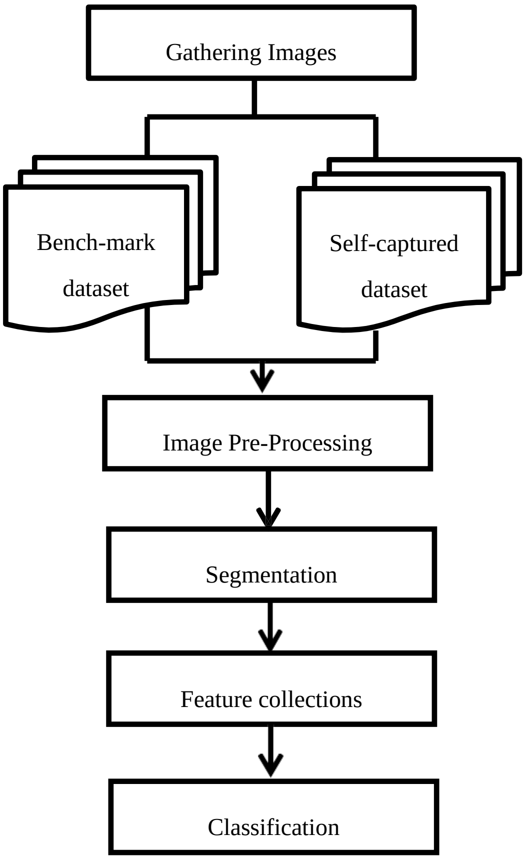


**Fig. 2.** Classification of fruit quality using traditional strategies

In recent years, academics have developed various methods for predicting and classifying fruit quality. Khojastehnazhand et al. [18] designed a VB lemon-grading algorithm. The algorithm eliminates background fruit. Offline calibration of lemon samples is performed on camera. Data from the sorting process is compared with information stored in a database to determine the final passing grade for fruits. Razak et al. [19] evaluated mangos. Measurable examination, content-based study, and improved fluffy image production were used. Fluffy image grouping was proposed and created, the optimum bunching calculation for neighbourhood mango in Perks was located and evaluated, the results of exploratory calculations were compared to those of human master reviewers, and the framework was advanced. Mango browning was identified with LS-SVM by Zheng et al. [20] using L*a*b* and Fractal Dimension for Degree Detection.

low-effort machine vision system that quickly and accurately identified guavas was demonstrated by Kanade et al. [21]. LabVIEW's express VI was used to strip RGB values from photos. Forty-nine unique varieties of Lucknow Guavas were chosen for this analysis. In this case, the availability of natural guava products is quantified using a division of shading images. An automated system was developed by Sahu et al. [22] to identify and categorize mango fruits according to their size, colouration, and form. As a first step, we'll employ pre-processing methods to convert our digital photographs of mangoes into binary images. Photos will be processed and sorted later. A reliable method for measuring the form of persimmon fruits was developed by Maeda et al. [23]. Two sets of 153 persimmons were considered for the scientific investigation. L/D (the length-to-width ratio) is used as the primary comparison metric. Elliptical Fourier Descriptors (EFDs) and the SHAPE software were used to obtain the longitudinal and transverse sections of fruits.

Two theories on the pre-effect processing of NIR spectra from fresh fruit are evaluated in [24]. The accuracy of model predictions can suffer if NIR spectra are pre-processed with scatter correction, which eliminates or dramatically reduces useful scattering information. As opposed to using PLS regression, DL is an optimal model for raw absorbance data. The authors in [25] provide a GUI-based toolbox for basic chemometric data processing. The GUI enables model maintenance and adaption in multi-batch NIR fruit studies. A case study demonstrates how well it adjusts for seasonality when predicting apple DM. The toolkit offers a push-button method for creating complex chemometric models of fruit quality. The performance of new batch models can be enhanced by variable selection and batch correction using DOP and TCA.

Fruits are classified by the authors of [28] using CNN, RNN, and LSTM. Preliminary statistics demonstrate that the recommended approach is precise and quantifiable. Real-time fruit classification will be made possible via fast computation. In [29], the authors show that hyperspectral imaging can be used to examine the fruit, vegetables, and mushrooms for quality characteristics such as maturity, ripeness, and sensory quality. To evaluate banana fruit quality during storage, the authors of [30] developed a digital twin of the fruit based on ML. Fruits being stored can undergo surface and physiological changes that the thermal camera can detect. The model was trained using SAP's intelligent technologies after creating a dataset with four different temperature data types. Based on heat data, the system monitors fruit status using a deep convolutional neural network, and training demonstrates better accuracy. Thus, 99% of predictions were correct, suggesting that this approach may be used to create digital fruit twins. Using ML, thermal imaging can decrease food waste by creating a digital fruit twin.

CNNs, transfer learning, and data augmentation are some of the strategies the authors of [31] recommend using to improve the Banana fruit sub-family and image categorization. They constructed a fundamental CNN and fine-tuned a MobileNet Banana classification model by using 3064 photos sourced from public sources and their collection. The accuracy of classifications made according to subfamily/variety and the accuracy of quality tests are 100% and 93.4%. The authors assessed the association between peach fruit quality and soil mineral nutrients [32] using an ANN. The four ANN models produced the most accurate findings. To meet consumers' demands, it is essential to evaluate and predict the quality of date fruit when it is being stored in freezing temperatures. Destructive approaches need excessive time and cannot simultaneously test more than one variable. The research works that have been proposed over the past few years are outlined in Table 1.

**Table. 1**. Recent works on fruit quality prediction using different strategies.

| Ref. | Type of fruit | Description/technique used | Metrics used |
|---|---|---|---|
| [19] (2012) | Mangoes | Fuzzy Classification | NA |
| [20] (2012) | Mangoes | LS-SVM | Accuracy=85.19% |
| [21] (2015) | Guavas | ANN | NA |
| [22] (2017) | Mangoes | NA | NA |
| [23] (2018) | Persimmon fruits | Elliptical Fourier Description | NA |
| [24] (2021) | Mangoes | PLS Regression | Accuracy =98%, RMSE |
| [25](2021) | Heterogeneous fruits | The authors used DOP and TCA methodologies to present a GUI for fruit quality prediction. | NA |
| [26] (2021) | Apple | The authors advocated for the use of non-destructive instrumental research in the field of apple fruit firmness measurement. | NA |
| [27] (2021) | Peach | A novel crop load fruit developing stage procedure was used to non-destructively analyze peach interior quality and maturity. | RMSEP |
| [28] (2022) | Apple | CNN, LSTM, and RNN | Accuracy=70%, RMSE |
| [29] (2022) | Banana | Deep CNN | Accuracy = 99% |
| [31] (2022) | Banana | CNN | Accuracy =93% |
| [32] (2022) | Peach | ANN | $R^2$ and RMSE |
| [33] (2022) | Heterogeneous | ANN + MLR | $R^2$ and RMSE |

## 3. Research Gaps and Limitations

The agricultural industry's primary concern is post-harvest. The key is the automatic detection of fruit disease and quality. The current state of fruit quality identification research has a narrow emphasis, which might lead to errors like duplicate photos, omitting damaged fruits, inadequate testing and training, etc. Only a few training images are used in existing works. Systems with few features determine quality. Some systems had lower test accuracy than training. The main issue is developing a system that evaluates fruit quality more precisely and accurately than earlier research works. Numerous academics have carefully studied the problem of identifying fruit quality using neural networks, clustering, SVM, PCA, and many others for feature extraction and classification. Existing systems have focused on improving accuracy and efficiency in resolving this problem through various image attributes. While the authors successfully developed effective methods for detecting fruit quality, they left room for future development. The following discussion delves deeper into these concerns as well as the consequences such concerns have for the results.

- The data was not uniformly distributed throughout the training and testing sets, and there weren't enough training images used. The 70:30 ratio is helpful for learning and making predictions.
- The use of computer vision has reduced the time, money, and labour required in the vegetable and fruit business. Defect Detection with computer vision typically employs automatic processing to save time.
- Since current approaches can only classify one fruit species, similar photos can result in classification errors. As a result, the algorithm has problems detecting images of a single fruit. This restricts the algorithm to only one type of fruit in a natural operational environment because there are many different types of fruit, and it would be impractical to design a system for each. There must be a method that works for all situations.
- Most research focused on narrow criteria that are insufficient to assess fruit quality. It raises the possibility of making an incorrect prediction and cannot be compromised people's health.
- It might be challenging to correctly recognize fruits and vegetables because of their wide variety in size, shape, and colour.
- Limitations associated with employing different images or datasets that cause results to change drastically.
- Fruits and vegetables are more delicate than other crops and can easily be harmed by their surroundings. Classifying these foods can be challenging because the same computer vision algorithm may generate variable degrees of accuracy on the dataset.
- Specific systems have valid input data and accuracy that indirectly relate to how effectively the tactics have not been used or the models' appropriate structure has been applied. This flaw is caused by incorrectly optimizing the structure of classifiers.
- Some systems fail to detect contaminated fruits while adequately distinguishing between photos of healthy and unhealthy fruits. This was due to a lack of focus on preprocessing and segmentation, which are critical in this industry, particularly agriculture.
- During the testing phase, the accuracy of some projects was discovered to be worse than during the training phase because of a phenomenon called overfitting.
- Some systems have struggled with adequately sizing objects in images, leading to inaccurate segmentation due to a lack of a suitable approach. Several investigations revealed this issue, demonstrating that the segmentation process does not consistently deliver correctly segmented images.

- If the entire contents of fruits and vegetables aren't carefully inspected, the likelihood of discovering flaws and quality analyses increases.
- Data does not constrain classifier selection. Dealt with appropriately. It is critical to consider all perspectives.
- criteria for selecting a suitable model, and then conduct a thorough search for any methods for classification's first four stages

## 4. Research Methodology

Convolutional neural networks and transfer learning networks were trained using Kaggle data. These images reveal critical physiological data on fruit health using ML, allowing for accurate prediction. Classification systems have made substantial use of deep learning. This instructional strategy is based on training inputs and expected outcomes. This method's effectiveness is increasing and is becoming more widely used in fields such as image processing and classification.

### 4.1 Dataset Collection

The Fruits 360 dataset was used for this study. This dataset has 90380 images of 131 different fruits and vegetables. Colour (RGB) images with a 100-by-100 pixel resolution (Hence, 3 values for each pixel). The training and testing datasets are extensive: 67,692 and 22,688 images, respectively. In this work, we use a small subset of the fruit 360 dataset consisting of just 10 different types of fruit: strawberries, apples, corn, bananas, tomatoes, potatoes, oranges, pineapples, and peaches. We picked out 70 categories of fruits; hence the dataset is smaller, and the neural network can be trained more quickly. Our training set consists of 35133 images, whereas our test set consists of 11804 images. The predictive model was developed by fine-tuning the CNN architecture using Google's Colab. The technologies make advantage of Tensor Flow, a robust deep neural network architecture. It's Google's open-source ML framework and is quite popular. The framework features state-of-the-art predictive modelling and deep neural networks.

### 4.2 Training

In the inference phase, the learned model analyses incoming information and makes predictions. Feature vectors are used as a representation of the actual data during the training and inference phases. To ascertain the model's final predictive capacity, prediction model testing involves evaluating the model's performance on fresh data. The model is used to conclude unexplored data during inference. The same flow is applied when using the model in testing. After the network is trained, predictions can be made by feeding it new information in real-time (Fig. 3). As a result, the file's history will be used to make a prediction, and alerts will be sent to users on the fruit's freshness.

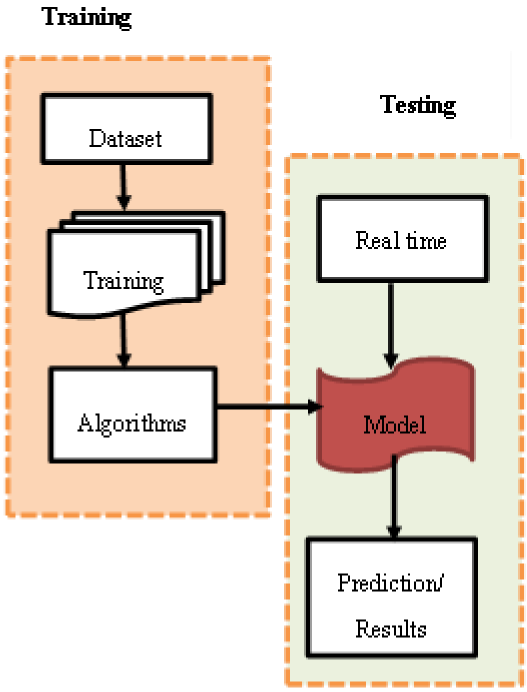


**Fig. 3**. The process of training and testing

### 4.3 Deployment

In contrast to traditional single-layer neural networks, convolutional networks consist of many hidden layers, as shown in Fig. 4. CNNs use convolutional layers and pooling layers for their architecture. Convolutional layers extract the images' features, and pooling layers reduce their dimensionality. The features are sent to the fully connected layers after the images have been shrunk to a tolerable size. The final softmax activation function classifies the labels according to their freshness as fresh fruit or rotten fruit. The feed-forward network is well-known for its ability to discern topological features in an image. Images can be trained using the back-propagation technique to identify patterns. All the neurons making up a feature have the same weights in feature extraction. This activation function's steepness can be attributed to mass. The parameter bias increases the activation function's steepness and sets the function's triggering speed, both of which help the model match the data as well as possible. Although all neurons have different input images, locate the same image feature.

The convolutional layer is the backbone of a CNN, which extracts features from data. The layer comprises a collection of programmable filters (kernels) that may be trained to identify specific types of visual content. When performing convolution, the dot product between the local regions of the input image and the filter is calculated as the filter is moved over the image. Each grid will create value since the pooling layer uses certain functions to summarise sub-regions, which minimizes the size of the feature maps. By crossing the input and output of a sliding window, this layer avoids overfitting. Because of this, the pooling layer reduces the overall network parameters and strengthens the resilience of the learned features by making them less sensitive to scale and orientation changes.

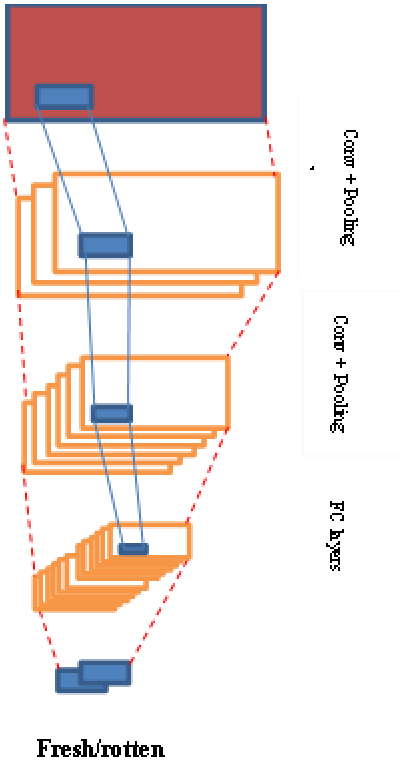


**Fig. 4**. The architecture of CNN

The output of the layer below the completely connected one is connected in a direct path to the input of the Fully Connected layer. It does this by connecting every neuron it possesses to every neuron in the layer below it. Learning non-linear combinations of these features is also possible by adding a fully connected layer

The goal of the training is to minimize the loss. As a result, the image classifier demonstrates decent performance after complete training, with reasonable accuracy. Cross-entropy loss should be as low as possible by the end of training. After that, we tested the model with new input data, and it performed admirably. The model's fruit-state predictions have proven accurate once the training phase has ended.

## 5. Results and Discussion

The proposed work includes two different architectures. The first architecture involves developing customized CNN. Using a CNN, a neural network can learn spatial and related features with remarkable efficiency. Before the advent of CNNs, it was challenging to train a neural network to recognize spatial relationships because the input data was typically presented in a tabular format. Neural networks can learn the connections between different parts of an image with the help of CNNs. The deeper one goes into a neural network, and the more nuanced the features learned will be. In this first method, filters with a size of 2 by 2, increasing the number of layers as we go deeper, and topping it all off with a 2 by 2 MaxPooling layer that picks the maximum value in a given region were utilized. As a means of eliminating linearity to learn non-trivial features, we will employ the RELU activation function. To avoid overfitting the model, we'll implement dropout regularisation, which selects a node according to a probability we define. Finally, the loss function will be determined with the help of a softmax unit for classification.

Table 2 outlines the input and output shapes and the number of parameters used in the customized architecture used to implement the fruit quality prediction. The output shape is a tuple excluded the first element, "None". Table 3 shows the convolutional blocks and the number of filters used in each. Each block uses the same amount of padding (=2), the same sized kernel (=2), and an activation function (relu). One hundred fifty and one hundred and twenty dense layers, followed by a softmax layer, make up the fully connected layers, which also use 30% and 40% dropouts.

**Table. 2.** Summary of the Customized Architecture

| Layer | Output Shape | Params |
|---|---|---|
| Conv2D | 100, 100, 16 | 208 |
| Activation | 100, 100, 16 | 0 |
| MaxPooling | 50, 50, 16 | 0 |
| Conv2D | 50, 50, 32 | 2080 |
| MaxPooling | 25, 25, 32 | 0 |
| Conv2D | 25, 25, 64 | 8256 |
| MaxPooling | 12, 12, 64 | 0 |
| Conv2D | 12, 12, 128 | 32896 |
| MaxPooling | 6, 6, 128 | 0 |
| Dropout | 6, 6, 128 | 0 |
| Flatten | 4608 | 0 |
| Dense | 150 | 691350 |
| Activation | 150 | 0 |
| Dropout | 150 | 0 |
| Dense | 120 | 0 |

**Table. 3.** Parameters utilized in each convolutional block

| Block number | Filters |
|---|---|
| Block1 | 16 |
| Block2 | 32 |
| Block3 | 64 |
| Block4 | 128 |

**Table. 4.** Evaluation results using customized CNN

| Measure | Value |
|---|---|
| Training loss | 0.02040 |
| Training accuracy | 99.39% |
| Validation loss | 0.00005 |
| Validation accuracy | 99.99% |
| Test accuracy | 99.41% |

During the model development, accuracy and the loss calculated using categorical cross entropy and the Adam optimizer are considered evaluation metrics. After 20 iterations of training, the model's performance has stabilized, and there has been no additional improvement in the validation loss. Table 4 presents the results of this experiment, which show that the model outperforms the best available methods. Sample predictions using the suggested methods are displayed in Fig. 5. Results of the loss function and precise computations are shown for all epochs in Fig. 6.

**Fig. 5.** Prediction results of the proposed methodology

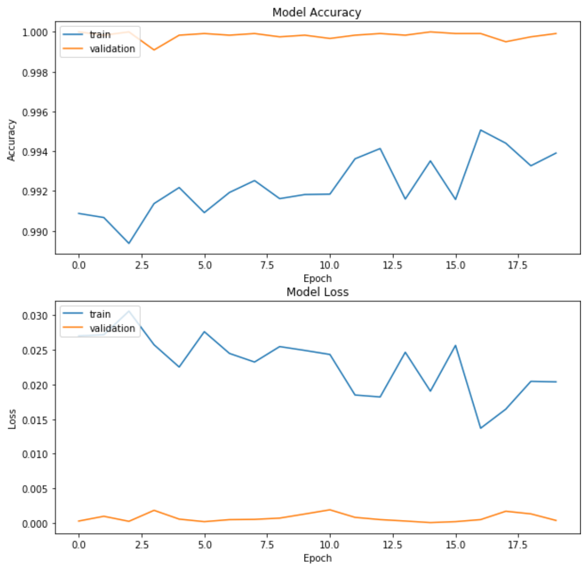


**Fig. 6.** The accuracy and loss of the model for different epochs

The second approach we utilized was transfer learning, and the flow of this work is shown in Fig. 7. A pre-trained model is applied to a new task through transfer learning. A model developed for one task is applied to another related task to speed up modelling. Performance is improved by transferring learning over training with a small amount of data. We can get our base layer ready with this strategy by employing transfer learning. To categorize 1000 different classes of images, VGG16 was trained on the imagenet dataset, and we'll use its pre-trained weights. The VGG16 model is trained on ImageNet architecture, and the last layers of this network are frozen and customized for quality prediction of the fruits. Table 5 displays the model's input, output shape, and parameters. The output shape is a tuple of values, except the first element, "None." The model's accuracy was determined using the categorical cross-entropy loss function and the adam optimizer. The model's training employs a batch size of 128, with 20 training iterations. Table 6 displays the transfer learning model's evaluation results, which show that the model achieves nearly 99% accuracy. Fig. 8 depicts the sample prediction results obtained through transfer learning techniques. Fig. 9 depicts the loss function results and accurate calculations for each epoch considered using transfer learning.

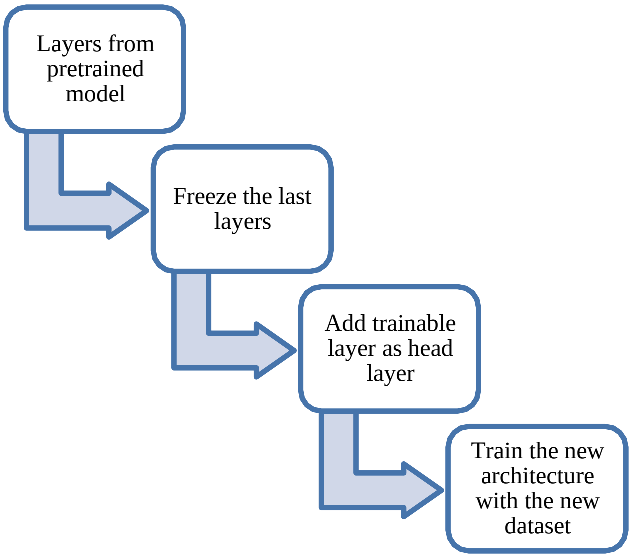


**Fig. 7.** The flow of transfer learning

**Table. 5.** Summary of the Customized Architecture

| Layer | Output Shape | Params |
|---|---|---|
| VGG16 | 3, 3, 512 | 14714688 |
| Conv2D | 3, 3, 1024 | 4719616 |
| Activation | 3, 3, 1024 | 0 |
| MaxPooling | 1, 1, 1024 | 0 |
| Dropout | 1, 1, 1024 | 0 |
| Flatten | 1024 | 0 |
| Dense | 150 | 153750 |
| Activation | 150 | 0 |
| Dropout | 150 | 0 |
| Dense | 120 | 18120 |

**Table. 6**. Evaluation results using Transfer learning

| Measure | Value |
|---|---|
| Training loss | 0.0295 |
| Training accuracy | 99.05% |
| Validation loss | 0.00037 |
| Validation accuracy | 99.99% |
| Test accuracy | 97.65% |

The results show that the two proposed architectures are giving better accuracy in the training and testing phases. Both the model's training and testing accuracy, training and validation loss are compared and represented in Fig. 10 and Fig. 11. In Fig. 10, comparison results of Customized CNN and Transfer Learning for training, validation accuracy, and training loss in fruit quality detection are displayed. Fig. 11 displays comparison findings of validation loss of Customized CNN and transfer learning in fruit quality identification.

**Fig. 8.** Prediction results of the transfer learning

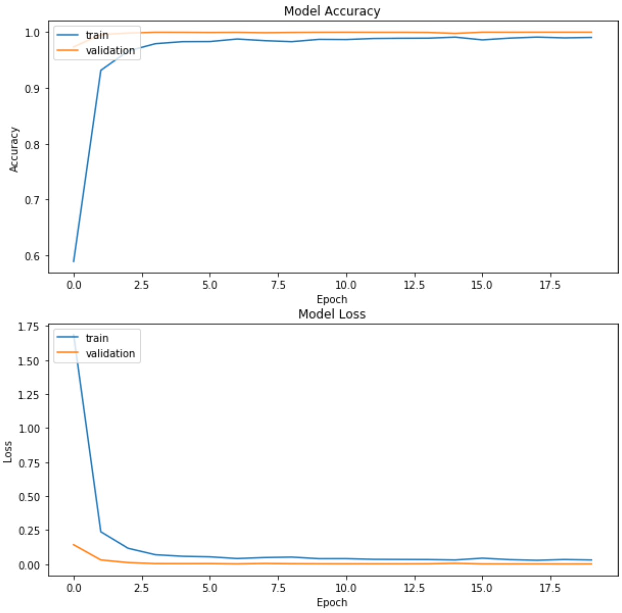


**Fig. 9.** The accuracy and loss of the model for different epochs using transfer learning

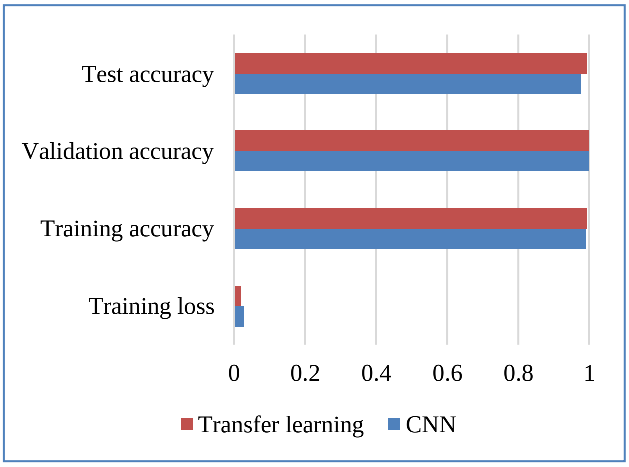


**Fig. 10.** Comparison results of training, validation accuracy and training loss of Customized CNN and transfer learning in fruit quality detection

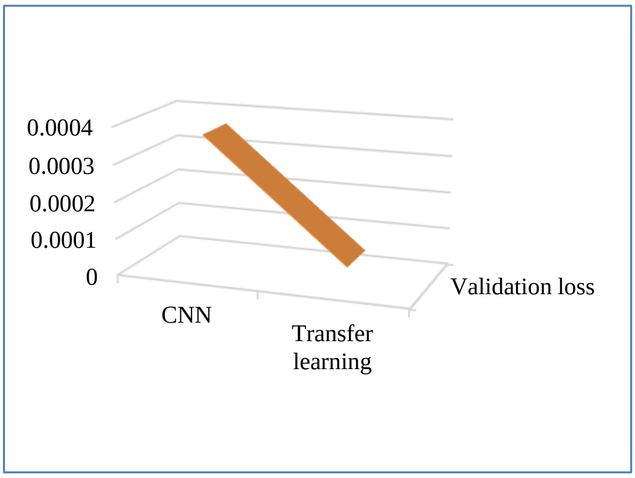


**Fig. 11.** Comparison results of validation loss of Customized CNN and transfer learning in fruit quality detection

## 6. Future Directions

Minimizing environmental implications through automatic fruit quality detection. Learning technologies have improved farming's future by making it safer, more environmentally friendly, and easier to predict crops' performance. Research and analysis have shown that the proposed system analysis can be used to assess crop health and productivity and the impact of external factors such as harmful chemicals or pesticides. Many different plants' leaves, shapes, and colours are very similar. Accordingly, computer software can now identify different kinds of plants and crops. As a result, efficiency and effectiveness are both improved. More advanced CNN models can be utilized to solve species identification and freshness detection problems for the same purpose. Multi-fruit systems that use dynamic feature extraction will benefit from future deep learning models. Recently developed AI techniques, such as federated learning, can enhance product quality. The sustainability, risk, and revenues of a crop can all be affected by the post-harvest actions made by the farmer. Using sensors and data-driven insights, DL-based farming aids decision-making. Predicting yield, profits, illnesses, and quality can all be done by machines without any human intervention.

## 7. Conclusion

People are concerned about their health and prefer to eat organic, fresh foods. As a result, before selling the fruits, sorting them and discarding the bruised ones is critical. Pre-harvest and post-harvest processing are required for fruits. Sorting and grading post-harvest fruits into edible and inedible categories is what fruit quality detection entails. Digital agriculture has resulted from new automated systems. As a result, fruit quality detection systems are automated structures that produce effective results at a low cost and time consumption. Our primary goal was to recommend a model with high accuracy for use in fruit detection to simplify the agricultural industry. In this study, we address several issues with fruit recognition and propose two frameworks for making fruit quality predictions. We created a custom CNN architecture and transfer learning models that achieve 99% accuracy in training and testing. The experimental analysis shows that the results are superior to previous research and have practical applications in modern farming. Even if adequate, accurate and efficient algorithms are developed, real-time systems remain inaccessible to the general public. Researchers in this field may be particularly interested in efforts to develop such a system. We plan to integrate this approach with the Internet of Things (IoT) so that computers can automatically identify rotten fruits.

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