# A PERFORMANCE ANALYSIS OF THE PROPOSED PLANT LEAF DISEASE DETECTION ALGORITHM WITH THE EXISTING PLANT LEAF DISEASE ALGORITHM

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*All living creatures and the ecosystem benefit from plants. Oxygen and carbon dioxide, two gases required for both human and animal life, are taken up and released by plants. Animals rely on plants for food, shelter, and water purification because plants have a built-in mechanism for removing dangerous contaminants from the air and water. The training of a plant pathologist is not complete until the diagnosis is mastered. Animals can find food and refuge in plants. A plant's principal job is to filter water. Without training in diagnosis, a plant pathologist's education falls short. Without a proper diagnosis, disease control can be time- and money-consuming and even result in plant death. Correct problem identification is essential. This paper explores a new plant leaf disease detection algorithm to identify plant leaf diseases and also conducts a comparison study with an existing algorithm.*

**Keywords:** Feature ex-traction , Antlion Algorithm for feature section, comparative study with existing algorithm

## 1. Introduction

Agriculture is one of the most important sectors and a foundational industry for our country. The agricultural sector appeals to a large segment of the Indian populace [1]. India is the world's second-largest producer of agricultural goods. The agricultural sector is vital to the Indian economy and provides livelihoods for as much as 70% of rural residents.Furthermore, it accounts for around 17% of the nation's gross domestic product and employs more than 65% of the population.Almost every crop, fruit, or vegetable may be grown via farming on soils that are warm to subtropical. It is possible to determine the total yield of these crops by measuring the robustness of their roots and leaves. However, because to the ever-changing dynamics of the environment, diseases usually reduce the output of these crops. Plant diseases, which damage crops by damaging their leaves, have several causes.Because of this, the country's economy takes a hit[2]. Meanwhile, agriculture provides a living for 90% of the world's population.Eighty percent of the world's food is

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produced by farmers, but sadly, more than fifty percent of that production is lost to plant diseases and pests [3–4]. A useful method for detecting agricultural diseases was proposed by the authors in [6]. It relies on machine learning and computer vision techniques like the R.F. algorithm. The proposed system could identify up to 20 different diseases in five typical plants with a 93 percent accuracy rate.In [7], the authors implemented machine learning and computer vision techniques to create a better disease diagnosis model. The method that was demonstrated involved obtaining the raw image of a leaf and using preliminary processing and separation to extract attributes like colour, veins, form, and so on. The researchers in [8] "investigated deep feature extraction models and transfer learning." The two classifiers that were utilised to categorise each and every feature that was retrieved were SVM and KNN. The Plant Village Dataset, which is available for free, allowed all of this work to be accomplished. The findings showed that SVM was the most effective classifier for determining if a leaf was infected. The goal of the research in [9] was to apply the R.F. algorithm to classify healthy and diseased photos from generated data sets. In order to classify the infected and healthy photos, this study's execution stages include feature extraction, dataset building, classifier training, and classification. Following R.F., The datasets comprising damaged and healthy leaves were combined and utilised for training purposes. They extracted features from an The utilisation of the Histogram of an 0riented Gradient (HOG) technique for image representation. . All things considered, using machine learning to train the enormous publicly accessible data sets offered a definite method for mass-scale plant infection identification."While monitoring plant infections by hand at every stage was highly difficult and required more labour and time, The focus of the study in [10] was on using ML algorithms and image processing to access and diagnose illnesses in plants. Plant disease signs were identified and classified using edge- and color-based image processing methods. Based on relevant data gathered from the diseased leaf portion, a multi-class Support Vector Machine was used to classify the type of disease. This study looked into plant diseases brought on by a variety of pathogens, including bacteria, fungus, and viruses, in an effort to identify plant diseases early and frequently."The research in [11] concentrated on machine learning and image processing methods for illness identification. The algorithm operated in the following steps: first, it located and captured the affected area; then, it processed the image in an initial manner; finally, it obtained the split portions; finally, it recognised the area of concern; and finally, it extracted features. Finally, SVM Classifiers were used to transfer the results in order to obtain the conclusions. SVMs outperformed earlier disease identification systems in the task of disease categorisation, and the results showed that the approach suggested in this research yielded significantly better results." Pests, diseases, and a few other undesired elements that crop up might cause agricultural productivity to drastically decline. There exists a direct correlation between the quantity of hazardous components present in agricultural goods and the overall losses and crop quality. "Pesticides" were developed to combat, control, and lessen the effects of illnesses on agricultural output [12]. Abiotic factors such as hail, spring frosts, changing weather patterns, chemical combustion, and so on can spread some diseases. These illnesses are less hazardous, non-communicable, and frequently preventable. [13].

## 2. LITERATURE REVIEW

In their work, the contributors of [14] used a combination of machine learning techniques and image processing to classify and identify plant diseases. In order to verify their methods, the authors collected standard photos of several plants. Prior to analysing the data for various features, the impacted region of the input picture was first divided and segregated. ROI achieved. Classification also made use of the SVM approach. The results of the experiment proved that the proposed method could correctly and consistently classify plant diseases. Using image processing methods, the researchers in [15] proposed an automated method for vision-based recognition of plant diseases. They utilised the "K mean algorithm" to categorise leaf ill-nesses and the GLCM approach to segment colours after identifying the plant leaf's typical colour. Both outcomes and efficiency improved as a consequence of this strategy. Finding grapevine diseases like "Leaf blight, Black rot, sta-ble, and Black measles" was the major goal of the study in [16]. Although many methods based on machine learning (ML) have been suggested for de-tecting illnesses in grapevines, none of these methods have been suggested for detecting all four diseases simultaneously. To assist with the Efficient Nett B7 deep architecture's transfer learning training, the technique was created utilising images from the plant village dataset. After that, logistic regression was used to down-sample the traits (yes or no, according to the observation data). In terms of identifying diseases in grapevines, the proposed model has an accuracy rate of 98.7 percent. A method developed for the accurate and efficient identification of plant diseases was employed in conjunction with an Extreme Learning Machine (ELM) by the same group of researchers in [17]. Many specialists have used various machine learning (ML) methods, such as "clustering, decision Tree, k-nearest neighbour, support vector machine, Naïve Bayes naive bayes, and so on," in their models to anticipate plant diseases in their early stages. Unfortunately, these ML approaches only work in very narrow, restricted contexts, which is a major problem. Additionally, overfit-ting issues plagued older machine learning algorithms, making them unable to handle complex and massive datasets. Researchers used Deep Learning tech-niques including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs), Bi-LSTMs, and so on

(A) Apple-black-rot (B) Corn-leaf-blight (C) Grapes-leaf blight (D) Potato bacterial-spot

FIGURE 1. Diseased Leaf

to get better and more accurate findings. When it comes to overfitting problems and huge, complicated datasets, DL techniques are more than capable. New hardware mechanics allow for the rapid application of deep learning approaches to previously intractable problems. The problem is that in order for DL methods to improve plant diagnostics, a mountain of data is required. This is problematic since the majority of currently available datasets are somewhat small and do not include a enough number of high-quality images. Images captured in various settings are essential for a comprehensive and relevant database. Conventional deep learning approaches have a lower classification accuracy rate when training data samples are too few. Using the RF method, the researchers in [18] attempted to distinguish between contaminated and uncontaminated photos in created datasets. Some of the steps involved in executing the present study include building the dataset, extracting features, training the classifier, and finally, classification. In order to distinguish between healthy and sick leaves, the produced datasets were pooled and reinforcement learning was used. In order to extract features from a picture, they used the Histogram of an Oriented Gradient. When these factors were evaluated, a method for diagnosing plant infections on a large scale using publicly accessible data sets trained using ML emerged. The research in [19] aimed to access and diagnose plant diseases using image processing and machine learning approaches since manually monitoring plant ailments at every stage was very laborious and time-consuming.Disease diagnosis via the use of image processing and machine learning was the primary emphasis of the research reported in [20]. The algorithm was designed to function in stages. It started by locating the damaged region. Then, it divided the picture into its component parts, performed basic image processing, identified the area of concern, and extracted characteristics. The findings were finally transferred to get the conclusions using SVM Classifiers. Results showed that the approach suggested in this work significantly improved results, and support vector machines (SVMs) outperformed previous illness identification systems in the disease classification test.

Table 1. Literature Review

| Author and Year | Findings | Journal Name |
|---|---|---|
| The author in 2022 [23] | The identification and diagnosis of numerous grapevine diseases, such as leaf blight, black rot, stable, and black measles, are the main topics of this study. The illness detection methodology that is utilised makes use of Logistic Regression technology. | Emerging Trends in Sensing and Imaging with Machine and Deep Learning |
| Xian, Tan Soo, and Ruzelita Ngadiran. 2021[24] | Healthy Identification of different plant diseases by analyzing leaf images.The technology employed in this study is the Extreme Learning Machine (ELM) in conjunction with a single layered feed-forward neural network. | IOP publishing |
| Kulkarni, Pranesh,2021 [25] | 20 distinct diseases in five standard plants(Technology Used: Computer vision based algorithm Accuracy :93%) | Computer Vision and Pattern Recognition |
| Murtaza Ali Khan, 2020 [26] | Plant leaf Disease detection .(Technology Used: Image Processing) | International Journal of Computer Trends and Technology |

## 3. METHODOLOGY OF PROPOSED WORK

Figure 2 shows the recommended technique, which is to build a model to help the system choose a set of qualitative features and extract data from many domains. In order to improve the recognition technique's reliability or detection rate, it is anticipated that this qualitative data gathering will aid in identifying noteworthy trends in the input photos. The main objective is to design the framework of a machine learning algorithm that can be used to tweak the algorithm's hyper parameters and improve the system's accuracy. An important part of the suggested approach is a suggestive model that may help the user determine the problem and provide possible remedies. All things considered, this approach for controlling plant diseases should be comprehensive.

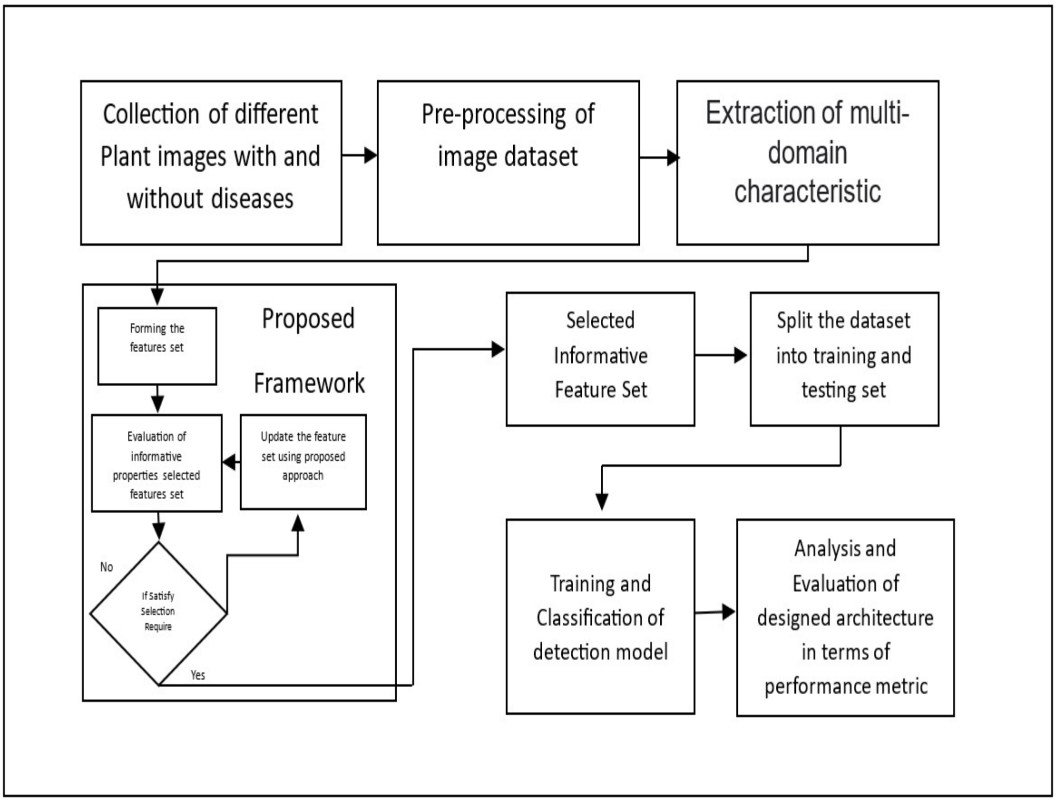


Figure 2. Proposed Algorithm for Phase of Selecting Qualitative Information Set

## 4. About the Dataset

The basic aim of various statistical analyses is to provide a description of The analysis of a particular dataset involves examining its central tendency and dispersion. An additional factor to take into account during the analysis of the data is its skewness and kurtosis.Skewness is a statistical measure utilised to evaluate the extent of symmetry, or absence thereof, inside a given distribution. A distribution, also known as a data set, is deemed to possess symmetry when it exhibits an identical visual pattern on both its left and right sides, with respect to its central point.Kurtosis is a statistical measure used to evaluate the extent to which a dataset differs from a normal distribution, particularly in relation to the presence of heavy-tailed or light-tailed properties. In alternative terms, datasets that demonstrate high kurtosis are distinguished by the existence of heavy-tailed distributions or exceptional observations. For the purpose of identifying plant leaf diseases in this study, the researchers used the author's open Plant Village dataset from [6]. Included in the dataset are 87,000 RGB images of plant leaves in both healthy and diseased states, categorized into 38

Table 2. dataset used in the experiment

| Plant | Disease Name | Number of Images |
|---|---|---|
| Apple | healthy | 2008 |
| | scab | 2016 |
| | blackrot | 1987 |
| | cedar apple rust | 1760 |
| Corn | Healthy | 1859 |
| | Cercosporin leafspot | 1642 |
| | Commonrust | 1907 |
| | Northern Leaf Blight | 1908 |
| Tomato | Healthy | 1926 |
| | Bacterialspot | 1702 |
| | Earlyblight | 1920 |
| | Lateblight | 1851 |
| | LeafMold | 1882 |
| | Septorialeafspot | 1745 |
| | Two-spotted spidermite | 1741 |
| | TargetSpot | 1827 |
| | Yellow LeafCurlVirus | 1961 |
| | Tomato mosaicvirus | 1790 |
| Potato | Healthy | 1824 |
| | Earlyblight | 1939 |
| | Lateblight | 1939 |
| Grapes | Healthy | 1692 |
| | Blackrot | 1888 |
| | BlackMeasles | 1920 |
| | Leafblight | 1722 |

different c ategories. Table 2 shows that we chose a total of 25 classes to serve as test cases for our method.

## 5. Feature extraction

For the purpose of feature extraction and data pre-processing, Figures 3 have been selected as samples. For every computer-based vision system, data preparation is essential. Reliable findings require reducing background noise before extracting the characteristics. Once the RGB image has been transformed to grey scale, it is smoothed using a Gaussian filter afterwards. The image is then binarized by applying the Otsu thresholding technique. Next, applying morphological transform on the binarized image, the small foreground gaps are filled. By bitwise ANDing the binarized image with the original colour image, the segmented leaf's RGB picture is created once the

(a) infected leave of apple (b) infected leave of corn

Figure 3. sample infected leave of apple and corn

foreground has been determined. At the moment, segmentation is the information obtained for the image's shape, texture, and colour. The context is utilised to compute the perimeter of the leaf. the path that joins any location inside an object's boundaries and that is Before it can reach its goal, it starts to dig to learn about it in general First, the percentage of hue (H) channel pixels with pixel intensities ranging from 30 to 70, as well as the total number of pixels to compute the quantity, are converted to the HSV colour space in a channel.green in the picture. The portion of an image that isn't green could be determined by subtracting the green element from 1. Consequently, It was possible for us to determine the texture of the image by applying the grey "level co-occurrence The colour information in the image was extracted using a matrix (GLCM).(7) pretrained model like alex-net has been implemented to select qualitative features from the extracted features using GLCM method.

Table 3. extracted features by GLCM

| Field | Value |
|---|---|
| Contrast | 0.1391 |
| Correlation | 0.8694 |
| Energy | 0.2954 |
| Homogeneity | 0.9347 |

## 6. Implementation

### 6.1. Existing Honey Badger algorithm

The activity honey badger is a inspiration for the recently developed metaheuristic algorithm known as the Honey Badger Algorithm (HBA), which mimics their digging and honey-finding strategies as they explore and use the search space. The author has suggested the HBA algorithm for solving optimisation problems [23]. In this paper, formulas have been collected to create fitness functions, and threshold values have been added to get the optimum value. Step-1:Initialise the population size of honey badgers (N) and their locations depending on Eq. (1):

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

Step 2:

$$I_i = r_2 \cdot \frac{S}{4\ \pi d_i^2} \tag{2}$$

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

In this case, r2 is an arbitrary value between 0 and 1. S specifies the strength or concentration of the source. Eq. (2) shows the separation between the badger and its prey.
Step 3:An efficient means of managing time-varying randomness is the density factor, which paves the way for a smooth shift from exploration to exploitation.

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

$$t_{max} = numberofiterations$$
$$whereCisaconstant >= 1(default = 2)$$

Step 4: Avoiding the best of the natives. Do this step and the two that follow to depart local optima zones. The technique provided in this scenario involves the utilisation of a flag, denoted as F, which serves the purpose of altering the search direction. This alteration is intended to optimise the agents' ability to thoroughly analyse the search region.
Step 5: The positions of the agents are being updated. The "digging phase" and the "honey phase," are the two phases of the HBA position update technique (xnew).

$$"P_{new} = P_{prey} + F \cdot r_3 \cdot \alpha \cdot d_i[\cos(2\pi r_4) \cdot [1 - cos(2\pi r_5)]]" \tag{4}$$

Step 6 As part of the digging phase, the honey badger uses "honey badger Equation (2)" to determine how far away from its target it is. r3, r4, and r5 are three distinct random integers chosen at random from an even distribution with values between 0 and 1. This flag was shown in

$$F = \begin{cases} 1 & if\ r_6 <= 0.5 \\ -1 & else, \end{cases} \tag{5}$$

### 6.2. Modified HBA

In order to demonstrate a decent result, we have created a fitness function using all of the existing HBA algorithm's formulas. Since it is impossible to have the best outcome in every iteration, we have put the threshold value at 5. We have employed antlion optimisation to obtain a new coordinate value if, up until the fifth iteration, the best value is not obtained. We have changed the HBA fitness function in this way. Threshold value is added to the existing HBA, and the Antlion algorithm is also added to get good optimization to enhance the accuracy of the proposed model. The algorithm of fitness function can be refered in 6.1.

**Algorithm 6.1** An algorithm of fitness function

$i \leftarrow 5$
**if** $i \geq 5$ **then**
  $i \leftarrow 1$
  $r \leftarrow$ *antlion* (dim,tmax,Lb, Ub,Xprey,t)
  *rnew* $\leftarrow$rnew(upadated value)
**end if**

### 6.3. Feature selection and optimization

Feature selection utilizing antlion optimization (ALO) as the underlying model. Feature sets sometimes contain duplicate, dependent, and correlated characteristics, which can significantly impact the performance of classification algorithms and lead to longer training times. Hence, the process of feature selection becomes imperative in order to eliminate unnecessary features and improve the generalization of categorization. Wrapper-based feature selection is a technique that aims to select a subset of Characteristics that optimize the efficiency of a specific classifier. This process necessitates the use of an efficient search method to identify the ideal combinations of features. In this study, the ALO algorithm is utilized as a search method to identify the ideal feature set that maximizes classification performance. A metaheuristic optimization algorithm (HBA) named after the Honey Badger. The suggested method takes cues from the honey badger's shrewd hunting habits in order to create a more practical search technique for resolving optimization problems through mathematics. Honey badgers have a dynamic search behavior that The activities of digging and honey-seeking are encompassed under the exploration and exploitation phases, as formalised in the Honey Badger Algorithm (HBA). In subsections 6.1 and 6.2, the implementation of the concept is carried out to develop a novel fitness function . In this study, feature selection is conducted using the Honey badger algorithm (HBA) in conjunction with a objective function (objfunc). The algorithm of Random walk Antilion algorithm can be found in 6.2. Dim is the dimensionality of the search space. Establish

**Algorithm 6.2** Random-walk-around-antlion Algorithm

**if** $size(Lb, 1)$ ←1 and $size(Lb, 2)$ ←1 **then**
  $Lb$ ←ones(1,Dim)*lb
  $Ub$ ←ones(1,Dim)*ub
**end if**
**if** $size(Lb, 1)$ ≥size(Lb,2) **then**
  $Lb$ ←Lb
  $Ub$ ←Ub
**end if**
$I$ ←1
**if** $currentiter$ >maxiter/10 **then**
  $I$ ←1+100*($currentiter$/maxiter)
**end if**
**if** $currentiter$ >maxiter/2 **then**
  $I$ ←1+1000*($currentiter$/maxiter)
**end if**
**if** $currentiter$ >maxiter*(3/4) **then**
  $I$ ←1+10000*($currentiter$/maxiter)
**end if**
**if** $currentiter$ >maxiter*(0.9) **then**
  $I$ ←1+100000*($currentiter$/maxiter)
**end if**
**if** $currentiter$ >maxiter*(0.95) **then**
  $I$ ←1+1000000*(currentiter/maxiter);
**end if**
$Lb$ ←Lb/(I)
$Ub$ ←Ub/(I)
**if** $rand$ <0.5 **then**
  $Lb$ ←Lb+antlion
**else**
  $Lb$ ← −Lb+antlion
**end if**
**if** $rand$ >=0.5 **then**
  $Ub$ ←Ub+antlion;
**else**
  $Ub$ ← −Ub+antlion
**end if**
$i$ ←1
**while** $i$ ≤Dim **do**
  $X \leftarrow [0cumsum(2 * (rand(max_iter, 1) > 0.5) - 1)]$
  $a$ ←min(X)
  $b$ ←max(X)
  $c$ ←Lb(i)
  $d$ ←Ub(i)
  $Xnorm$ ← ((X-$a$). ∗ (d-$c$))./(b-$a$)+c
**end while**

the lower bound (lb) and upper bound (ub) of the search space. Specify the maximum number of iterations (tmax) and the quantity of harmony vectors (N). The algorithm (HBA) utilising the provided parameters and record the outcomes in the variables Xprey, Food Score, and CNVG. In order to improve the suggested model, the existing HBA is supplemented with a threshold value and the Antlion algorithm. This addition aims to achieve effective optimisation. The variables maxiter, lb, ub, antlion, and currentiter are utilised within the algorithm in step 6.

## 7. Result and Discussion

After implementing the above-mentioned code, we received the desired out put.In the confusion matrix at figure 6, we take class 1 as healthy, class 2 as blackrot, class 3 as blackmeasles, and class 4 as leafblight.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

so accuracy=94.1+88.2/94.1+10.3+5.9+88.2=92

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

Precision=94.1/94.1+5.9=94.1

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

Recall=94.1/94.1+10.3=90.1

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

F1-Score=2 $\times$ 94.1 $\times$ 90.1/94.1 + 90.1=91.85

Based on above mentioned coding the performance of the proposed algorithm has been computed .It is clear that the confusion matrix has been used to assess a model's performance. Figure 6 clearly shows that the suggested approach outperforms the current technique in Figure 5 in terms of performance.

TABLE 4. Performance Metrics of Proposed Model for Grapes

| Diseases | Healthy | black rot | black measle | leaf blight | Accuracy | Precison | F1 -Score |
|---|---|---|---|---|---|---|---|
| Healthy | 94.1 | 10 | 0 | 0 | 94.1 | 90.1 | 91.85% |
| black rot | 5.9 | 88.2 | 0 | 0 | 96 | 97 | 96% |
| black measle | 0 | 1.5 | 100 | 0 | 97 | 97 | 90% |
| leafblight | 0 | 0 | 0 | 94 | 97 | 1 | 98% |

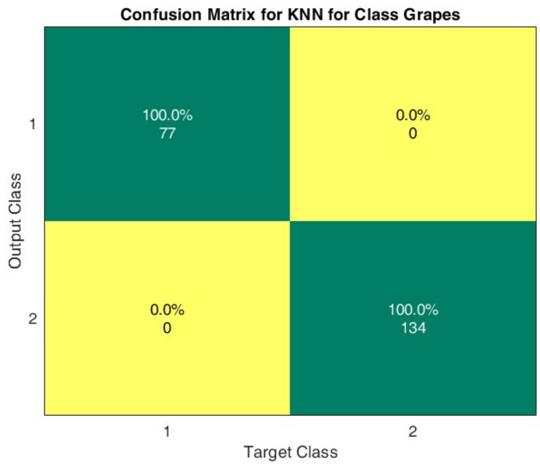


FIGURE 4. Confusion Matrix for class Grapes

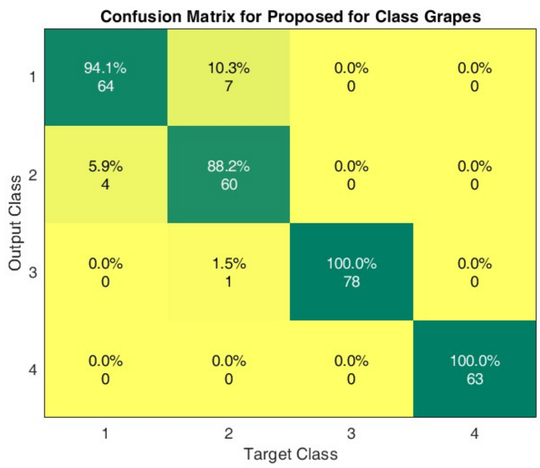


FIGURE 5. Confusion Matrix Proposed for class Grapes

Additionally, In table 4 the accuracy, precision, and F1 scores of the proposed method have been evaluated for Grape, and the findings are promising when compared to the performance of the current system. The suggested algorithm is shown in Figure 8 to perform well in terms of accuracy, F1 score, and precision. Hence measuring early illness identification in plants is acceptable.Same way performance matrix of corn has been calculated from figure 7 Infected leaves from apples, corn, grapes, potatoes and tomatoes have been taken into account for the experiment using the current algorithms. However, after the proposed algorithm was put into practise, it demonstrated good performance, and optimisation also seemed promising in comparison to other current algorithms.The suggested method's effectiveness has also been evaluated by contrasting it with the current approach for other model performance metrics including recall and precision.Good results were also shown in Figures 8 and Table 6 has a comparison analysis based on figure 8, and the results show that the proposed method, HBAFS, performs well.

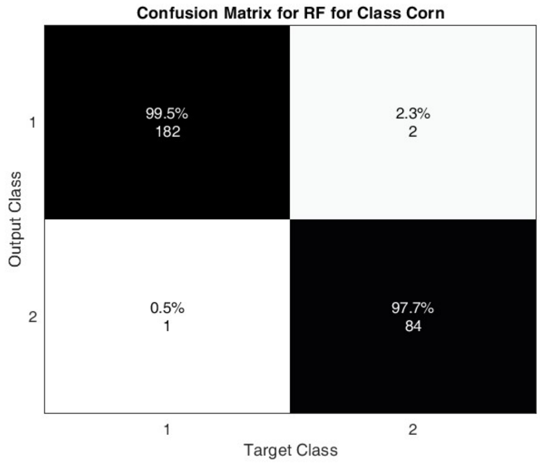


FIGURE 6. Confusion matrix using RF for class corn

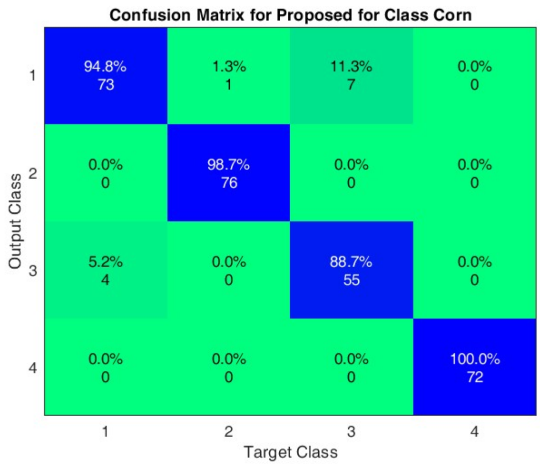


FIGURE 7. Confusion matrix proposed for class corn

In this experiment, deep learning components are configured in Matlab, and a performance analysis was done with respect to other algorithms. Firstly, features are extracted using Alexnet, and from the collected features, the best Features are selected using the Ant-lion feature selection algorithm. Then They are optimized using the HBA algorithm, giving a good result. Figure 8 shows Recent algorithms like SSAF (swarm algorithm for feature selection),SVM, hyperspectral SVM, and CNN have lower accuracy, and it is also found that old algorithms like KNN and RF accuracy are lower than the proposed algorithm.

Table 5. Performance Metrics of Proposed Model for Corn

| Diseases | Healthy | Cercosporin leafspo | Common rust | Northern Leaf Bligh | Precision | Recall | F1 |
|---|---|---|---|---|---|---|---|
| Healthy | 94.8 | 1.3 | 11.3 | 0 | 98 | 93 | 95 |
| Cercosporin leafspo | 0 | 98.7 | 0 | 1.2 | 97 | 97 | 96 |
| Common rust | 5.2 | 0.0 | 88.7 | 0.0 | 98 | 97 | 90 |
| Northern Leaf Blight | 0.0 | 0 | 0 | 100 | 98 | 1 | 98 |

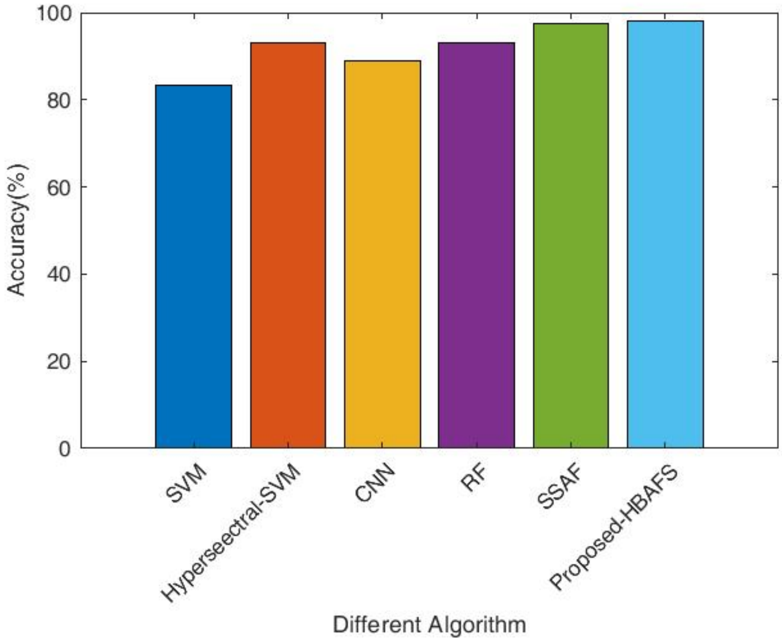


Figure 8. Comparison of different algorithms vs proposed algorithm

Table 6 shows the accuracy value of different algorithms compared to the proposed one. An algorithm's or measure's progress over time can be shown visually in a convergence graph. You can tell if a measure has converged well by looking at the convergence graphs.In Figure 9 and Figure 10, the fitness vs iteration graph have been discussed, and the convergence of HBAFS was found to be good over SSAF (swarm algorithm for feature selection) for both A training set comprising 80% of the data and a test set comprising 20% of the data were both taken from the dataset. The model underwent training on the train set and validation on the test set.

Table 6. Comparative study of different algorithm with proposed lgorithm

| Algorithm Name | Disease Name | Detection Accuracy |
|---|---|---|
| SSAFS | BlackMeasles,Blackrot,Leafblight | 94.1% |
| SVM | BlackMeasles,Blackrot,Leafblight | 83% |
| Hyperspectral SVM | BlackMeasles,Blackrot,Leafblight | 93.5% |
| CNN | BlackMeasles,Blackrot,Leafblight | 87% |
| RF | BlackMeasles,Blackro,Leafblightt | 91% |
| HBAFS | BlackMeasles,Blackrot,Leafblight | 96.1% |

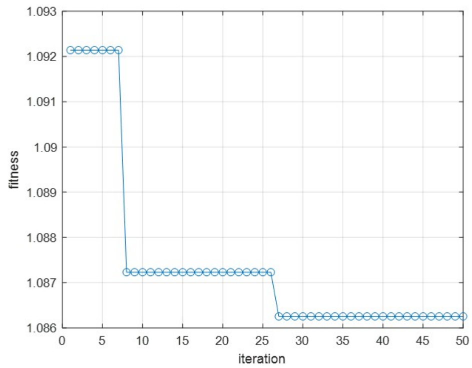


Figure 9. convergence of fitness function using exiting algorithm

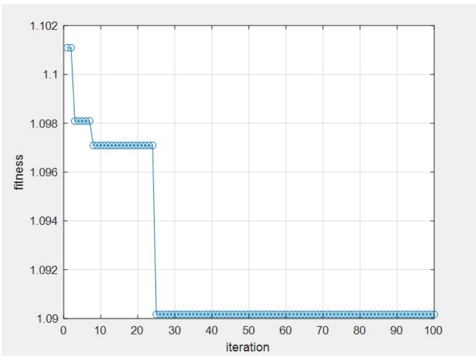


Figure 10. convergence of fitness function using proposed algorithm

## 8. **Conclusion and Future scope**

Table 5 and Table 6 shows the performance matrices for model built for each plant leaf. As we can see, the accuracy scores and f1 ratings are fairly similar. This occurs as a result of an equal number of inaccurate projections, both positive and negative. This is the ideal situation for any machine learning system. The typical accuracy measured at 96% at figure 8.The farmland is regularly monitored by the suggested way. It has been found that the proposed method performs effectively and is well-optimized after using antlion feature selection and the HBA optimisation technique. A Performance Analysis between the proposed algorithm and all currently used machine learning techniques has been conducted using HBA optimisation on the suggested algorithm. In comparison to the prior algorithm, it discovered a decent result.In the near future, a recommended system will be implemented that will help agriculturalists find plant leaf disease at an early stage.

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