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Design and Implementation of Alex Net-Honey Badger Fusion Algorithm for Feature Selection and Classification Using Multiclass Support Vector Machine Classifier to Recognize Plant Leaf Disease

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Abstract: In agricultural practices, spotting disease on a crop's leaf is an important yet time-consuming task. Specialized labour and a sizable quantity of time are both required. This paper proposes a computer vision and machine learning-based methodology for the early detection of agricultural leaf disease. An Alex net-Honey badger fusion algorithm for feature selection and classification using multiclass support vector machine classifier to recognize plant leaf disease has been applied in this work. Using Alex Net, features will be extracted and optimized using the HBA fitness function. This performs well in terms of F1 score, recall, precision, and accuracy when compared to previous methods. Using the Honey Badger optimization methodology, the recommended algorithm was further optimized. The exploration and exploitation phases of the HBA model describe the honey badger's dynamic search activity, which includes digging and honey-seeking strategies. In addition, HBA keeps the population diversity sufficient even when the search process comes as a result of carefully chosen randomization procedures. The newly suggested approach is found to have a satisfactory convergence rate using the Alex net-HBA fusion algorithm.

Keywords: *Feature ex-traction, GLCM, Honey Badger Algorithm (HBA), Alex net-HBA fusion feature selection and multi SVM classification algorithm*

1. Introduction

One of the difficult and important tasks in agricultural practices isthe detection of disease on crops leaf. It takes a lot of time and requires skilled workers. In this work, computer vision and machine learning techniques are suggested as a clever and practical strategy for identifying agricultural diseases. The suggested method can distinguish between 20 different plant diseases. In terms of agricultural productivity, India ranks second in the world.Agriculture supports up to 70% of India's rural areas, contributing significantly to the nation's economy. It also generates about 17%of the country's GDP and employs about 65% of the population. In warm to subtropical temperatures, practically all types of crops, fruits, and vegetables are produced. farming is the practice of using land and its properties. Based on the durability of the leaves and roots, it is possible to estimate the total yield of these crops. The productivity of these crops is usually negatively impacted by illnesses due to the dynamic changes in the environment. There are numerous reasons behind this. The appearance of pests, illnesses, and other unfavorable components in harvests can lower agricultural yield. Regarding crop quality and overall loss, the effect of these dangerous components on agricultural output is closely correlated. The term "pesticides" was invented to prevent, manage, and mitigate the impacts of illnesses on output. The use of pesticides is a workable approach for protecting crops from different diseases and increasing overall production. In order to increase food production and our capacity to meet rising food demand, farmers have been using pesticides since 1950. The environment system is negatively impacted by these chemicals' ongoing usage, nonetheless, in a few ways. Agriculture is considered as the backbone and one of the major sectors of our country. A large number of the people of India are more likely to pique agriculture as their occupation [1]. In terms of agricultural productivity India is ranked at the second position in the world. The contribution of agricultural production to the Indian economyis significant and supports up to 70% of the rural areas. Moreover,it roughly employs around 65 percent of the entire population and also generates about 17 percent of the country's total GDP. Farming encompasses the cultivation of nearly all types of crops, fruits, and veggies in a warm to subtropical environment and soil conditions. Based on the strength of leaves and roots, the total production of these crops can be determined. However, due to the changing dynamics of the environment, the productivity of these crops is usually reduced by diseases. Several factors are responsible for causing the disease in leaves of plants which results in crop destruction This has a negative influence on the country's economy [2]. Meanwhile, the 90% of the total world population depends on the agriculture. The producers provide 80% of the world's food but unfortunately, due to the plant pests and pathogens over 50% of the production quantity is lost [3-4]. Moreover, if these diseases are not detected on appropriate time, it may lead to food insecurity. As per the report generated by the Food and Agriculture Organization (FAO), the total productivity of agriculture should rise up by around 70% till 2025 so that the increasing demand of food can be fulfilled [5]. single layered feed- forward neural network for identifying different plant diseases by analyzing leaf images. In the suggested scheme, the feature imagesserved as the input which were alter on pre-processed by using the HSV color space and after this important and crucial feature were extracted by using the Hara lick textures. The extracted characteristics were then used to train and evaluate the ELM classifier. After the testing was completed, the

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ELM precision wascomputed. The dataset utilized was a subset of the Plant-Village dataset made up of tomato plant leaves. When compared to other models such as the SVM and Decision Tree, the ELM's results indicate a higher rate of accuracy of 84.94 percent. The authors in [6] suggested an effective agricultural disease's detection technique based on computer vision and ML techniques such as R.F. algorithm. The suggested algorithm worked with a 93 percent accuracy rate and could detect up to 20 distinct diseases in five standard plants.

The authors in [7] focused on developing an improved disease detection model in which they utilized computer vision and ML methodologies. The presented method worked by taking a leaf's raw image and retrieving properties such as shape, color, texture, vein, and so forth by preliminarily processing and separating. After that the leaf image was categorized using a variety of ML classifiers like R.F., SVM, K-Nearest Neighbor and ANN. In comparison to other classifiers, the suggested prediction model performed well with R.F.

1.1. Present Detection Systems and Related Issues

Early plant leaf disease identification is crucial for a production to be reliable and abundant. In the past, a manual approach was used to study the structure, appearance, and other traits of plant leaves in order to find disease [8]. Most farmers lack the essential professional skills and education. They find it difficult to recognize the condition, which leads to mistakes, lost productivity, and financial losses [9]. One of the most popular techniques for detecting plant diseases is visual based examination, which a skilled person can use to recognize and spot the plant disease with the unaided eye. This necessitates sizeable professional personnel as well as ongoing competent monitoring, both of which are highly expensive when harvests are enormous. When compared, it is possible that farmers in other nations lack the requisite infrastructure or even know how to contact experts. Therefore, consulting a specialist is expensive and time-consuming [10]. The detection procedure must be automated due to its complexity, ineffectiveness, and inappropriateness.

Section 2 literature review, Section 3 Feature extraction using alex-net. Section 4 honey badger algorithm, section 5 data augmentation, section 6 proposed algorithm section 7 result discussion and section 8 conclusion and future scope has been discussed.
The objective of the paper is to design an optimized algorithm for plant leaf disease recognition

2. Literature Review:

The authors of [11] employed machine learning (ML) and image processing techniques to identify and classify plant diseases. The authors collected the usual photos of many plants in order to evaluate their methods. The supplied input image was first segmented and isolated to isolate the diseased area, and then the data was mined for several properties. realized ROI. The SVM technique was further used for classification. The testing outcomes demonstrated that the suggested model could correctly classify and detect plant diseases with high rates of accuracy. The researchers in [12] proposed an automated system based on vision and image processing techniques for diagnosing plant diseases. They recognized the hue characteristic of the plant leaf and using the colour segmentation and leaf infection classification The GLCM algorithm and the K mean approach, respectively. Shiroop Madiwalar and Medha Wyawahare investigated several image-processing techniques for identifying plant diseases in this work [2]. The authors investigated the capacity to identify plant sickness using colour and textural attributes. They evaluated their algorithms using the Dataset of 110 RGB images. The features obtained for classification included the GLCM features, the mean and standard deviation of the image convolved with the Gabor filter, as well as the mean and standard deviation of the RGB and YCbCr channels. A support vector machine classifier was used for classification. The researchers concluded that GCLM features can be used to identify healthy leaves. At the same time, it is believed that colour characteristics and Gabor filter qualities are the best for identifying leaf spots. The researchers in [15] proposed a vision based automated plant disease identification system wherein they utilized the image processing techniques. They recognized the colour feature of the plant leaf and then "K mean algorithm" and GLCM algorithm were utilized for colour segmentation and categorizing leaf infection respectively. This approach showed effective performance and results. The research in [16] focused on detecting diseases like "Leaf blight, Black rot, stable and Black measles" in grapevines. Several ML based approaches were proposed for detecting diseases in grapevines; however, no one had yet proposed a detection technique that could detect all four diseases. The algorithm was made using the images that were gathered from the plant village dataset which would assist in training the Efficient Net B7 deep architecture using transfer learning. The features that were then obtained were down-sampled using an approach known as logistic regression (yes or no based on the observation data). The suggested model was able to detect diseases in grapevines with an accuracy of 98.7 percent. Similarly, the researchers in [17] used Extreme Learning Machine (ELM) along with a have been developed for detecting diseases in plants effectively and efficiently.

fig 1 Apple black rot

figure 1 shows apple black rot while preprocessing an infected leaf

fig 2 shows Grapes-leaf blight while preprocessing aninfected leaf

fig 3 potato-bacterial-spot while preprocessing an infected leaf

3. Feature Extraction using Alex-net

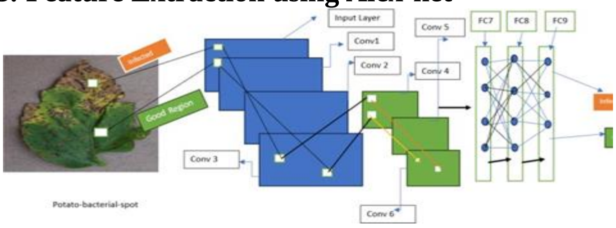


Fig 4: Alex net Model for features Extraction

In Figure 4, the pre-trained Alex-Net model extracts informative features from the images. The Alex-Net model has one input layer, five convolution layers, and three fully connected layers. After that, all the features are stored in an array variable and fed to a multiclass support vector machine for classification of informative features, and the same is optimized using the HBA-Alex net fusion algorithm for better results.

4. Honey Badger Algorithm (HBA)

General biology Honey Badger [21] The determined honey badger is a mammal with black and white fluffy fur that lives in semi-deserts and rainforests in Africa, Southwest Asia, and the Indian subcontinent. This dog-sized (60–77 cm in length and 7–13 kg in weight) daring forager preys on 60 different species, including poisonous snakes. It is a tool-using, clever mammal that adores honey. It likes to live alone in self-dug tunnels and only interacts with other badgers for mating is divided into two phases which are "digging phase" and "honey phase," The mathematical formulation of the suggested HBA method is introduced in this section. Theoretically, HBA is a global optimi-sation method because it includes both the exploration and exploitation stages. The suggested HBA's mathematical stages are described asfollows

Step 1: Initialization phase:

Initialize the number of h0ney badgers (population size N) and their respective positions based on given equation

$$X_i = lb_i + r_1 * (ub_i - lb_i) \tag{1}$$

"Where X_i is ith honey badger position referring to a candidate solution in a population of N, while lb_i and ub_i are respectively lower and upper bounds of the search domain."

Step 2: Establishing intensity (I):

The prey's level of focus and the distance between it and the honey badger both affect intensity. According to the Inverse Square Law [35], described by Eq. (2), it represents the prey's scent intensity; if the smell is strong, the motion will be quick, and vice versa

$$I_i = r_2 * s / 4\pi d_i^2 \tag{2}$$

$$S = (x_i - x_{i+1})^2$$

$$d_i = x_{prey} - x_i$$

r_2 is a random number between 0 and 1 here S denotes the intensity of the source or concentration It is Eq. (2) represents the separation between the badger and the prey.

Step 3: Density factor is updated:

To guarantee a seamless transition from exploration to exploitation, the density factor () regulates time-varying randomness. Using Eq. (3), modify the decreasing fraction that falls over iterations to reduce randomness over time

$$\alpha = C * \exp\left(\frac{-t}{t_{max}}\right) \tag{3}$$

t_{max} =number of iterations

where C is constant >=1(default=2)

The figure 1 depicts the framework inside the intended scheme that will work on designing a model that will assist the overall system to extract multi domain features and selection of qualitative feature set. These qualitative information set is expected to be effective in extracting valuable pattern from input images, and improving the detection system's accuracy or detection rate.

Step 4: escaping the local best

To leave local optima areas, take this step and the two ones after it. In this situation, the suggested method makes use of a flag F that modifies search direction to provide agents the best possible chance to thoroughly explore the search space.

Step 5: the position of the agents being updated.

The" digging phase" and the" honey phase," as was previously mentioned, are the two phases of the HBA position update process (x_{new}). the explanation that follows is more helpful.

$$X_{new} = X_{prey} + F*r_3*\alpha *di [\cos(2\pi r_4) *[1-\cos 2\pi r_5] \quad \ldots\ldots\ldots(4)$$

Step 6: drilling stage.

A honey badger executes actions resembling a cardioid shape [2] during the digging phase, as seen in Fig. 3. Equation (4) can replicate the cardioid motion: where xprey denotes the prey's current position, which is also known as the best position ever discovered globally. The honey badger's capacity to obtain food is represented by 1 (default = 6). The distance di between the prey and the ith honey badger is given in equation (2). Three distinct random integers from 0 to 1 are called r_3, r_4, and r_5. The flag that is used in F

$$F(x) = \begin{cases} -1 & r6 \leq 0.5 \\ 1 & ,Else \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Above mentioned HBA algorithm has been implemented to create informative features set which is new in this algorithm it not found in previous technique. Here is the proposed algorithm.

5. Data Augmentation

We used the Plant Village dataset, an open access repository dataset, in this paper It includes pictures of 5 different crops' leaves, such as apples, tomato, potato, grape, corn etc. There are 25 classes in total, with various illness photos for each crop. For our research, we have picked the apple, tomato, potato, grapes and corn and have narrowed down three types of diseases: black rot, leaf blight, early blight, late blight, Black Measles, Northern Leaf Blight . The Dataset becomes unbalanced as a result. Results from the classification process may be skewed and biased due to the imbalanced Dataset. Image data has been enhanced using outward scaling by 20%, rotation in a 40-degree clockwise direction, shifting with width shift = 0.2 and height shift = 0.2, and horizontal flipping. When an image is outward scaled, the resulting image is cropped to match the size of the original.

6. Design and Implementation of Alex net-Honey badger fusion algorithm for feature selection and classification using multiclass support vector machine classifier to recognize plant leaf disease

Algorithm:

Step1: Collect the plant leaf images with and without diseases.
Step2: Preprocessing of Images
Step3: Feature extraction of multidimensional characteristic using Alex net .
Step4: Calculate the skewness, kurtosis, RMS (root mean square), and other statistical features.
Step5: Append the calculated features to the mlXTrain array.
Step6: Append the label for the current image to the Label array.
Step7: Create an imageDatastore imds with the 'Dataset Resize' folder as the source, enabling it to include subfolders for labels.
Step8: Load the pre-trained AlexNet model using alexnet and store it in net.
Step9: Specify the layer from which to extract features, such as'fc8', and store it in layer.
Step10: Extract the features from the images in imds at the specified layer using activations and store them in featuresTrain.
Step 11: Assign the extracted features to XTrain and convert the labels to a double array, storing them in YTrain.
Step 12: Create a cross-validation partition for the training data, holding out 30% of the data for testing, using cv partition.
Step 13: Split the feature data and labels into training and testing sets based on the partition indices.

- xTrain and yTrain contain the training data.
- xTest and yTest contain the testing data.

Step 14: Create a structure named Dataset and store the training and testing data in it.
Step 15: Set the random number generator seed to 1 using rng.
Step 16: Train a multiclass SVM classifier (fitcecoc) on the training data in Dataset.xTrain and Dataset.yTrain, storing the model in Mdl.
Step 17: Use the trained SVM model to predict the labels for the testing data in Dataset.xTest and store the predictions in mDTPredict.
Step 18: Create a subset of the training data (mlXTrain and Label) for the random forest and k-nearest neighbours models.
Step 19: Train a random forest classifier (TreeBagger) with 50 trees on Dataset1.xTrain and Dataset1.yTrain, enabling OOB prediction and storing it in MdlRf.
Step 20: Use the trained random forest model to predict the labels for the original testing feature data and store the predictions in rDTPredict.
Step 21: Convert the predicted labels from strings to numeric values.
Step 22: Train a k-nearest neighbors classifier (fitcknn) on Dataset1.xTrain and Dataset1.yTrain, and store it in Mdlknn.
Step 23: Use the trained k-nearest neighbors model to predict the labels for the original testing feature data and store the predictions in knnDTPredict
Step 24: The resulting statistics and evaluation metrics are stored in the arrays accuracyP, precisionP, recallP, FscoreP for SVM, accuracyRF, precisionRF, recallRF, FscoreRF for random forest, and accuracyKNN, precisionKNN, recallKNN, FscoreKNN for k-nearest neighbors.

Table1: Acronyms with Full form

Acronyms	Full form
RMS	Root Means Square
mlXTrain	Variable to store features
imds	variable
Fc8	Fully connected layer 8
XTrain	X Training Data
YTrain	Y Training Data
Xtest	X Testing data
Ytest	Y Testing data
rng	Random function
Mdl	Variable to store model
OOB	Out-Of-Bounds
HBA	Honey Badger Algorithm
accuracyP	Accuracy of proposed algorithm
precisionP	Precision of proposed algorithm
recallP	Recall of proposed algorithm
FscoreP	F1 score of proposed algorithms
SVM	Support Vector Machine
accuracyRF	Accuracy of Random Forest
precisionRF	Precision of Random Forest
recallRF	Recall of Random Forest
FscoreRF	F1 score of Random Forest
accuracyKNN	Accuracy K-nearest neighbour
precisionKNN	Precision of K-nearest neighbour
recallKNN	Recall of K-nearest neighbour
FscoreKNN	F1 Score of K-nearest neighbour

Medlar	Random forest storing Model variable
mDTPredict	Model Dataset Test Predict
Fitcecoc()	Fitness function for prediction
RF	Random Forest
KNN	K-nearest-neighbour
FitKnn	Fitness function of KNN
Ybcr	represents color as brightness

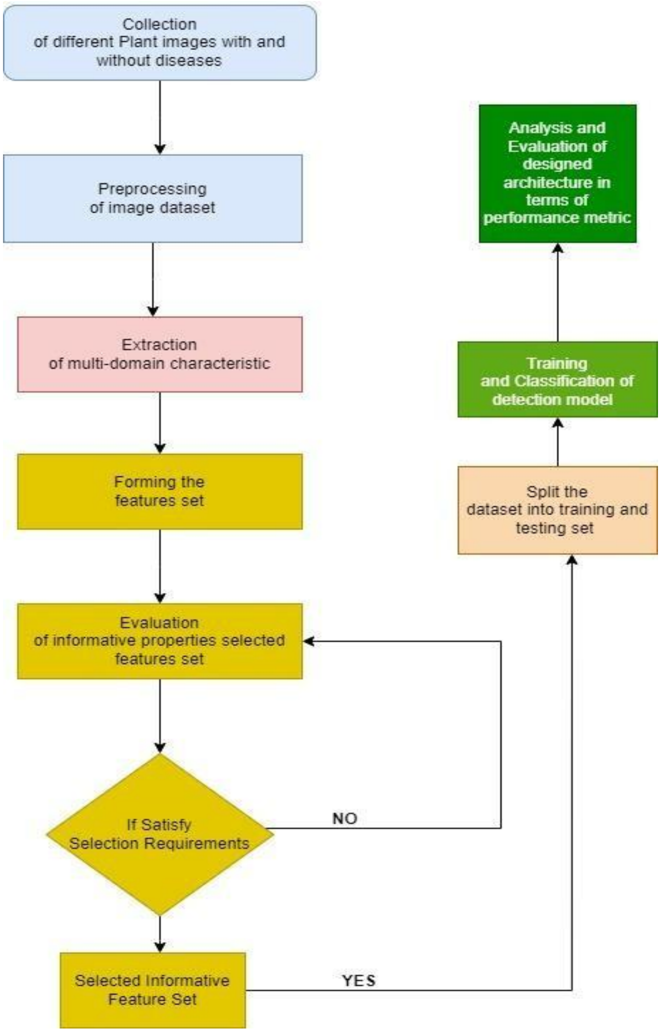
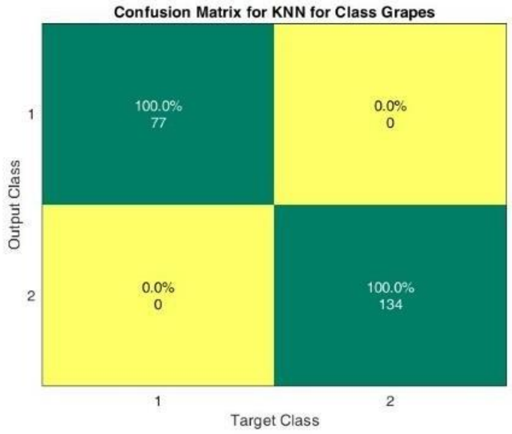


Fig 5: Proposed flowchart for Phase of Selecting Qualitative Information Set

7. Result and Discussion

Here, a modified HBA algorithm has been implemented, and It is evident that a model's performance was evaluated using the confusion matrix. Figure 6, 7, 8 and 9 demonstrate unequivocally how the new strategy exceeds the existing method in terms of performance. This is the confusion matrix for the existing method, and it has been shown that the confusion matrix for the recommended algorithm in Figure 5 is superior to the one used by the current algorithm. Additionally, the suggested method's accuracy, precision, and F1 scores have been assessed, and the results are encouraging compared to the existing system's effectiveness. Figure 6 illustrates how well the recommended approach performs regarding the accuracy, F1 score, and precision. Consequently, it is permissible to measure early disease detection in plants. The experiment's algorithms have considered infected leaves from apples, maize, grapes, potatoes, and tomatoes. However, The suggested technique showed decent performance once used, and optimization was promising compared to other algorithms. The usefulness of the recommended strategy has also been assessed by comparing it to the present method for additional model performance measures, including recall and accuracy. Positive outcomes might also be shown in Figures 7 and 8. Figure 9 clearly shows that the F1 score of the suggested method is greater than that of the existing "Random Forest" approach. Compared to "the current Random Forest algorithm," Figure 5 likewise shows great accuracy. The random forest classifier is used for classification and detection tasks. As part of ensemble learning, the result is predicted using a range of base estimators [17]. It is common practice to employ decision trees to improve accuracy. However, they are prone to overfitting issues. This issue is solved with a random forest classifier, which is made up of several decision trees. Different subsets of the entire Dataset are used to train each tree, which may prevent overfitting and increase the classifier's accuracy. To fit the model, a train set (80%) of the Dataset was employed, and a test set (20%) was used to verify the model. The score for accuracy



.Fig 6: Confusion Matrix of class grapes using KNN

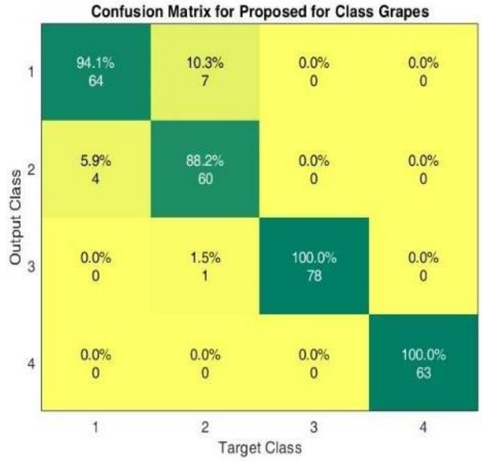


Fig 7: Proposed Confusion Matrix for class grapes

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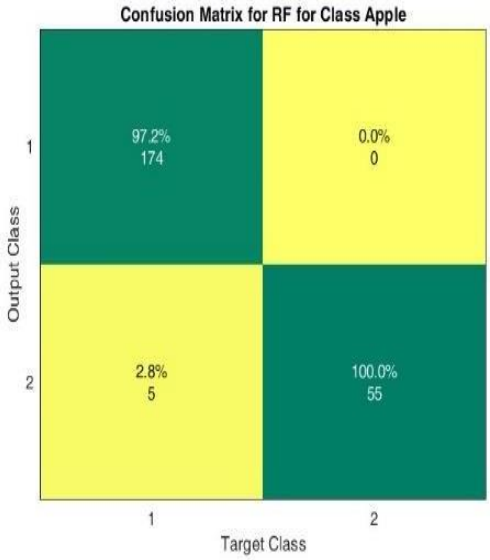

Fig 8: Confusion Matrix for class Apple using Random Forest

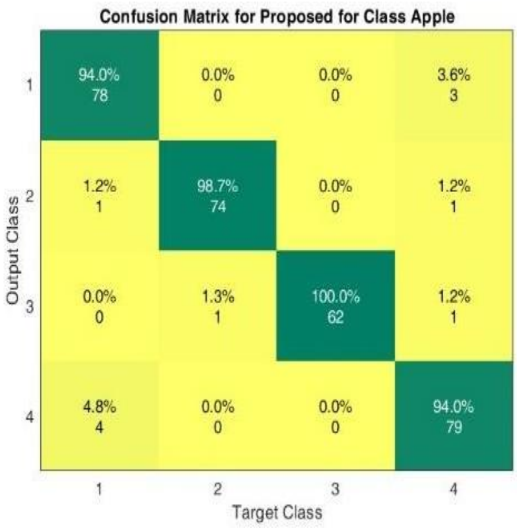

Fig9: Proposed confusion matrixfor class apple

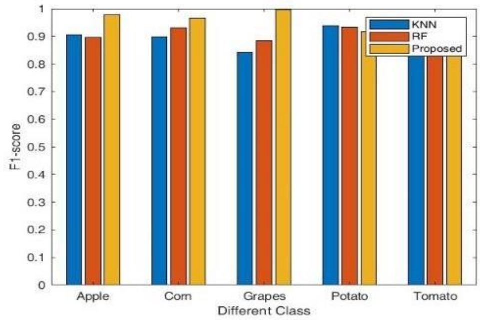

Fig 10: Comparative study among of proposed algorithm random forest algorithm and KNN in-terms of F1-score for class Apple, Corn, Grapes, potato, and Tomato The yellow bar graph is the output of proposed algorithm blue and red graph are performance of KNN and RF algorithm

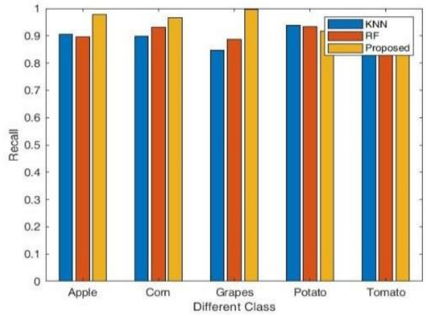

Fig 11: Comparative study among of proposed algorithm random forest algorithm and KNN in-terms of recall for class Apple, Corn, Grapes, potato and Tomato The yellow bar graph is the output of proposed algorithm blue and red graph are performance of KNN and RF algorithm

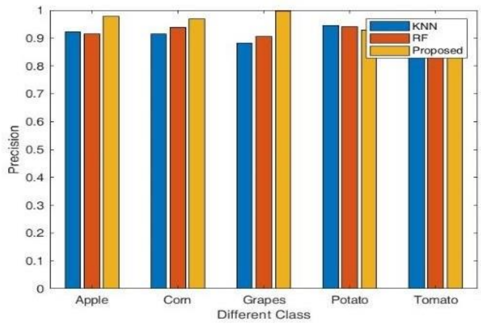

Fig 12: Comparative study among of proposed algorithm random forest algorithm and KNN in-terms of precision for class Apple, Corn, Grapes, potato and Tomato The yellow bar graph is the output of proposed algorithm blue and red graph are performance of KNN and RF algorithm

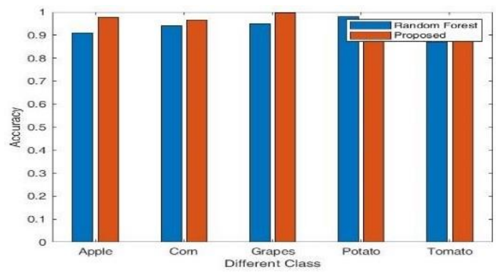

Fig 13: Comparative study of proposed algorithm and random forest algorithm in-terms of accuracy for class Apple, Corn, Grapes, potato, and Tomato

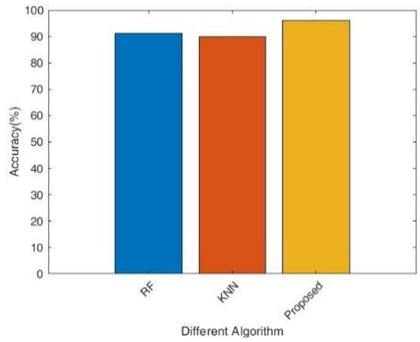

Fig 14: Proposed Algorithm performs well compare toRF and KNN

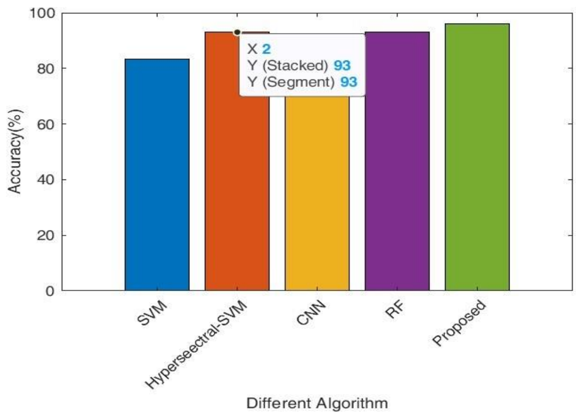

Fig 15: Accuracy of Proposed algorithm found goodcompare to other existing algorithm

7. Conclusion and Future Scope

In the result and discussion section, the proposed algorithm has been applied to each crop leaf separately and found good results. After analyzing the results, it has been concluded that the proposed algorithm performs well in accuracy, precision, and recall compared to the existing algorithms. The previous research did not implement the Alex net-HBA fusion feature selection and multi-SVM classificationalgorithms. Still, in this paper, the new algorithm has been proposed and compared to all existing machine learning algorithms in the result and discussion portions. In Figure 15, abar chart shows that the green block is the outcome of the proposed algorithm, and compared to support vector machine (SVM), hyperspectral support vector machine, convolution neural network, and random forest algorithms, theirperformance is not up to par with the proposed algorithm. The experimental result shows good performance after using the HBA optimization technique. It could be implemented in the future for a better result. Based on the proposed algorithm, an application could be created to detect the infected leaf accurately. It must help the farmer to protect the crops from pesticides and pathogens to save humanity.

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