AI in Agriculture: Classifying Citrus Fruits with Machine Learning

Karan Bhatt
Computer Science and Engineering, Graphic Era Hill University
Dehradun, India
karanbhatt.220112074@gehu.ac.in

Parveen Dhoundiyal
Computer Science and Engineering, Graphic Era Hill University
Dehradun, India
dhoundiyalparveen@gmail.com

Aman Singh Rawat
Computer Science and Engineering, Graphic Era Hill University
Dehradun, India
amansinghrawat.220112617@gehu.ac.in

Vikrant Sharma
Computer Science and Engineering, Graphic Era Hill University; Adjunct professor, Graphic Era Deemed to be University, Dehradun, India.
vsharma@gehu.ac.in

Satvik Vats
Computer Science and Engineering, Graphic Era Hill University; Adjunct professor, Graphic Era Deemed to be University, Dehradun, India.
svats@gehu.ac.in

***Abstract*— Citrus fruit detection is essential for early predicting citrus fruit yield in agricultural fields, food processing, and quality control. notably when dealing with issues of fruit occlusion brought on by overlapping or densely packed fruits. Detection of citrus fruits become more rigorous because of their wide variety, similar shape, appearance, and outer flesh. Addressing the same problem, it put forward an algorithm for detecting citrus fruits using images. We have used 5 different algorithms for the detection of citrus fruits that are KNN, Decision Tree, Random Forest, Gradient Boosting, and AdaBoost. We used 80% data from the dataset for training the models and 20% data was used for testing purposes.**

Keywords—citrus fruit, occlusion, detection, prediction, appearance, KNN, Decision Tree, Random Forest, Gradient Boosting, AdaBoost.

I. INTRODUCTION

In Asian countries, citrus fruits are popular and India is the 3rd largest producer of citrus fruits with an annual production of about 8.6 million metric tons with so many varieties. however, it can be challenging to differentiate between similar fruits. This predicament can potentially create issues, making it an intriguing research topic.

Numerous citrus species can be found in Northeastern India, where they are grown in their natural or semi-wild habitats without much attention or commercial production. Due to population growth and farmers' preference for cash crops, valuable genetic resources are being eroded and many are at risk of extinction. Rare and endangered resources should be conserved by the scientific community and must utilize citrus as a raw material for making several products. [1]

Citrus is grown all over Pakistan, but Punjab accounts for 95% of the country's production due to its diverse ecological environment and ample water resources, both natural and man-made. Of all the districts in Punjab, Sargodha is the biggest producer of citrus. Since it is the central hub of citrus production, the country's price and marketing of citrus products are largely influenced by the Sargodha district. [2],(Akhter et al., 2021)

A project called CITRUS ROBOT, a joint venture between Spain and France has been underway since 1987. The primary objective of this project was to design a highly sophisticated vision system to locate fruits accurately and direct the robot arm to pick them with precision.[4]

The probability of affection from the surrounding environment, pests, and diseases to citrus fruit at its starting stage i.e. when it is green is high. Having a well-designed scientific strategy for preserving and reducing the number of fruits is essential for ensuring a robust citrus harvest. During the green fruit phase, the fruit's growth is vulnerable to various factors, including pests, diseases, and the overall surroundings. As a result, the fruit may become misshapen, suffer from physical harm, or be plagued by pests and illnesses. The fruits that are not yet ripe have very little nutritional value and provide minimal financial advantages. As citrus fruits grow, they tend to take in some of the nutrients from the tree. This can cause a waste of nutrients and result in an insufficient supply of normal fruits. Moreover, mature citrus trees often have an excess of fruits, which leads to competition for nutrients. It is essential to use scientific methods to correctly identify the green stage of citrus and extract the fruit to improve citrus yield.[5]

Citrus is a highly valued fruit worldwide, known for its health benefits and its dietary, nutritional, medicinal, and cosmetic properties. It contains several valuable components like vitamins C, carotenoids, flavonoids, pectin, calcium, potassium, and more. Citrus fruits are an excellent source of both soluble and insoluble fiber, which can help in removing toxic substances from the body and provide various other benefits.[6], [7]

As all citrus fruits are mostly circular, some citrus fruits vary in circular shape among different types of citrus fruits. Some are purely round but others are oval, ellipse, parabolic, elongated, and circular shapes.

Image classification is accomplished by utilizing CV techniques that can detect and categorize objects [8], [9] [10], [11]. These techniques are generally accurate, although they have their advantages and disadvantages. The most frequently used techniques include color-based and shape-based methods.[3]

Threshold values in the hue value were set for the citrus fruits to differentiate them by Slaughter and Harrell, 1989, Harrell et al., 1989. In 1989 Ness showcased a way to solve the fruit recognition problem based on the color contrast between citrus fruit and foliage. Based on R and G components Moct et al. (1992) exhibited an approach for differentiating between the citrus fruit and leaves. Xu et al. (2005) and Zhang et al. (2009) developed a technique to distinguish citrus fruits from the background by analyzing the difference between their R (red) and B (blue) elements.(Detecting Citrus Fruits and Occlusion Recovery under Natural Illumination Conditions - ScienceDirect, n.d.), (Lu & Sang, 2015)

A model was created by Slaughter and Harrel (1989) which can differentiate oranges from their natural background in an orange grove using only color information in a digital image. This was intended to aid in the robotic harvesting of oranges. Later, Pla et al. (1993) developed an efficient model that showcased a way for characterizing spherical objects in a digital image and used it to detect citrus fruits under natural conditions. [13]

Annamalai and Lee (2003), Annamalai et al. (2004), and Chinchuluun and Lee (2006) For estimation of citrus yield created colour vision systems. Ragunathan and Lee (2005) delimited citrus fruit from the background in tree images and estimated the fruit size. Additionally, Chinchuluun and Lee (2006) developed a fruit identification method that uses the Watershed transform to segment and split touching fruit, which provides accurate fruit counts and yield estimates.[13]

Categorization of methods for object detection in the agricultural field can be done as non-deep learning and deep learning approaches. [14].

Lu et al. introduced a technique for identifying citrus fruits based on color and contour information, which can even detect them under varying lighting conditions. Although this method performs well in complicated natural environments, it is not as efficient in detecting smaller citrus fruits. In 2013, Lin et al. proposed an enhanced technique that uses the circular random Hough transform (CRHT) to detect camellia fruit that are concealed.

In 2015, Lu et al. (2015) developed a method for recognizing citrus fruits using their colour and contour, even in complex and diverse lighting and backgrounds. However, this method struggles to detect smaller fruits. Lin et al. (2013) proposed an improved approach based on the circular random Hough transform (CRHT), which can detect occluded camellia fruits to address this issue.(Lin et al., 2024) (Lu & Sang, 2015).

II. Literature Review

Citrus fruit detection is crucial for an agricultural yield of citrus fruit because it is the raw material for so many products like Juices, flavonoids, skin care products, and many more. In this section, we will discuss various research done in previous years.

Research on 14 Feburary1992" Feature extraction of spherical objects in image analysis: an application to robotic citrus harvesting" proposed a method of depicting round objects in digital images. This presented a method for segmentation and the extraction of spherical features. This was trial and tested with a total of 22 images taken from a monochrome camera and conveyed to a digitizing card set in a computer. This was also tested on citrus under natural conditions. They got an accuracy of 90% when the fruit surface was visible more than 50% and 97% when the fruit surface was visible more than 75%. They proposed an efficient way for extracting feature of spherical objects in the image. [4]

In the research paper published on 24/10/2020 Naeem Akhter and his teammates made a model that can detect citrus fruits based on shape and texture using principal component analysis which had an accuracy of 84%. The dataset of fresh citrus fruits was taken through the digital camera and used coral draw for manual measurement and MS Paint to convert images from JPG to BMP. After feature extraction b11 was used for qualification. They used 4 citrus family members:fruiter(89.6%),kinnow(84.4%),sour orange(86.8 %),musambi(78.8%) with 250 images of each selected samples. And having an average accuracy of 84.9%. [3]

Jianqiang Lu and his team in China researched upgrading the Mask-RCNN algorithm (mask-region convolutional neural network) with a focus on improving its accuracy. In the study, the researchers employed a combination of deep and shallow feature fusion techniques to merge the ResNet architecture. In addition, they implemented a combined connection block to optimize the model's precision. The research involved capturing images of green citrus fruits utilizing both handheld and wireless zoom cameras, all through a cloud platform. The team meticulously classified a total of 3273 green citrus fruit samples into various categories, with 200 images taken using handheld cameras and 357 images captured through cloud platforms. The upgraded algorithm achieved a total accuracy of 95.36%, slightly better than the original Mask-RCNN algorithm. [5]

In February 2023, Lijia Xu and their team conducted research using the HPL-YOLOv4 algorithm along with other algorithms. They used the ghost net backbone network to make YOLOv4 lighter and perform better for enhancing citrus feature extraction. In the neck network, they utilized depth-wise separable convolution and the Mish activation function. Additionally, they utilized an efficient channel attention mechanism (ECA) to improve the multi-scale feature weight. Finally, they optimized the bounding boxes screening using the soft DIOU non-maximum suppression (DIoU-NMS) algorithm. They gathered a dataset from a Mi10 mobile phone and achieved an average precision of 98.21% and a precision rate of 93.45%. [15]

The research paper "Design of Citrus Fruit Detection System Based on Mobile Platform and Edge Computer Device" done by Heqing Huang and his team uses the YOLO5s network for the detection of citrus fruit further for the reduction in the amount of model calculation and parameters, pruning method was used. They used a self-made citrus dataset and an unmanned aerial vehicle. A total of 1800 images were taken out of which 400 were used as test sets, 1300 as training sets, and 100 as verification tests. Three data enhancement methods were used mix-up, cutout, and cut mix. They achieved an accuracy of 93.32% in the edge computing device. This model can be efficiently used for mountainous orchard citrus detection. [16]

III. Methodology

A. *Dataset:* In our study, the Data set was collected from an external source Kaggle. The data contains a total of 8 classes of different citrus varieties and a total of 21738 images.18669 jpg images were used for training the model, and 2069 jpg were used for the test.90% of the data is used for purpose models training and 10% for testing purpose. These classes are described in

Class	**Training images**	**Testing images**
LIMON CRIOLLO	2256	250
LIMONMANDARINO	2439	270
LIMON TAHITI	3074	341
MANDARINA ISRAELI	2228	247
MANDARINA PIELDESAPO	2322	257

NARANJA VALENCIA	2375	263
TANGELO	1877	208
TORONJA	2098	233

B. . The image of each dataset is given in .

C. Feature Extraction:
The Local Binary Pattern feature extraction method is used to extract microstructure data, such as flat surfaces, edges, lines, and spots from images. The data can be scaled using histograms. LBP is a technique that uses binary codes to describe the image neighbourhood. It is commonly used to
analyze local image properties and identify individual image characteristics. This is used to extract features from the dataset of citrus fruits.

D. Model used: A total of 5 algorithms were used for the classification of citrus fruit for 8 different classes and we came up with different accuracies and results. All the algorithms are discussed in brief below.

K-Nearest Neighbour: K-Nearest Neighbour is based on a supervised learning technique and machine learning model that is used for the regression and classification of objects.

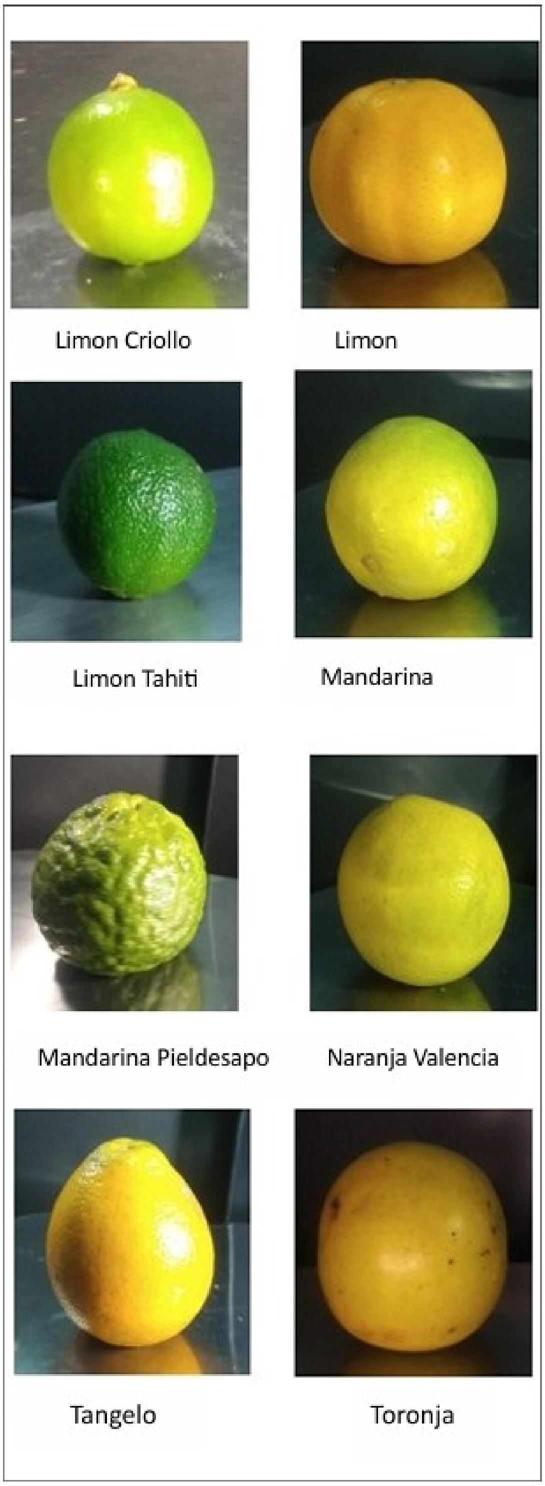

Figure 1: Citrus fruit dataset images

The K-Nearest Neighbors (KNN) algorithm accurately predicts the classification of test data by precisely calculating the distance between the test data and all training points. using methods such as Euclidean, Manhattan (for continuous data), and Hamming distance (for categorical data). K is the total number of neighbors of the object.

Distance is calculated by the following equations $\boldsymbol{i = 1 k (xi - yi)\text{^}2}$
$(1, \boldsymbol{i = 1 k xi - yi}$
$(2, D_H = i{=}1 k xi - y_i$ **(3**.

Euclidean:

$$\sqrt{\sum_{i=1}^{k} (xi - yi)\text{^}2} \quad (1)$$

Manhattan:

$$\sum_{i=1}^{k} |xi - yi| \quad (2)$$

Hamming distance:

$$D_H = \sum_{i=1}^{k} \left| x_i - y_i \right| \quad \textbf{(3)}$$

We have employed this algorithm in our citrus detection model to accurately classify citrus. This method is simple and easy to implement.

Decision Tree: A Decision Tree is also a supervised machine learning Powerful and versatile model that is used for classification and regression.

TABLE 1. CITRUS CLASSIFICATION AND QUANTITY OF IMAGES

Class	**Training images**	**Testing images**
LIMON CRIOLLO	2256	250
LIMONMANDARINO	2439	270
LIMON TAHITI	3074	341
MANDARINA ISRAELI	2228	247
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It is a hierarchal organization of different elements in the shape of a binary tree where the root node denotes the dataset, internal nodes denote the conditions and the leaf node denotes the result of the dataset.

For every node, it calculates the entropy which is the degree of uncertainty in the dataset and it is calculated by the equation $H_i = - \kappa\varepsilon K n P(\mathrm{i}, k)$ *log2Pi,k* *(4.*

At every level, the uncertainty of the dataset reduces which is calculated by the equation and this is called information gain or variance. Refer to equation $Information\ Gain(H, A) = H - \sum \frac{|Hv|}{|H|} H_v$ *(5).*

$$H_i = - \sum_{\kappa\varepsilon K}^{n} P(i,k) \log_2 P(i,k) \quad (4)$$

Where H_i=entropy k= k is the class from K classes,
p(k)= proportion of the data points that belong to class k.

$$Information\ Gain(H, A) = H - \sum \frac{|Hv|}{|H|} H_v \quad (5)$$

Where A =class label or specific attribute, |H| is the entropy of dataset sample S, $|H_V|$ is the number of instances in the subset S *that have the value v for attribute A*

This is also used as an alternative to the KNN model for the detection of citrus fruits it is simple to understand and it needs less data cleaning compared to other models.

Random Forest: Random Forest is an enhanced and better version of a decision tree however it is also a machine learning algorithm that is based on the supervised learning technique which is implemented through a decision tree and used in regression and classification problems. It is a collection of decision trees and it gives the result based on several votes. The more the decision trees the higher the accuracy.

We used the Random Forest for detection of citrus fruits and the results were best through this compared to other models. This is also used for detection problems and many other problems and provides high-accuracy prediction.

Gradient Boosting: Gradient Boosting is based on a supervised learning technique and on an ensemble boosting technique which is highly versatile and can be used for classification and regression problems. Weights are assigned to the data values. It takes a learner or model that has better prediction than the preceding weak learner. Weak learners are decision stumps or decision trees with one node and 2 leaf nodes. The loss function is used for finding the loss i.e. the difference between the actual value and the predicted variable given in the equation $L\ (f) = \ i{=}1NLyi,fxi$ (6).

$$L(f) = \sum_{i=1}^{N} L(y_i, f(x_i)) \quad (6)$$

Where L(f) = loss function, y_i= targetvalues, $f(x_i)$=function to map the input features x to target values y.

This was used for the classification of citrus fruit in our study and trained over 80% of i.e. 18669 jpg images and the results were optimal.

AdaBoost: Adaptive Boost is a powerful machine learning ensemble boosting technique used for classification and regression problems. It iterates through all the weak learners which are decision stumps (a tree having one node and 2 leaf nodes) is trained on the given training dataset and combines these models to provide better results and predict the output of the problem. Steps of AdaBoost:

- Weight is initialized for each data point. Let's say if there are N datapoint then weight W{i}=1/N.
- Iteration through weak classifier is done and they are trained on the dataset.
- Error rate is calculated for each weak classifier and the importance of each weak model through equation
- $importance = 1/2 * log(1 - totalerror/\ totalerror)$ *(7.*
  $importance = 1/2 * log(1 - totalerror/\ totalerror)$ *(7)*
- Weights of the data points are updated through the given equation NewSampleWeight = sampleweight*exp^importance *(8.*
  NewSampleWeight = sampleweight*exp^importance *(8)*
- To obtain the sum of weight 1 we normalize the weights using the equation $W\{i\} = W\{i\}/sum(W)$ *(9.*
  $W\{i\} = W\{i\}/sum(W)$ *(9)*
- These steps are repeated until all stumps are iterated.

This model is also used in this study for the classification and detection of citrus fruit.

IV. RESULT AND DISCUSSION

A total of 8 citrus families (Limon Criollo, Limon Mandarino, Limon Tahiti, Mandarina Israeli, Mandarina Pieldesapo, Naranja Valencia, Tangelo, and Toronja) were classified based on texture parameters. Combinedly 2069 images taken in normal conditions were used for testing the models. Table 2 Shows the average accuracy, precision, recall, and F1 scores of all the algorithms used in this study. The brief discussion of accuracy of each model is given below:

Table 2: Average Accuracy, Precision, Recall and F1-score

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-score**
K-Nearest Neighbors	74.90%	75%	75%	75%
Random Forest	75.75%	76%	76%	76%
Decision Tree	63.18	63%	63%	63%
Gradient Boosting	73.86%	74%	74%	74%
AdaBoost	47.69%	47%	48%	46%

1. **K-Nearest Neighbours:**

A total of 20% of data was used for the testing of the model i.e. a total of 2069 images collectively of all classes of citrus were provided and we came up with an accuracy of 74.90% i.e. roughly 1550 images were detected correctly and a confusion matrix for the same is given in
Fig 1.

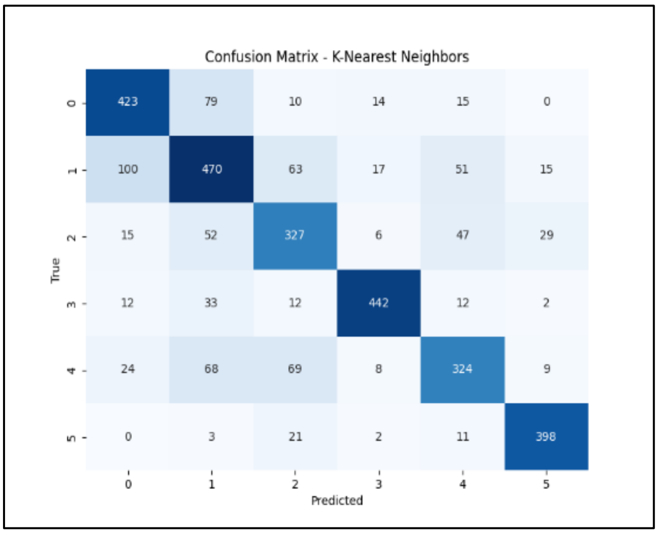

Fig 1. KNN

2. **Decision Tree** In this also we gave 2069 images for model testing and it came up with an accuracy of 63.18% i.e. 1308 images were detected without any problem.

The confusion matrix for this is given in

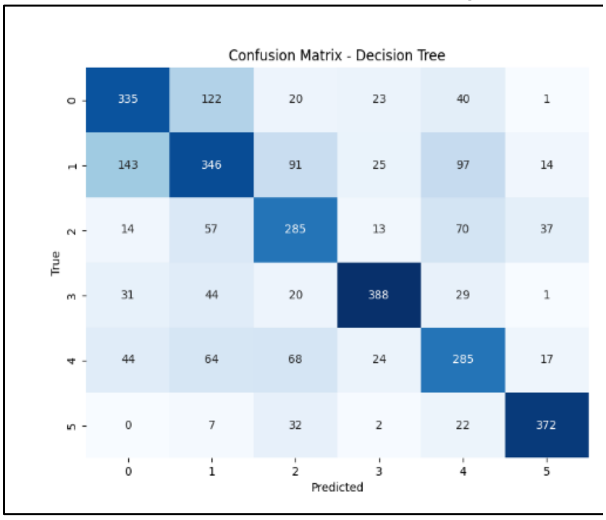

Fig 2.

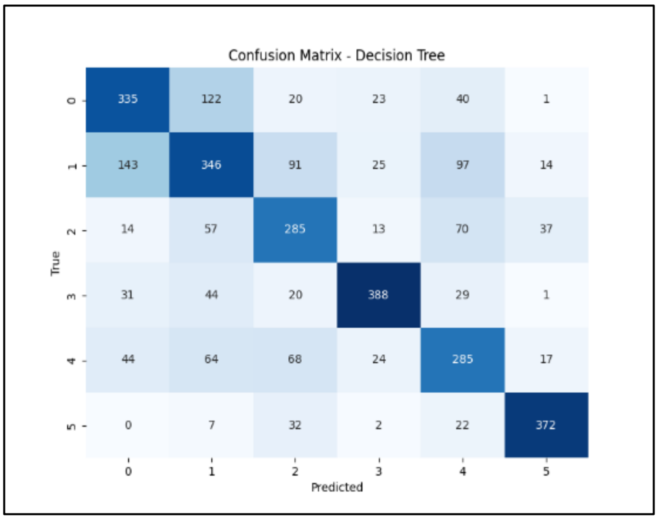

Fig 2. Decision Tree

3. **Random Forest:**
This model gave us the best accuracy compared to all the algorithms for the 2069 images of the citrus dataset. The accuracy was 75.75% i.e. 1568 images were detected without any problem.
The confusion matrix for this is given in *Fig 4*.
4. **Gradient Boosting:**
This algorithm also came up with 1528 successful detection out of 2069 images and gave an accuracy of 73.86%.
The confusion matrix for gradient boosting is given in

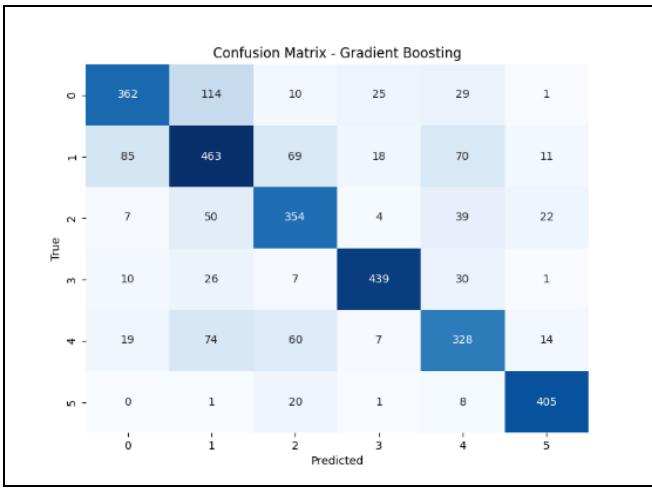

Fig 3. Confusion Matrix-Gradient Boosting

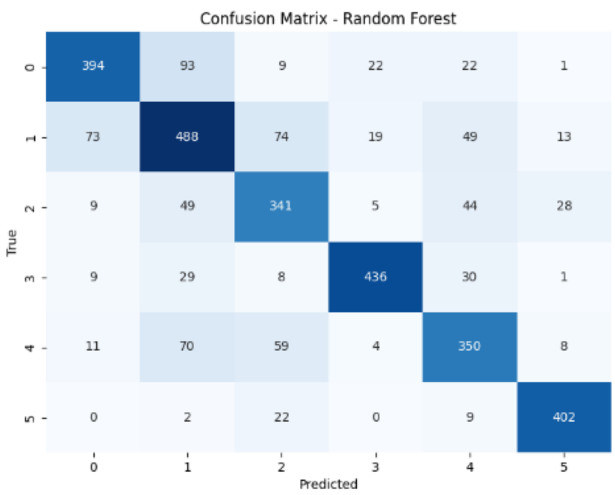

Fig 4. Confusion Matrix-Random Forest

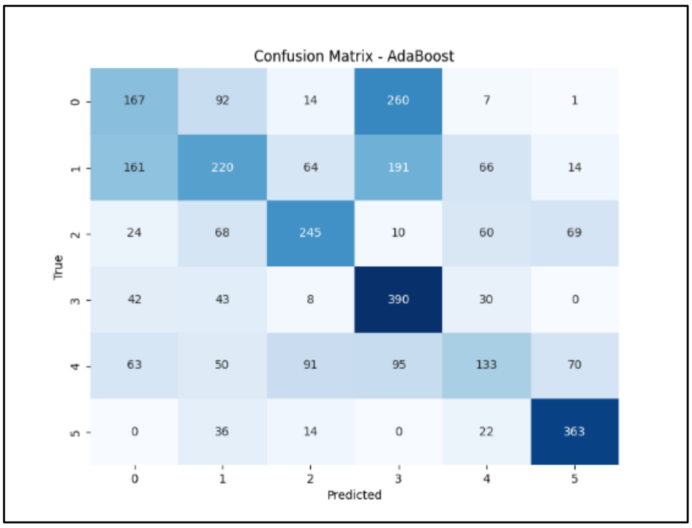

Fig 5. Confusion Matrix-AdaBoost

V. CONCLUSION AND FUTURE SCOPE

In this research, we have proposed 5 different methods for the detection and classification of citrus fruits based on supervised learning techniques. We first acquired the data from Kaggle and used the LBP local binary pattern for the data feature extraction from the jpg images of the dataset. We used KNN, Decision Tree, Random Forest, Gradient Boosting, and AdaBoost. The average accuracies of the model were 74.90%,63.18%,75.75%,73.86%, and 47.69%.

It has so many applications in the future and presents also it can be used in predicting the yield of citrus fruit in the agricultural fields, we can use it in Citrus picking robots or in any (UAVs) i.e. unnamed aerial vehicles, detecting citrus is also necessary if any citrus is used as a raw material for making any final product. furthermore, it can be used in shops to detect the category of citrus fruit people buy or sell. it can also be used for the differentiation of healthy and bad citrus fruit.

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5. **AdaBoost:**
   Again, this Boosting algorithm successfully came up with the detection of 987 images out of 2069. This gave the lowest accuracy of 47.69%.

The confusion matrix for AdaBoost is given in *Fig* 5**Error! Reference source not found.**.

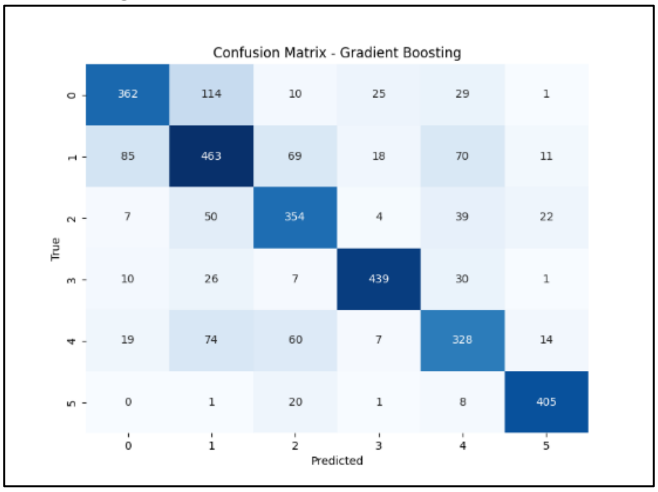


Fig 3. Confusion Matrix-Gradient Boosting

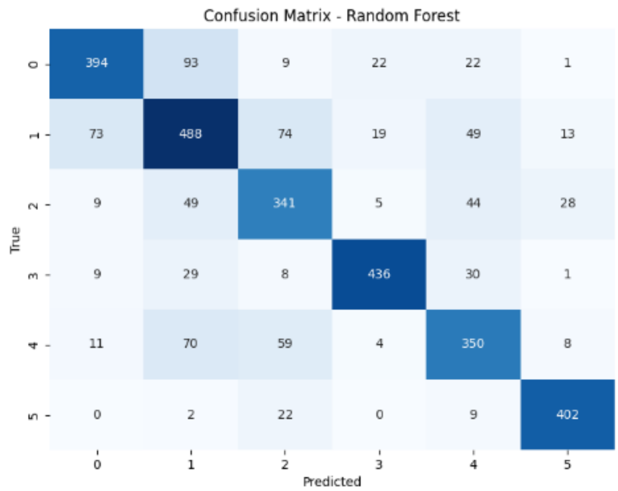
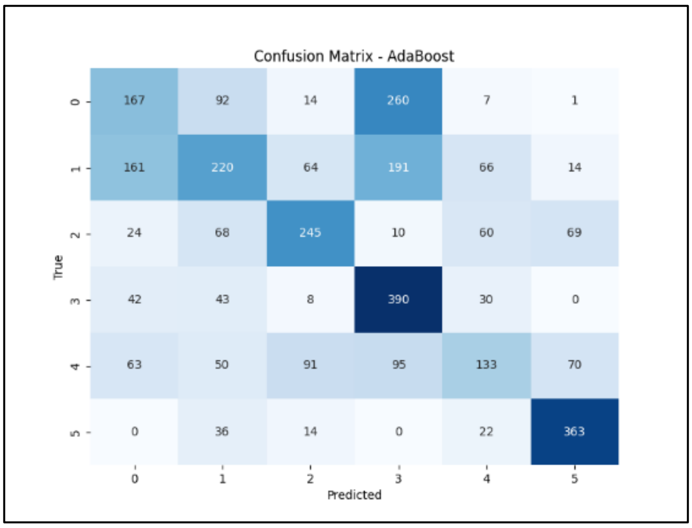


Fig 4. Confusion Matrix-Random Forest



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