International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Detection of Fresh and Root Apples Using the TensorFlow Lite Framework with EfficienDet Lite-2

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Submitted: 03/11/2023 **Revised:** 24/12/2023 **Accepted:** 03/01/2024

Abstract*:* Apples are one of the fruits that are widely consumed by the people of Indonesia. Not all areas in Indonesia are suitable for growing apples, apple plants will grow and produce well on land with an altitude of 700 - 1,200 meters above sea level (asl), with temperatures ranging from 16 0 - 25 0 C. There are three largest apple producing areas namely Pasuruan, Malang and Batu City. These three regions are the largest suppliers of apples in various regions in Indonesia, to keep apples fresh until they reach the hands of consumers, after the apples are picked, they must be distributed immediately, but the process of sorting apples takes quite a lot of time if done manually, deep technology learning is able to overcome this problem. In order to evaluate the effectiveness of the detection model, fruit detection is evaluated in real time using an Android handset. The study uses the TensorFlow Lite framework with the EfficientDet Lite 2 model architecture to examine the accuracy of detecting fresh and rotten apple objects. The test results demonstrate that the detection model performs rather well on Android smartphones, with an average detection accuracy of 91.02% for fresh apples and 88.07% for rotten apples.

Keywords: *Apple fruit detector, TensorFlow Lite, EfficienDet Lite 2, Deep Learning*

1. Introduction

Apples are one of the fruits that contain carbohydrates and protein, many vitamins are contained in apples including vitamin A, vitamin C, vitamin B2, vitamin B1 and many other vitamins (Wijaya & Ridwan, 2019, p. 74). Apples are one of the fruits that are widely consumed by the public, in Indonesia alone there are three largest apple producing regions, namely Pasuruan, Malang and Batu City. These three regions are suppliers of apples in various regions in Indonesia [1].

Apples before being distributed must go through a sorting process first so that only good and fresh apples are distributed, but the sorting process will take a lot of time if it is done manually while the apples must be distributed immediately so that when they arrive in the hands of consumers Apples are still fresh.

The detection of fresh and root apples is an important task in the food industry, as it helps ensure the quality and safety of the produce. However, existing methods for detecting apples can be limited in their accuracy and efficiency. In this paper, we propose a machine learning model for detecting fresh and root apples using the TensorFlow Lite framework with the EfficienDet Lite-2 architecture [2].

The EfficientDet Lite-2 architecture is a lightweight and efficient object detection model that has shown promising results in various applications. We trained our model on a dataset of images of fresh and root apples using transfer learning with pre-trained weights from the COCO dataset. We then evaluated the performance of our model using precision, recall, and F1-score metrics and compared it to existing state-of-the-art methods for apple detection.

Our results show that our model performs competitively with existing methods, suggesting that it has the potential to be a useful tool for the food industry. Furthermore, we tested our model on a Raspberry Pi 4 with the Coral Edge TPU, demonstrating its feasibility for use in real-world applications.

In this paper, we provide a detailed description of our machine learning model and the experimental results. We also discuss the limitations of our approach and potential future directions for research in this area. Overall, our work contributes to the development of more accurate and efficient methods for detecting fresh and root apples, which can improve the quality and safety of the produce [3].

This work used deep learning to create a system for determining the freshness of apples based on an image of the apple's skin [4]. TensorFlow Lite is the framework used in the apple freshness detection model training procedure. The research employs EfficientDet Lite2 as its model architecture. By applying deep learning in the detection of fresh apples and rotten apples, the apple sorting process will be faster and more efficient

2. Literature Review

2.1. Literature Review

The literature on apple detection using machine learning approaches is limited, but there have been several studies that have explored this topic. For example, in a study published in the Journal of Food Engineering, researchers used computer vision algorithms to detect apples based on their color and shape features. However, this approach was found to be limited in its accuracy, as it did not account for variations in lighting

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conditions and apple orientation. More recently, deep learning-based approaches have been explored for apple detection. For instance, in a study published in the Journal of Agricultural Science and Technology, researchers proposed a deep learning model for detecting apple diseases based on color images. The authors used a CNN architecture to classify apple diseases, achieving high accuracy levels.

Similarly, in a study published in the journal Computers and Electronics in Agriculture, researchers proposed a deep learning-based system for detecting apple defects based on images captured under natural lighting conditions. The system used a YOLOv3 object detection model and achieved high accuracy in detecting apple defects such as bruises and scabs. However, to the best of our knowledge, there has been limited research on using machine learning models for detecting fresh and root apples. Our study aims to fill this gap by proposing a machine learning model based on the EfficientDet Lite-2 architecture for detecting fresh and root apples using the TensorFlow Lite framework. We trained and evaluated our model on a dataset of images of fresh and root apples and demonstrated its feasibility for use in real-world applications. Our results show promising performance, suggesting that this approach has the potential to improve the efficiency and accuracy of apple detection in the food industry.

2.2. Deep Learning

As a subset of machine learning, deep learning entails creating and honing multi-layered neural networks in order to extract features and generate predictions from data. These neural networks are made to learn from vast amounts of data and are modelled after the composition and operations of the human brain [5]. Deep learning is a very successful method for handling complicated tasks like natural language processing, image and speech recognition, and even Go and Chess game play. Deep Learning algorithms can also be used in various domains, including healthcare, finance, autonomous vehicles, and robotics [6].

Some popular deep learning frameworks and libraries include TensorFlow, Keras, PyTorch, and Caffe. These tools provide developers with a set of APIs and tools to build and train deep learning models efficiently [7].

Overall, Deep Learning has proven to be a highly effective and powerful tool for solving a wide range of real-world problems, and its potential applications are constantly expanding.

2.3. Convolutional Neural Network (CNN)

One kind of deep learning algorithm that works particularly well for tasks involving the recognition of images and videos is the CNN [8].

Convolutional, pooling, and fully linked layers are among the layers that make up a CNN. The network applies a series of filters to the input image in a convolutional layer, which aids in the extraction of significant information from the image. In a pooling layer, the convolutional layer's output is down sampled by the network to assist prevent overfitting and lower the dimensionality of the feature maps [9].

CNNs are particularly well-suited for image recognition tasks because they can learn to recognize patterns and features within an image, such as edges, corners, and textures [10]. They can also learn to recognize higher-level features, such as shapes and objects, by combining lower-level features [11].

Numerous applications, such as object identification, facial recognition, and picture categorization, have made use of CNNs [12]. By seeing text as a two-dimensional picture, they have also been applied to natural language processing tasks including text classification and sentiment analysis [13].

2.4. Apple

Apple is a type of fruit that is widely cultivated and consumed around the world. It is a round or oval-shaped fruit with a red, green, or yellow skin, and a white, juicy flesh inside. Apples are rich in fibre, antioxidants, and various vitamins and minerals, making them a healthy and nutritious food [14].

Apples can be eaten raw or cooked in various dishes, such as pies, sauces, and juices. They are also used to make cider, vinegar, and other fermented products. In addition, apples are often used in the food industry for the production of apple-based products such as jams, jellies, and apple butter.

Apples come in many different varieties, each with its own unique flavour and texture. Some of the most popular apple varieties include Granny Smith, Honeycrisp, Gala, Red Delicious, and Fuji. The cultivation and breeding of apple varieties is an ongoing process, with new varieties being developed to meet consumer preferences and market demands [15].

Overall, apples are a popular and versatile fruit with numerous health benefits and culinary uses. They are an important crop in many regions around the world and play a significant role in the food industry.

3. Research Method

Python and Java programming languages are utilised in the construction of the fresh apple and rotten apple detection system. The Tensorflow Lite framework and the EfficientDet Lite2 model architecture are used to train the data. This study was conducted in phases using Figure 1's 7 Steps of Machine Learning flow as a guide.

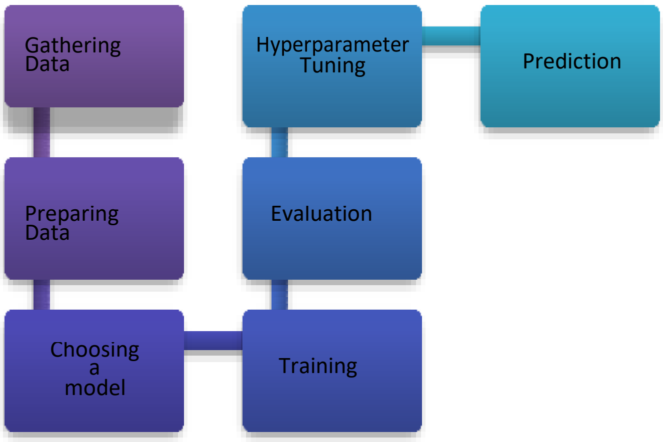

Fig 1: Researh Method

3.1. Data Gathering

The quality of the data will have a direct impact on the object detection model that will be created, making this stage of data collection crucial. In this study, there were 276 images consisting of fresh apples and rotten apples obtained from Google.

3.2. Preparing Data

After the image data is collected, it is labelled using the tools on the Roboflow website. The dataset is then exported in the form of the labelled image by applying preprocessing and augmentations data with the distribution of the dataset, which is 60% for training data, 20% for validation data, and 20% for test data. This stage is known as data preparation.

3.3. Choosing a Model

The second stage involves choosing a model. For this investigation, the EfficientDet Lite 2 model architecture is used; it is a derivative of the EfficientDet model, which continuously outperforms earlier models in terms of accuracy and efficiency (Tan et al., 2020, p.10788). Eight models make up EfficientDet, notably D0-D7, wherein the model's accuracy and temporal complexity rise with model size (Song et al., 2021). Figure 2 displays the model size contrast.

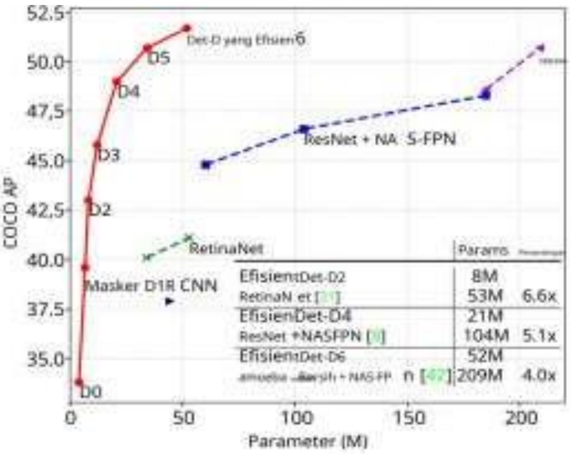

Fig 2 : Model Size Comparison Source (Tan et al., 2020)

The study's model architecture, the EfficientDet Lite 2, is a derivative of the EfficientDet model, which continuously outperforms earlier models in terms of accuracy and efficiency (Tan et al., 2020, p.10788). The next step in the process is choosing a model. Eight models: D0-D7 are part of EfficientDet; as a model grows in size, so do its accuracy and temporal complexity (Song et al., 2021). Figure 2 shows the comparison of the model sizes.

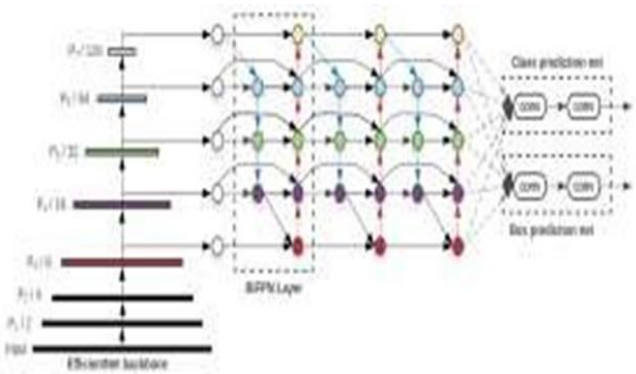

Fig 3: EfficienDet Model Architecture Source: (Tan et al., 2020)

The EfficientDet model is based on the EfficientNet architecture as the backbone network, which was designed to optimize both accuracy and efficiency by using a compound scaling method to balance network depth, width, and resolution.

The feature network of EfficientDet is based on the Bidirectional Feature Pyramid Network (BiFPN) architecture, which is a scalable and efficient way to fuse multi-scale features. BiFPN consists of multiple levels of nodes that integrate information from different scales and propagate the information bidirectionally, both top-down and bottom-up. This allows EfficientDet to capture features at multiple levels of abstraction, which is important for accurate object detection.

Finally, the EfficientDet model uses a shared class and box prediction network, which predicts the class and location of each object in the image. This network is applied to the feature maps produced by the BiFPN layers, and the predictions are then refined through a post-processing step that uses non-maximum suppression to remove overlapping bounding boxes.

The number of BiFPN layers and the number of repetitions of the shared class/box prediction network can be adjusted based on resource constraints, such as the amount of available memory and computation power. This allows EfficientDet to be customized for different applications and hardware configurations.

3.4. Training

The training process is then initiated. Colab Notebooks uses the Tensorflow Lite framework for this training, with a batch size of 8 and 100 training epochs. With this configuration, the processing time per epoch is 24 seconds on average, meaning that the model training process takes about 40 minutes in total.

3.5. Evaluation

When training is finished, an evaluation stage is conducted using previously separated validation data to determine whether the model is good. During this evaluation stage, the trained object detection model is tested using previously unseen image data, allowing us to observe the model's performance before it is applied directly to real-world scenarios.

3.6. Tuning Hypermater

Overparameter In this investigation, no parameter resetting was done because the accuracy attained after training was deemed sufficient. Tuning is the process of further improving the model's accuracy after training by setting multiple parameters.

3.7. Prediction

After going through various processes, this stage is the core of all the processes that have been passed, where the value of machine learning is realized to detect fresh apples and rotten apples, the completed model is then deployed to android mobile devices for real. see the accuracy of the model predictions when applied to the device and for use by the public.

4. Results and Discussion

A detector model that yields the most accurate detection performance is selected after the training procedure and the parameters have been reset. This model is then applied to an Android application so that it can be tested on mobile devices in order to evaluate the performance of the directly trained model. A screenshot of the model applied to the Android application is shown below; Figure 4 shows the application.

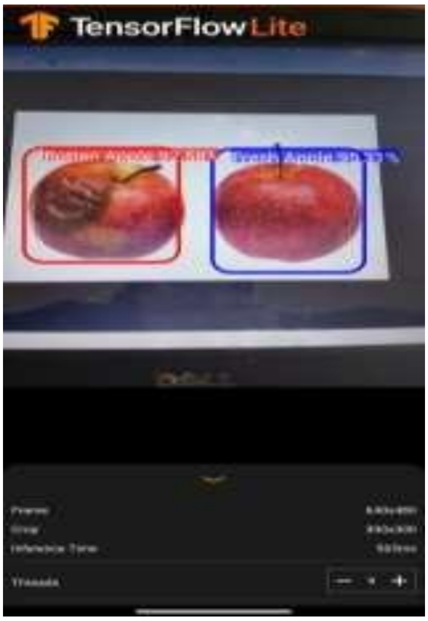

Fig 4: Screenshoot of the Android Application for Detecting Fresh Apple and Rooten Apples

The detection test was carried out using 20 images of fresh apples and 20 images of rotten apples obtained from Google, the test results can be seen in Table 1.

Table 1. Detection Results

Apple	Detected Correct	Detected Wrong	Average Accuracy
Fresh Apple	20	0	91.02%
Rotten Apple	20	0	88.07%

The model's 0% detection error indicates that it can distinguish between rotten and fresh apples with great accuracy, according to the data in Table 1. The detection confidence level for fresh apples was 91.02% on average, with 95.31% being the highest detection confidence result and 87.11% being the lowest.

The average level of confidence in the detection of rotten apples is slightly lower than the detection of fresh apples, which is 88.07% with the highest detection confidence of 95.14% and the lowest of 75.39%.

5. Conclusions and Suggestions

Based on research that has been done on the detection of fresh apples and apples that are not fresh or rotten, we get 0% error in detection with an average detection accuracy of 91.02% for fresh apples and 88.07% for rotten apples. With a relatively small dataset, using only 276 images from Google and accurate detection results, it can be concluded that the EfficientDet Lite 2 model architecture combined by the TensorFlow Lite framework is able to work well. To further improve the accuracy and performance of the model, further retraining of the model will be carried out with more datasets and with longer training to produce more optimal performance.

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