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Generalized Framework for Fruits Defect Detection using Deep Learning

Dr. Jyoti Deshmukh, Sumit Chavan, Sakshi Chalak, Shruti Ghogare, Aditi Ghadge

Pillai College of Engineering, New Panvel, Maharashtra, India

Abstract: *In agricultural applications, machine learning techniques are important for computerized fruit grading and quality assessment. Automation in agriculture boosts a nation's economic growth, productivity, and quality. Fruit quality grading is a crucial export market metric, particularly when it comes to surface fault detection. Given the popularity of mangoes in India, this is particularly relevant. Mango grading by hand, however, is a laborious, erratic, and subjective procedure. In order to discover defects in mangoes, a computer-assisted grading method has been devised. Lately, effective classification outcomes in digital image classification have been attained through the application of machine learning approaches, such as the deep learning approach. In particular, automated fault identification in mangoes uses the convolution neural network (CNN), a deep learning technology. This paper suggests a CNN-based computer-vision approach for classifying excellent mangoes. The NIR scanner will be used to scan the mango, and the data it collects will be sent to the software. It will be able to tell whether a mango is defective or not after training and testing the data*

Keywords: Mango defect detection; machine learning; deep learning; convolutional neural network; Mango; Scanner

I. INTRODUCTION

One of India's main fruit crops, mangos are high in vitamins and minerals. An estimated 50.6 million tons of mangoes are produced worldwide, with 39% of that amount coming from India. China and Thailand are the following top manufacturers. India's top producing states include Uttar Pradesh, Tamil Nadu, Telangana, Andhra Pradesh, Kerala, Bihar, and Karnataka. Despite India's annual growth in mango production, the country exports relatively little mango fruit since there are insufficient automated tools and procedures that are reliable, high-quality, and nondestructive.

Mangoes with green spots and yellowish speckles on their skin are known for their quality. Mango fruit quality grading in India is carried out manually by skilled assessors using a system based on surface flaw identification. Workers that undertake manual sorting must engage in prolonged, high-capacity sensory tasks. As a result, manually grading mango fruit takes a lot of time. Furthermore, a large number of workers are needed for this process, which raises the cost of manufacturing and raises the possibility of erroneous results due to the subjectivity and consistency of individual assessments across fruit items. Computer image sensors are needed to help overcome these constraints in order to be more productive and successful. As a result, we suggest a computer vision system and a dependable technique for automatically detecting mango defects.

The goal of this work was to use advanced machine learning techniques, like the convolutional neural network (CNN), to construct a computer vision system for mango fault identification. Defect identification consists of three macrosteps for the computer vision system processing of mango fruits: input image preprocessing, feature extraction, and input image classification. Fruit grading is a crucial step in selecting high-quality fruits, and computer vision systems in agriculture improve the quality of food goods for the export market. For fruit grading, a sophisticated computer vision system is therefore required.

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II. LITERATURE SURVEY

R. Nithya , B. Santhi , R. Manikandan , Masoumeh Rahimi and Amir H. Gandomi [1]
“Computer Vision System for Mango Fruit Defect Detection Using Deep Convolutional Neural Network”. The experimental results demonstrate that the suggested strategy achieved an accuracy of 98% when the system was trained and tested using a mango database that is accessible to the general public.
Dameshwari Sahu, Chitesh Dewangan [2]
"Using Image Processing to Identify and Classify Mango Fruits" In agriculture, image processing technology has been applied extensively. Initially, texture analysis and morphological operations on digital photos of various mango fruits will be used as pre-processing approaches to generate the binary image. The processed photos will next undergo additional classification using an appropriate classification technique.
Vijay C.P, Yashpal Gupta S. [3]
"Automated Mango Varieties Classification." Conventional organic product ordering strategies have frequently relied on laborious, time-consuming, and contradictory manual tasks that rely on visual capacity. The primary focal point for characterising natural products is their outer shape appearance. In the natural product industry, PC machine vision and image processing techniques have recently been found to be increasingly valuable.
Anitha Raghavendra, Dr. Mahesh rao [4]
"A Survey on Non-Intrusive Techniques for Detecting Internal Defects in Fruits." Summary: Fruits' internal and external quality, which is determined by their colour, texture, and flaws, is crucial to the food industry. One such area of study would be the application of pattern recognition and image processing techniques, which can be used to reduce post-harvest losses in the supply chain and to non-destructively detect and categorise the quality of mango fruits.
Varsha Bhole, Arun Kumar [5]
"Applying Deep Learning Technique to Grade Mango Quality: Views from the Food and Agriculture Sectors" The mango, or Mangifera indica L., is a highly favoured and nutrient-dense fruit. In India, it is also referred to as the "king of fruits." Mango fruit quality is determined by its outward appearance, including its size, shape, colour of flesh and skin, flavour, sweetness, and aroma.
K. Wang et al [6]
"Using a handheld Vis-NIR spectrometer, non-destructive prediction and detection of internal physiological disorders in 'Keitt' mangos" A popular tropical fruit, the mango (Mangifera indica L.) is susceptible to internal physiological disorders in its later stages of ripening. These include black flesh, which has a diffuse brown discoloration covering the seed, and jelly seed, which has transparent, jelly-like tissue surrounding it that eventually turns into a brown ring.
Inference for the literature survey are as follows-
A literature review is a critical and objective summary of published research that is pertinent to the framework that is being considered for research on the deep learning detection of fruit diseases. The synopsis is shown below:

SN	Article Name	Author Name	Year of Publication	Observations & Takeaways	Tools & Techniques
1.	Computer Vision System for Mango Fruit Defect Detection Using Deep Convolutional Neural Network[1]	R. Nithya , B.Santhi, R.Manikandan, Masoumeh and Rahimi H. Amir Gandomi	2022	This study aimed to develop a computer vision system for defect identification in mangoes using advanced machine learning techniques.	Techniques Used = Advanced machine learning techniques. Accuracy = 97.5%

2.	Non-destructive detectionof internal quality of mango using hyperspectral imaging technique[2]	K. Wang et al	2021	The authors found that the technique was effective in detecting these attributes and had potential for use in the mango industry.	Techniques Used = Hyperspectral imaging technique. Accuracy = 95.8%
3.	Classification of Mango Varieties using Machine Algoritham [3]	Vijay C.P, Yashpal Gupta S	2021	This study aimed to collected mango images and the mango image is converted to binary image and perform individual RGB colors. Feature extraction are applied to the segments to obtainfeatures. Then mango fruit image can be described by the set offeatures such as color, shape, and texture.	Techniques Used = Machine algorithms and Segmentation technique Accuracy = 90.3%
4.	Mango Quality Grading using Deep Learning Technique[4]	Varsha Bhole,Arun Kumar	2020	The usage of any deeper network is dependent on available hardware resources. We have triedvarious pre-trained networks and executed the experiments numerous times for evaluating their performance with respect toaccuracy and training time.	Techniques Used = DeepLearning algorithms Accuracy = 91.1%
5.	A Survey on Internal Defect Detection in fruits by Non-Intrusive Methods[5]	Anitha Raghavendra, Dr. Maheshrao	2016	The authors strongly feel that the NIR imaging techniques may be one potential area which can be applied to internal defect tracking in Mangoes thus helping with the exportof the same for India.	Techniques Used = NIR imaging Techniques
6	Identification and Classification of	Dameshwari Sahu,Chitesh	2016	Due to the growing demand of quality mango fruit, an automatic and reliable identification and classification mechanism to handle the bulk of data are implemented.	Techniques Used Image Processing

Table 1. Summary of literature survey

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III. METHODOLOGY AND TECHNIQUES

CNN Algorithm:

Convolutional neural networks, or CNNs, are deep learning algorithms that are frequently applied to tasks involving object detection and image classification. CNNs can be used in fruit defect detection to recognise and categorise various fruit defects, including blemishes, insect damage, and bruises. Convolutional, pooling, and fully connected layers are among the layers found in a typical CNN architecture. By applying a set of learnable filters to the input image, the convolutional layers extract features from the image. In order to lower computational costs and improve robustness to changes in the input image, the pooling layers down sample the feature maps. The features that are taken out of the convolutional and pooling layers are used by the fully connected layers to perform classification. CNNs are typically trained on large datasets of labelled fruit images for the purpose of fruit defect detection. In order to reduce the error between the predicted and true labels, the network's parameters are optimised during the training process. Once trained, the CNN can be used to categorise fresh fruit photos according to whether or not they have defects.

Dataset collection

The information was gathered from an image database that is publicly available and contains both healthy and defective fruit photos. To put the suggested framework into practise, data pertaining to fruit species was taken into consideration from that specific database. There are 150 fruit photos in the acquired dataset. There are roughly 75 healthy leaves and about 75 diseased leaves in the image database. Two databases, such as the training database and the testing database, were created from the image database. In Figure 1, the sample dataset is displayed.

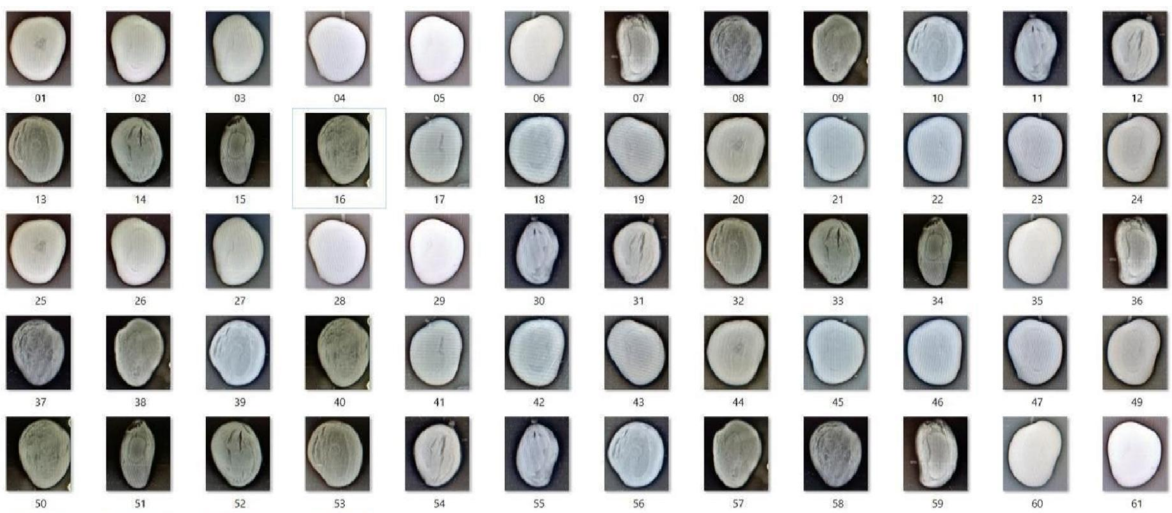

Figure 1. Sample of dataset

Image pre-processing

Pre-processing photos is crucial because we require consistency and a shared backdrop in our images. It will contribute to the neural network model's increased accuracy. However, in this case, we are not pre-processing the images in any way before training the model. The pre-built CNN model receives direct training from the gathered dataset. We are rotating every fruit image in the gathered dataset from 0-360º, or from every angle, to lessen the model's overfitting. It facilitates the dataset's expansion.

Deep learning model

A deep learning model called Convolution Neural Network (CNN) is used to detect fruit defects. It is constructed on top of the open-source neural network library Keras and the TensorFlow GPU backend. A sequential model is used to build the CNN model, stacking layers of a convolution neural network sequentially from input to output. Dense is used to gather the output from every neuron in the previous layer and send it to the one after it, Drop out is used to prevent overfitting in CNN layers, Flatten is used to flatten the data into one dimension, and Max Pooling2D is used to lower the computational cost. Fig. 2 shows the table that was produced as the sequential model's output.

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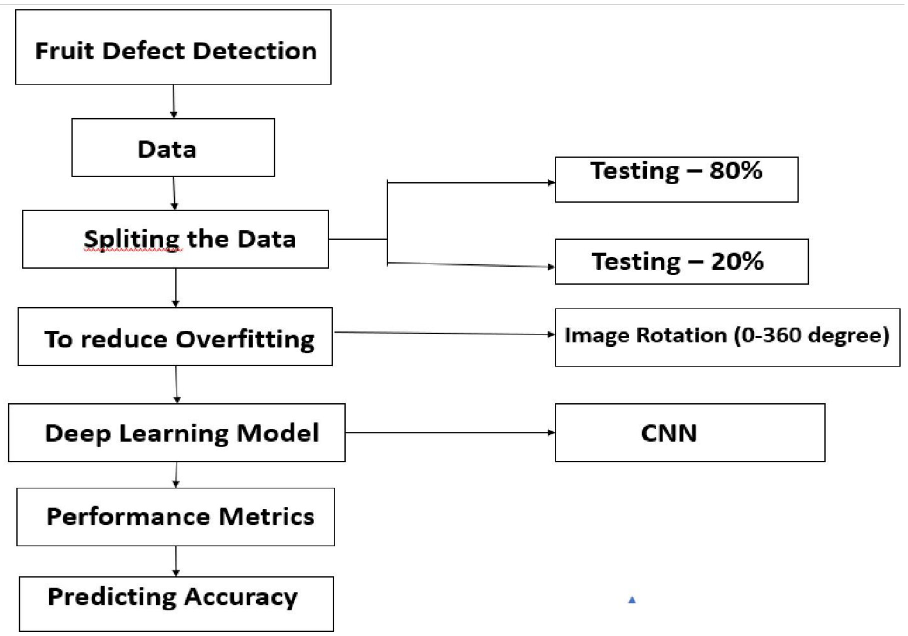

Figure 2. Deep Learning Model

The CNN architecture is available in numerous forms, such as the well-known VGG, ResNet, and Inception networks. The specific requirements of the fruit defect detection project, including the size and complexity of the dataset, the available computing resources, and the required accuracy and speed of the system, determine which CNN architecture is best.

VGG 16

Convolutional neural networks (CNNs) with the VGG-16 architecture are frequently used for image classification applications, such as mango defect detection. The Oxford Visual Graphics Group introduced VGG-16, or Visual Geometry Group 16-layer, during the 2014 ILSVRC (ImageNet Large Scale Visual Recognition Challenge) competition. Mango defect detection using the VGG-16 model requires customising the architecture for your particular issue. The Visual Graphics Group at Oxford University introduced the VGG-16 model, a well-liked convolutional neural network architecture mainly intended for image classification tasks. With its 16 weight layers, the model is easy to understand and highly efficient.

A few important things to keep in mind when modifying VGG-16 for mango defect detection are as follows:

Preprocessing of the input: VGG-16 normally captures 224 x 224 pixel images with three RGB colour channels. Before uploading your mango photos to the network, resize and adjust them.

Transfer learning is often used in conjunction with VGG-16. You can extract important features from a large dataset without having to start the model from scratch by using the pre-trained weights.

Custom Output Layer: Since mango defect detection is probably a multi-class classification issue, the VGG-16 model's output layer needs to be changed. The number of neurons in the output layer, each of which represents a class, will be proportionate to the number of defect classes.

Loss Function and Metrics: Select the right loss function (categorical cross-entropy, for example) and metrics to track during training (accuracy, for example) for multi-class classification. These decisions are based on the makeup of your dataset and the types of defects in your classes.

Data Augmentation: When training deep learning models, especially with a small dataset, data augmentation is essential. By using methods like rotation, flipping, and scaling to produce different versions of your mango photos, you strengthened the model.

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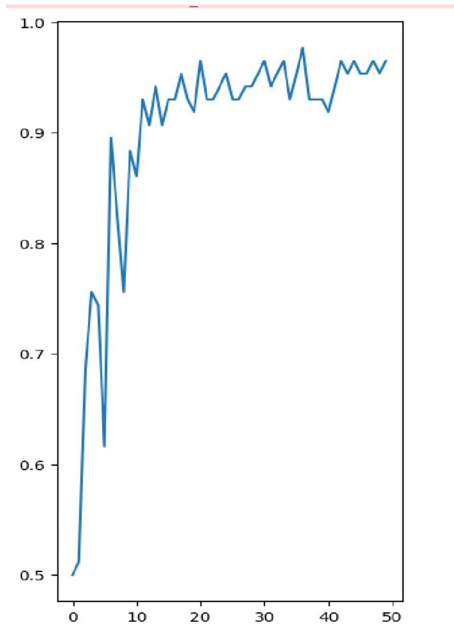
Training and Evaluation: Using your preprocessed data, train our custom VGG-16 model, then assess its performance on a different test set. Keep an eye out for overfitting during the training phase and, if needed, modify the model architecture or add regularisation strategies

Accuracy Validation-



Accuracy of VGG19 model

VGG 19

The Oxford University Visual Graphics Group introduced the VGG-16 model, which is expanded upon by VGG-19. As its name implies, VGG-19 is a deeper iteration of the VGG-16 model with 19 layers. With 19.6 billion floating-point operations, it is a lot bigger and more intricate than VGG-16. The architecture of VGG- 19 is known for its simplicity; it consists of a sequence of convolutional layers, max-pooling layers, and fully connected layers for classification. There are five important factors to take into account when modifying VGG-19 for mango defect detection:

Data Preprocessing: We first converted our mango pictures into a format compatible with the VGG- 19 model's input specifications (224 x 224 x 3), then we normalised the pixel values to fall between 0 and 1. VGG-19 can be utilised in conjunction with transfer learning. Load the pre-trained VGG-19 model (without the top classification layers) using weights that were learned from ImageNet. Next, include personalised classification layers appropriate for your task of detecting mango defects. You can specify how many mango defect classes you wish to find by changing the value of num_classes in the code.

Gather the Model: assembled the model using the proper loss function, optimizer, and assessment metric(s) for the particular issue at hand

Data augmentation: To increase the robustness and generalisation of your model, create variations of your training data using data augmentation techniques.

Training and Evaluation: We used our preprocessed data to train the model, and we assessed its performance using a different test set. Keep an eye out for overfitting during the training phase and, if needed, modify the model architecture or add regularisation strategies.

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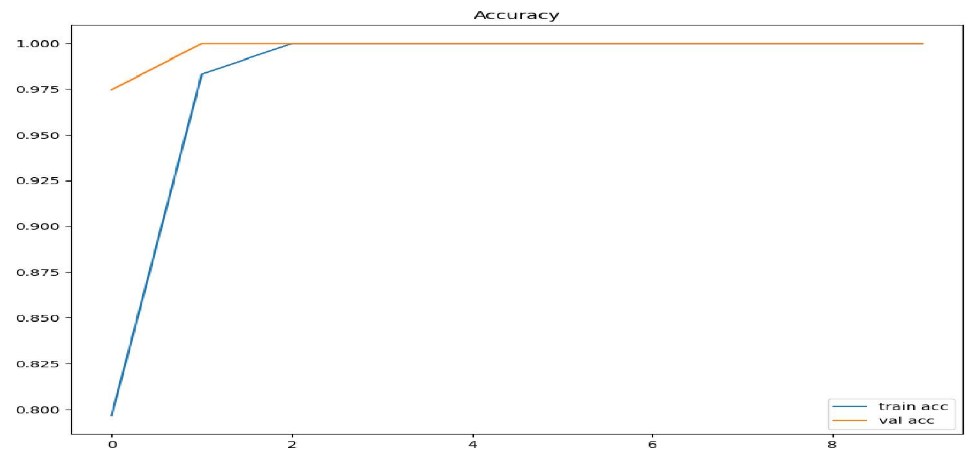
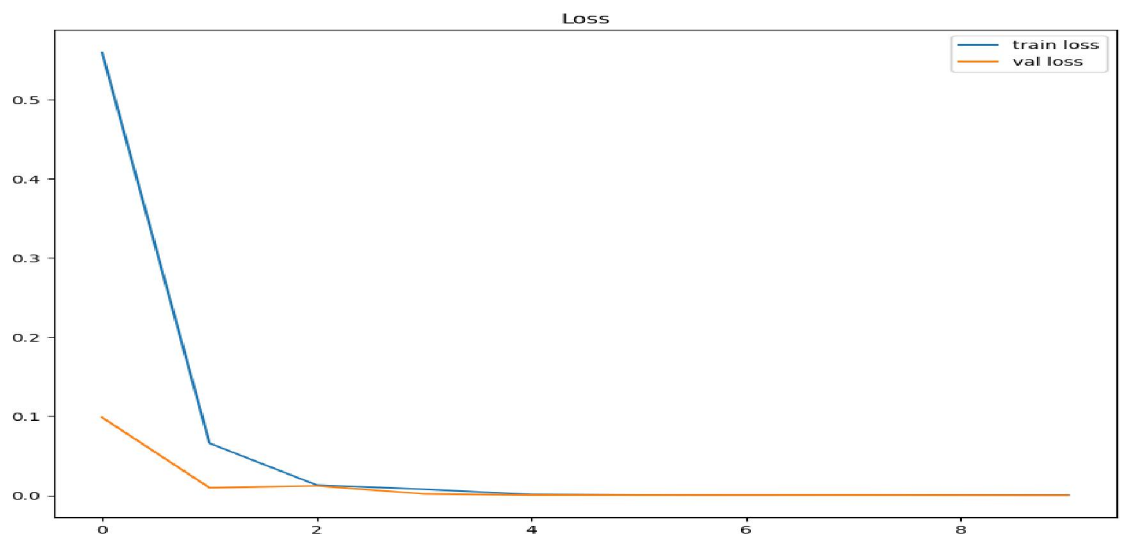
Accuracy Validation-



Accuracy of VGG19 model

Loss Validation-



Loss of VGG19 model

ResNet101

Microsoft Research first presented the deep convolutional neural network architecture known as ResNet-101, or Residual Network with 101 layers, in their 2016 paper "Deep Residual Learning for Image Recognition." A version of the original ResNet model called ResNet-101 was created to solve the vanishing gradient issue and enable the training of extremely deep neural networks. The utilisation of residual blocks, which include shortcut connections that omit one or more layers, is the primary innovation in ResNet architectures. These short cuts allow gradients to flow more easily during backpropagation, which makes it possible to train incredibly deep networks.

Transfer Learning: ResNet-101 is compatible with transfer learning, just like VGG-16 and VGG-19. Remove the top classification layers from the pre-trained ResNet-101 model, which was trained on a sizable dataset such as ImageNet. You can specify how many mango defect classes you wish to find by changing the value of num_classes in the code.

Training and Compilation: Assembled the model using the suitable evaluation metric(s), loss function, and optimizer for your particular issue. Utilising our preprocessed data, train the model.

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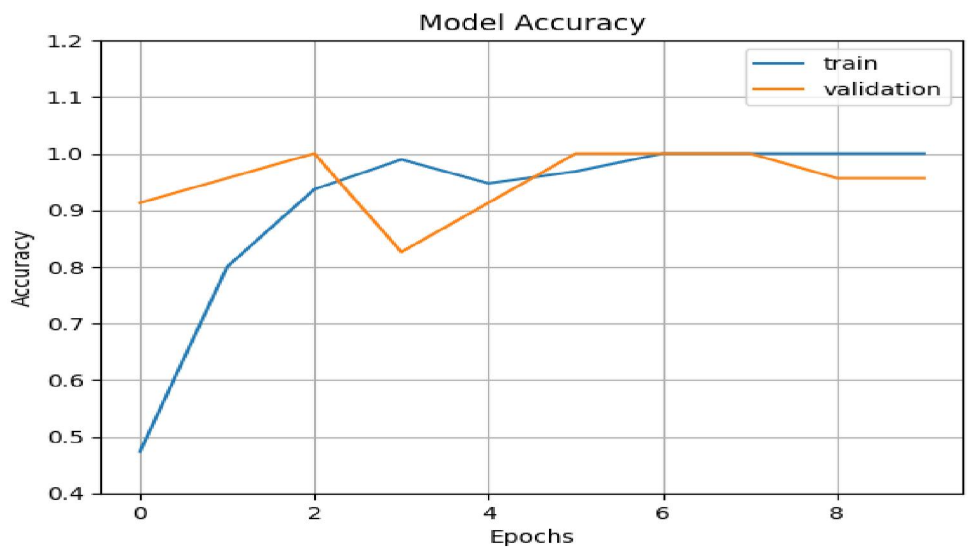
Data Augmentation: To improve the model's generalisation, we created variations of our training data using data augmentation techniques.

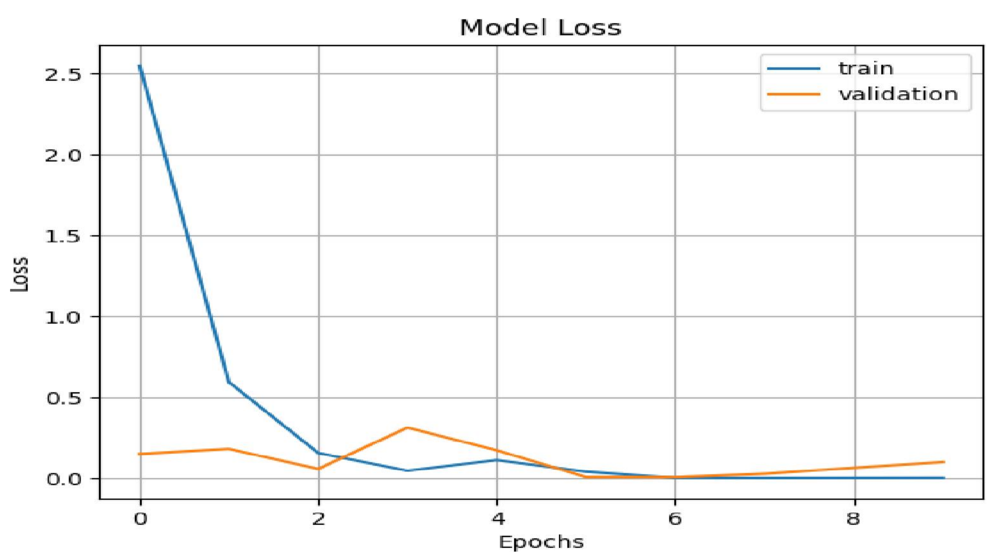
Assessment: Examine the model's performance using a different test dataset in order to determine its accuracy and other pertinent parameters.

Accuracy Validation-



Accuracy of ResNet101 model

Loss Validation-



Loss of ResNet101 model

System Description

The suggested framework was put into practise using an Intel(R) Core(TM) i5-9300H CPU running at 2.40 GHz on Windows 11 with 8 GB of RAM.

Using CNN, TensorFlow, data augmentation, and the TF dataset to build a model ML Operations and Backend Server:TF Serving, FastAPI

Model Optimisation: Tensorflow Lite and Quantization Deployment: GCP (Google cloud platform), GCF (Google cloud functions) Frontend: React JS, React Native

To Train A Model We Do following steps**:**

Developing a Normalisation and Resizing Layer

We should resize our images to the correct size before feeding them into the network. Additionally, we ought to normalise the image pixel value in order to enhance model performance. This ought to occur during both inference and training. As a result, we can include that in our sequential model as a layer. You may be wondering why it's necessary to resize the image to (75, 75) once more. You are correct that we don't have to, but knowing this will help when we finish the training and begin utilising the model to make predictions. At that point, this layer will resize any image that someone supplies.

Data Augmentation

When we have less data, we must use data augmentation to improve the accuracy of our model

Model Architecture

In the output layer, we employ a CNN in conjunction with a Softmax activation. Additionally, we add the first layers of data augmentation, normalisation, and resizing. Here, convolutional neural networks, or CNNs, will be used. For image classification tasks, CNN is widely used.

Assembling the Framework

We employ accuracy as a metric, Sparse Categorical Crossentropy for losses, and the Adam Optimizer.

Keeping the Model Safe

We add the model as a new version to the list of models.

Testing and Validation:

A different set of images would be used to test and validate the trained model. To find out how well the model detects potato leaf disease, its accuracy, precision, and recall would be assessed.

Function to Split Dataset:

The dataset ought to be divided into three subsets, specifically:

A dataset is used for training

It is validated and tested against during training

It is tested against after a model has been trained.

Deployment:

For on-device inference, the trained model would be installed on a mobile or embedded device. This would eliminate the need for specialised tools or in-depth knowledge and allow farmers and other agricultural workers to harvest quickly and accurately in the field.

All things considered, the suggested deep learning and TensorFlow-based fruit defect detection system has the potential to increase the effectiveness and precision of defect detection in fruit cultivation, resulting in better control strategies and higher yields

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UML Diagram

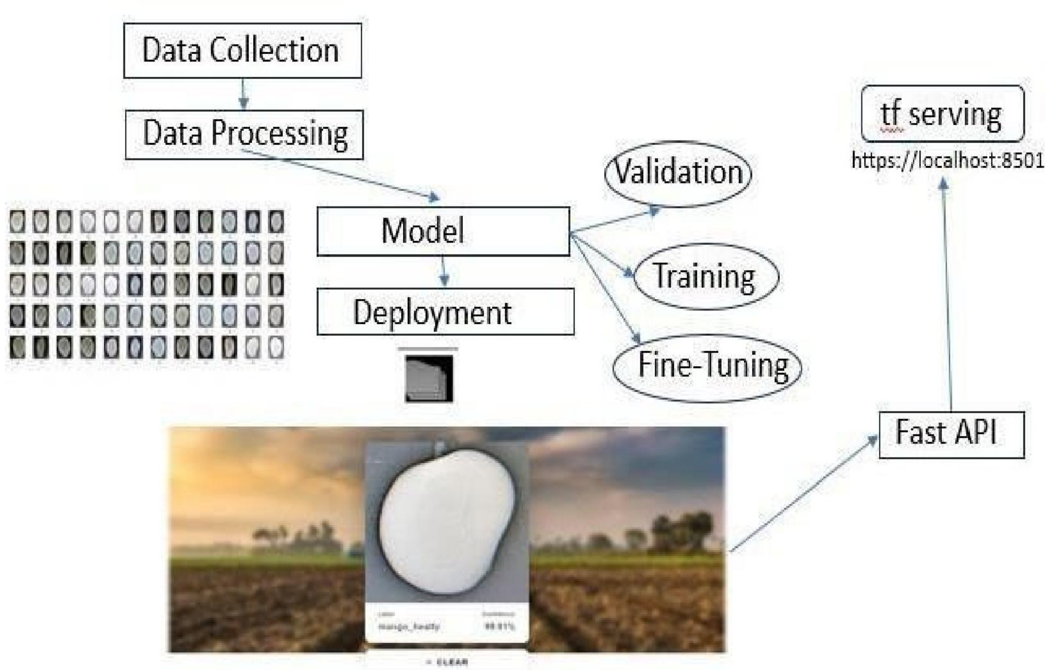


Figure 3.UML Diagram

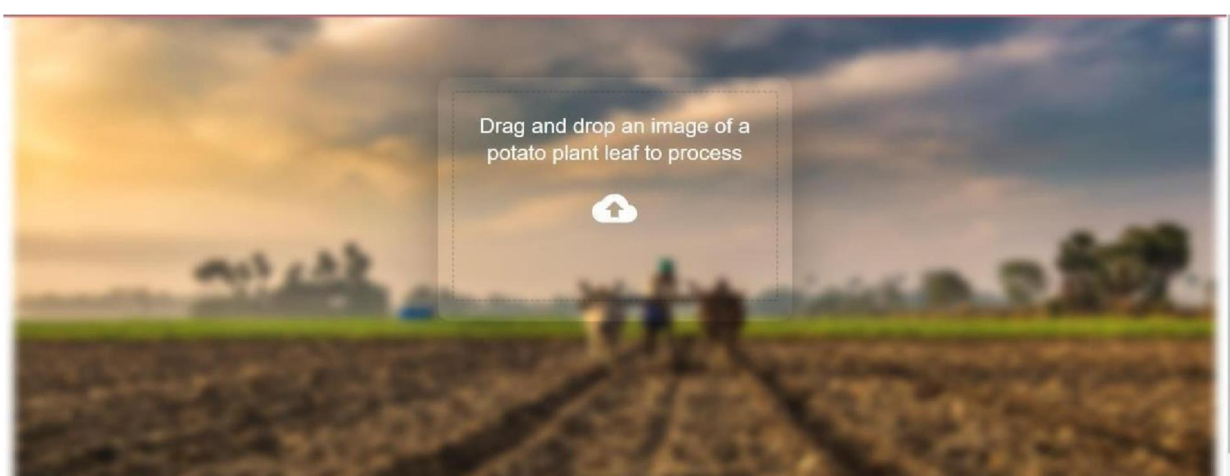
The system's general flow is depicted in the diagram. A fruit image is used as the input at first, and preprocessing is applied to get the image ready for analysis. A convolutional neural network (CNN) is then fed the preprocessed image in order to extract features and classify the image. The predicted defect class for the input image is
the CNN's output.

The system consists of four primary parts:

Fruit Image: This is the system's input. It is a digital picture of fruit that was taken with a camera or another gadget.

Preprocessing: This step gets the input image ready for examination. It could involve actions like noise reduction, image resizing, and pixel value normalisation

IV. IMPLEMENTATION AND DISCUSSION



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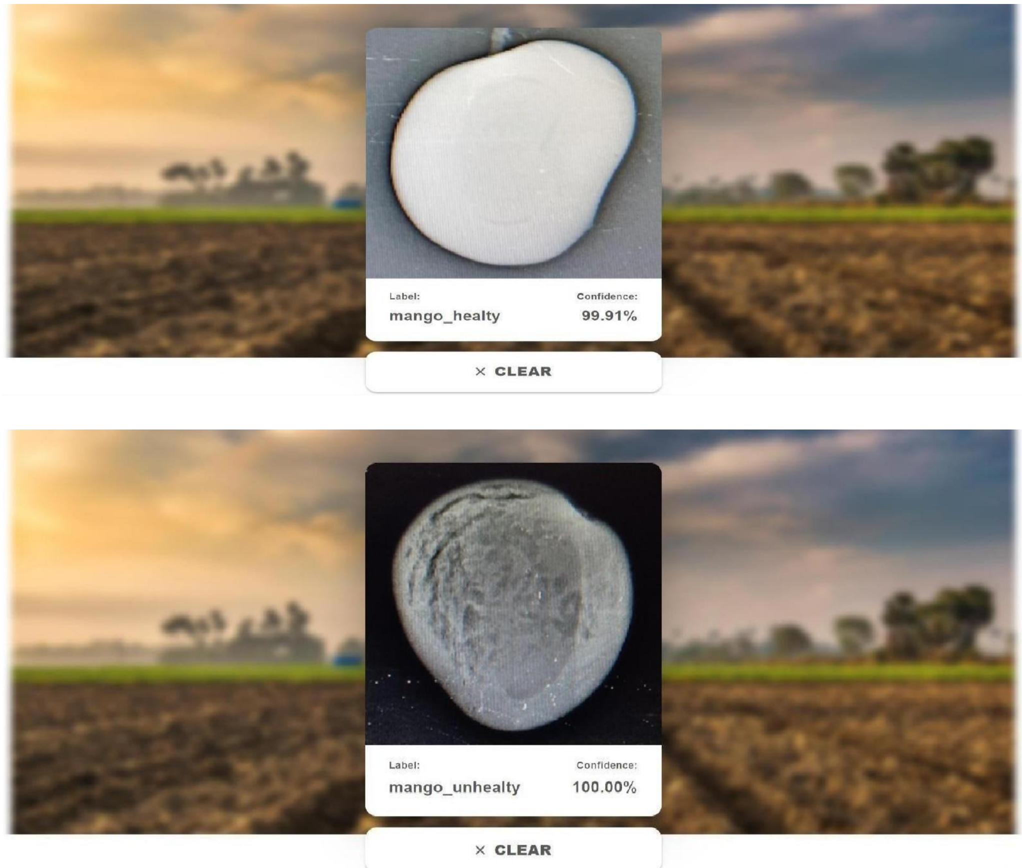

Figure 4. Screenshot of Output

Performance Evaluation

The suggested framework is made up of supervised deep learning techniques for model formation. Additionally, the ResNet101, VGG19, and VGG16 algorithms were used to solve the classification problem. With an accuracy of 97.69%, the VGG16 model performed mediocrely when compared to other models. With an accuracy of 95.94%, the VGG19 model ranks second among the other models. This indicates that the 19- layer Convolutional Neural Network architecture of the VGG19 model was more effective in detecting osteosarcoma. When compared to other models, the ResNet101 model's accuracy is the highest at 99.36%.

ResNet architectures are a good option if computational resources permit, particularly ResNet-50 or deeper variants.They are easier to train in very deep configurations and are capable of capturing complex features. VGG16 may be a good option if processing power is limited because it strikes a balance between model complexity and accuracy. If a slightly deeper network is required, VGG19 can be used, but it may take longer to train and require more memory than VGG16.Generally speaking, it's best to begin with a more basic architecture, such as VGG16, and if needed, look into more intricate models, such as ResNet. Additionally, take into account methods such as transfer learning, which involve using a pre-trained model and refining it using your own mango defect detection dataset.

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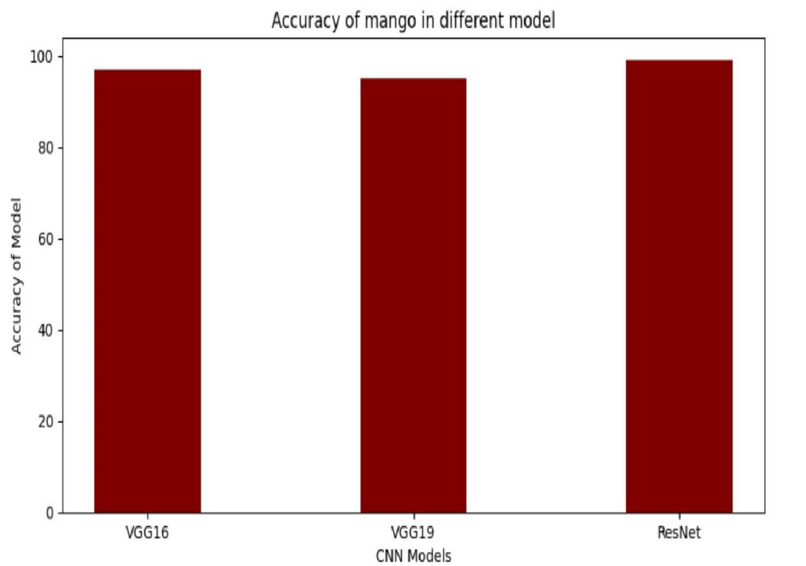

Figure.5 Comparison of all models

V. CONCLUSION

In order to improve growth and yield protection, digitalization should be incorporated into agriculture as it is becoming more and more prevalent in all other fields. With this goal in mind, the suggested model to identify and categorise the impacted and unaffected fruits is developed. The current state of research on deep learning and Tensorflow-based fruit defect detection suggests that these technologies have a great deal of promise for precisely identifying and categorising various fruit defects. Convolutional neural networks (CNNs), one type of deep learning algorithm, can help overcome the drawbacks of conventional techniques and produce more accurate and effective detection results.

The suggested approach achieved 97.8% accuracy, high precision, and recall after being trained on the dataset both with and without data augmentation techniques. Compared to the state-of-the-art methods, it was simpler and required fewer parameters, which resulted in significant computational savings and speed improvements.

Future Scope

Future iterations of this research would detect more than one disease on a single fruit, localise the diseases, estimate the severity of the diseases, improve the PLD dataset, create an IoT-based real-time monitoring system, create a website, and release a mobile application. We think this work has a lot to offer farmers worldwide and the agricultural industry.

To increase the accuracy and generalizability of these methods across various datasets and environments, more research is required to optimise and refine them. Prospective avenues for future investigation could encompass investigating the application of transfer learning, optimising models for particular environmental circumstances, and incorporating supplementary data sources like soil and climate information.

Furthermore, it is imperative to undertake endeavours to enhance the accessibility and user-friendliness of these technologies for farmers and other stakeholders who might lack profound technical proficiency. To make adoption and implementation easier, this could entail creating user-friendly interfaces and integrating the technology with other tools for agricultural management.

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