A Deep Learning Approach for Detection of Disease and Classification of Fruits

Dr. Sharanabasappa Madival[1]
Department of Computer Science and Engineering
Faculty of Engineering & Technology (Co-Education)
Sharnbasva University
Kalaburagi, India

Mary Sushmita[2]
Department of Artificial Intelligence and Data Science
Sharnbasva University
Kalaburagi, India

Abstract:- The calorie component of fruit is identified using a common photo dataset and several machine learning advancements, including Pre-processing, segmentation, function extraction, and classification which is primarily based on size and shape. Using image processing methods, the dimensions of fruit objects are calculated. Finally, we'll provide users and patients with the best advice for fruit consumption based on our best estimates of the number of calories in the fruit. To help farmers save time and money while improving the accuracy of plant disease detection, we have developed a technology. Thanks to the usage of many speed-enhancing methods, it outperforms competing systems. An easy-to-implement method for picture segmentation, classification, and reconstruction, the SVM Algorithm is what we're employing here. Even when the objective function isn't acting well, it may nevertheless perform well during global optimization.

Keywords:- *Image Processing, Smart Farming, Fruit Grading.*

I. I.INTRODUCTION

India is the world's second-largest producer of organic goods, with its rural population producing 44.04 million tons of soil products each year. Ten percent of the world's natural products are produced in India. Ranchers in India cultivate a wide variety of organic fruits and vegetables, including watermelon, papaya, guava, mango, citrus, grapes, and more. The natural products sector accounts for around 20% of the country's GDP. The surprising improvement of natural goods, the nonappearance of maintenance, and manual assessment have all contributed to a decrease in the creation of valuable natural products. Pesticides and other chemical pollutants degrade both the quantity and quality of rural goods. Infections and microbes are the primary causes of diseases caused by natural products. Horrible environmental conditions also contribute to the spread of the illnesses. Such natural product diseases have a wide range of characteristics and behaviors, many of which are difficult to identify. An important perspective is the diagnosis of organic product disease. A method of manual monitoring is necessary for farmers in this area. Unfortunately, the outcome will not be precise every time. So, we want a single intelligent OS that can identify both healthy and diseased crops.

By applying machine learning techniques such as pre-processing, segmentation, feature extraction, training, and classification based on shape and size, the calorie content of a piece of fruit can be identified using a standard photo dataset. Using image processing methods, the dimensions of fruit objects are calculated. The last thing to do is figure out how many calories are in the fruit and then provide the patients and users with the best advice on how much fruit to eat. Various methods for estimating calories are discussed and evaluated. Season, weather, state, nation, usage, etc. are some of the fruit attributes that we also included.

II. LITERATURE REVIEW

In 2015, Dr. Agrawal et al. [1] presented a method that made use of the Internet of Things for its implementation. This approach shows the plant diseases that have been found, the reasons behind them, and the best way to manage them. Consider the leaf: it shows the leaf's wetness, humidity, temperature, and more. It makes use of an LCD monitor, MATLAB, and Arduino software, among other things.

In 2015, Bharwad et al. [2] followed the same process as the one we are using in our work at the moment. Factors such as form, color, and texture were used for extraction. Additionally, several algorithms are used for distinct processes.

In 2016, Bhange et al. [3] proposed an image-processing technique for detecting diseases in fruit plants. They used a Support Vector Machine (SVM) with an accuracy of 82 percent. Their approach, similar to ours, involved different components such as color coherence vector, intent search, dataset preparation, and morphology to achieve results.

In 2011, Jaymala Patil et al. [4] advanced the study of plant diseases by reviewing 24 papers and identifying various methods for disease detection. They found that new techniques were continually being introduced, each with varying levels of accuracy. Examples include wavelet-based techniques, stereomicroscopic methods, integrated image analysis, and artificial vision systems.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177

S.E.A. Raza et al. [5] 2015 developed a for remotely detecting infected plants when two types of plants are present in the same image using a machine-learning system. Using thermal imaging to examine plants for unhealthy zones is a rapid and non-destructive method. Their goal in writing this research is to provide a way for automated disease identification in plants using machine learning approaches by combining data from stereo visible light pictures with thermal images. This will help them overcome challenges like temperature change, leaf angles, and environmental variables.

In 2015, Patil et al. [6] introduced two fascinating new key topics: detection and classification. To boost plant production and economic development, it is crucial to detect and classify plant diseases. The picture undergoes a series of operations, including pre-processing, segmentation, feature extraction, and classification, to identify plant diseases. Based on the characteristics that are chosen, it sorts the data.

In 2015, Rastogi et al. [7] proposed a system split into two stages. During the initial stage, the plant is identified through the analysis of leaf characteristics, which involves pre-processing leaf images, followed by training and classifying the images using an Artificial Neural Network (ANN). In the next phase, the disease on the leaf is identified using K-Means segmentation to isolate the affected areas, followed by extracting features from these infected regions. An artificial neural network (ANN) is then employed to classify the disease. The severity is determined by evaluating how extensively the leaf is infected.

In 2015, Bed et al. [8] surveyed methods for identifying diseased leaves. The paper examined a range of techniques, including Probabilistic Neural Networks, Principal Component Analysis, and Genetic Algorithms. It determined that Probabilistic Neural Networks is the most accurate method for identifying the affected areas of leaves.

In 2015, Rajleen Kaur et al. [9] employed an SVM classifier to detect plant diseases. The process begins with capturing the original image, followed by image processing. The image is then separated into its hue and saturation components, and finally, the diseased areas are identified. This approach utilizes an Enhanced SVM method, which offers improved accuracy compared to previous methods.

In 2012, Anand H. Kulkarni et al. [10] started by capturing images, which were then filtered and later segmented using a Gabor filter. From the segmented images, texture and color features were extracted. The combination of these features, along with the use of an Artificial Neural Network (ANN), provided better accuracy.

In 2012, Dheeb Al Bashish et al. [11] proposed a framework with two key steps: first, segmenting images using the K-Means algorithm, and then analyzing the segmented images with a pre-trained neural network.

In 2015, Sachin D. Khirade and colleagues used techniques such as boundary and spot detection, k-means clustering, the Otsu threshold algorithm for segmentation, and the CCM method for extracting features and classification by applying the backpropagation method of ANN.

III. SYSTEM ARCHITECTURE

➤ *Flow Chart*

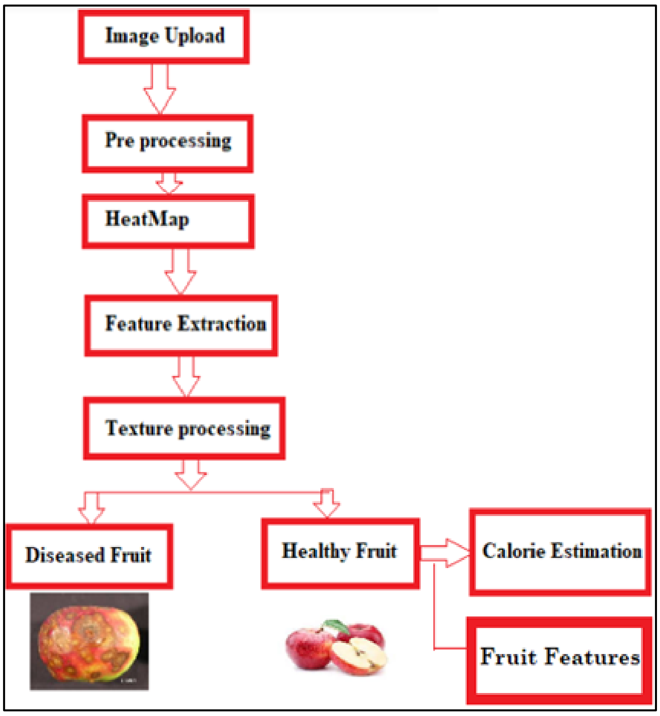


Fig 1 Flow Chart

IV. IMPLEMENTATION

➤ *Modules*

- *Capturing Image*

The first stage in detecting a plant illness is to take a picture of the affected plant. We can use digital cameras and mobile devices with at least 8 megapixels.

- *Preprocessing:*

Images are gradually included in the program. Preprocessing enhances the image's clarity, allowing us to make out even the tiniest of elements. We employ Median filters to isolate pictures and eliminate noise. By applying a median filter to a picture, we may keep the relevant details while eliminating the noise.

- *Feature Extraction:*

The process begins with picture extraction and continues with applying various filters. Next, things that seem contaminated are grouped. Partitioning and extracting features are two applications of region growing. Because these pixels are used in the absence of an edge, it is entirely dependent on the pixels immediately around them. This makes use of routines that compute values and keep doing so until all of the values have been used up.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177

- *Segmentation:*

This module splits the photos into many sections. For image segmentation, a mask or labeled image is used to divide a picture into smaller, more manageable pieces. Rather than processing the whole picture, only the relevant parts may be processed by segmenting it.

- *Classification:*

As a supervised learning approach, SVM is useful for regression and binary classification. As such, it serves as a coordinate for certain observations. The foundation of this system is decision planes, which outline the limits of decisions. It did the same thing for objects of various classes, dividing them apart.

- *Color moments:*

When it comes to color indexing, color moments are gold. When using it for picture retrieval, it just takes the first three color seconds into account. You may use it to see how the two photographs stack up in terms of color.

- *HOG function:*

In vision and image processing, the histogram of oriented gradients (HOG) is used as a feature for identifying objects. Cells are tiny, linked sections in the picture. It remains unchanged after geometric changes since it operates on local cells.

- *Hue Saturation Value (HSV) Appearance:*

HSV is a measure of color, saturation, and brightness. Consequently, color position and color purity may be utilized to search using the color detection method. The pixels are detected by it.

- *Estimation of Calorie:*

After the fruit's area has been identified, its volume is mostly determined by its unique forms. An apple has been used in our instance. You may get the first radius by dividing it by pi (3.14).

As a result, the formula to get the calorie value is:
The volume of a sphere is (4/3)*pi*radius*radius* radius

✓ Using the appropriate volume formula, one may determine the volume of various fruit forms, such as cylinders (bananas) and ellipsoids (pears, mangoes).

The fruit's mass was determined by comparing the computed volume value with the density data. The overall calorie content of the fruit was calculated by taking the food value per 100 grams into account.

Estimated Weight = Actual Density × Estimated Volume

✓ Estimated Calories = (Estimated Weight × Calories per 100 grams) / 100

V. METHODOLOGY

➢ *Image Segmentation:*

Algorithm for K-Means image segmentation – as given in steps

- Read the input picture.
- Move the picture from the RGB color space to the L*a*b* hue.
- Sort colors into 'a*b*' categories using K-Means clustering.
- Using the K-Means findings, assign a name to each pixel in the picture.
- It is possible to create pictures by dividing them up according to color.
- Find the part that has the illness and pick it out.

➢ *Feature Extraction:*

One common and well-liked method for detecting and extracting picture object edges is canny edge detection. One method used in image processing to identify the borders of objects in a picture is edge detection. When the intensity of individual pixels in a picture suddenly changes, we say that there is an edge. The edges of a picture show the limits of different things or areas with different shades of gray.

➢ *CNN Algorithm:*

In a CNN model, the input data passes through multiple layers, each layer extracting increasingly complex features, before the final classification is performed. The main elements of a CNN include convolutional layers that use filters to identify features and pooling layers that downsample the data to decrease its size. Following multiple rounds of convolution and pooling, the data is flattened and fed into fully connected layers, which then handle classification or regression using the extracted features.

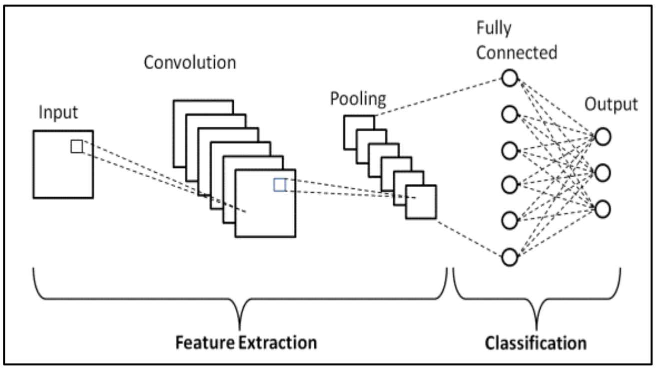


Fig 2 CNN Architecture Model

➢ *The CNN model consists of two main components: Feature Learning and Classification.*

- *Feature Learning*

Feature learning refers to the methods used to automatically extract and learn features from input images. In a CNN, this process is carried out using two main components: the Convolution Layer and the Pooling Layer. Let us explain each of these layers individually.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177

✓ *Convolution Layer:*

The convolution layer is responsible for extracting features. It does this by first applying a convolution function and then an activation function to the result. Multiple convolution layers may be used to enhance feature extraction. A kernel or filter is a linear function used in this process to identify features.

Suppose we have an input image described by tensor **I** of dimension a1 × a2 × bc.

Where,

$$a_1 = \textit{height of image}$$

$$a_2 = \textit{width of image}$$

$$b_c = \textit{number of channels}$$

We use a filter, which is also a tensor with dimensions n1×n2×nc (where the number of channels in the filter matches that of the input image). The filter slides across the image from left to right, performing element-wise multiplication between the corresponding section of the input image I and the filter K, and then summing these products. The stride specifies the step size for moving the filter across the image. The result of applying I and K is a new tensor with dimensions (a1−d1+1)×(a2−d2+1)×1

Here,

$$\textit{dim of } I = a_1 \times a_2 \times b_c$$

$$\textit{dim of } K = d_1 \times d_2 \times d_c$$

$$\textit{dim of } F = (a_1 - d_1 + 1) \times (a_2 - d_2 + 1) \times 1$$

And,

$$\mathrm{F[i,j]} = (I * K)_{[i,j]}$$

The entry of position (i,j) in the feature map is calculated as:

$$\mathrm{F[i,j]} = \sum_{x}^{a1} \times \sum_{x}^{a1} \times \sum_{x}^{a1} \times \, K_{(x,y,z)} \, I_{(i+x-1,j+y-1,z)}$$

This process is repeated using various filters, each capturing different features of the image such as blur or sharpness. Multiple filters can be applied, which is related to the concept of stride.

✓ *Padding:*

A limitation of the described method is that the filters tend to emphasize the center of the image more than the corners. This issue can be mitigated by using padding. Typically, zero padding is employed, which involves adding a border of zeros around the input tensor on all sides.

✓ *Activation Function:*

Generally, a bias term ‘b’ is added to the result of the convolution, followed by the application of the activation function

$$c = F + b$$

$$c = I * K + b$$

$$Conv(I, K) = \emptyset_a (c)$$

$$= \emptyset_a (I * K + b)$$

$$\textit{where } \emptyset_a \textit{ represents Activation Function}$$

Some of the activation functions, like sigmoid, tangent, and hyperbolic tangent functions. ReLu is the most commonly used activation function which removes negative values.

$$R(x) = \text{maximum}(0, x)$$

4	2	-8
0	5	1
-4	-2	6

ReLu →

4	2	0
0	5	1
0	0	6

✓ *Pooling Layer:*

The pooling layer reduces the spatial dimensions of the features obtained from the convolution layer, thereby capturing the most prominent features of the imageA pooling function is utilized on the output from the convolution layer to accomplish this. Let's consider:

$$Conv(I, K) = C$$

$$P = \emptyset_p (C)$$

$$\textit{where } \emptyset_p \textit{ is an pooling function}$$

The dimension of the pooled part is given as :

$$\dim of\ P = \left(\frac{m_1 + 2p - n_1}{s}\right) \times \left(\frac{m_2 + 2p - n_2}{s}\right) + m_c$$

Where,

$$m_1 \times m_2 = \textit{the dimensions of input image}$$

$$n_1 \times n_2 = \textit{the dimensions of padding kernel}$$

$$\textit{here, s stands for stride and p stands for padding}$$

- *Classification*

In this approach, multiple hidden layers (comprising both convolutional and pooling layers) are used to extract features. The output is compressed into a single vector after the process of feature extraction. Classification is performed in this single vector which serves as the input for the fully connected layer.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177

✓ *Fully Connected Layer:*

This layer takes the flattened vector and generates a new vector within machine learning models, some classes may appear more frequently than others. To address this issue, balanced weights are assigned to the pooled data, a bias term is introduced, and an activation function is applied.

The mathematical description is as below:

$$X = \sum_i w_i P_i + b'$$

$$z = g(X)$$

$Where\ g\ is\ an\ activation\ function\ for\ fully\ connected\ layer$

In this method, weights are added to the pooled data at each layer, followed by the application of an activation function. Multiple hidden layers are involved, with the final layer using an activation function to perform classification by determining the probability for each class.

➢ *Here's a summary of the process:*

- The input image is processed through a series of convolutional layers that use filters to extract features.
- Each layer's output is then passed through a rectified linear unit (ReLU) activation function to add non-linearity.
- Pooling layers are employed to reduce the output dimensions and enhance model efficiency.
- The convolutional and pooling layers can be stacked multiple times, depending on the problem's complexity.
- The output from the final convolutional layer is flattened and then passed into a fully connected layer, which uses the extracted features to perform classification or regression.
- The FC layer's output is processed through an activation function, such as softmax or logistic regression, along with cost functions, to generate a class label for the input image.

VI. VII.RESULT

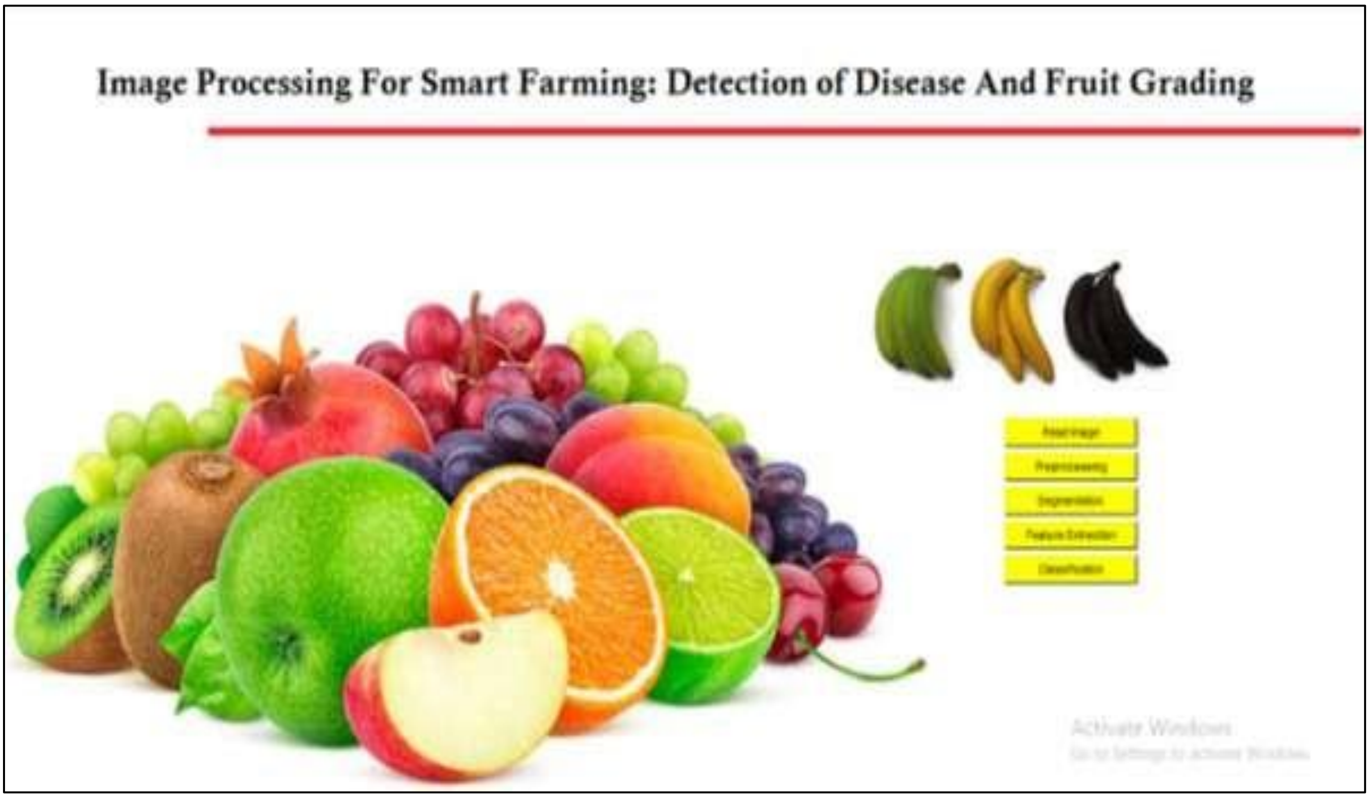


Fig 3 Menu

Fig 4 Preprocessing

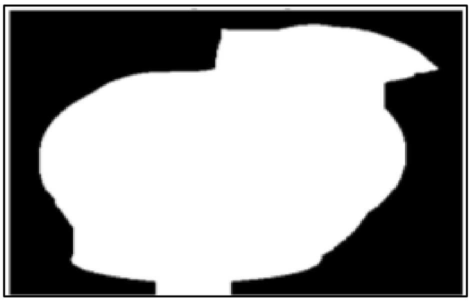
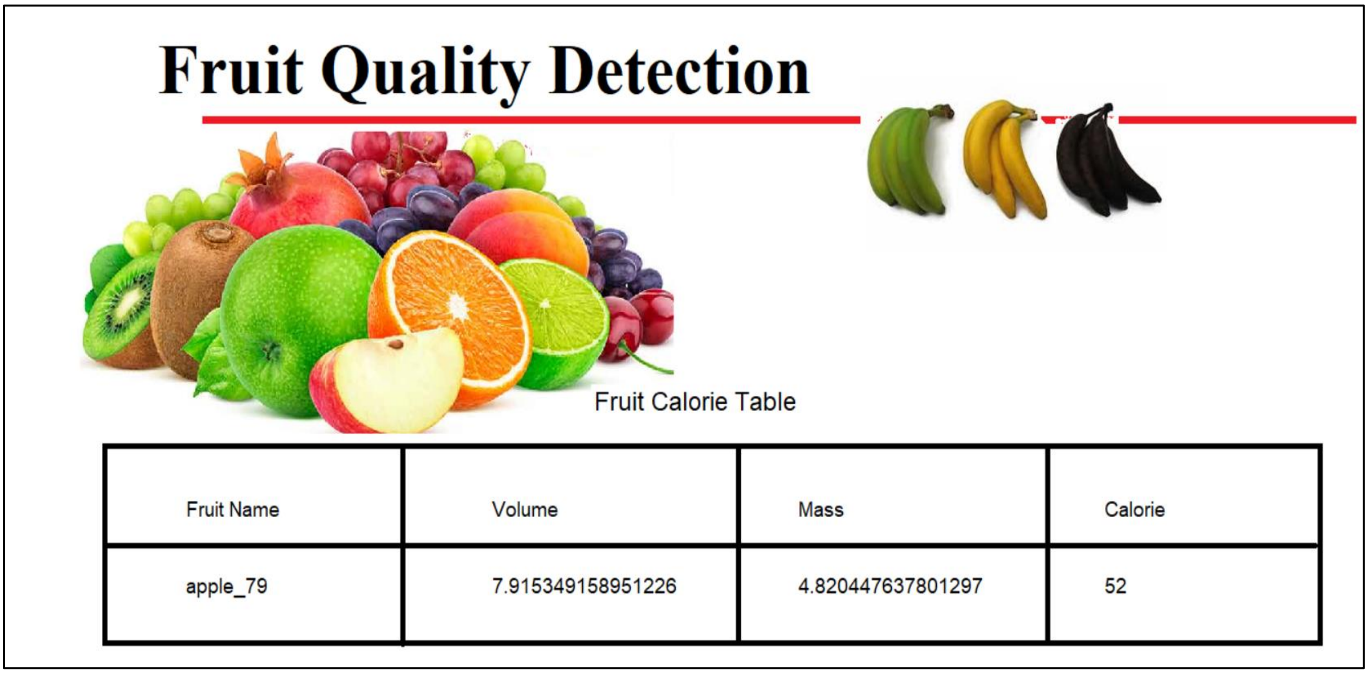


Fig 5 Image Segmentation

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177



Fruit Name	Volume	Mass	Calorie
apple_79	7.915349158951226	4.820447637801297	52

Fig 6 Calorie Table

Table 1 CNN Report

	precision	recall	f1-score	support
0	1.00	0.50	0.67	2
1	1.00	0.50	0.67	2
2	0.00	0.00	0.00	0
3	1.00	1.00	1.00	1
4	0.00	0.00	0.00	0
accuracy			0.60	5
macro avg	0.60	0.40	0.47	5
weighted avg	1.00	0.60	0.73	5

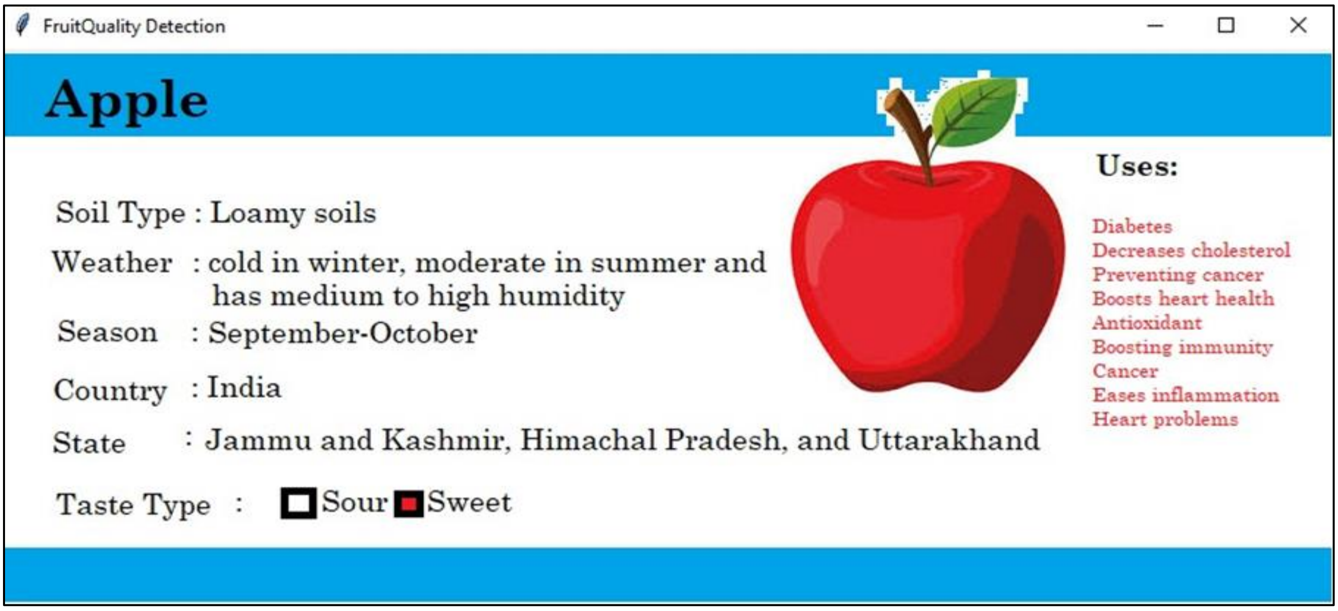


Fig 7 Fruit Features

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24AUG177

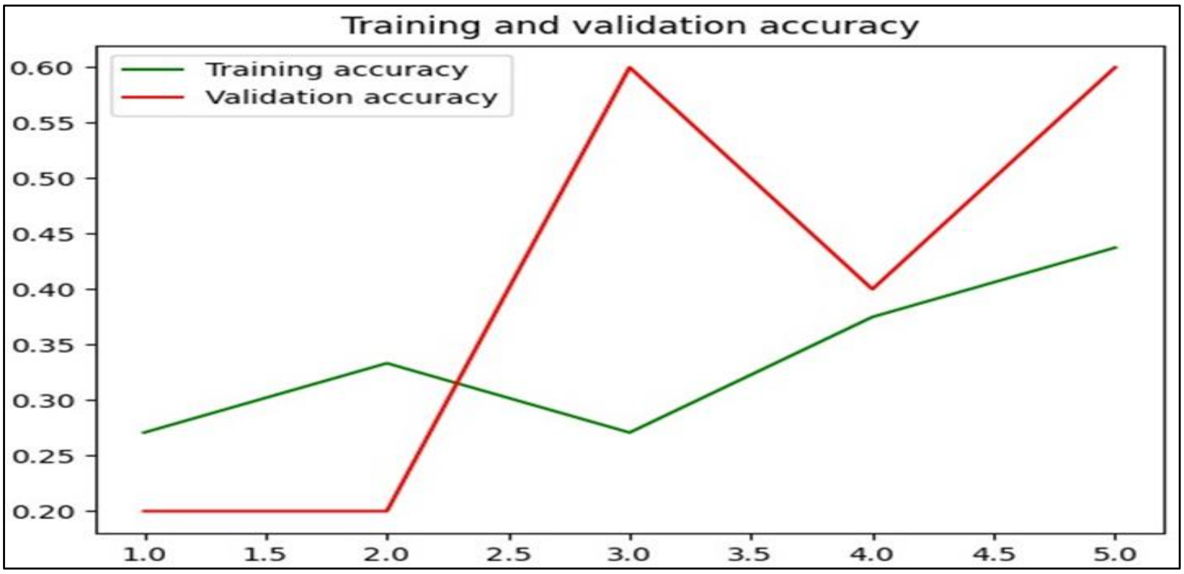


Fig 8 Training Accuracy V/s Validation Accuracy

VII. CONCLUSION

As a result, we have developed a technology that accurately diagnoses plant diseases while simultaneously saving time and money for farmers. Due to the use of several methods, it outperforms competing systems in terms of speed. Our method is based on the SVM Algorithm, which is easy to apply and has several applications in image processing, including segmentation, classification, and reconstruction. Using the CNN algorithm we can predict the quality of fruit and differentiate them with their respective fruit features. The calorie content of fruit is identified using a standard image dataset by applying techniques such as pre-processing, segmentation, feature extraction, training, and classification based on shape and size, all facilitated by machine learning methods. Even when the objective function isn't acting well, it may nevertheless perform well during global optimization.

REFERENCES

[1]. Dr.G. H. Agrawal, Prof. S. G.galande and Shalaka R.Londhe "Leaf disease detection and climatic parameter monitoring of plants using IOT." International Journal of Innovative Research in Science, Engineering and Technology, volume-4,issue-10, pp. 9927-9932, Oct- 2015.
[2]. Viabhavi S.Bharwad and Kruti J.Dangarwala" Recent research trends of plants disease detection." International Journal of Science and Research, volume-4,issue-12, pp. 843- 845, Dec-2015.
[3]. Manisha Bhange and H.A.Hingoliwala "Smart framing: pomegranate disease detection using image processing." Second International Symposium on Computer Vision and the Internet (VisionNet'15), pp.280-288.
[4]. Jaymala K. Patil and Raj Kumar "Advances in image processing for detection of plant disease." Journal of Advanced Bioinformatics Applications and Research, pp. 135-141, June 2011.
[5]. Shan-e-Ahmed Raza, Gillian Prince, John P.Clarkson and Nasir M. Rajpoot "Automatic detection of diseased tomato using thermal and stereo visible light images." PLOS-One, April-2015.
[6]. Sagar Patil and Anjali Chandavale"A survey on methods of plant disease detection." International Journal of Science and Research, volume-4,issue-2, pp. 1392-1396, Feb- 2015.
[7]. Aakanksha Rastogi, Ritika Arora, and Shanu Sharma "Leaf disease detection and grading using computer vision technology and fuzzy logic."International Conference on Signal Processing and Integrated Networks, 2015.
[8]. Bed Prakash and Amit Yerpude "A survey on plant disease identification."International Journal of Advanced Research in Computer Science and Software Engineering, volume 15, issue-3, pp. 313-317, March 2015.
[9]. Rajleen Kaur and Dr. Sandeep Singh Kang "An enhancement in classifier support vector machine to improve plant disease detection." IEEE 3rd International Conference, pp. 135-140,2015.
[10]. Anand H Kulkarni and Ashwin Patil R. K "Applying image processing technique to detect plant disease." International Journal of Modern Engineering Research,volume-2, issue-5, pp. 3661-3664, 2012.
[11]. Dheeb Al Bashish, Malik Braik, and Sulieman Bani-Ahmad "A framework for detection and classification of plant leaf and stem disease." International conference on signal and Image Processing pp. 113-118,2012.
[12]. Sachin.D.Khirade and A.B.Patil "Plant disease detection using image processing." in International Conference on Computing Communication Control and Automation, pp. 788-771,2015.
[13]. Shirke, Suvarna, S. S. Pawar, and Kamal Shah. "Literature Review: Model Free Human Gait Recognition." Communication Systems and Network Technologies (CSNT), Fourth International Conference on. IEEE, 2014.