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Identification of Crop Pests using Machine Learning Classifier System

K. Sree Vikas¹, D. Ajay Kumar Reddy², B. Pavan Ganesh³, Mr. Jani Basha Syed⁴, Ms. K. Naga Mallika⁵

^{1, 2, 3}UG Student, ^{4, 5}Assistant Professor, Kallam Haranadhareddy Institute of Technology, Guntur

Abstract: Agriculture plays a key role in the development of human civilization. A lot of research has been done to protect crops. The important aspect of agriculture is pest management. When a farmer has best strategies to encounter pests and other diseases, their crop would be more productive.

Pest management is difficult as it includes pest monitoring, pest identification requires much more than “see and spray” approach- use pesticides only when essential. Pest detection using multiple classifier system (MCS) is a systematic approach to find pests that combines a variety of image processing and machine learning concepts. This is the system which uses three classifiers.

They are decision tree, Naïve-Bayesian, K-NN. Each classifier gives an output of which type the pest is. In the final, the voting method or the weighted average method is used for fusing the member classifiers outputs and the final label of the pest is given. MCS is used to increase the accuracy in identification of the pest.

Keywords: Decision tree, Naïve-Bayesian, K-NN

I. INTRODUCTION

Agriculture not just provides food for the human existence, it is also a science of cultivating soil, harvesting crops. As we know out of the population of any country two-third of them are engaged in agriculture activities. There are many types of farming like primitive subsistence farming, intensive subsistence farming, commercial farming. The farming can be done in different ways but for any type of farming pest attacks are common it means different types of pests will attack the crop so there is a difficulty in identifying the type of pest to a human on his intelligence.

In small fields only it is difficult in this way it is too difficult in large fields. With knowing or unknowingly huge amount of money are being spent to safeguard the crops annually but still the damage of the crops are not reduced and they are effecting the overall growth of the crop, simultaneously it reducing economy of any country as it is a main source. One method to protect the crop is early pest detection so that the crop can be protected from pest attack. The pest attacks are not only affecting the crops but also to the finished products which are getting ready for sale in lots.

To get off these problems there is a solution that is examining the crops in a particular time schedule. This work can be done by a system which gives an accurate result by telling the type of pest and it can be helpful to have an exact remedy. As there is a famous quote “A goal without a plan is just a wish”, therefore when the farmer had this plan he can reduce the loss and in return gain profit by giving a healthy yield and also lot of benefits mainly to the economy of the country.

The leaves image is given as an input and the type of the pest is given as class labels by using three different classifiers DECISION, NAÏVE-BAYESIAN, KNN which are supervised learning techniques in Machine learning.

II. LITERATURE SURVEY

According to the paper “Automatic classification for field crop insects via multiple-task sparse representation and multi-kernal” by Jie Zhang and Li states that classification of insect species of field crops such as corn, soybeans, wheat, and canola is more difficult than the generic object classification because of high appearance similarity among insect species.

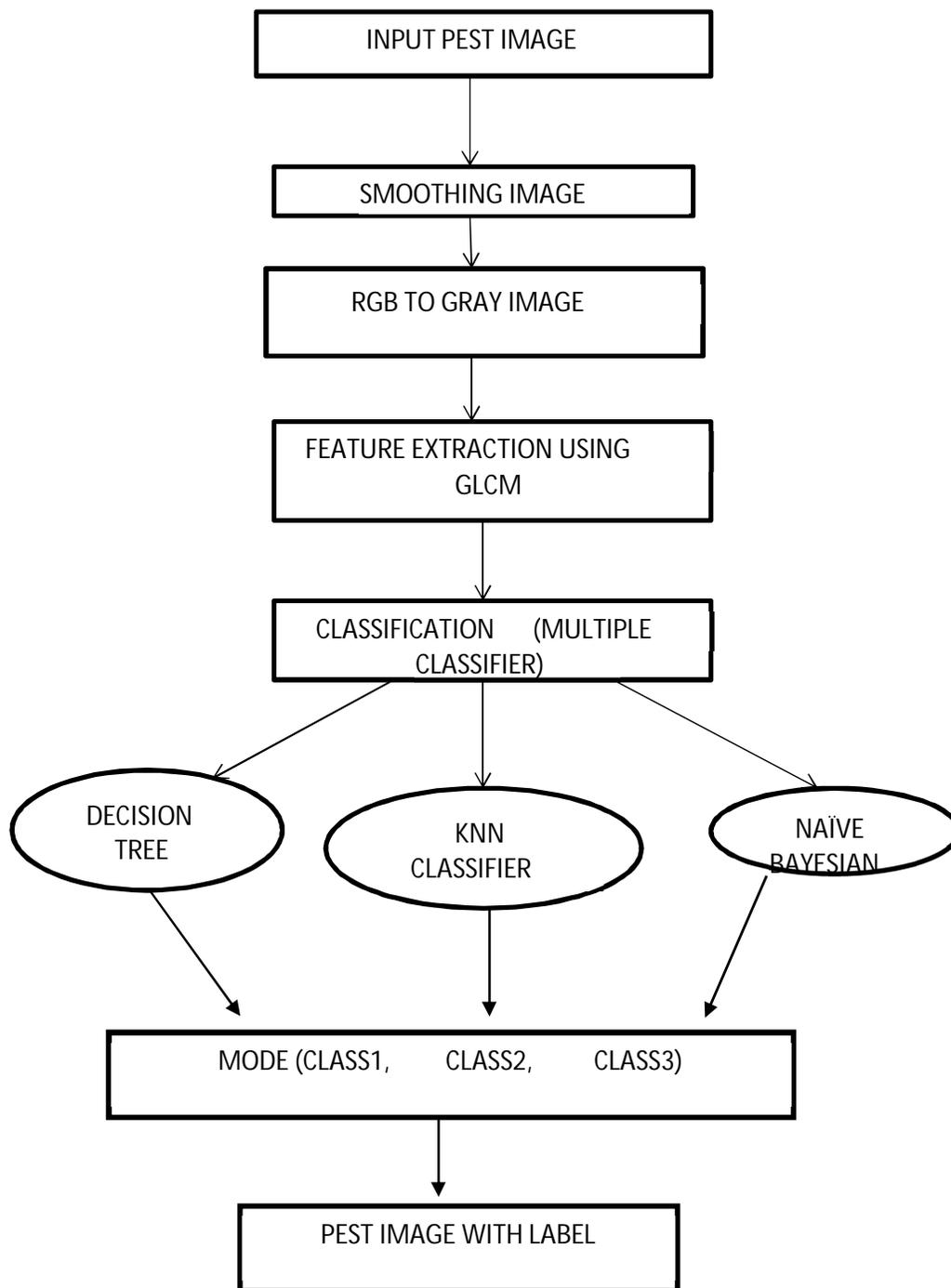
To improve the classification accuracy, we develop an insect recognition system using advanced multiple-task sparse representation and multiple-kernel learning (MKL) techniques.

As different features of insect images contribute differently to the classification of insect species, the multiple-task sparse representation technique can combine multiple features of insect species to enhance the recognition performance. Instead of using hand-crafted descriptors, our idea of sparse-coding histograms is adopted to represent insect images so that raw features (e.g., color, shape, and texture) can be well quantified. Furthermore, the MKL method is proposed to fuse multiple features effectively.

III. PROPOSED SYSTEM AND IMPLEMENTATION

The proposed system is mainly useful to the farmers or for the people who are interested in doing house farming as it is the latest habit for many of the people. The main purpose of this system is, it finds out the type of pest using multiple classifiers using the OpenCV library on Anaconda platform. Instead of predicting the pest by sight of eye the pest can be identified through this system as the level of identification of different type of unknown pests to a human can be increased by using different classifier system. The proposed system has been elaborated to stop misclassification done by humans extremely by the farmers. When ever the person can't identify the type of pest which will destroy the crop or plant then taking the picture or image of the pest and giving the image as the input to the system then the pic undergoes various process by considering 14 features which are extracted from image i.e those are haralick features and gives the output with the pest name on the given image.

The working of the system is shown in the below block diagram.



IV. EXPERIMENTAL SETUP AND RESULTS

We can train the data set by clicking “ TRAIN ” button in Training, otherwise insert the image by selecting “choose image” option in Test data .

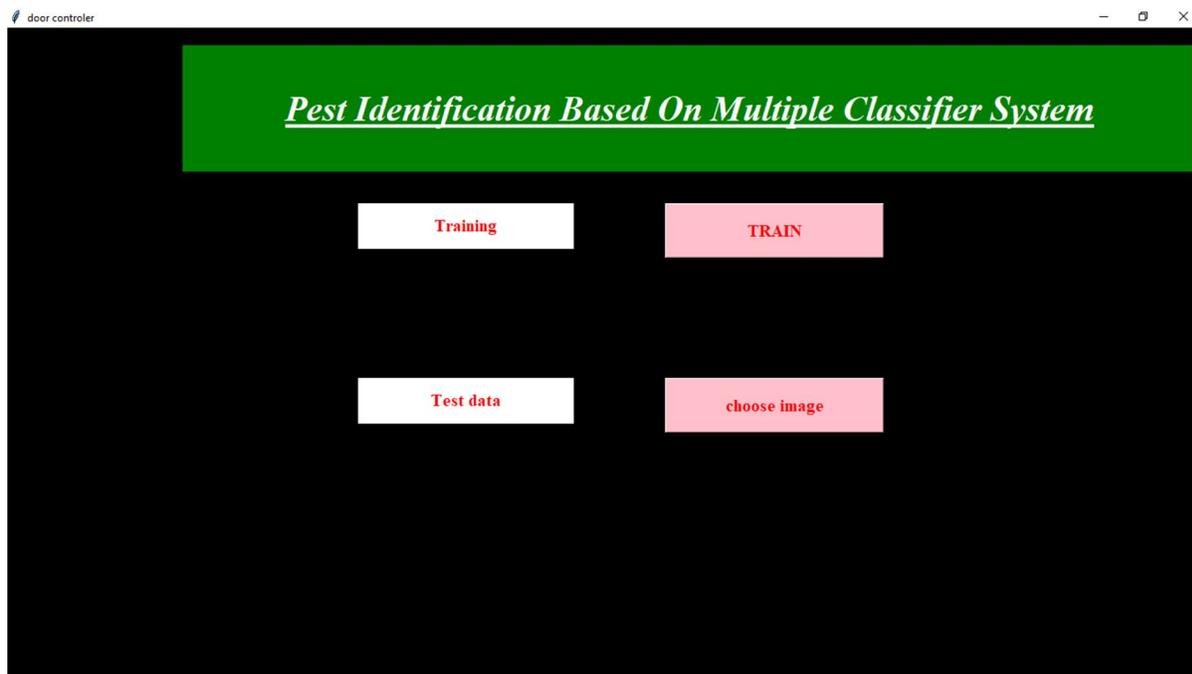


Figure 1: Main page dialog box

If you choose train data we can get the features of the images in the dataset and the system get trained and ready to check the image with the values which are given during training of dataset.

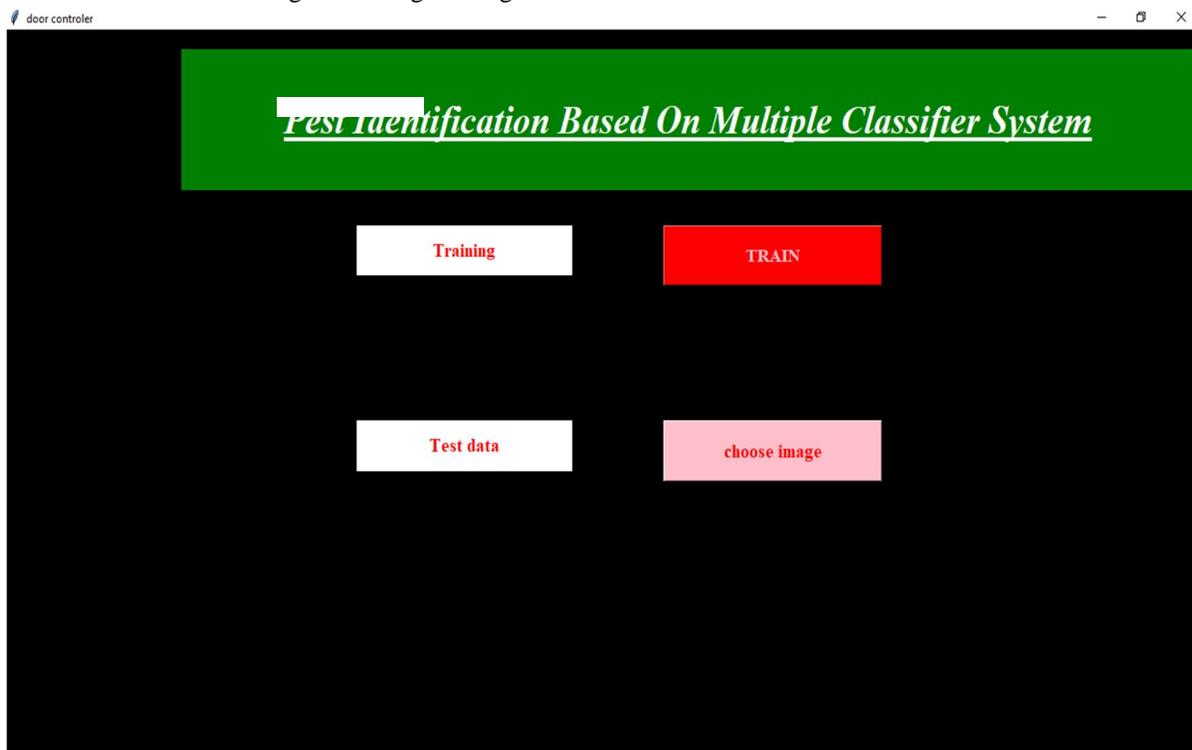


Figure 2: Main page selecting TRAIN option

Here are some of the features of the dataset.

```

1.79997385e+03,
7.78387168e-02, 3.06598423e+02, 6.56688791e+03, 8.33955495e+00,
1.35449458e+01, 9.53223519e-05, 5.58925527e+00, -1.72439343e-01,
9.59225301e-01]], array([ 7.87311135e-04, 1.83546615e+02, 8.86388735e-01,
8.07524906e+02,
2.18043051e-01, 2.64218326e+02, 3.04655301e+03, 7.56840798e+00,
1.17098261e+01, 2.54625768e-04, 4.49127768e+00, -2.33499298e-01,
9.75678292e-01]], array([ 3.89258193e-03, 2.47688746e+02, 9.54319555e-01,
2.71111627e+03,
2.38287180e-01, 1.80728861e+02, 1.05967763e+04, 8.28527169e+00,
1.23162467e+01, 2.32592494e-04, 4.70295982e+00, -3.26797827e-01,
9.95676460e-01]], array([ 8.79083132e-05, 2.12389841e+03, 6.91802401e-01,
3.44548749e+03,
4.70213578e-02, 2.49635823e+02, 1.16580516e+04, 8.57586653e+00,
1.44430301e+01, 4.08795051e-05, 6.51169425e+00, -1.26269475e-01,
9.25202312e-01]], array([ 4.58192542e-04, 3.27247151e+02, 7.20734392e-01,
5.85757720e+02,
9.72025753e-02, 2.91590845e+02, 2.01578373e+03, 7.05493730e+00,
1.18444061e+01, 1.43971652e-04, 5.05543946e+00, -1.03321333e-01,
8.47621370e-01]], array([ 1.25009981e-04, 8.28095173e+02, 7.67941991e-01,
1.78397906e+03,
5.47010982e-02, 2.39123109e+02, 6.30782106e+03, 8.09414045e+00,
1.35687679e+01, 7.32663390e-05, 5.82852063e+00, -1.27157604e-01,
9.16413698e-01]], array([ 3.84146079e-04, 2.40956039e+02, 9.11782269e-01,
1.36544905e+03,
1.23511852e-01, 2.35678796e+02, 5.22084017e+03, 7.72619250e+00,
1.22637331e+01, 1.74930678e-04, 4.83062091e+00, -1.93560788e-01,
9.61415119e-01]], array([ 2.64635229e-02, 1.32940314e+02, 9.79614813e-01,
3.26059789e+03,
3.90712192e-01, 1.27373067e+02, 1.29094512e+04, 6.92390745e+00,
9.88613962e+00, 4.92932039e-04, 3.80310021e+00, -3.79238633e-01,
9.94764840e-01]], array([ 9.83825474e-05, 8.08331836e+02, 8.49093789e-01,
2.67775053e+03,
6.88888290e-02, 1.99235421e+02, 9.90267027e+03, 8.30043107e+00,
1.37139593e+01, 7.76802406e-05, 5.80880639e+00, -1.55999877e-01,
9.48771551e-01]])
Training features: (105, 13)

```

Figure 3: Haralick features of dataset

During the process the image will get converted from RGB to Gray image. we can see below how the image will get converted.



Figure 4: RGB Image



Figure 5: Gray Image

Here is the sample dataset.

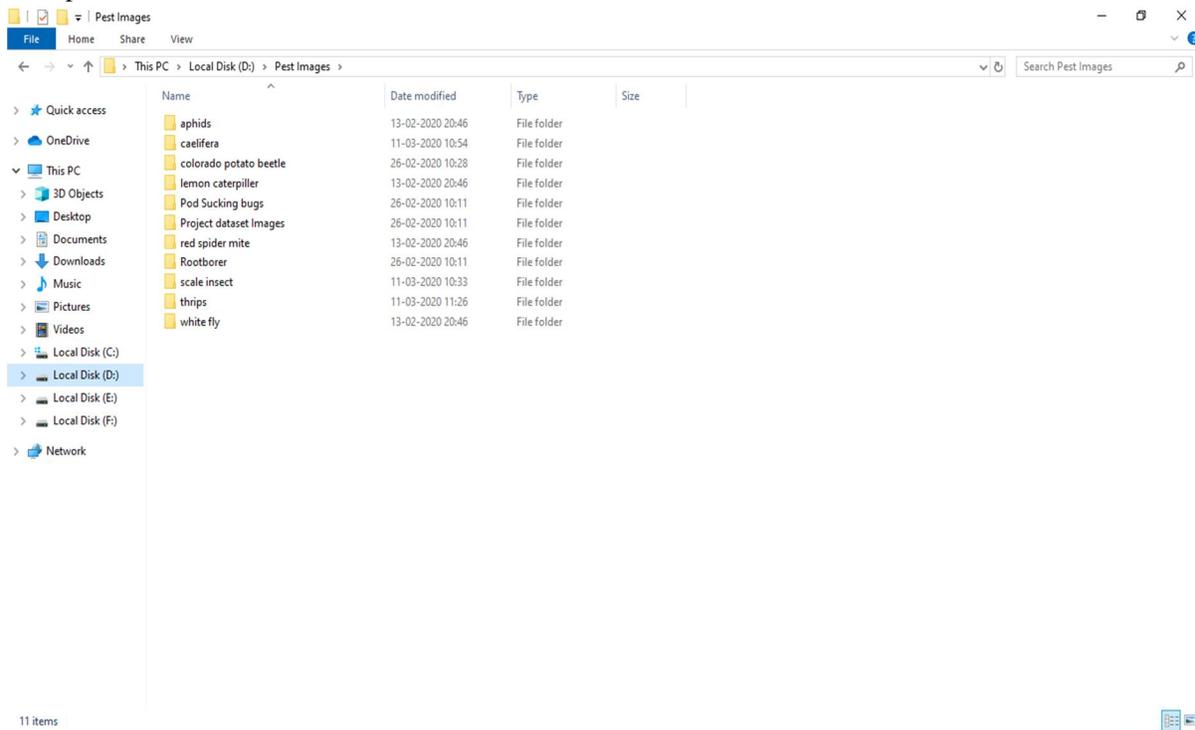


Figure 6: Sample dataset

Once the data set get trained we can choose a pest image to know type of the pest and it is processed in the same way as the dataset got trained.

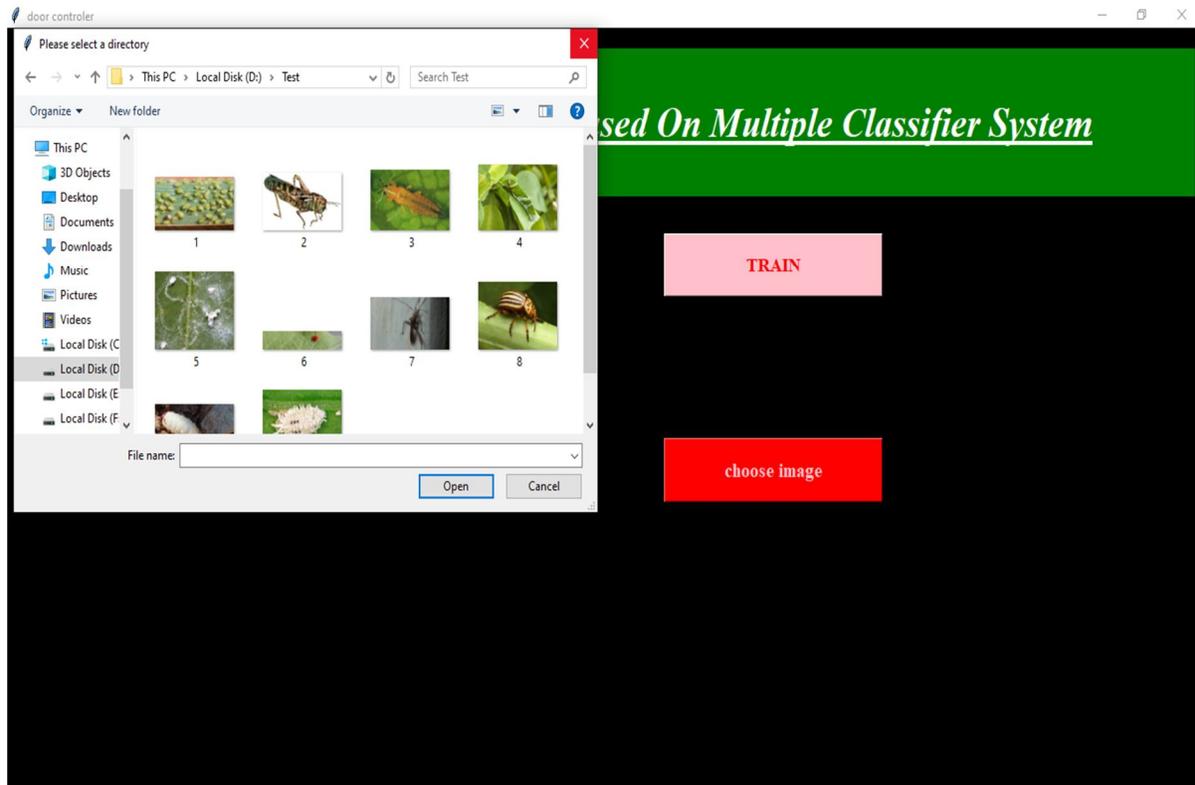


Figure 7: Selecting a image for testing

By choosing the image we will get the pest name on the input image and display it as the output. Here are some output images

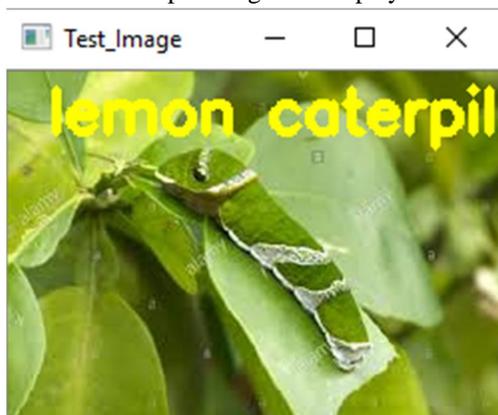


Figure 8: output 1

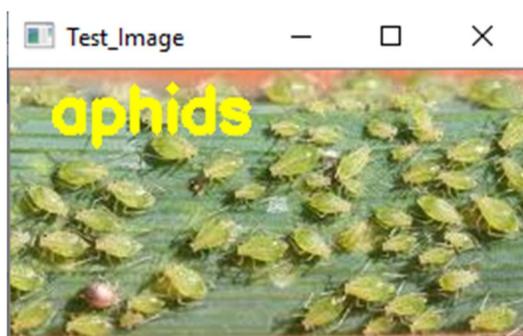


Figure 9: output 2

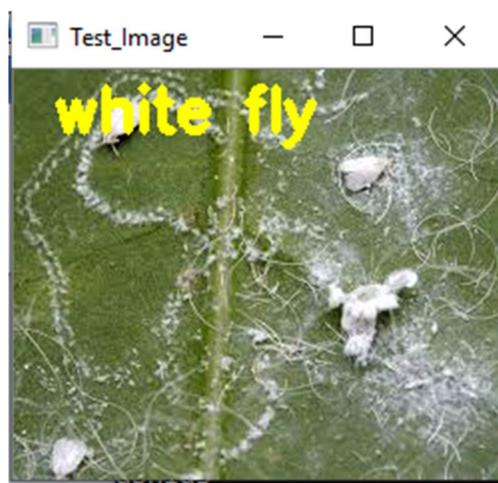


Figure 10: output 3

V. CONCLUSION

The proposed system is an innovative method because we have used multiple classifiers which gives more accuracy in classification of the type of pest. The accuracy we got is about 90%. This helps the farmers in early detection of pests and low usage of pesticides could be used which gives raise more yield.

VI. FUTURE SCOPE

In present work the focus is on extraction of texture features only, if the feature considered is done more diversly i.e along with texture features some features such color, size, features could be considered to increase the accuracy to some level. This System could be converted into a mobile Application as everyone in the world are using mobiles it would be more useful.



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