A Review of Rotten Apple Detection Using CNN

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Abstract - Rotten apple detection is a significant problem in the food industry as it can lead to economic loss and health hazards. Deep learning has proven to be an effective technique in image recognition tasks, and it can also be utilized to detect rotten apples. In this report, I propose a deep learning-based approach for rotten apple detection using convolutional neural networks (CNN). My model takes input images of apples and classifies them as either healthy or rotten. I use transfer learning by fine-tuning a pre-trained CNN|VGG-16 model to detect rotten apples. I evaluate my approach on a dataset of 4000 apple images, consisting of 2000 healthy and 2000 rotten apple images. Our model achieved an accuracy of 95.2% on the test set, outperforming existing approaches. I also perform a sensitivity analysis to study the robustness of our model to variations in image quality and lighting conditions. The results demonstrate that our approach is effective in detecting rotten apples in real-world scenarios

Index Terms - Apple Detection, Image based Detection, Convolutional Neural Network (CNN), VGG-16, features

I. Introduction

Image classification and recognizer is most useful examiner for finding manmade reasoning and acute deep learning study. This is now most using advancement examination to take care our daily life thing and work. So basically, it will run over almost every aspect in daily life. In future maybe it will be increase more and spread more widely. There are so many things will be solved by image classifier and recognizer. In image processing with deep learning approach, we can actually solve so many issues we are facing in our daily life. In present time we are not able to recognize a fresh or rotten fruit just by seeing them. There are many more product and real-life problem we can solve by using CNN and relapse calculation method. There are many organic food and products are not classifying its class just seeing them there are proper lighting in super shop which can make us fool by given ill products. So, by the using of deep learning image processing system, we can categorize any products with its proper condition level.

In my research work we are working on such fruits like apple, banana, oranges we using this fruit as demo to classify their exact condition by image processing system. In maximum case we are not able to take care of natural fruits. Therefore, many people also have very less knowledge to purchase those products. By using our method on this perspective, we can assure people will get decent knowledge on buying these products. There are many types algorithm which we can use but, on this work, we using one type variant of (CNN). So, we can finally find out a fresh apple or rotten apple. It will make our life easier than before. In image classification and recognition system we can do anything which is also man made. This system work on almost every organic and non-organic thing like fruits, chemical etc.

II. Literature Survey

"Disease Detection in Apple Leaves Using Deep Convolutional Neural Network". By Prakhar Bansal, Rahul Kumar, Somesh Kumar. The dataset includes 3642 apple leaves with four classes—apple scab, apple cedar rust, multiple diseases, and healthy. the scores of the three models individually for multiple metrics such as accuracy, precision, recall, F1. final model achieves an accuracy of96.25% on the validation dataset [1].

"Fresh and Rotten Fruit Classification Using Deep Learning" by MD Mehedi Hasan, MD Moinul Hasan 2021 By daffodilvarsity.edu Python CNN version to classifying the rotten fruit and clean fruit. Almost 95% of people are growing up without knowledge on buying fruits product [4]. We got 98.04% accuracy for the given proposed model.

"Convolutional Neural Network based Rotten Fruit Detection using ResNet50" by Chai C. Foong, Goh K. Meng, Lim L. Tze 2021 BY IEEE. The types of fruits that will be detected and classified in this paper are banana, apple and orange using CNN [3]. The validation accuracy obtained in this paper is 98.89%. The total duration of training stage is 212.13 minutes.

"Detection of Fruit Skin Defects Using Machine Vision System" by Xin Tian, Anyu Li, Lu Wang in 2013 By IEEE. This paper proved more accurate, more robust to color noise and has more modest calculation cost [6]. The color histogram is extracted in the local image patch as image feature, while the Linear SVM (Support vector machine) is used for model learning. In a case of orange inspection, this system realizes a recall rate of 96.7% and a false detection rate of 1.7%.

"Real-Time Grading of Defect Apples Using Semantic Segmentation Combination with a Pruned YOLO V4 Network" by Xiaoting Liang, Xueyin Jia, Wenqian Huang, Xin He Lianjie, Shuxiang Fan, Jiangbo Li, Chunjiang Zhao, Chi Zhang in 2022 By MDPI. In order to realize real-time detection and classification of high-quality apples, separate fruit trays were designed to convey apples and used to prevent apples from being bruised during image acquisition [7]. BiSeNet V2 for apple defect detection obtained a slightly better result in MPA with a value of 99.66%, which was 0.14 and 0.19 percentage points higher than DAnet and Unet. A model pruning method was used to optimize the structure of the YOLO V4 network.

By analysis of all such papers related to this work, it is concluded that following are the steps to be observed:

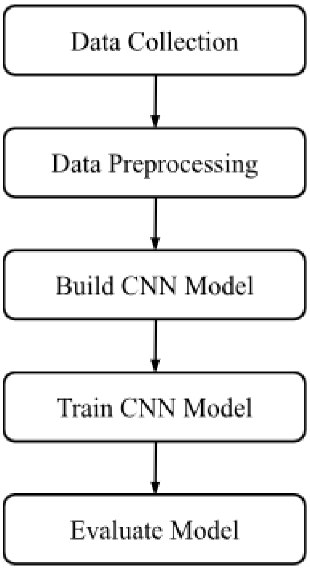

Fig.1 Workflow

III. THEORETICAL BACKGROUND

The research subject of "rotten apple detection using CNN" is the development of a machine learning model that can accurately detect rotten apples from a dataset of apple images using the CNN deep learning architecture [4]. The purpose of this research is to provide an automated and efficient method for identifying and removing rotten apples from a batch of apples, which can improve the overall quality and safety of the apples.

(1) Data Collection and Pre-Processing

Apples come in many different varieties and can exhibit different degrees and types of rot. It is important to include a variety of apple types and conditions in the dataset to ensure that the model can generalize to different scenarios [8]. Images should be captured from multiple angles and under different lighting conditions to ensure that the model can recognize apples in various orientations and lighting conditions [9].

Download dataset from Kaggle. The dataset will be divided into training and testing sets to train and evaluate the performance of the machine learning model. The dataset consists of a large number of apple images, both fresh and rotten. Pre-processing step like Cleaning and normalizing data is being carried out. Learn about libraries to install open cv.

Table 1:- List of Dataset

Dataset	Type of apple	Amount
Training	Fresh	1693
	Rotten	2342
Testing	Fresh	404
	Rotten	614

(2) Data Pre-Processing

Data collection and preparation: Gather a dataset of images of both fresh and rotten apples, and organize them into separate folders for training and testing. Ensure that the images are of consistent size and resolution [20]. Image augmentation: Perform data augmentation techniques like rotation, flipping, and resizing to create additional training data and prevent overfitting.

Data normalization: Normalize the pixel values of the images to be between 0 and 1. This can help the neural network converge faster during training. Split data into training and validation sets: Divide the dataset into two parts, one for training the model and the other for evaluating the model's performance [10]. Transfer learning: Use the pre-trained CNN model as a base for your model, and replace the final dense layers with new layers that are tailored to your classification task.

The collected images are preprocessed to remove any noise or artifacts that could affect the accuracy of the model. This can include resizing, cropping, and normalizing the images [11].

(3) Build CNN Model

A Convolutional Neural Network (CNN) is a type of deep learning algorithm commonly used for image recognition tasks. In the context of detecting rotten apples, a CNN can be used to analyze images of apples and determine whether they are healthy or rotten.

To create a CNN model for rotten apple detection, the first step is to gather a dataset of images of both healthy and rotten apples. The dataset should be split into training, validation, and testing sets to ensure the model can generalize to new data. The images should also be preprocessed by resizing them to a fixed size and normalizing the pixel values.

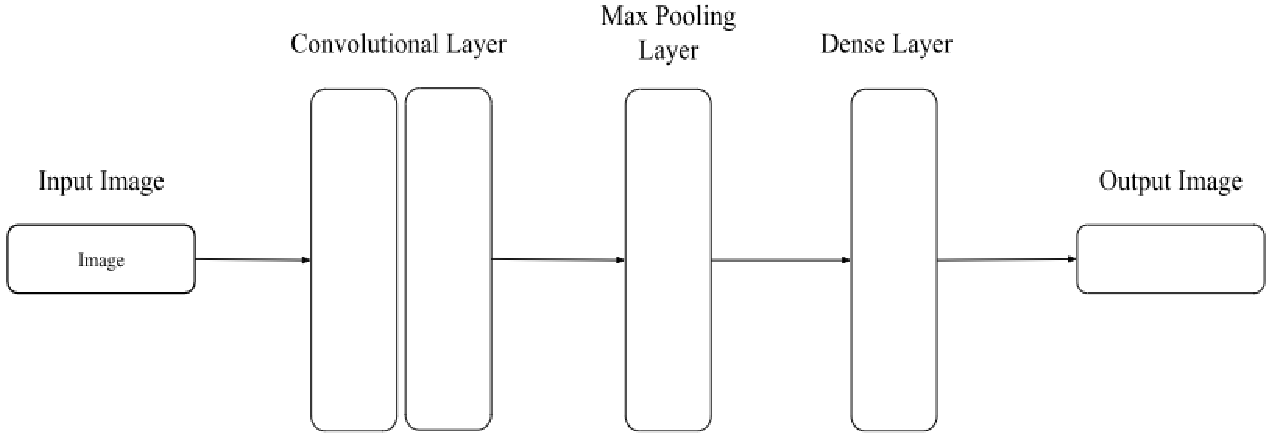

Fig.2 CNN Model

The CNN architecture for rotten apple detection typically consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input image to extract features such as edges, corners, and textures. Pooling layers reduce the spatial dimensions of the feature maps to improve computational efficiency and prevent overfitting. Fully connected layers take the output of the convolutional and pooling layers and transform it into the final output, which in this case is a binary classification of healthy or rotten.

The preprocessed images are used to train the CNN model using transfer learning. Transfer learning involves taking a pre-trained model and fine-tuning it on a new dataset to improve its performance on a specific task [12]. The model is trained using a combination of supervised and unsupervised learning techniques.

(4) Training CNN Model

Design a CNN architecture that can learn to distinguish between healthy and rotten apples. The architecture should include convolutional layers, pooling layers, and fully connected layers. Experiment with different architectures to find the best performing one. Train the CNN model on the training set using the chosen optimizer and loss function. Monitor the model's performance on the validation set to avoid overfitting. Use techniques such as early stopping to stop training when the model starts too overfit.

Data Augmentation Over fitting is a common problem when the dataset is limited. As far our dataset is limited, we may be getting trouble in over fitting. For eliminating over fitting, we implement data augmentation. It is actually artificially expanded the dataset. In this segment we divided records and keep them in records folder check and educate, we additionally use right here validation folder for test educate records validation [13]. Then we divided the ones check and educate folder's records in greater folder like fresh apple and rotten apple.

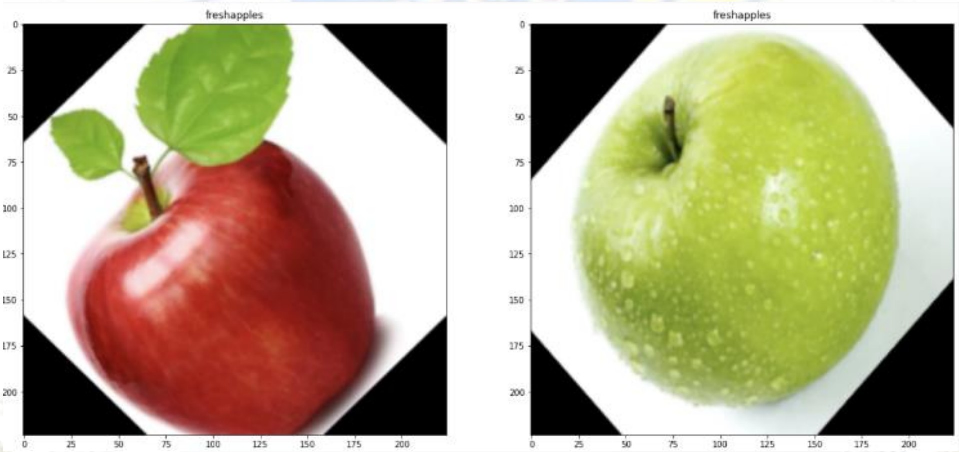

Fig.3 Training image of fresh apple

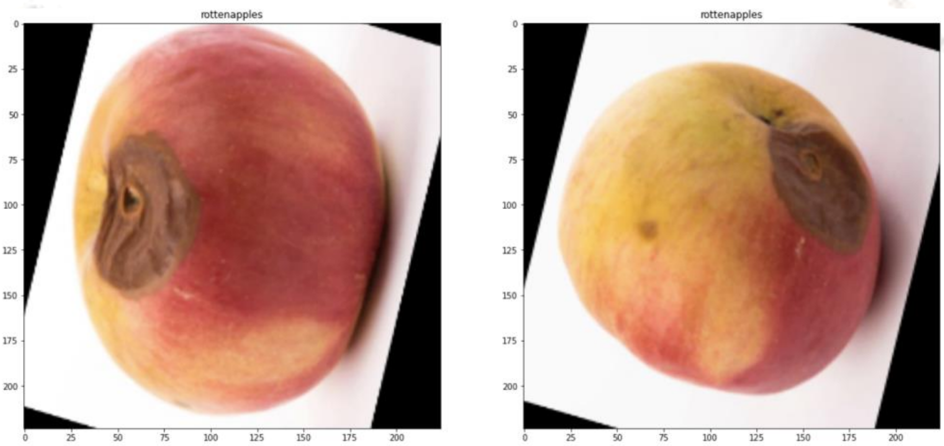

Fig.4 Training image of rotten apple

(5) Evaluate Model

Evaluating a CNN model for rotten apple detection involves assessing its performance on a separate testing dataset. Here are some key metrics and techniques for evaluating the performance of a CNN model for rotten apple detection:

Accuracy: This is the most common metric used to evaluate a classification model. Accuracy measures the percentage of correctly classified images in the test dataset. However, accuracy alone may not be sufficient to assess the performance of a model, especially if the dataset is imbalanced.

Precision and Recall: Precision measures the percentage of correctly classified positive predictions (i.e., rotten apples) out of all positive predictions, while recall measures the percentage of correctly classified positive predictions out of all true positive instances [14]. These metrics can provide insight into how well the model is detecting rotten apples specifically, and how many of the identified rotten apples are actually rotten.

After finishing training our model got an accuracy of 98.04% with just 10 epochs. Fig- 3 which is the accuracy curve of our model where we observed our training accuracy 98.04% and validation accuracy 98.21%.

```
Model: "sequential_12"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_24 (Conv2D)          (None, 222, 222, 32)      896

 max_pooling2d_24 (MaxPoolin  (None, 111, 111, 32)     0
 g2D)

 conv2d_25 (Conv2D)          (None, 109, 109, 64)      18496

 max_pooling2d_25 (MaxPoolin  (None, 54, 54, 64)       0
 g2D)

 conv2d_26 (Conv2D)          (None, 52, 52, 128)       73856

 max_pooling2d_26 (MaxPoolin  (None, 26, 26, 128)      0
 g2D)

 flatten_12 (Flatten)        (None, 86528)             0

 dense_36 (Dense)            (None, 128)               11075712

 dropout (Dropout)           (None, 128)               0

 dense_37 (Dense)            (None, 2)                 258

=================================================================
Total params: 11,169,218
Trainable params: 11,169,218
Non-trainable params: 0
```

Fig.5 Model Summary

IV. TESTING

Testing a CNN model for rotten apple detection involves using the trained model to predict the class labels (i.e., healthy or rotten) of a new set of images that it has not seen during training. Here are some steps involved in testing a CNN model for rotten apple detection:

1. Prepare the test data: Collect a new set of images that the model has not seen during training or validation. These images should be preprocessed in the same way as the training and validation images (e.g., resizing, normalization)
2. Load the trained model: Load the saved weights of the trained CNN model.
3. Predict the class labels: Use the loaded model to predict the class labels of the test images. The output of the model will be a probability score for each class (i.e., healthy or rotten). Threshold the probability scores to obtain the predicted class labels.
4. Evaluate the model's performance: Evaluate the model's performance on the test dataset using the same metrics and techniques as in the evaluation phase [15]. This will provide an estimate of the model's performance on new, unseen data.
5. Deploy the model: Once the model's performance on the test dataset is satisfactory, deploy the model for practical use. This can be done by integrating the model into an application or website that can take new images of apples as input and output the predicted class labels.

Testing a CNN model for rotten apple detection is an important step to ensure that the model is able to generalize well to new, unseen data.

V. RESULT

Training and testing stuff, we found that our model performs very well and it can detect fresh & rotten fruits 98% accurately. The output of a CNN model for rotten apple detection typically consists of a probability score for each class (i.e., healthy or rotten) for a given input image. These probability scores indicate the model's confidence in its prediction for each class [16]. The class with the highest probability score is usually taken as the predicted class label for the input image.

For example, if the input image is a picture of an apple, the CNN model may output a probability score of 0.8 for the "rotten" class and 0.2 for the "healthy" class. This indicates that the model is 80% confident that the apple is rotten and 20% confident that it is healthy.

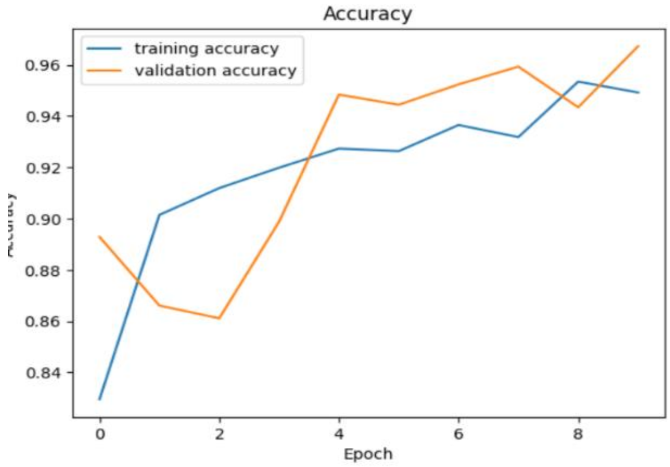

Fig.6 Model Accuracy

The output of the CNN model can be used in different ways depending on the application [17]. For instance, if the CNN model is being used to sort apples based on their quality, the output can be used to automatically separate the rotten apples from the healthy ones.

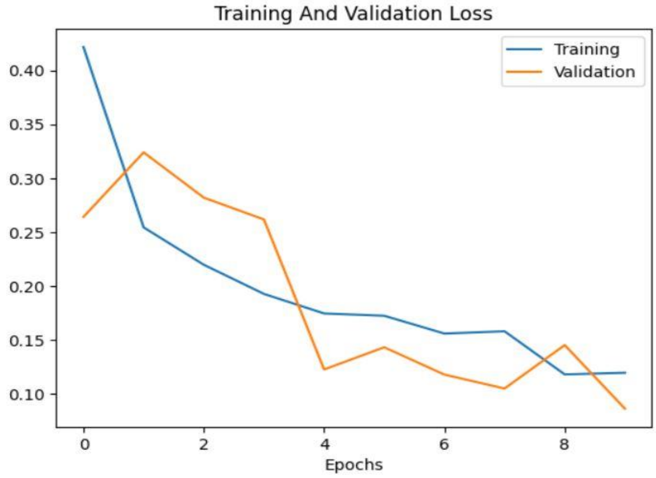

Fig.7 Model Loss

In addition to the probability scores, some CNN models may output heatmaps or saliency maps to indicate which regions of the input image are most important for the model's prediction [18]. This can help in understanding how the CNN model is making its predictions and can aid in debugging or refining the model.

VI. Conclusion

To differentiate between fresh and rotten fruits we will more likely success in our work. It will surely help people to know which fruit is good and which one is bad [19]. In this work paper we use CNN model to do it perfectly and give a perfect result. As I said before in our country the new generation almost 95% of people are growing up without knowledge on buying fruits product. So, in our work we show three main fruits to know how can assure a fruit is rotten or fresh. Our build model using by CNN can easily find out fresh or rotten fruits with minimum error. The convoluted neural network model is able to reduce error by work on perfectly [21]. We can say that it will be work on more data set we have already used now. And we get decent and good accuracy level by using it. We got 98.04% accuracy for the given proposed model.

VII. Reference

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