# IDENTIFICATION OF FRUITS AND VEGETABLES USING CONVOLUTIONAL NEURAL NETWORK

**A PROJECT REPORT**

***Submitted by***

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***in partial fulfilment for the award of the degree***

***of***

**BACHELOR OF ENGINEERING**

***in***

**COMPUTER SCIENCE AND ENGINEERING**

**RAJALAKSHMI ENGINEERING COLLEGE**

**ANNA UNIVERSITY, CHENNAI**

**MAY 2024**

## RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

## BONAFIDE CERTIFICATE

Certified that this Thesis titled **“FRUITS AND VEGETABLES CLASSIFICATION USING CNN**” is the bonafide work of “**MURSHID AHMED S (2116210701171)** who carried out the work under my supervision. Certified furtherthat to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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## Abstract:

In this work, we introduce a thorough machine learning methodology based on convolutional neural networks (CNNs) for the identification and categorization of different fruits and vegetables. By utilising a dataset that includes a wide range of produce photos, our CNN model is trained to effectively differentiate between various fruits and vegetables. The dataset is carefully preprocessed and enhanced through augmentation approaches to improve the resilience and generalisation of the model. On training and testing datasets, the CNN architecture performs remarkably well, attaining high accuracy rates. To further improve classification efficiency and accuracy, pretrained CNN models are leveraged through the use of transfer learning algorithms. The suggested paradigm has great potential for use in supply chain management, food quality evaluation, and agricultural automation, improving productivity and sustainability in fruits and vegetables industry.

**Keywords:** CNN, accuracy,prediction,abnormalities.

## I. INTRODUCTION

The need for reliable and effective techniques of identifying fruits and vegetables is constantly increasing in the fast-paced world of today. Automated identification has come a long way since machine learning techniques, especially Convolutional Neural Networks (CNNs), were developed. The goal of this project is to create a reliable system that can recognise different fruits and vegetables by utilising CNN models. We aim to develop a system that not only simplifies the identification process but also has a great deal of potential for use in the retail, food processing, and agriculture industries by utilising the power of deep learning.

In order to extract features from input data, CNNs, or convolutional neural networks, use a hierarchical structure of interconnected layers. These layers are made up of fully linked, pooling, and convolutional layers. Convolutional layers employ filters to identify patterns in input data, such as edges or textures. Pooling layers preserve significant features while lowering computing complexity by lowering the spatial dimensions of the data. Lastly, classification using fully connected layers is carried out using the features that were extracted. CNNs are especially well-suited for tasks like object detection and image classification since they are able to identify intricate patterns in images through multiple repetitions of this procedure.

Furthermore, the application of CNN-based machine learning techniques to agricultural processes has the potential to boost production overall, enable data-driven decision-making, and improve accuracy and efficiency. Farmers, distributors, and retailers can maximise resource allocation, save labour costs, and minimise waste by automating the identification process. This will support sustainability objectives and financial sustainability. CNN models are also highly adaptable and scalable, which makes them suitable for use in a variety of agricultural contexts, ranging from small-scale farms to large-scale commercial enterprises. This study looks at the performance and viability of CNN-based methods for fruit and vegetable identification in an effort to add to the expanding body of research in agricultural automation and precision agriculture. We aim to clarify the advantages and disadvantages through thorough testing and analysis.

## II. LITERATURE REVIEW

A study related to early identification in fruits and vegetables focuses on detecting abnormalities at the produce level using a deep learning framework based on images of fruit and vegetable tissues. A Convolutional Neural Network (CNN) model is employed to analyze and characterize images of abnormal produce. For this study, 672 images of various fruits and vegetables were collected, with reports of abnormalities, totaling 52 different types of produce. By preprocessing the data significantly and utilizing augmentation methods, a total of 2688 images were generated. The CNN model achieved promising results with an accuracy of 91.65% on the training dataset and 89.3% on the testing dataset. Furthermore, an algorithm based on three-dimensional convolutional neural networks (3DCNN) was utilized for the early detection of abnormalities in produce. Comparisons were made with traditional 2D-CNN techniques, with the 3DCNN demonstrating superior performance, indicating potential advancements in computed tomography for produce prognosis techniques. Additionally, novel techniques utilizing deep convolutional neural networks were applied for automated detection and classification of abnormalities in fruits and vegetables. The deep CNN model was partitioned into segmentation and classification stages, achieving high accuracy rates of 91.4% on a dataset of 100 images and 94.5% on a dataset of 500 images used for training normal produce tissue. Another deep learning approach was developed for the automated detection and classification of abnormalities in fruits and vegetables, showing promising results for early identification of produce defects. This approach utilized deep neural network architectures for image classification and object detection, achieving F1-scores of 87.07% and 71.18%, respectively. Furthermore, a study focusing on automated detection and classification of abnormalities in produce aimed at identifying potentially harmful defects. The approach involved using computer vision techniques with photographic images to automatically detect and classify abnormalities in fruits and vegetables. The study utilized a two-stage approach involving detector networks for identifying abnormal regions and classifying detection areas into respective classes.

A study focused on early diagnosis in fruits and vegetables aimed to detect signs of spoilage or disease at the tissue level using a deep-learning framework based on fruit and vegetable tissue images. The study employed a Convolutional Neural Network (CNN) model to analyze and characterize images of diseased fruit and vegetable tissues. Utilizing preprocessing techniques and augmentation methods, a dataset comprising 672 tissue images obtained from 52 samples of various fruits and vegetables was prepared. After data augmentation, the dataset expanded to a total of 2688 images. The CNN model achieved promising results with an accuracy of 91.65% on the training data and 89.3% on the testing data. Additionally, identification of specific diseases or spoilage patterns was explored using advanced techniques such as three-dimensional convolutional neural networks (3DCNN). Comparisons were made between 3DCNN and traditional 2D-CNN models to highlight the advantages of leveraging 3D structure information for accurate identification and prognosis of fruit and vegetable diseases. The results indicated that 3DCNN outperformed 2D-CNN in terms of accuracy, showcasing the potential of 3D imaging techniques for improving diagnostic accuracy in fruit and vegetable quality assessment and disease detection.

In a complementary study, a deep learning approach was developed for the automated detection and classification of specific diseases or defects in fruits and vegetables to facilitate early intervention and quality control measures. This approach employed a deep neural network architecture, with ResNet-101 utilized for image classification and object detection conducted using Faster R-CNN. The image classification component yielded an F1-score of 87.07%, while object detection achieved a score of 71.18%, demonstrating significant potential for the early detection and classification of fruit and vegetable abnormalities. Similarly, another study explored a deep learning strategy for automatically identifying and classifying specific defects or diseases in fruits and vegetables, aiming to enable early intervention and quality control measures. This method employed a deep neural network architecture, specifically ResNet-101 for image classification and Faster R-CNN for object detection. Both image classification and object detection components exhibited comparable F1-scores, further highlighting the efficacy of deep learning approaches in enhancing fruit and vegetable quality assessment and disease detection.

Moreover, the advent of edge computing has sparked interest in deploying lightweight deep learning models directly on agricultural sensors and devices situated at the edge of the network. This approach enables real-time analysis of produce images at the point of harvest, eliminating the need for data transmission to centralized servers for processing. By harnessing the power of edge computing and deep learning, farmers can swiftly identify abnormalities in fruits and vegetables right in the field, allowing for immediate interventions and minimizing post-harvest losses. Furthermore, interdisciplinary collaborations between agricultural scientists and materials engineers have led to the exploration of novel sensing materials embedded within packaging materials. These smart packaging materials, equipped with sensors capable of detecting biochemical changes associated with produce spoilage or disease, work in tandem with deep learning algorithms to provide early warnings of quality degradation. This integration of sensing materials with deep learning holds promise for revolutionizing the way we monitor and maintain the freshness and safety of fruits and vegetables throughout their shelf life.

## III. PROPOSED SYSTEM

In this study, we investigate a novel method of fruit and vegetable identification by providing the corresponding photos as input. Predictive models in this method created a new way to handle massive datasets.

The new approach to identify is represented in Fig. 1.

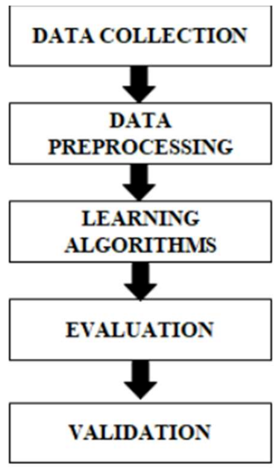



Fig. 1. Workflow of Experimental Set-Up

The 100 photos in the train dataset, 10 in the test dataset, and 10 in the validation dataset make up the three sets of images. There are 36 directories altogether.

In the Google Colab platform we have implemented this model. Firstly in the training model, the required packages are imported particularly tensorflow. Then data pre-processing has been done. The training image dataset is loaded using keras and the properties are set. The model has identified 36 classes. Then the CNN model is built. Then the 2D convolution layer is built using keras.layers.

**CNN:**

A subclass of deep learning neural networks called convolutional neural networks (CNNs) is especially made for handling structured, grid-like data, like photographs. They have formed the mainstay of many cutting-edge computer vision tasks and are inspired by the structure of the animal visual cortex. Convolutional, pooling, and fully linked layers are among the layers that make up a CNN.

The CNN architecture is given in Fig. 2

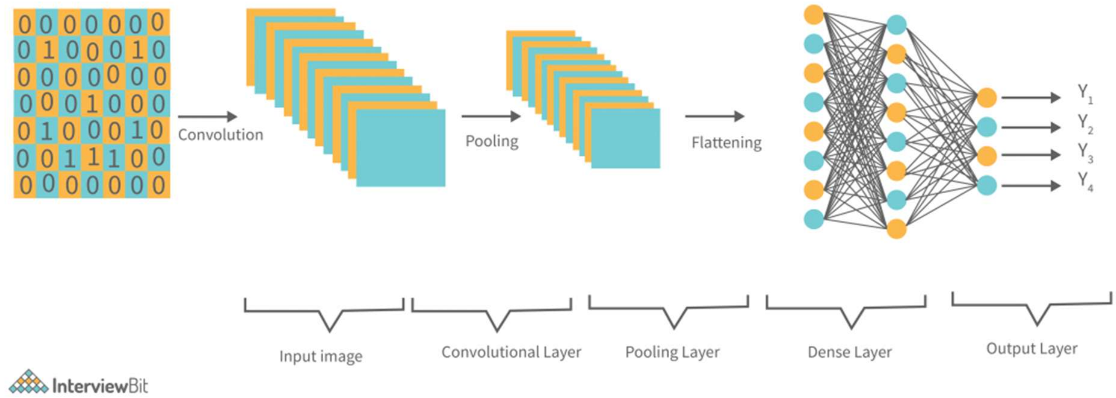



Fig. 2

1. The initial step in a CNN involves the input layer, where the network receives raw image data. This data is represented as a multi-dimensional array of pixel values, denoting the image's width, height, and color channels (e.g., RGB). Through the input layer, the image data is introduced into the network.

2. CNNs predominantly comprise convolutional layers, responsible for creating feature maps. These layers consist of learnable filters, also known as kernels, which convolve with the input image to extract various local patterns or features like edges, textures, or shapes. Feature extraction and spatial hierarchies are managed by the convolutional layers within the network.

3. Adding non-linearity to the network, an activation function is applied element-wise to the feature maps produced by convolutional operations. Activation functions such as Rectified Linear Unit (ReLU), sigmoid, or hyperbolic tangent (tanh) are commonly utilized. ReLU, being effective at addressing issues like vanishing gradients, is a popular choice due to its simplicity and efficiency.

4. Pooling layers are inserted between convolutional layers to decrease the spatial dimensions of feature maps while retaining essential information. Techniques like max pooling and average pooling aggregate data from adjacent regions of feature maps, effectively downsampling them and improving computational efficiency. Additionally, pooling introduces translational invariance, enhancing the network's robustness to slight variations in input.

5. Positioned towards the end of CNN architectures, dense layers, or fully connected layers, comprise neurons interconnected with all neurons in the preceding layer. These layers integrate and utilize high-level feature representations learned from earlier layers for tasks involving classification or regression. Through non-linear transformations, fully connected layers enable the capture of intricate correlations between features in the input data.

6. The output layer of a CNN generates final predictions or outputs. The number of neurons in the output layer corresponds to the classification task's number of classes or categories. Typically, a softmax activation function is applied to the output layer to convert raw scores into probabilities, indicating the likelihood of each class for tasks like image classification.

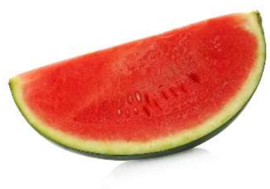
Types of Pooling:

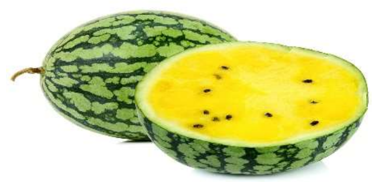
1. Max Pooling: In this method, each window covering the input feature map retains only the highest value within its region. By preserving dominant characteristics while discarding less significant data, max pooling effectively downsamples the feature map and offers resistance to noise, providing a form of translation invariance.

2. Average Pooling: Here, each window computes the average value of elements within the input feature map region. While also downsampling the feature map, average pooling tends to blur features by averaging data. Although less common than max pooling, it can aid in reducing overfitting and computational complexity in CNNs.

## IV. RESULT

Some examples of dataset is given below.





After compiling, summary of the layers are obtained using the summary function. Now the data is trained using fit. This process runs on epoch for about 1 hour in which all 30 epochs are calculated. Each epoch gives output containing training loss, accuracy, validation loss and accuracy. The 30th output is given in Fig. 3.

```
Epoch 29/30
98/98 [==============================] - 118s 1s/step - loss: 1.0450 - accuracy: 0.8276 - val_loss: 1.5014 - val_accuracy: 0.9174
Epoch 30/30
98/98 [==============================] - 119s 1s/step - loss: 0.9843 - accuracy: 0.8417 - val_loss: 1.4048 - val_accuracy: 0.9117
```

Fig. 3

The CNN output is saved in h5 format for further use. Now the accuracy of the model achieved is obtained using the history function and given in Fig. 4

```
print("Validation set Accuracy: {} %".format(training_history.history['val_accuracy'][-1]*100))

Validation set Accuracy: 91.16809368133545 %
```

Fig. 4

The training accuracy graph of the model is given in Fig. 5.

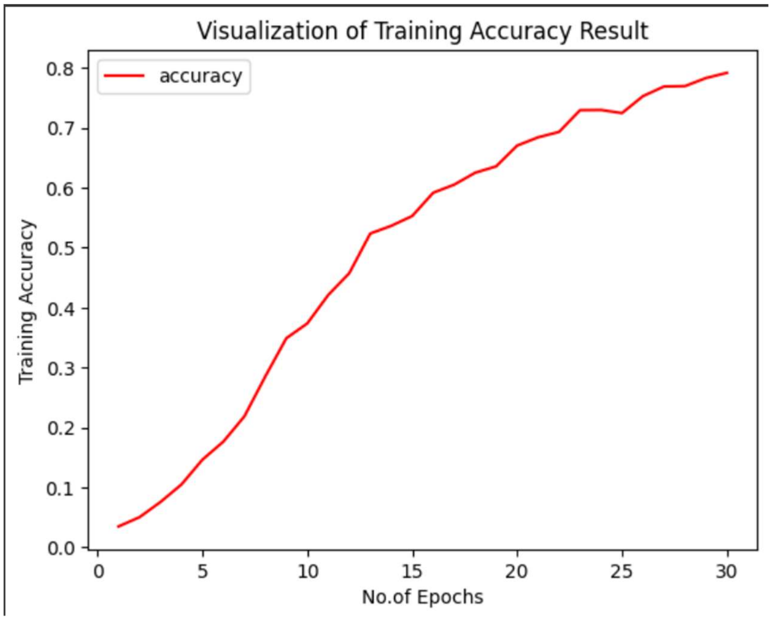
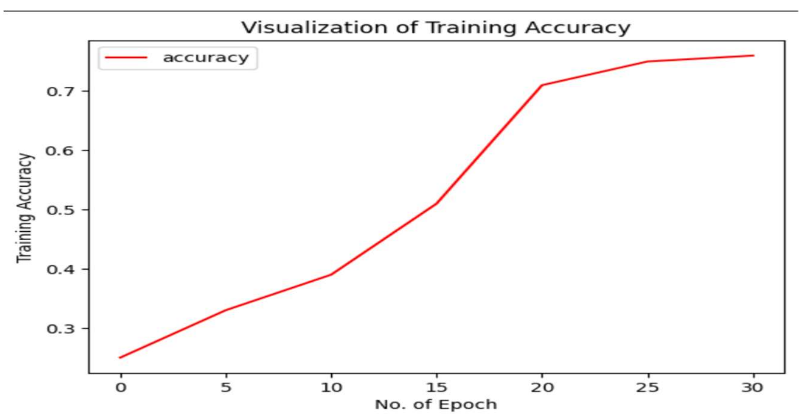



Fig. 5

Comparison of graphs with better accuracy




The validation accuracy graph of the model is given in Fig. 6.

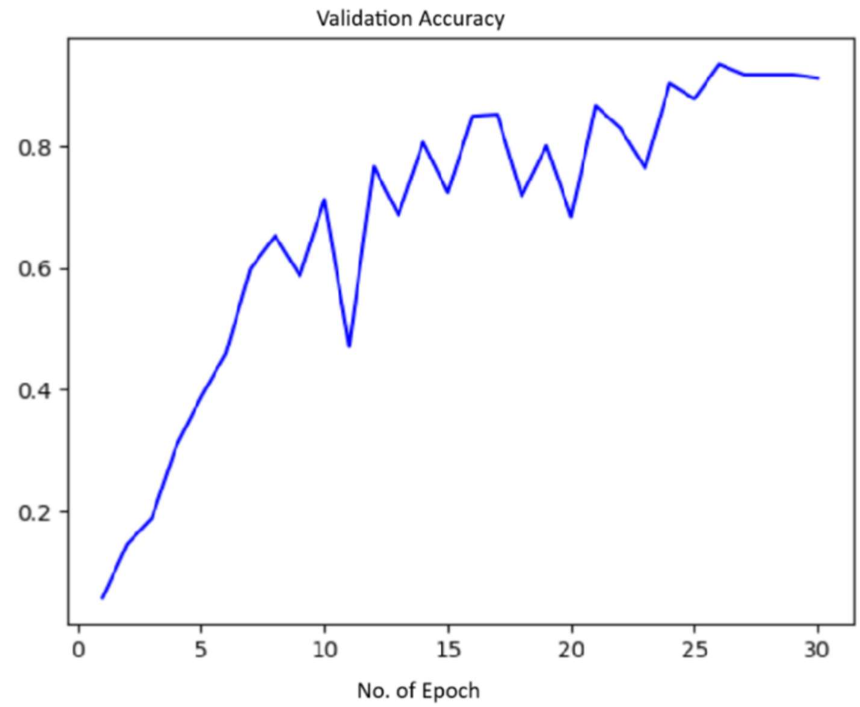



Fig. 6

Now the testing model is built and image for testing is loaded using the image functions.

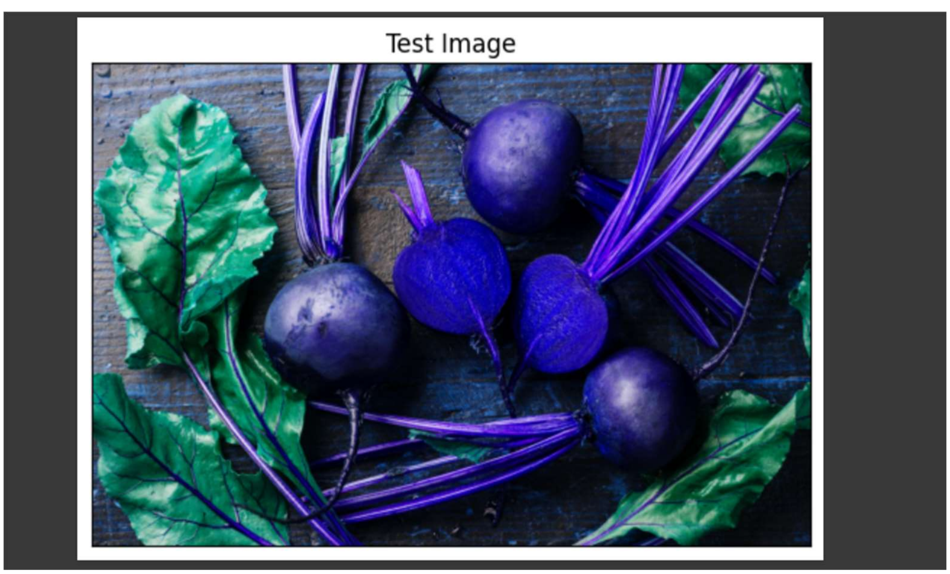



Fig. 7

Firstly image pre-processing is done. Then the image is converted into array. Then the predictions are taken as output using the cnn.predict function.

```
[ ]  print(predictions)

     [[1.1816459e-30 0.0000000e+00 1.0000000e+00 0.0000000e+00 0.0000000e+00
       0.0000000e+00 0.0000000e+00 0.0000000e+00 1.7114400e-36 0.0000000e+00
       0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00
       0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00
       3.0163963e-34 0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00
       0.0000000e+00 1.4988401e-34 0.0000000e+00 0.0000000e+00 0.0000000e+00
       0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00
       0.0000000e+00]]
```

Fig. 8

Now the properties are set and 36 classes are found as in the training model. Now single prediction is done and output is derived. It is shown in Fig. 9.

```
#single pred
print("It is a {}".format(test_set.class_names[result_index[0][0]]))

It is a beetroot
```

## IV. CONCLUSION

In conclusion, the application of Convolutional Neural Networks (CNNs) in the identification of fruits and vegetables has shown promising results for early detection of diseases, spoilage, and abnormalities at the tissue level. By leveraging advanced deep learning frameworks and techniques such as data preprocessing, augmentation, and three-dimensional convolutional neural networks (3DCNN), significant strides have been made in accurately classifying and detecting issues in fruit and vegetable samples. The studies discussed highlight the potential of CNN models, particularly in combination with techniques like ResNet-101 and Faster R-CNN, to achieve high accuracy in both image classification and object detection tasks. These findings underscore the importance of utilizing deep learning approaches for enhancing fruit and vegetable quality assessment, disease detection, and early intervention measures in agricultural and food industries. Moving forward, continued research and development in this field hold promise for further improving the efficiency and effectiveness of automated fruit and vegetable identification systems, contributing to the enhancement of food safety, quality, and sustainability.

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