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Machine Learning-Based Detection Of Fruit Freshness: A Data-Driven Approach For Quality Assessment

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This Research Aims To Create An Efficient And Reliable System For Assessing Fruit Freshness In Large-Scale Environments Like Juice Production Facilities, Supermarkets, And Storage Warehouses. The Goal Is To Enhance Processes Related To Fruit Grading, Packaging, And Overall Supply Chain Management. While Convolutional Neural Networks (Cnns) Are Exceptional At Automatic Image Recognition, Distinguishing Fruits That Share Similar Shapes And Colors Presents A Notable Challenge. To Address This, We Introduce A Deep Learning Model Designed To Classify Fruits According To Their Freshness Across Six Distinct Fruit Categories. The Model Harnesses The Power Of Three Pre-Trained CNN Architectures—VGG-19, Resnet50v2, And Densenet201—To Extract Robust And Significant Features From Fruit Images. Additionally, We Employ Two Image Enhancement Techniques: The Discrete Wavelet Transform (DWT) For Noise Reduction And Seg.Net For Improved Image Segmentation. Our Proposed System Achieved A Remarkable Accuracy Rate Of 98.05% On The Test Dataset. These Findings Demonstrate That The Integration Of CNN Models With Sophisticated Pre-Processing Strategies Significantly Boosts Both Accuracy And Reliability. This Framework Provides A Practical Solution For Automated Fruit Grading And Freshness Evaluation, Enabling Industries To Uphold Superior Quality Control And Enhance Efficiency Within Agricultural Supply Chains.

Keywords: *Deep Learning, Convolutional Neural Networks (CNN), Fruit Grading, Image Segmentation, DWT, Seg.Net, VGG-19, ResNet50V2.*

I. INTRODUCTION

Fruit plays a significant role in fresh produce production and storage. Fruit Shops: Fruit screening, statistics, and transporta- tion systems are improved by supermarkets or shops. Fruits come in a wide variety and are sometimes uneven in shape and color, making grading them a very challenging challenge. The primary goal of the fruit classification method suggested in this paper is to identify the freshness of juicy fruits using an improved convolutional neural networks. Vitamins, dietary fiber, and a variety of micronutrients necessary for our bodies to function properly are all found in fruits, which also contain critical nutrients. Their consumption has been linked to public health nutrition with significant demonstrated data. Numerous organizations, including the United States Department of Agriculture, the Food and Agriculture Organization, the European Food Safety Authority, and the World Health Organization (WHO), advise eating fruits because of the health advantages that come from their high fiber and micronutrient content. According to various studies, fruits can help prevent and treat conditions like heart disease, hypertension, and stroke. The need to assess the quality of fresh fruit has grown significantly over the past ten years as a result of food supply chain safety and hygiene concerns. Additionally, buyers are increasingly aware of the caliber of the goods they buy. Produce quality is determined by chemical analysis, which leads to sample damage, lengthy testing times, intricate procedural steps, and an inability to detect in real-time. Although hyperspectral imaging and near-infrared spectroscopy have become popu- lar nondestructive physical detection techniques, the spectral shifts brought on by food's physical characteristics can obscure their efficacy. Routine procedures based on consumer preferences through sensory evaluation and individual satisfaction levels are still used to assess the quality of agricultural and food goods. Fruit color and product quality have a strong correlation that can influence consumer preference. In this sense, identifying the freshness of fruits can be aided by an image recognition technique. Freshness detection is an important task in the fruit supply chain. The traditional and effective method for assessing fruit freshness is the human sensory evaluation, but this approach is often susceptible to subjective influences from the evaluators. As a result, mass spectrometry and chromatographic detection techniques have become a new alternative to traditional ways of freshness detection. Mass spectrometry and chromatographic techniques provide non-destructive detection and are less susceptible to subjective biases from the operators [1].

II. AUTHOR CONTRIBUTION

- 12 distinct image modalities from the open source dataset were employed; we only used juicy fruits from this dataset to train our freshness recognition model.
- De-noising of natural images by discrete wavelet tech- niques (DWT). The Discrete Wavelet Transform (DWT) is a commonly used technique for image de-noising. It operates by decomposing an image into different frequency components using wavelet filters. It helped us to improve accuracy of our suggested model
- Different CNN intelligent paradigm like VGG-19, Resnet50v2, and Densenet201 are used for automatic feature selection from DWT extract frequency band. ResNet-50 encoder-decoder has also been utilized to generate image encoded vector.
- Obtaining a dataset, generating features of independent variables, and applying them to the prediction of a dependent variable or target class are the fundamental steps of classification modelling. The Extreme Boost (XG-Boost) Classifier is used in this paper for further improvement in face detection and recognition process.

III. ARTICLE ORGANIZATION

This is how the rest of the paper is structured. Existing approaches and related work are examined in Section 4, and the methodology section, which also contains the data preparation subsection, is described in Section 5.

The fundamental system architecture for a luscious fruit freshness detecting system is shown in Section 6. In this section, the suggested approach framework is described. The pre-trained models are also explained. The results and experimental outcome of the suggested model are assessed in Section 7. Section 8 discusses the research work's conclusion.

IV. RELATED WORK

This section provides a quick overview of current study that use machine learning and image processing to categorize different fruits. The summary of recent works in the field is shown in Table**?** The study's authors [2] suggested a technique to identify the fruit in a picture and calculate the extent of the fruit damage. To enhance fruit disease detection and identification, the Inceptionv3 model was employed. The study [3] creates an automated fruit grading system for apples to categorize them according to their outward characteristics. Various combinations of many characteristics are analyzed based on the extent of apple fruit damage. In this work, the SVM was trained using these attributes as input. Two distinct apple databases were used to test the classifier: one contained 100 color photos of apples, 24 of which featured fruits with various flaws, and the other contained 112 photos of apples, 56 of which featured apples with various flaws. For the two datasets, the greatest accuracy was 93.00% and 96.81%, respectively. The experiments [4] were carried out in MATLAB using the suggested framework. At 97.2%, the high- est accuracy was achieved. The paper presents deep learning-based external tomato fault identification. A wide range of fruits, such as apples, sugarcane potatoes, grapes, tomatoes, and maize, as well as numerous plant diseases, were the focus of the study in. To train the models to identify plant illnesses, the researchers [5] used photos of both healthy and damaged plant leaves. With a 96.5% accuracy rate, the system was 100% accurate in identifying and distinguishing between the kind of plant and the plant disease. A deep learning architecture-based segmentation of the apple's rotten area is presented in the work in [6]. With impressive outcomes, U-Net and its improved counterpart, Enhanced U-Net (En-UNet), have been employed for image segmentation tasks. The En-UNet model demonstrated remarkable training and validation accuracies of 97.46% and 97.54%, respectively, while the original U-Net architecture reached an accuracy of 95.36%. When evaluated against a 0.95 criterion, En-UNet recorded an IoU score of 0.866, significantly outperforming U-Net's score of 0.66, highlighting a notable enhancement in segmentation effectiveness. The research also explored the use of tools like SSD and YOLOv2 for detecting defects in apples. In a focus on transfer learning strategies, the authors of [7] introduced a model designed to differentiate between fresh and decayed fruits, using images of bananas, oranges, and apples. Their CNN model's performance was benchmarked against well-known architectures including Mobile.Net, VGG16, VGG19, and Xception. A thorough examination of various hyper parameters-such as batch size, optimizer type, learning rate, and training epochs—was conducted to pinpoint the optimal setup for precise fruit classification. Including batch size, optimizer, learning rate, and epoch count. The results demonstrated that, with an accuracy of 97.82%, the proposed CNN model performed better than transfer learning techniques in correctly distinguishing fresh and rotting fruits. In order to recognize and classify ripe Medjool dates, the researchers in [8] assessed the performance of many CNNs while accounting for transfer learning for their training and a few hyper parameters.

The CNN architectures that were assessed were CNN created from scratch, VGG16/19, and ResNet50/101/152. The batch size, optimizer, learning rate, number of layers, and epochs were the hyper parameters that were examined. They found that the VGG19 model performed best with a batch size of 128 with a learning rate of 0.01 and an Adam optimizer, achieving an accuracy of 99.32%. The study [9] determined the mellowness of the dragon fruit using the ResNet152 model. Python and Tensor Flow were used to train the model. After being trained with pictures of the dragon fruit at different mellowness levels, the resulting structure was tested with 100 more samples using the ROC and the confusion matrix. Epoch numbers between 10 and 500 were used for the experiment. Compared to VGG16/19, the results were more accurate.

V. METHODOLOGY

Our developed method has various interconnected modules as shown in Figure 1. Below, we describe the various modules that are used in our developed algorithm.

A. Data Description

In order to create our method for classifying the freshness of fruits, we obtained data on various fruit photos from Kaggle (www.kaggle.com). The Kaggle dataset is openly accessible and includes classes of diverse fruits, including oranges, apple, and grapes. There are three types of fresh and decaying photos in the fruits image collection that Kaggle has made available. Additionally, the fruit dataset includes photographs of rotting apples, rotten grapes, rotten oranges, fresh apples, and fresh grapes in distinct files. Figure 2 represents the sample data from the database.

1) Dataset 1: 3375 different photos of both fresh and rotten fruit types are included in this data set [10]. In particular, there are ten distinct classes in this dataset. Mangos, oranges, apples, and grapes are the most common fruit categories collected in this dataset. There are at least 500 photographs in each of the dataset's new categories, including at least 500 images in the rotten category.

2) Dataset 2: 12045 photos of both fresh and decaying fruits make up this dataset. There are a total of six classes in this dataset, with three classes for each of the fresh and rotting apple, orange, and grape varieties. The dataset's details are shown in Table I. Table I makes it evident that there are at least 1400 photos in this collection for the fresh fruit categories of apples, oranges, and grapes. In contrast, there are more than 3980 photos in the fresh fruits categories and 4583 photos in the rotten fruits collection.

Authors	**Years**	**Datasets**	**Methodology**
Nikhitha et al. [2]	2019	ImageNet, and Fruit Classification dataset from GitHub containing 522262 images	
Bhargava et al. [3]	2020	Dataset was created using the photos captured from mobile phone	
Costa et al. [4]	2020	An uncensored dataset with 43,843 images including external defects was built during this study	
Militante et al. [5]	2019	The study utilized dataset from	

The fruit image data set from Plant village Dataset Dalila et al. [8] 2021

Used Inception V3 model to detect grading of disease in Apple fruit

Datasets are used to train Support Vector Machine (SVM.)

A ResNet50 with all of its layers optimized was the best model.

Artificial Neural Network (ANN) is used
Roy et al. [6] 2021

Palakodati et al. [7] 2020
Kaggle.com containing 1693 fresh apple and 2342 rotten apple's images

The dataset is obtained from Kaggle which has three types of fruits-apple, bananas, and oranges with 6 classes.

U-Net and a modified version of it is used.

Soft-max is used to categorize the input fruit photos into fresh and rotting fruits after a Convolutional Neural Network (CNN) has extracted the characteristics from the images.

The image data set contained 1002 images in
JPG format. data is collected from various sources.

The CNN architectures evaluated were VGG-16, VGG-19, ResNet-50, ResNet-101, ResNet-152, Alex.Net, Inception V3

Vijayakumar et al. [9] 2020 Data is collected from different sources.

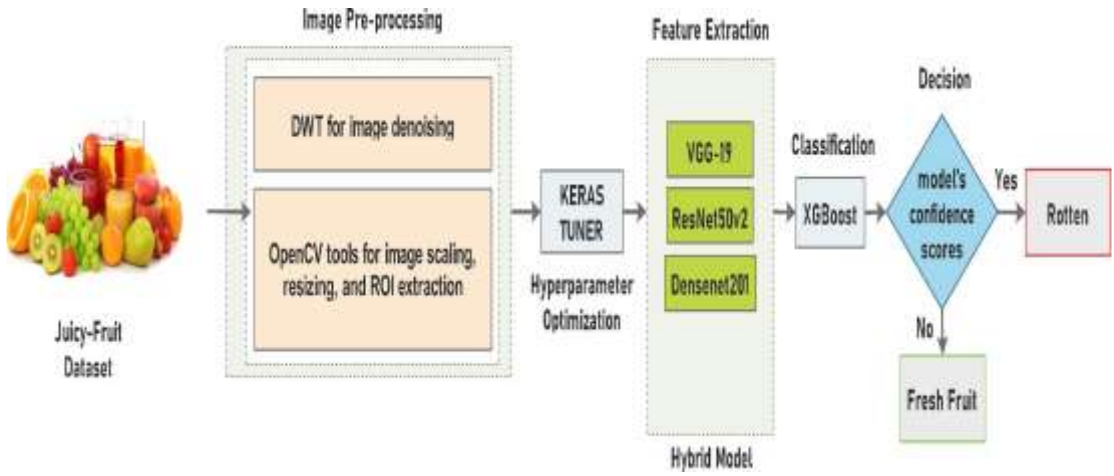

Fig. 1: Block diagram of methodology used to detect freshness in juicy fruits

B. Pre-processing

A preprocessing step is done to the fruit images since they originate from various datasets with varying image sizes and acquisition settings, which, if not dealt with, could hurt the models' performance. As a result, it's likely that a wide variety of cameras, each with its own technology and pixel count, were utilized to capture the images.

C. Image Segmentation

Figure 3 illustrates how the photographs in this study were resized to 224 x 224. In order to remove the fruit regions and the identical black backgrounds before using them to train the VGG-19, the segmentation approach using images of the same size was presented. Specifically, the HSV colour space and histogram thresholds were used to create binary pictures prior to segmentation in order to generate the same background and fruit sections.

D. KERAS Tunner

A robust library for fine-tuning hyper parameters in deep learning models constructed using Keras is called Keras Tuner. Hyper parameters like learning rate, number of layers, and number of units in each layer, dropout rates, and more may all be optimized with it. The Keras tuner was used to tune the learning rate and dropout values.

The hyper parameter search was conducted at [0.03, 0.003 0.0003] and [0.65, 0.70, 0.75] for learning rate and dropout, respectively [11]. The batch size value was selected in accordance with low-performance computing guidelines. Although 0.001 is the default value for the Adam optimizer, 0.0003 is a frequently used figure, which was taken into consideration when choosing the learning rate settings. Thus, an order of magnitude reduction,

Fig. 2: Few sample images of fresh and rotten fruits.

Dataset-1	**Fresh Fruits**	**Rotten Fruits**
Apple	552	436
Orange	480	536
Grapes	385	485
Dataset-2	**Fresh Fruits**	**Rotten Fruits**
Apple	1826	2258
Orange	1624	2040
Grapes	1992	2305

TABLE I: Summary of collected data used in training and testing the proposed model.

Ranging from 0.03 to 0.0003, was employed. Because the pre- trained model's amplitude could lead to the predictive model overfitting, high dropout levels were selected.

E. **XG-Boost**

Based on gradient-boosted decision trees, the XG-Boost model is renowned for its effectiveness in handling missing data and determining the significance of features. By including error-minimizing trees, this model repeatedly improves pre- dictions [12]. The prediction challenge was handled using the XG-Boost regression model. Grid search and threefold cross- validation were used to optimize the model's hyper parameters. To reduce the squared error. The model was trained on the whole training dataset once the ideal hyper parameters were determined, and it was then assessed on the test set.

VI. PROPOSED MODEL

We used two Kaggle datasets to demonstrate the effective- ness of our proposed model for fruit freshness identification. The section of the paper above describes this dataset. Data pre-processing, picture encoding, data splitting, feature ex- traction, classification, and freshness detection are among the fundamental phases in our suggested approach. Our suggested model's block diagram is presented in Figure 1 below. The first step in the recommended approach for detecting freshness in juicy fruits is to obtain facial shots or images of varying quality, after which the selected image is de-noised.

$$Dc = \sigma^{\surd}(2 \log L) \qquad (1)$$

Where L is the data length, Roh is the predicted noise variance of the data according to the equation, and Dc is the universal threshold value. Universal threes holding is non-data dependent since it does not statistically verify every piece of data. Nevertheless, it is definitely an adaptive threshold technique because its formulation incorporates factors such as L and. Every level of breakdown has two stages. Figure 4 illustrates how phase I filters horizontally and phase 2 filters vertically. When the input image is N x N in size, the first- level decomposition produces the three sub bands LH, HL, and HH, each of which has a dimension of N/2 X N/2. The three N/4 X N/4 sub bands LLLH, LLHL, and LLHH are the outputs of the second-level decomposition, with the LL band acting as the input. The third-level decomposition uses the LLLL band as its input and the four N/8 x N/8 sub bands (LL)2LL, (LL)2LH, (LL)2HL, and (LL)2HH as its thresholder outputs
[13] [14]. After thresholding, the image is rebuilt using the inverse wavelet transform.

We used the Seg.Net network to work on the picture seg- mentation process in the next phase. Seg.Net is a three-depth encoder-decoder deep neural network. The VGG16 network's Convolution layers resemble Seg.Net encoder. The decoder in SegNet uses pooling indices from the matched encoder's maximum pooling to build the segmentation mask.

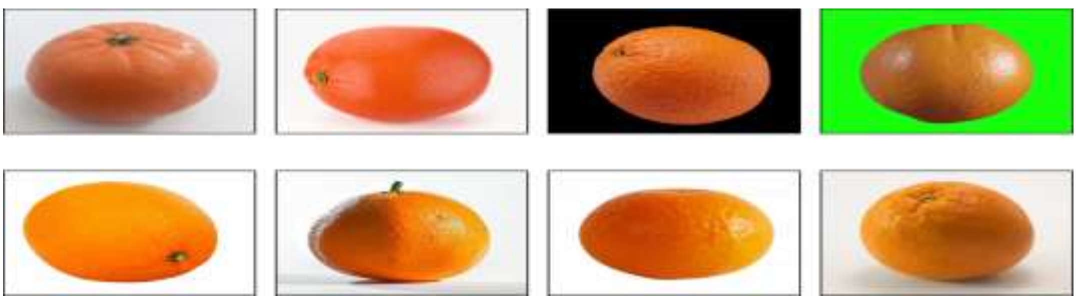

Fig. 3: Preproessed and resized images from datasets

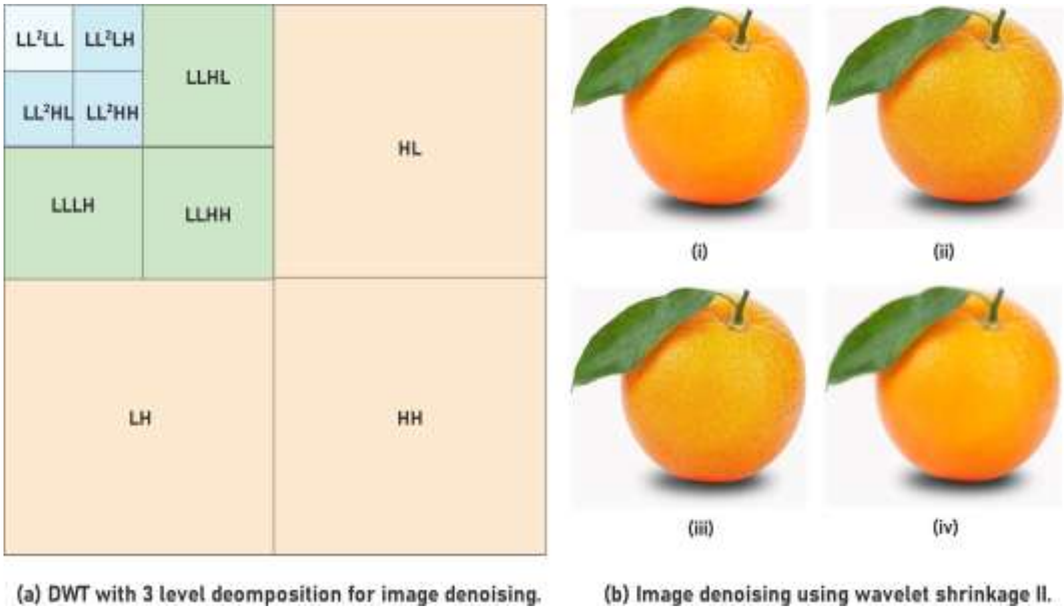

Fig. 4: Pre-processing for image-de-noising using DWT

A. Pre-trained CNN

Image classification is one of the most fundamental and useful fields of research in computer vision. Convolution neural networks (CNNs) have achieved remarkable success in image classification in recent years due to its fully trainable network structure and fast and accurate feature extraction Function. The groundwork for the future CNN was established in the 1990s.

B. VGG-19

With 19 connection layers—16 convolution layers and 3 fully connected levels—the VGG-19 is a deep learning neural network. The fully connected layers will categorize the leaf photos based on the attributes that the convolution layers have extracted from the input images. Furthermore, the max-pooling layers will prevent overfitting and minimize characteristics.

C. ResNet50v2

A deep convolutional neural network commonly used for image recognition and computer vision tasks is the ResNet50 (Residual Network with 50 layers), of which ResNet50v2 is a version. In the study, it was presented as a member of the ResNet-v2 family [15]. We chose this model because it

A number of evaluation criteria, such as accuracy, precision, F1-score, specificity, sensitivity, and positive likelihood ratio (+LR), are used to assess the performance of the suggested model. Table II displays the metrics' formulation together with the parameters that go with them.

TABLE II: Formulae for Evaluation Metrics
Uses identity mappings to skip some levels, making it easier for gradients to flow during backpropagation. In very deep networks, these links aid in mitigating the vanishing gradient issue.

D. Densenet201

We developed a convolutional neural network (CNN) ar- chitecture, usually pre-trained on the dataset we used in this article, and optimized it for the particular job of categorizing fruit freshness using Dense Net for fruit freshness detection. Dense Net is ideally suited for extracting significant characteristics from images due to its dense connection and effective parameter usage. Figure 5 depicts the basic architecture of Densent201.

VII. RESULT AND DISCUSSION

This part also includes the tests conducted to assess the efficacy of the suggested approach as well as the multi-spectral databases that were utilized in the dataset. Our research then focusses on the Res.Net CNN layers that need to be adjusted to improve the quality of the picture embedding. We then investigate which classifiers are more effective at identifying the freshness of the fruit's layers using the 256-d embedding. In the final study, the best classifier is compared to the most sophisticated methods for multi-spectral picture degradation recognition. After that, we used a skin detector, which operates at the pixel level. At this point, the normalized difference between each fruit's face channels is determined as.
Pd $[d_i, d_j]$.

$$Pd\,[d_i, d_j] = {}^{di - dj} \qquad (2)$$

Where d is the pixel intensity value for channels a and b with i j n and id is the number of channels accessible in the presentation assault detection module, indicated by n. The range of the normalized differences is 1 Pd[di, dj] + 1. The normalized difference values are used by the fruit's image pixel detector to classify the pixels as "skin" or "not skin". A binary map is used to represent the skin pixels, with 1 standing for skin and 0 for not-skin. This binary map is used to determine the number of fruit's layers landmarks that the presentation attack detector deems to be skin. The pre-processing stage's results form the basis of the modules for identifying freshness. Images of fruits are cropped, scaled, and normalized to match the proportions of the suggested CNN. After that, the CNN analyses the image to determine its 256-d embedding vectors. To ascertain which layer should be adjusted using domain- specific data and what kind of classifier parameter yields the best results, a variety of experiments were carried out.

Parameter	Formula	
Precision	$TP * 100$	$TP + FP$
Recall or Sensitivity	$TP * 100$	$TP + FN$
Specificity	$TN * 100$	$FP + TN$
	$2*(PPV * Sensitivity)$ $PPV + Sensitivity$	F1-Score $* 100$
Accuracy	$TP + TN$ $* 100$	$TP + FN + FN + TN$

When a model is being trained and tested, a convergence curve shows the optimal value of the learning parameter in terms of the accuracy of the model in relation to the loss function. The convergence curves of the suggested and alter- native models are shown in Figure 6. VGG-19, Resnet50v2, Densenet201, and the suggested method are each shown by a sub-figure. The suggested models' 200-epoch training and validation accuracy curves are shown. The training and vali- dation accuracy of the proposed model show a faster rate of convergence and an accuracy of 98.05%, which is higher than the accuracy of the models that were previously developed.

VIII. CONCLUSION

In this study, we evaluate the model using different epochs and batch sizes using the Adam optimizer until we obtain a good result, as shown in Table III. In this experiment, our suggested model achieves 98.05% accuracy, while the VGG-
19 model achieves 95.22% accuracy, Resnet50v2 achieves 97.10% accuracy, and Dense net achieves 97.54% accuracy. The convergence and roc curves have been used to gauge the effectiveness of our strategy. The performance of the Dense net network improved with XG-Boost is higher. One goal unites all machine learning algorithms: a reduced loss. The loss function can also be referred to as the cost function. In contrast to VGG-19 (training loss = 0.024%) and LBPH (training loss = 0.045%), our proposed study reveals that Dense net generates the most reliable outcomes. proposed study.

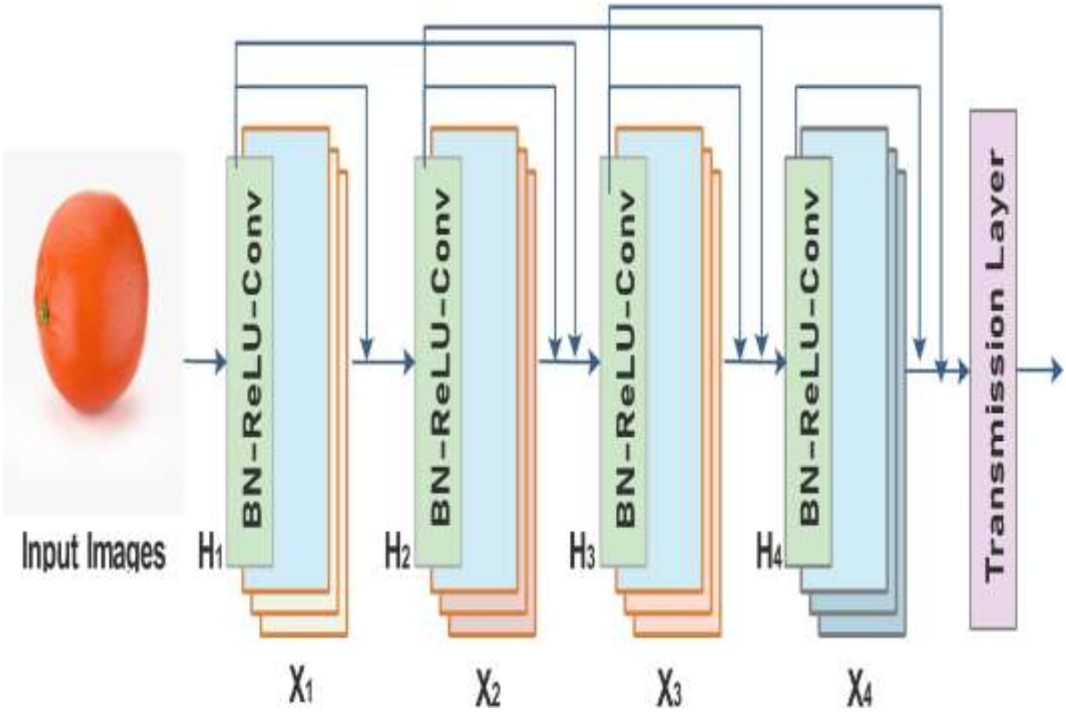

Fig. 5: Basic architectural diagram of Densenet201 model.

TABLE III: Performance Evaluation: Model comparison metrics for prepared dataset

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	F-1 Score (%)	Specificity (%)	+LR
VGG-19	95.22	96.16	95.56	95.50	94.32	18
Resnet50v2	97.10	96.55	97.84	97.11	96.56	28
Densenet201	97.54	97.53	97.88	97.56	97.24	35
Proposed	**98.05**	**98.31**	**98.17**	**98.15**	**97.25**	**43**

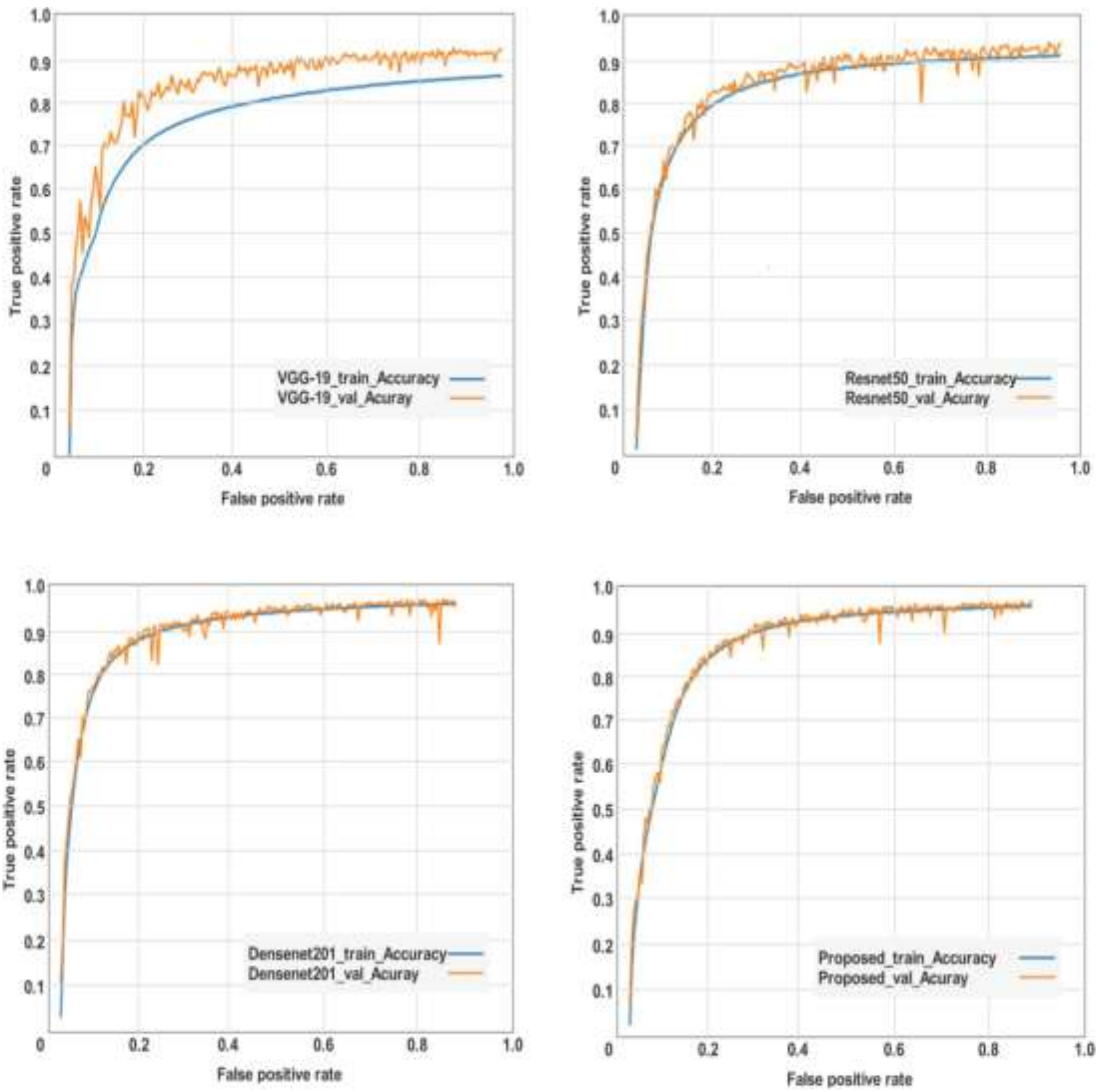

Fig. 6: ROC urve analysis

References

1. Y. Zhang, X. Yang, Y. Cheng, X. Wu, X. Sun, R. Hou, and H. Wang, "Fruit freshness detection based on multi-task convolutional neural network," Current Research in Food Science, vol. 8, p. 100733, 2024.
2. M. Nikhitha, S. R. Sri, and B. U. Maheswari, "Fruit recognition and grade of disease detection using inception v3 model," in 2019
3. 3rd International conference on electronics, communication and aerospace technology (ICECA). IEEE, 2019, pp. 1040–1043.
4. Bhargava and A. Bansal, "Machine learning based quality evaluation of mono-colored apples," Multimedia Tools and Applications, vol. 79, no. 31, pp. 22 989–23 006, 2020.

5. Z. Da Costa, H. E. Figueroa, and J. A. Fracarolli, "Computer vision based detection of external defects on tomatoes using deep learning," Biosystems Engineering, vol. 190, pp. 131–144, 2020.
6. S. V. Militante, B. D. Gerardo, and N. V. Dionisio, "Plant leaf detection and disease recognition using deep learning," in 2019 IEEE Eurasia conference on IOT, communication and engineering (ECICE). IEEE, 2019, pp. 579–582.
7. K. Roy, S. S. Chaudhuri, and S. Pramanik, "Deep learning based real- time industrial framework for rotten and fresh fruit detection using semantic segmentation," Microsystem Technologies, vol. 27, no. 9, pp. 3365–3375, 2021.
8. S. S. S. Palakodati, V. R. R. Chirra, D. Yakobu, and S. Bulla, "Fresh and rotten fruits classification using cnn and transfer learning." Rev. d'Intelligence Artif., vol. 34, no. 5, pp. 617–622, 2020.
9. Pe´rez-Pe´rez, J. P. Garcia Vazquez, and R. Salomo´n-Torres, "Evaluation of convolutional neural networks' hyperparameters with transfer learning to determine sorting of ripe medjool dates," Agriculture, vol. 11, no. 2, p. 115, 2021.
10. T. Vijayakumar and M. R. Vinothkanna, "Mellowness detection of dragon fruit using deep learning strategy," Journal of Innovative Image Processing (JIIP), vol. 2, no. 01, pp. 35–43, 2020.
11. M. Mukhiddinov, A. Muminov, and J. Cho, "Improved classification approach for fruits and vegetables freshness based on deep learning," Sensors, vol. 22, no. 21, p. 8192, 2022.
12. T. O'Malley, E. Bursztein, J. Long, F. Chollet, H. Jin, L. Invernizzi et al., "Keras tuner," 2019.
13. T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, 2016, pp. 785–794.
14. S. G. Chang, B. Yu, and M. Vetterli, "Adaptive wavelet thresholding for image denoising and compression," IEEE transactions on image processing, vol. 9, no. 9, pp. 1532–1546, 2000.
15. S. K. Mohideen, S. A. Perumal, and M. M. Sathik, "Image de-noising using discrete wavelet transform," International Journal of Computer Science and Network Security, vol. 8, no. 1, pp. 213–216, 2008.
16. K. He, X. Zhang, S. Ren, and J. Sun, "Identity mappings in deep residual networks," in Computer Vision–ECCV 2016:
17. 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14. Springer, 2016, pp. 630–645.