International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1280-1286
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0181

Automated Apple Defect Detection Using Transfer Learning with Mobile Net

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Abstract
This study investigates for utilizing the MobileNet with transfer learning for automated detection and classification of flaws in "Chaubattia Anupam apple". To distinguish between rotting, bruised, damaged and healthy apples, using machine learning and object detection methods, the model was trained on a dataset comprising 2,000 annotated images were preprocessed and improved for performance and consistency. The model's practical efficacy was demonstrated by its 90.4% accuracy for defected apples including (bruised apples, rotten apples and damaged apples), 56.4% accuracy for good apples. It ensured accurate defect identification with a mean Average Precision (mAP) of 92% (IoU 0.50–0.95) and 68% mAP at IoU 0.50. A custom built separator is used to separate the defected apples using MobileNet to deploy on Raspberry pi to send the signal in relay to separator. This approach makes easier with high accuracy, less data required and faster training.
Keywords: *MobileNet, Transfer Learning, Apple Defect Detection, Machine Learning, Object Detection, Separator and defect classification*

1. Introduction
Apples (Malus sp.) are among the most commonly sold fruits worldwide. In 2013, global apple output reached around 67.9 million metric tons, and it is expected to continuously expand in the next years. The processing of approximately 18% of this production yields a substantial number of byproducts [1]. Since 2000, apple production has surged by 51.1%, mirroring the urban population's growth of 50.3%, while the total global population has increased at a slower pace of 25.8% (WB, 2019). Regarding fruit consumption trends, global daily intake per capita is expected to rise from 204 grams to 242 grams by 2025 and 2050, respectively. Developing countries are anticipated to see an increase from 172 grams to 213 grams per day, whereas industrialized nations will likely experience growth from 336 grams to 388 grams per capita during the same period (Kearney, 2010) [2]. Fruit losses, including apples, range between 5% and 35% annually, with developing countries facing significantly higher losses of 20% to 50%. These losses are mostly the result of poor harvesting practices, inadequate transportation, and unsuitable storage, all of which encourage fungal infection, notably by Botrytis species [3]. These difficulties necessitate significant labor efforts while decreasing harvesting efficiency. The use of computer vision technologies for real-time picture analysis can alleviate these issues by automating problem detection and reducing reliance on manual labor [4]. To increase efficiency, an SSD (Single Shot Multibox Detector) architecture uses a lightweight deep learning model based on MobileNet as its fundamental network. This method greatly reduces computational expenses and processing time for extracting image features. The TensorFlow-based model is trained on the COCO (Common Objects in Context) dataset before being put through comparative tests to determine item identification accuracy and speed [5]. MobileNet-based lightweight

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feature extraction has yielded excellent results, with a classification accuracy of 99.5% [6].

Compared to traditional deep learning models, this approach is more cost-effective because it can be deployed on mobile devices with limited resources. Additionally, it eliminates the requirement for professional assistance, allowing anyone to successfully diagnose apple disease using the proposed method. Furthermore, MobileNet reaches precision levels comparable to more complicated deep learning frameworks. Several experimental validations have been performed to establish the model's efficacy in detecting apple illnesses [7]. Utilizing a convolutional neural network (CNN) structure, the model extracts visual features and employs convolutional layers to predict the position and type of defects accurately. MobileNet's architecture allows for high-speed processing while maintaining accurate object detection. CNN-based models have been frequently utilized to categorize and assess the quality of agricultural products [8]. The use of CNNs for fruit identification and quality evaluation has been shown to be quite effective in the agriculture industry. These models have successfully identified illnesses in crops such as tomatoes, grapes, and apples by evaluating leaf photos [9]. CNN-based approaches help farmers optimize crop health management by accurately classifying various kinds of diseases [10]. There are many methods which is used for other than apples like mangoes in an separated environment for taking visual images and to detect defect using YOLOv8 methods [11]. This research aims to develop a computer vision application for detecting defects in apple fruits using the MobileNet (Transfer Learning) architecture. The proposed system seeks to utilize computer vision to automate the inspection process. By leveraging the efficiency of MobileNet, this study aims to enhance existing quality control techniques. The specific objectives are as follows:

- Collect and preprocess a comprehensive dataset of apple fruit images.
- Train the MobileNet (Transfer Learning) model using the preprocessed dataset.
- Evaluate the trained MobileNet model performance using metrics such as Average Recall (AR) and mean Average Precision (mAP).
- Implement the trained model in a real-time application and assess its accuracy.

2. Materials

This research demonstrates the simple integration of both hardware and software components to ensure precise and efficient detection of apple defects. It's detailed process is shown in the Figure 1. designing the hardware set-up (Controlled Set- up), Collecting data, training the model Transfer learning(MobileNet) and using the model to classify the apple defects. (Figure 1)

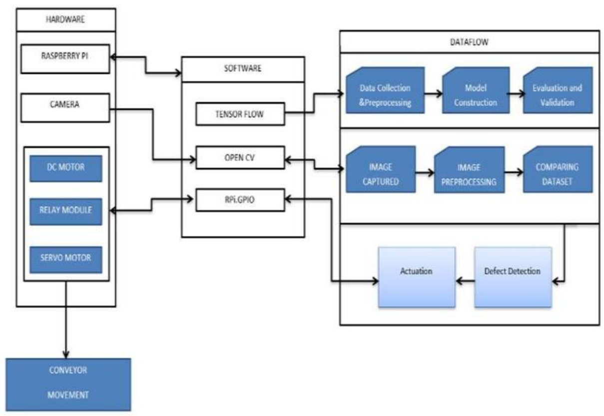

Figure 1 Block Diagram of the System

2.1. Hardware Setup

A DC motor with an apple mount is used to start the Conveyor belt with motor driver of this automated system. When the apple is positioned so that the camera is focused, it takes pictures of it and sends those pictures to a microprocessor for the classification of defects. If the apple is defective, MobileNet in the system can identify it and send a signal to the relay to the servo motor, which is a section that separates defects. In this system, we use Raspberry Pi 4 with Raspbian OS as a microprocessor, which can be a computational demand for their lower run, efficiently with MobileNet. The overall system is powered by using Power supply (SMPS).

2.2. Software Section

The operating system is used for Raspberry Pi 4 is Raspbian OS, and the programming language is python. Here, we use the libraries and frameworks for ML inference, for image processing, for numerical computations and for hardware interfacing. The TensorFlow Lite is a lightweight version of TensorFlow optimized for edge computing which is used for ML inference. It enables real-time inference on Raspberry Pi, allowing the system to classify apples efficiently with minimal processing power. OpenCV is used for capturing and preprocessing images.It performs operations such as resizing, normalization, and augmentation, ensuring that input images are correctly formatted for the model.NumPy supports numerical operations such as array manipulations, which are essential for image processing and model input handling. RPi.GPIO enables communication between the Raspberry Pi and external hardware components such as motors, actuators, and relays.It ensures that defective apples are correctly sorted based on the model's output.

2.3. Conveyor Setup

The conveyor system acts an automated system which helps to classify the defected apples by using the sorting mechanism Figure2. In this conveyor system, the hardware components are placed such as DC motor with motor driver for running the conveyor, the camera is mounted above the conveyor belt and the sorting mechanism which consists of relay and servo motor when the defected apple is placed. (Figure 2)

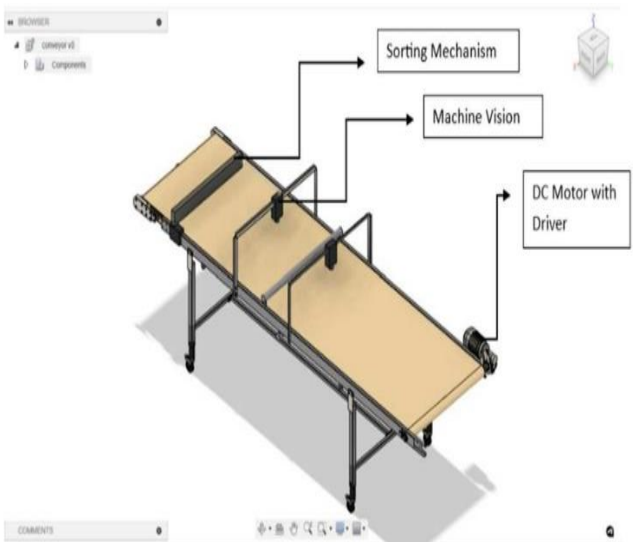

Figure 2 Conveyor System with Hardware Setup

3. Methodology

The research flow for this research demonstrates the integration of both hardware and software components to ensure precise and efficient detection of apple defects. It details the process flow as shown in Figure 3. integration of both hardware and software components.

3.1. Data Collection and Model Training

A total of 600 apple defect images were collected and classified into three categories: rotting, bruised, damaged and healthy apples. These categories were defined based on the defect colour: Brown Spot with brown and dried skin, and apple scab with brown and black scabs. as shown in Figure 4. There were 500 photos in each class, each with an original resolution of 3072 x 3072 pixels at 72 dpi. To improve model performance, picture transformations were optimized as part of the data pretreatment phase. For MobileNetV2 compatibility and processing efficiency, photos were scaled to 224x224 pixels, and the Auto-Orient feature fixed EXIF rotations and standardized pixel ordering. Augmentation approaches were used to improve model resilience and dataset variety, including:(1)Flip, Lessens the model's sensitivity to the orientation of the apple.(2)Rotation and Bounding Box Adjustments, which Increases resistance to minute changes in placement.(3)Shear makes it more resilient to deviations in the positions of the camera and the apple fig.5.The dataset grew to 2000 photos after augmentation, comprising 1600 for training 200 will be used for testing, 200 for validation, and 200 for training. After that, the dataset was prepared for MobileNetV2 training, producing the proper annotations and labels for supervised learning. architecture allows for high-speed processing while maintaining accurate object detection. CNN-based models have been frequently utilized to categorize and assess the quality of agricultural products If the apple is defective, MobileNet in the system can identify it and send a signal to the relay to the servo motor, which is a section that separates defects. In this system, we use Raspberry Pi 4 with Raspbian OS as a microprocessor, which can be a computational demand for their lower run, efficiently of the form (Figure 3,4)

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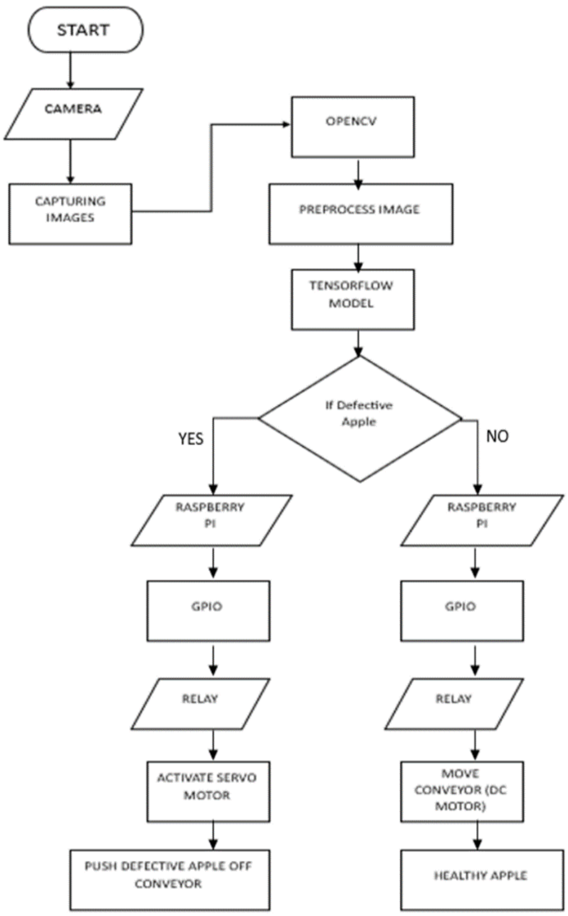

Figure 3 Flow Chart of the System

Figure 4 A. Apple Bruished, B. Apple Rotten

MobileNetV2, a lightweight Convolutional Neural Network (CNN) designed for real-time picture categorization, is used in the main method. It makes use of: Depthwise Separable Convolutions which is used for their accuracy is maintained while computational cost is decreased. Improving the efficiency of feature extraction with inverted residuals and linear bottlenecks. ImageNet weights that have already been trained, this enables transfer learning to modify the model for detecting Apple defects. Using transfer learning techniques, the model was optimized to accurately categorize apples as either healthy or defective. An Adam optimizer was used for training and model predictions were improved by using a categorical cross-entropy loss function. (Figure 5)

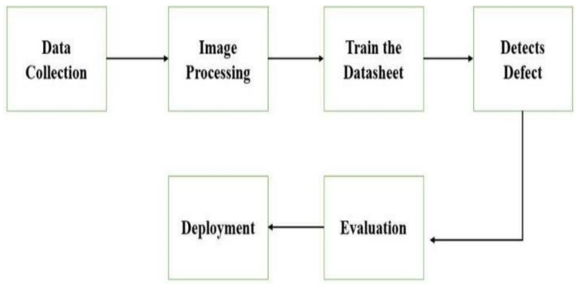

Figure 5 Process Flow

3.2. Apple Defect Detection and Classification

The Apple Defect Detection System integrates machine learning and embedded systems to automate the apple sorting process. Using MobileNetV2 and TensorFlow Lite, the system achieves real-time defect classification and efficient apple separation.

Detailing the procedural steps for classifying and detecting apple defects using the hardware setup and application,

These steps are outlined as follows:

- Connecting the microprocessor to the Hardware Setup with conveyor system: The first step involves establishing a connection between the microprocessor and the hardware configuration, which includes a high-definition camera, separating mechanism, and for capturing images of apple defects which is done in conveyor system.
- Running the Application: Once the connection is established, the software application on the microprocessor is launched. This application interfaces with the hardware setup to execute the necessary image processing and classification tasks.
- Placing the apple in the conveyor belt: The apple is positioned within the angle for capturing images by camera. This setup

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minimizes variability from external factors, ensuring the capture of high-quality, consistent images.

- Defect apple sorting mechanism: The defected apples like bruished, rotten and damaged apples are detected using MobileNet and is send the signal to relay using numpy for signal transmission 0 and 1 to servo motor which acts as a sorting mechanism these are integrated by using RPi.GPIO to control relay switches for actuator and stepper motor to implement a real-time response mechanism for efficient sorting.

3.3. Testing/Evaluation of the System

In testing and evaluating the system's effectiveness, the confusion matrix was used as a visual tool to evaluate the model's performance, which aids in determining the algorithm's accuracy in detecting defects in apple. The confusion matrix is a table that compares the algorithm's predictions to the actual class labels in the dataset. It is usually arranged in columns and rows. The accuracy can be computed from the confusion matrix using the provided formula. Equation (1) is

$$Accuracy = TP+TN \ (\ P+TN+FN+FP \ ) \times 100\% \quad (1)$$

Additionally, 500 images of apple samples were used to test the model's effectiveness, with 250 images taken from each apple sample and assigned in the classification category: defected apple and good apple. The device will also detect small to medium sized images to further challenge the trained model. Higher accuracy will indicate greater effectiveness.

4. Results and Discussion

4.1. Results

The results and conclusions from assessing and testing the model outlined in methodology are presented in this section. By validating the trained model's performance on unseen data is the goal. Here we use, confusion matrix which comprising mean Average Precision (mAP) and IoU (Intersection over Union) from evaluating 250 images from the validation dataset. With a mAP of almost 92% across all item sizes and IoU thresholds between 0.50 and 0.95, the model showed respectable accuracy in identifying objects of different sizes. The model achieved a mAP of 68% at an IoU threshold of 0.50 for all item sizes, demonstrating great precision at this particular threshold. However, the average Average Precision for IoU thresholds between 0.50 and 0.95 was approximately 92%.

Table 1 Model Accuracy

Class	Accuracy
Defected Apple	90.4%
Good Apple	56.4%
Overall	73.4%

Table 2 Mean Average Precision

IoU	Epoch	mAP
50-95	200-300	92%
50	100-200	68%

4.2. Discussion

Overall, the model exhibits satisfactory performance in terms of mean Average Precision (mAP) and an outstanding performance in terms of model accuracy. The accuracy evaluation was conducted in real-time, capturing 250 images for each class of mangoes from different angles and assessed using a confusion matrix. figure 6. summarizes The categorization model's performance model. Utilizing the accuracy formula from Equation (1), the model achieved an accuracy rate of 73.4%. Specifically, all 226 images of defected apple category were maximum identified. In the good apple category, 141 images were correctly classified while 109 were undetected. For the defected apple category include bruished, rotten and damaged 226 images were correctly classified and 24 were undetected. Although no apple defects were misclassified, the model had difficulty detecting certain forms and sizes within the rotten and black dots classes. The accuracy for each class was calculated individually, revealing 90.4% accuracy for defected apples(bruished, rotten and damaged), 56.4% for good apple, as shown in Table 1. Overall, the model achieved an accuracy of 73.4%, indicating a decent classification performance. (Figure 6,7)

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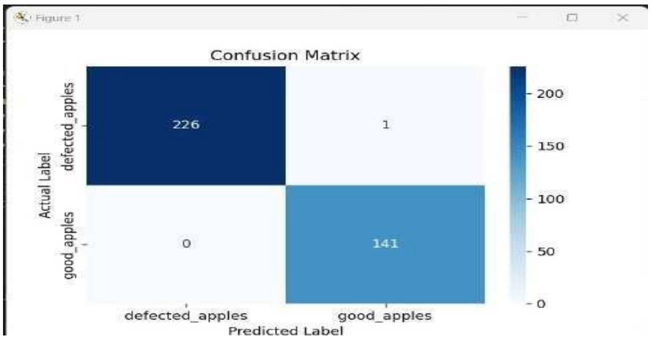

Figure 6 **Confusion Matrix**

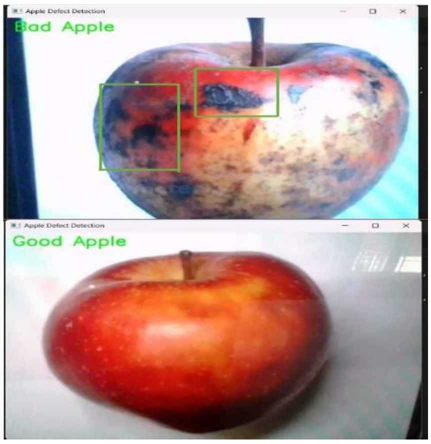

Figure 7 **Sample Images During Defect Detection**

Conclusion and Future Works

The implementation of a automated apple defect detection and sorting system by utilizing the MobileNet(Transfer Learning) has proven effective. A resilient system has been developed, demonstrating an overall accuracy of 73.4% during real-time testing. The individual accuracy rates were 90.4% for defected apples and 56.4% for good apples. Analysis of the confusion matrix showed that there were very few incorrect classifications, demonstrating the model's excellent accuracy. The high-definition images captured within the ensured the MobileNet model's proficiency in distinguishing between various apple defects. However, challenges persist in accurately classifying rotten and black dots, primarily due to variations in the size of spots and scabs.Performance could be further enhanced by addressing these issues with improved model adaptation, sophisticated picture processing methods, and dynamic lighting modifications.The Apple Defect Detection System uses machine learning and integrated technologies to efficiently automate apple sorting. The system uses TensorFlow Lite and MobileNetV2 to achieve efficient apple separation and real-time defect classification. Future research should concentrate on expanding the dataset to include additional images of apple flaws taken in various settings and customizing edge AI for various apple varieties in order to enhance the model's resilience and generalization capabilities.

References

[1]. Holy Nadia Rabetafika, Brahim Bchir , Christophe Blecker , Aurore Richel "Fractionation of apple by-products as source of new ingredients: Current situation and perspectives"- Trends in Food Science & Technology Volume 40, Issue 1, Pages 99-114, November2014,https://doi.org/10.1016/j.tifs.2014.08.004.

[2]. Natalia Vasylieva (Ukraine), Harvey James (USA) "Production and trade patterns in the world apple market"- 16 Innovative Marketing, Volume17,Issue1,2021,http://dx.doi.org/10.21511/im.17(1).2021.02.

[3]. Anbesse Girma Shewa "Review on postharvest quality and handling of apple"- International Journal of Agricultural Science and Food Technology,January 2022, DOI:10.17352/2455-815X.000141.

[4]. Gurjot Kaur, Rahul Chauhan, Hemant Singh Pokhariya "Fruit and Vegetable Classification Using MobileNet V2 Transfer Learning Model"-3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), December 2023.

[5]. Jipan Li, Keqiang Tian, Shuzhi Jing; Ke Xu, Weiling Wang, Dejian Liu "Moving Object Detection and Recognition Algorithm Based on Deep Learning"- IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), 28 May2023,DOI:10.1109/ICIBA56860.2023.

[6]. Xiaoyao Yang, Wenyang Zhao, Yong Wang, Wei Qi Yan & Yanqiang Li "Lightweight and efficient deep learning models for fruit detection in orchards"- Scientific Reports

volume 14, Article number: 26086 (2024).

[7]. Chongke Bi, Jiamin Wang, Yulin Duan "MobileNet Based Apple Leaf Diseases Identification"-Mobile Netw Appl 27, 172–180 (2022), doi.org/10.1007/s11036-020-01640-1.

[8]. F. Yu et al., "Progress in the Application of CNN-Based Image Classification and Recognition in Whole Crop Growth Cycles," Remote Sens (Basel), vol. 15, no. 12, p. 2988, Jun. 2023, doi: 10.3390/rs15122988.

[9]. S. Takkar et al., "Recognition of Image-Based Plant Leaf Diseases Using Deep Learning Classification Models," Nature Environment and Pollution Technology, vol. 20, no. 5, Dec. 2021, doi: 10.46488/NEPT.2021.v20i05.031.

[10]. A . S. Paymode, S. P. Magar, and V. B. Malode, "Tomato Leaf Disease Detection and Classification using Convolution Neural Network," in 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), IEEE, Mar. 2021, pp. 564–570.doi: 10.1109/ESCI50559.2021.9397001.

[11]. Kaycee Kaye Villanueva , Juvy Amor M. Galindo, Apple Joy R. Tamayo , Jamie Eduardo C. Rosal Daryl Ivan E. Hisola,"Development of a Computer Vision Application for Mango (Mangifera indica L.) Fruit Defect Detection using YOLOv8 Architecture ",2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET),doi:10.1109/IICAIET62352.2024.10730444.