IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 5, Issue 3, January 2025

Fruit Export and Advisory App using Deep Learning

Prof. Shegar. S. R.[1], Wakchaure Siddhant Sanjay[2], Bhor Pradyumna Machhindra[3], Somvanshi Harish Ambadas[4]

HOD, Department of Computer Engineering[1]

Students, Department of Computer Engineering[2,3,4]

Samarth College of Engineering & Management, Belhe, India.

Savitribai Phule Pune University

hodcompcoe@gmail.com, wakchauresiddhant5@gmail.com

pradyumnabhor@gmail.com, harishsomvanshi4@gmail.com

Abstract: *Because of the agriculture sector's vital role in global food production and sustainability, fruit quality is critical. Traditional methods of fruit quality evaluation are time consuming and subjective, resulting in inefficiencies in the supply chain and significant food loss. Our research provides a novel solution. By evaluating fruit photos, our algorithm detects fresh versus sub optimal quality fruits using cutting-edge machine learning techniques. Our model correctly identifies ripeness, flaws, and deformities across multiple fruit varieties using deep learning with CNNs at its heart and transfer learning. Implementing this technology reduces food waste and promotes sustainable agriculture by streamlining fruit quality testing. It helps farmers, distributors, and consumers by guaranteeing that only the best fruits make it to market. Our study provides a cost effective, environmentally friendly, and long-term solution.*

Keywords: Fruit quality assessment, deep learning, CNN, transfer learning, sustainable agriculture, food waste reduction, fruit grading, mobile application, agriculture technology, image processing

I. INTRODUCTION

Ensuring the quality of fruits is a critical factor in the agricultural industry, impacting consumer satisfaction, market value, and overall profitability. Traditionally, fruit quality assessment has relied on manual inspection, which is labour-intensive, subjective, and prone to errors. The introduction of automated fruit quality detection using image processing and machine learning, specifically convolutional neural networks (CNNs), offers a promising solution to this challenge. Convolutional Neural Networks (CNNs), a type of deep learning model, have proven to be highly effective in tasks involving image classification and pattern recognition. By leveraging CNNs for fruit quality detection, it becomes possible to accurately classify and grade fruits based on various visual features such as colour, texture, shape, and surface defects. Image processing techniques play a crucial role in preprocessing and enhancing the quality of input images, enabling the CNN model to focus on relevant features for accurate detection. The proposed system involves capturing images of fruits using a standard camera, preprocessing the images through techniques such as noise reduction, resizing, and normalization, and then passing them through a CNN model trained to distinguish between high-quality and defective fruits. The CNN analyses features like bruises, discoloration, irregular shapes, and other imperfections that impact fruit quality. This automated approach not only improves the speed and accuracy of quality assessment but also reduces labour costs and minimizes human error.

II. LITERATURE REVIEW

It has led to some important developments by integrating deep learning and machine learning technologies within the agricultural domain with regard to automated detection and evaluation of fruit quality and diseases. Conventional methods of testing fruit quality have traditionally been labour-intensive, often inconsistent, and therefore inefficient in the supply chain for agriculture.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 5, Issue 3, January 2025

A. Fruit Quality Detection using Deep Learning for Sustainable Agriculture by B Lakshmi Sirisha, B Jayendra Nayak, sai Sndhya, J Eswara Rao, M Devisri

Because of the agriculture sector's vital role in global food production and sustainability, fruit quality is critical. Traditional methods of fruit quality evaluation are time consuming and subjective, resulting in inefficiencies in the supply chain and significant food loss. Our research provides a novel solution. By evaluating fruit photos, our algorithm detects fresh versus suboptimal-quality fruits using cutting-edge machine learning techniques. Our model correctly identifies ripeness, flaws, and deformities across multiple fruit varieties using deep learning with CNNs at its heart and transfer learning. Implementing this technology reduces food waste and promotes sustainable agriculture by streamlining fruit quality testing. It helps farmers, distributors, and consumers by guaranteeing that only the best fruits make it to market. Our study provides a cost effective, environmentally friendly, and long-term solution.

B. A Review on Automated Detection and Assessment of Fruit Damage Using Machine Learning by YONASI SAFARI, JOYCE NAKATUMBA-NABENDE, ROSE NAKASI, AND ROSE NAKIBUULE

Automation improves the quality of fruits through quick and accurate detection of pest and disease infections, thus contributing to the country's economic growth and productivity. Although humans can identify the fruit damage caused by pests and diseases, the methods used are inconsistent, time-consuming, and variable. The surface features of fruits, typically observed by consumers who seek health benefits, significantly affect their market value. The issue of pest and disease infections further deteriorates fruits' quality, becoming a mounting stressor on farmers since they reduce the potential revenue from fruit production, processing, and export. This article reviews various studies on detecting and classifying damages in fruits. Specifically, we review articles where state-of-the-art approaches under segmentation, image processing, machine learning, and deep learning have proved effective in developing automated systems that address hurdles associated with manual methods of assessing damage using visual experiences. This survey reviews thirty-two journal and conference papers from the past thirteen years that were found electronically through Google Scholar, Scopus, IEEE, ScienceDirect, and standard online searches. This survey further presents a detailed discussion of previous research done in the past while emphasizing their strengths and limitations as well as outlining potential future research topics. It also reveals that much as the use of automated detection and classification of fruit damage has yielded promising results in the horticulture industry, more research is still needed with systems required to fully automate the detection and classification processes, especially those that are mobile phone-based towards addressing occlusion challenges.

C. An Integrated Framework of Two-Stream Deep Learning Models Optimal Information Fusion for Fruits Disease Recognition by Unber Zahra , Muhammad Attique Khan , Member, IEEE, Majed Alhaisoni , Areej Alasiry, Mehrez Marzougui , and Anum Masood

Diseases impact the rates of production of many agricultural goods. These diseases require detection, which is difficult to do manually. Therefore, the creation of some automated illness detection systems is urgently required. Deep learning showed significant success in the area of precision agriculture for the recognition of plant disease. Compared with the traditional techniques, the deep learning architecture automatically extracts deep features from the deeper layer. In this work, we proposed a new automated method for classifying apple and grapefruit leaf disease recognition utilizing two-stream deep learning architecture. The proposed framework entails several steps. The first phase is picture contrast enhancement, which combines the information from DnCNN and top–bottom hat filtering to create a better image. Then, the augmentation process uses horizontal and vertical flips to increase the dataset's original size. The Inception-ResNet-V2 deep learning model is then adjusted and trained using deep transfer learning on the expanded dataset. After being extracted from the training model, the best features are chosen using two techniques—an entropy-based strategy and tree growth optimization. Finally, a new effective method combines the chosen features, and machine learning classifiers are used to complete the classification. On the augmented dataset, the proposed framework correctly classified apple and leaf diseases with the accuracy rates of 99.4 respectively.

D. Fruit Quality Recognition using Deep Learning Algorithm by Prof.Sarika Bobde, Prof.Pradnya Kulkarni, Pranav Khode, Sarthak Jaiswal, Omkar Patil, Rishabh Jha

Fruit classification is essential in various industrial settings, such as factories, supermarkets, and other places. Fruit classification may also be beneficial to persons with unique nutritional needs who utilize it to choose the proper fruits. Manual sorting was formerly used for fruit classification is time-consuming and requires continual human presence. Many fruit classification machine learning techniques have been proposed in the past. Deep learning may be a powerful engine for generating actionable results in today's reality because of its detection and classification abilities. As a result, a convolutional neural network was employed to construct an effective fruit classification model. It makes use of the fruits 360 dataset, which contains 131 different fruit and vegetable varieties. In this paper, we used three fruits, divided into three categories: good, raw, and damaged. The model was made in Keras. It had been trained for 50 epochs and had a 95% accuracy.

E. Highly Efficient Machine Learning Approach for Automatic Disease and Color Classification of Olive Fruits by NASHAAT M. HUSSAIN HASSAN, A. A. DONKOL, M. MOURAD MABROOK AND A. M. MABROUK

The following ends have been established via an in-depth examination and assessment of numerous prior studies on olive fruit classifications: First, several of these researches rely on the use of an unrelated image library. Since every image features a single fruit with a background that contrasts sharply with the fruit's hue, they are all ready for testing. As was previously stated, this issue is unrelated to reality. In practical application, one must deal with a frame that holds hundreds of fruits. To keep the fruits steady, they are put on a conveyor with multiple channels. It's also notable that the majority of this study offered suggestions for useful technology that could yet be developed. Finally, it is important to emphasize that processing speed data is essential in this type of application and has not been collected in many of these experiments.

III. METHADOLOGY

The methodology adopted in this research involves a sequence of structured steps to achieve precise results and efficient implementation of the proposed system.

1. Data Collection

The data set utilized in this research is the Fruits-360 Dataset, which contains high-resolution images of different fruits categorized based on their types and qualities. The data set is split into three primary sets:

• Training Set: Utilized for model training and learning feature representations.
• Validation Set: Utilized for model parameter tuning and assessment of its performance during training.
• Testing Set: Utilized to assess the final performance of the model after training.

The data set contains images of fruits such as apples, bananas, grapes, and oranges with different levels of quality, which is important for the grading process.

2. Data Preprocessing

• 2.1 Image Resizing

To normalize the input size for the model, images are resized to 224x224 pixels. This provides uniformity across the data set and is appropriate for the EfficientNetB5 model, which needs a specific input size.

• 2.2 Normalization

Image pixel values are normalized by scaling them to a range of 0 to 1. This is done by dividing pixel values by 255, which facilitates easier learning by the model and faster convergence during training.

• 2.3 Data Augmentation

To enhance model generalization and avoid overfitting, different data augmentation techniques are employed, including:

• Flipping: Horizontally flipping images to provide diversity.
• Rotation: Random rotation of images to mimic different orientations.
• Brightness Adjustment: Adjustment of the brightness of images to compensate for illumination variations in real-world environments.

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 5, Issue 3, January 2025

3. Model Architecture

The central model for fruit classification and grading is EfficientNetB5, a pre-trained Convolutional Neural Network (CNN) that is highly accurate and efficient. The model architecture is as follows:

- Base Model (EfficientNetB5): Trained on ImageNet dataset to benefit from transfer learning. The model learns high-level image features such as texture and shape that are applicable for fruit classification.
- Additional Layers: Following the base model, fully connected layers are added to classify finally into fruit types and predict quality grade. The output layer employs softmax activation for multi-class classification.

4. Training AND VALIDATION

4.1 Optimizer

The model is trained with the Adam optimizer, which is efficient in dealing with sparse gradients. A starting learning rate of 0.001 is employed, which is adjusted based on validation performance.

4.2 Loss Function

The loss function employed is Categorical Cross-Entropy, which is appropriate for multi-class classification tasks, where each fruit type and quality grade is considered an individual class.

4.3 Training Procedure

The model is trained for 50 epochs to offer adequate time for learning, with a batch size of 32. Early stopping is employed during training to avoid overfitting by stopping training when the validation accuracy does not improve for a few epochs.

4.4 Evaluation

Following training, the model is tested on the testing set to estimate its accuracy and loss. The evaluation metrics offer an estimate of the performance of the model on unseen data.

5. Model Deployment

Following training and evaluation, the model is converted to TensorFlow Lite (TFLite) format to enable it to execute on mobile devices for real-time fruit quality Export Advisory.

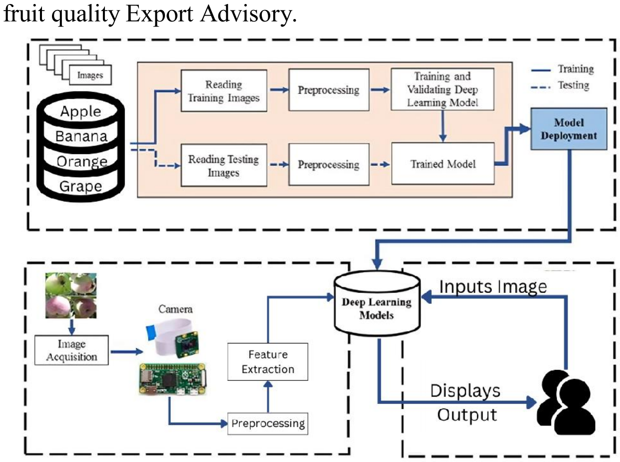


Fig (A).: System Architecture

6. Results and Performance

The performance of the model is tested on:

- Classification Accuracy: Accuracy of correct classification of fruit types and their corresponding quality grades.
- Inference Speed: Speed of the TFLite model to execute real-time predictions on mobile devices.

- Deployment Viability: How well the model can be deployed on Android devices, ensuring that it runs well with less computational power.

IV. ALGORITHM USED

This section describes the algorithm used to solve the fruit quality classification problem. The method proposed uses a Convolutional Neural Network (CNN), with EfficientNetB5 as the base model. The model development and deployment step-by-step process is described below.

1. Data Collection and Preprocessing

The dataset utilized in this research is the Fruits-360 Dataset, which consists of high-resolution images of fruits, divided into various classes. The dataset is divided into three sets: Training, Validation, and Testing sets. • Data Augmentation: For handling overfitting and dataset diversity, common image augmentation operations were used, including: o Flipping (horizontal) o Rotation (random angle) o Brightness adjustment • Normalization: Images were resized to 224x224 pixels, and pixel values were normalized to the range [0, 1] to ensure uniformity and ready the images for model input.

2. Model Architecture

The base model utilized is EfficientNetB5, a highly efficient and accurate CNN pre-trained on the ImageNet dataset. EfficientNetB5 balances performance and computational efficiency and is well-suited for real-time inference on mobile devices. The model architecture includes:

- Convolutional layers for feature extraction
- Batch Normalization layers to stabilize training
- Fully connected layers to output the class probabilities

3. Model Training

- Optimizer: The Adam optimizer was utilized with an initial learning rate of 0.001, adjusting the learning rate during training to enhance convergence.
- Loss Function: Categorical cross-entropy was utilized as the loss function, as the problem is multi-class classification. • Early Stopping: Training was performed for 50 epochs, with early stopping based on validation accuracy to prevent overfitting.
- Batch Size: A batch size of 32 was utilized for efficient training.

4. Model Evaluation

The performance of the trained model was assessed using the testing dataset, and evaluation metrics such as accuracy were calculated to assess its generalization capability.

5. Model Conversion for Mobile Deployment

To run the model on Android mobile phones, the trained model was converted to TensorFlow Lite format. This is the most suitable format for running on mobile phones, which will run efficiently with low resource consumption.

6. Real-Time Inference

The TensorFlow Lite model is embedded in the Android application during deployment. It does real-time inference to classify users' uploaded fruit images and gives insights into fruit quality.

IV. RESULT

1. Quantitative Results

The model attained the following performance measures:

- Training Accuracy: 99.38%

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 5, Issue 3, January 2025

- Validation Accuracy: 98.72%
- Test Accuracy: 98.50%

These measures show the high-performance level of the model in correctly classifying the fruit categories.

2. Visual Representation

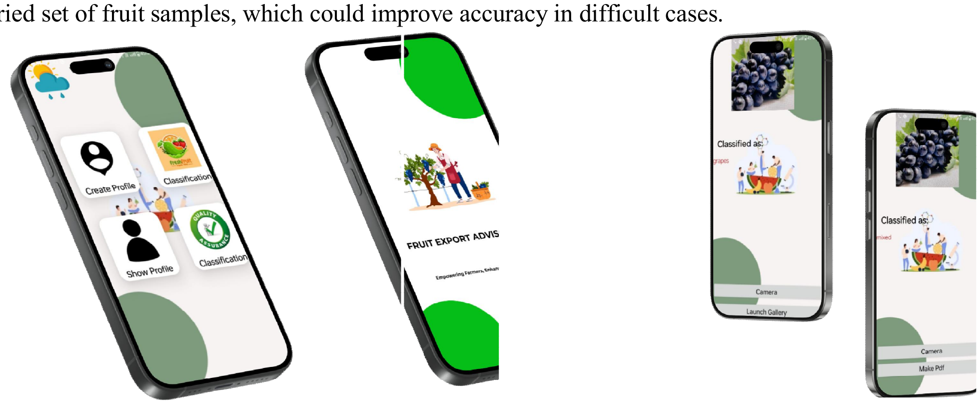
- Accuracy and Loss Curves: The charts revealed consistent learning without any indication of overfitting, reflecting successful model training.
- Confusion Matrix: The confusion matrix verified low misclassification, demonstrating the strength of the model in fruit categorization.
- Sample Predictions: Correct identification of healthy and discoloured fruits was emphasized, with the test images clearly indicating the model's strength in identifying both healthy and defective fruit samples.

3. Comparison with Existing Systems

Compared to traditional grading methods and earlier fruit classification systems, this model demonstrated superior accuracy and real-time usability. Its precision in categorizing fruits highlights its potential for real-world applications, especially in automated sorting systems.

4. Analysis

The results demonstrate the effectiveness of utilizing EfficientNetB5 as the base model for fruit grading. However, some slight misclassifications were noticed in edge cases, signifying the need for further dataset growth to include a more varied set of fruit samples, which could improve accuracy in difficult cases.



V. CONCLUSION

The combination of CNNs with fruit quality detection is a huge leap in agriculture to boost efficiency, accuracy, and sustainability. It provides real-time, automatic rating that improves sorting and quality control along the supply chain- from orchards, through cold stores and warehouses, and on to the retail shelf. This eliminates human error while speeding up decision-making to assist in maintaining high standards, reducing waste, and maximizing operational efficiencies. Their versatility allows them to be used for numerous fruits; thus, they can also assist with diversified agricultural requirements that accompany those relating to quality measures. The development of CNN technology will not only continue to transform innovation in quality detection but also ensure a healthy practice that further solidifies food security and consumer satisfaction. This is more efficient in producing and supplying the harvest, and it ushered in the responsible future in the agriculture sector of food production.

VI. FUTURE SCOPE

The future scope of your Fruit Export Advisory App is:

1. Real-Time Quality Assessment: Add IoT sensors and mobile scanning for real-time grading.
2. Expand to Other Products: Include vegetables, grains, and processed items.

3. Ripening Prediction: Predict ideal times for harvest.
4. Blockchain for Transparency: Track supply chain and certifications.
5. Compliance & Pricing Tools: Help exporters with customs and price predictions.
6. Farmer Insights: Offer farming advice and yield forecasts.
7. Enhanced Features: Add AR, voice commands, and multilingual assistance.
8. Collaborations: Partner with Aggrotech and NGOs for wider reach.
9. Model Improvement: Add more data and sophisticated methods for accuracy.
10. Sustainability: Reduce waste by identifying local market alternatives.

REFERENCES

[1] Hongshe Dang, Jinguo Song, Qin Guo, "A Fruit Size Detecting and Grading System Based on Image Processing," 2010 Second International Conference on Intelligent Human-Machine Systems and Cybernetics,pp83- 86.

[2] John B. Njoroge. Kazunori Ninomiya. Naoshi Kondo andHideki Toita, "Automated Fruit Grading System using ImageProcessing," The Society of Instrument and Control Engineers(SICE2002), Osaka, Japan, August 2002, pp 1346-1351.

[3] J. V. Frances, J. Calpe, E. Soria, M. Martinez, A. Rosado, A.J.Serrano, J. Calleja, M. Diaz, "Application of ARMA modeling to the improvement of weight estimations in fruit sorting and grading machinery," IEEE 2000, pp 3666-3669.

[4] Wong Bing Yit, Nur Badariah Ahmad Mustafa, ZaipatimahAli, Syed Khaleel Ahmed, Zainul Abidin Md Sharrif, "Design and Development of a Fully Automated Consumer-based Wireless Communication System for Fruit Grading", ISCIT 2009, pp 364- 369.

[5] D. Lee, J. Archibald and G. Xiong, "Rapid Colour Grading for Fruit Quality Evaluation Using Direct Colour Mapping", IEEE Transactions on Automation Science and Engineering, Vol 8, No.2, pp.292-302, April 2020