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ORIGINAL

Plant Leaf Disease Detection and Recommendation System using Alex Net-Honey Badger Fusion Algorithm

Sistema de detección y recomendación de enfermedades de las hojas de las plantas que utiliza el algoritmo de fusión Alex Net-Honey Badger

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ABSTRACT

Introduction: plant diseases pose a significant challenge to the agriculture sector, affecting crop yield and quality, and thereby impacting the global economy. This paper discusses the urgent requirement for effective and precise detection and management of plant diseases.
Objective: utilizing the latest developments in machine learning and deep learning, specifically Convolutional Neural Networks (CNNs), we present a streamlined algorithm for identifying plant leaf diseases and providing treatment recommendations. To increase feature selection and classification accuracy, this method combines the strengths of the Honey Badger method (HBA) and antlion optimisation (ALO).
Method: this research thoroughly validates the suggested algorithm on a dataset of 87,000 RGB images that are categorised into 38 distinct plant diseases in order to compare it with state-of-the-art methods already in use.
Results: the outcomes demonstrate outstanding performance with respect to accuracy, precision, recall, and F1-score, outperforming traditional models like Random Forest (RF), Support Vector Machine (SVM), and other deep learning models. By adding a recommendation mechanism to the algorithm, this work significantly advances the field by providing useful guidance on the management and prevention of diseases.
Conclusions: the study has important ramifications for plant pathology and agricultural technologies. It offers farmers practical ways to successfully fight plant diseases, hence lowering food insecurity and improving crop productivity.

Keywords: Modified HBA; Comparison with Existing Algorithm; Recommendation System.

RESUMEN

Introducción: las enfermedades de las plantas suponen un reto importante para el sector agrícola, ya que afectan al rendimiento y la calidad de los cultivos y, por tanto, repercuten en la economía mundial. En este artículo se analiza la necesidad urgente de una detección y gestión eficaces y precisas de las enfermedades de las plantas.
Objetivo: utilizando los últimos avances en aprendizaje automático y aprendizaje profundo, concretamente las redes neuronales convolucionales (CNNs), presentamos un algoritmo optimizado para identificar enfermedades de las hojas de las plantas y proporcionar recomendaciones de tratamiento. Para aumentar la selección de características y la precisión de la clasificación, este método combina los puntos fuertes del método Honey Badger (HBA) y la optimización de hormigas león (ALO).

Método: esta investigación valida exhaustivamente el algoritmo sugerido en un conjunto de datos de 87 000 imágenes RGB que se clasifican en 38 enfermedades vegetales distintas para compararlo con los métodos más avanzados que ya se utilizan.
Resultados: los resultados demuestran un rendimiento excepcional en cuanto a exactitud, precisión, recuperación y puntuación F1, superando a modelos tradicionales como Random Forest (RF), Support Vector Machine (SVM) y otros modelos de aprendizaje profundo. Al añadir un mecanismo de recomendación al algoritmo, este trabajo supone un avance significativo en el campo al proporcionar una guía útil sobre el manejo y la prevención de enfermedades.
Conclusiones: el estudio tiene importantes ramificaciones para la fitopatología y las tecnologías agrícolas. Ofrece a los agricultores formas prácticas de combatir con éxito las enfermedades de las plantas, reduciendo así la inseguridad alimentaria y mejorando la productividad de los cultivos.

Palabras clave: HBA Modificado; Comparación con el Algoritmo Existente; Sistema de Recomendación.

INTRODUCTION

As the backbone of human civilization, agriculture is essential to keeping life alive and feeding billions worldwide.[1] The significance of agriculture can be accounted since the inception of human civilization. In nations such as India, where farming is not merely an economic activity but also a way of life for the great majority of people, the enormous importance of agriculture is brought to light.[2] Crop cultivation is essential to human existence, whether on little subsistence farms or massive commercial agricultural facilities. However, this crucial sector's problems are as old as the business itself: diseases brought on by viruses, bacteria, fungi, and other microbes.[3] Plants are essential to the world's food supply. However, they are prone to diseases because of various environmental conditions, which results in noticeable output deficiencies.[4] Traditional manual detection techniques are widely used but are labour-intensive and prone to errors such as misclassification, reducing their reliability for early disease detection and diagnosis.[5] Globally, tomatoes (Solanum Lycopersicon) are essential economic crop consumed in large quantities. Approximately 4,582 million hectares are used for tomato agriculture worldwide; China leads in the area and production of tomatoes. India ranks second in both categories. Other important tomato-producing nations include Egypt, Turkey, Italy, and the United States. Tomatoes are a natural crop, yet most people think of them as vegetables. They include vitamins C, B9, potassium, and K and are high in lycopene, an antioxidant associated with heart health and cancer prevention. About 0,812 million hectares of tomatoes were grown in India in 2019–20, producing roughly 20,5 million tons, primarily for fresh food. If local production rises, there is potential for the tomato processing industry in India. Many diseases influence tomato agriculture and have an impact on productivity. Disease diagnosis can be addressed using machine learning, image processing, and computer vision techniques; deep learning, particularly convolutional Neural Networks (CNNs), is a potent strategy.[6] Furthermore, if these diseases are not promptly diagnosed, food insecurity may ensue. In order to meet the increasing demand for food, an approximate 70 % increase in overall agricultural output is required by 2025, according to research conducted by the Food and Agriculture Organization (FAO).

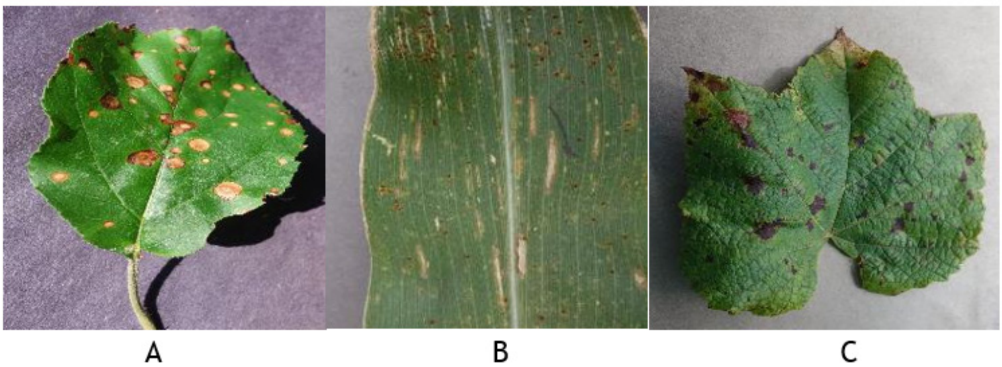

Figure 1. a) Apple-black-rot b) Northern leaf blight c) Grapes-leaf blight

Decision Tree: Sharma et al.[6] suggested a practical technique for identifying diseases in agriculture. It is dependent on computer vision and machine learning methods such as the Random Forest algorithm and Convolutional Neural Network (CNN).[7,8] With a 93 percent accuracy rate, the suggested approach could detect up to 20 distinct diseases in five common plant species. The authors of[9] used computer vision and machine learning methods to improve their disease diagnosis model. To extract characteristics like colour, veins, form, and so forth, the method that was demonstrated entailed first acquiring the raw image of a leaf and then applying basic processing and separation.(10) In figure 1, a sample diseased leaf is shown.

The objectives of the paper

- To design an optimized Alex net Honey badger fusion algorithm for plant leaf disease recognition and treatment recommendation.
- To compare and validate Alex net Honey badger fusion algorithm with existing state-of-art techniques.

Literature survey

Di et al. used machine learning and image processing techniques to identify and classify plant illnesses.(11) Standard images of several plants were collected to validate their methodology. After segmenting and separating the impacted area of the input image, many traits were looked for in the data. For classification, the SVM approach was applied. Brahimi et al. proposed an automated method for the vision-based identification of plant diseases.(12) After analyzing the plant leaf's colour characteristic, they classified leaf disease using the K-means algorithm and the GLCM method, respectively. This strategy is able to achieve produced successful outcomes and performance.

Finding grapevine diseases like "Leaf blight, Black rot, stable, and Black measles" was the main goal of the study in.(13) There are numerous machine learning (ML)-based methods that have been put forth for the diagnosis of grapevine diseases, but none of them can simultaneously detect all four illnesses. The technique was created to support the Efficient Nett B7 deep architecture's transfer learning training using images from the plant village dataset. Next, using a method called logistic regression, the attributes were down-sampled (yes or no, depending on the observation data). The proposed model's accuracy rate in identifying diseases in grapevines was 98,7 %. Like this, Pooja et al. combined an Extreme Learning Machine (ELM) with a system designed for the accurate and efficient diagnosis of plant diseases.(14) Various researchers have used a variety of machine learning (ML) techniques, such as "clustering, decision Tree, k-nearest neighbour, support vector machine, Naïve Bayes naive bayes, and so on," into their models to forecast plant diseases at an early stage.(15) The disadvantage of these ML techniques is that they work best in only small isolated environments. Furthermore, the conventional machine learning algorithms suffer from overfitting related issues, making it impossible for them to handle complicated and sizable datasets. To achieve more accurate and efficient outcomes, the researchers employed Deep Learning techniques such as CNN, RNN, LSTM, Bi-LSTM, and so forth. Large, complicated datasets and overfitting problems are easily handled by Deep Learning (DL) approaches.(16) Owing to the developments in hardware mechanics, complex problems can now be solved quickly with deep learning approaches. Nevertheless, to achieve better results for plant diagnosis, DL techniques require a considerable amount of data. This is an issue because most currently accessible databases are small and lack high-quality images. A suitable and helpful database should have images from a variety of conditions. Standard deep learning algorithms suffer from low classification accuracy rates due to insufficient sample sizes in the training data.(17) Table 1 presents the various types of diseases and the recommendations suggested for their treatment.

Table 1. Types of Diseases in Plants and the Recommendations for their Treatment

Class/Name	Recommendation	Source (Year & Authors)
Apple scab	Select cultivars resistant to scabs, alter your watering schedule, and cover with compost	Kumar and Singh, 2022(18)
Apple Black rot	Use fungicides and clear the surroundings of the l which has been infected with the disease.	Sun, G., Gleason, M. L., Zhang, R., and Liang, X. (2022)(19)
Apple Cedar_apple_rust	Select resistant cultivars when they are offered. Take out the diseased juniper's galls. Gather and get rid of falling leaves.	W. W. Turechek (2004)(20)
Corn_(maize) Cercospora_ leaf_spot Gray_leaf_spot	Remove weeds to ensure adequate vantilation of crop; plant late to prevent unfavourable planting circumstances. Use fungicides. Scheme Long-term crop switching Introducing plant cultivars that are resistant	J. M. J. Ward and D. C. Nowell (1998)(21)

METHOD

To facilitate a comprehensive understanding of the framework, the following figure illustrates the overall design and the interrelationships between its various modules.

Phase-1

The methodology of the suggested approach is depicted in figure 2, which will work towards creating a model that helps the overall system extract multi-domain features and choose a set of qualitative features. These qualitative data sets should be useful in helping to improve the accuracy or detection rate of the detection system by recognising important patterns in the input images.

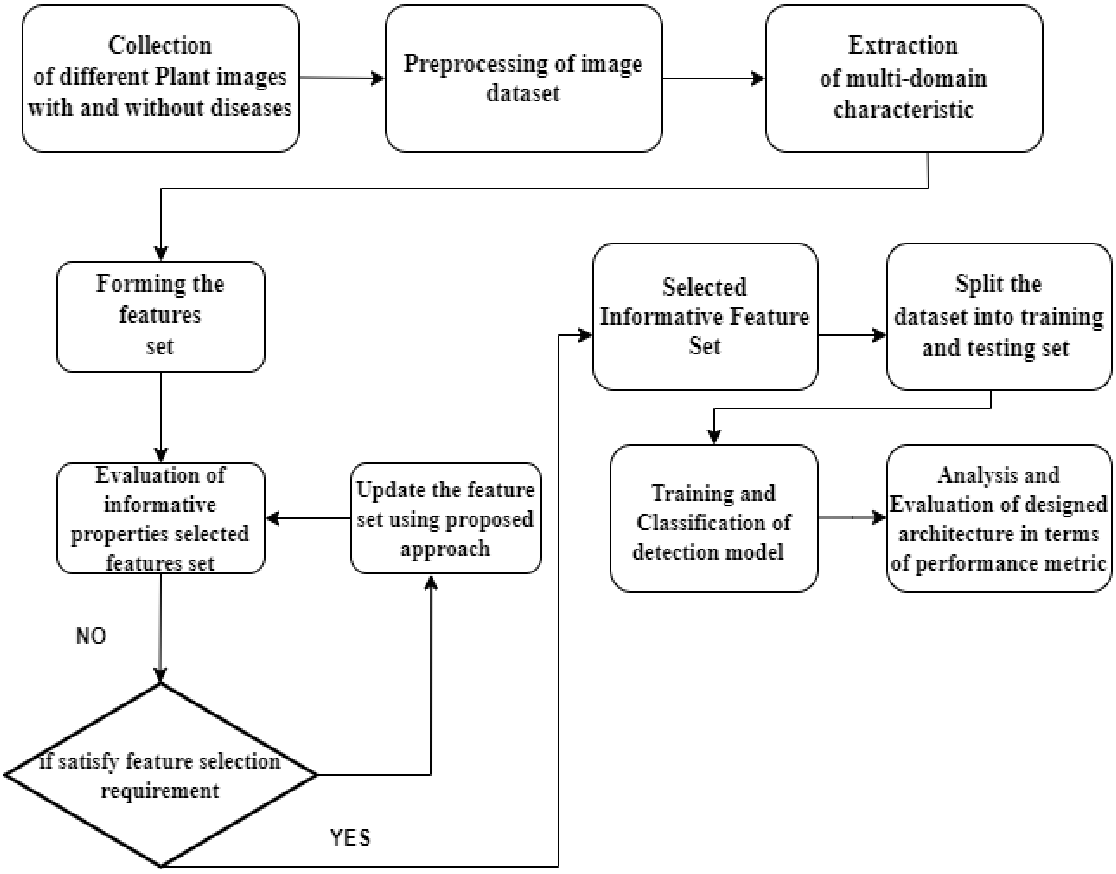

Figure 2. Proposed methodology for the phase of selecting qualitative information set

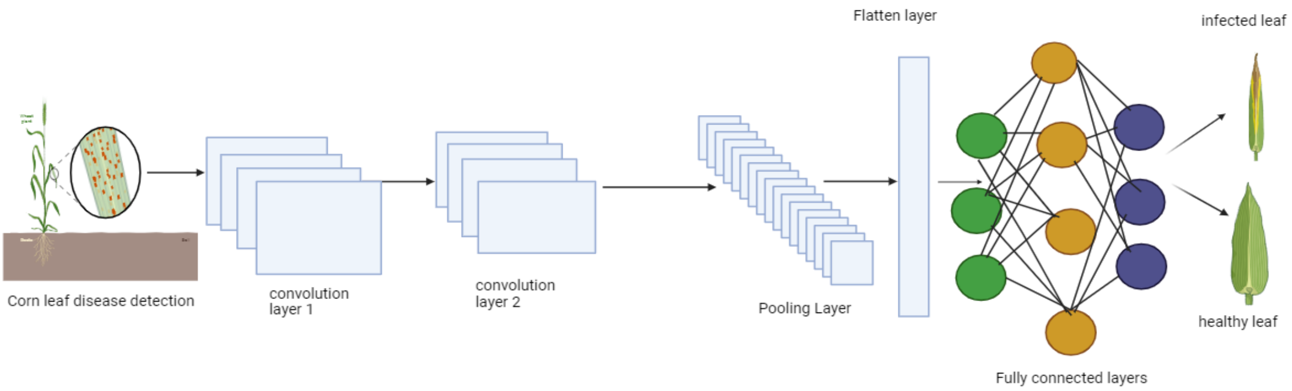

Figure 3. Extracting Multi-domain characteristic mentioned at 3rd step of proposed Methodology

Following this phase, the next phase as shown in figure 3 gives the proposed methodology that will be operational under adaptive network. The major goal of this phase is to plan a ML algorithm that will have capability to tune its hyper parameters so that the model's overall accuracy can be enhanced. Other main feature of the proposed scheme will be that it will have a suggestive model that will assist the user not only to identify the disease also will be capable to recommend the solution for the detected disease. This is expected to be an overall plant disease management system.

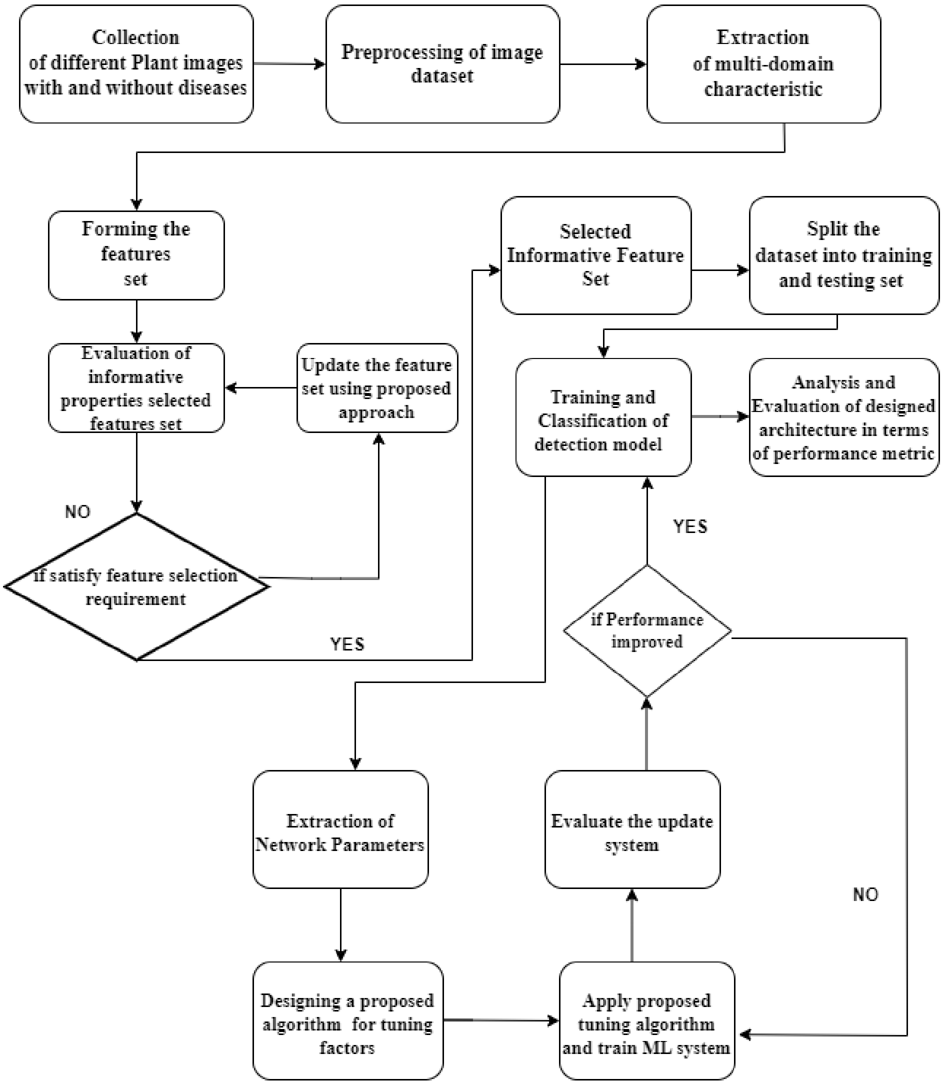

Figure 4. Proposed Disease Management Architecture

Existing Honey Badger algorithm

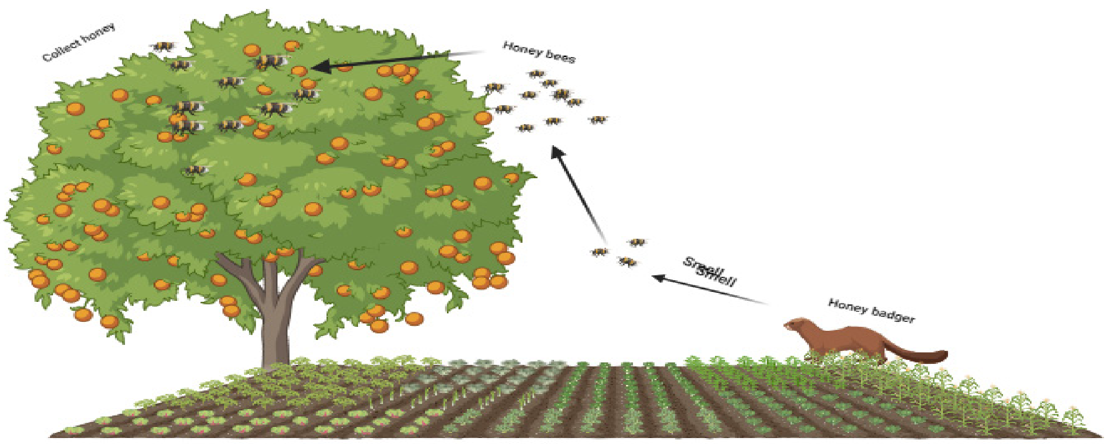

Figure 5. Honey Finding Phase of Honey Badge

The Honey Badger Algorithm (HBA), a recently developed meta-heuristic algorithm, draws inspiration from the highly efficient and adaptive foraging behavior of honey badgers, known for their ability to exploit a variety of resources in diverse environments. It imitates their digging and honey-finding techniques as they

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explore and utilize the search space. The author has introduced the HBA algorithm to address optimization challenges.[22] The algorithm mimics the biological efficiency of the honey badgers, aiming to find optimal solutions in a multidimensional search space through a process that simulates the honey badgers' exploration and exploitation phases.

The HBA algorithm is operationalized through a series of steps that collectively form the mechanism by which the potential solutions are explored and refined. The initial population is established and distributed throughout the search space as the first phase in this process. The following are the steps that have been provided.

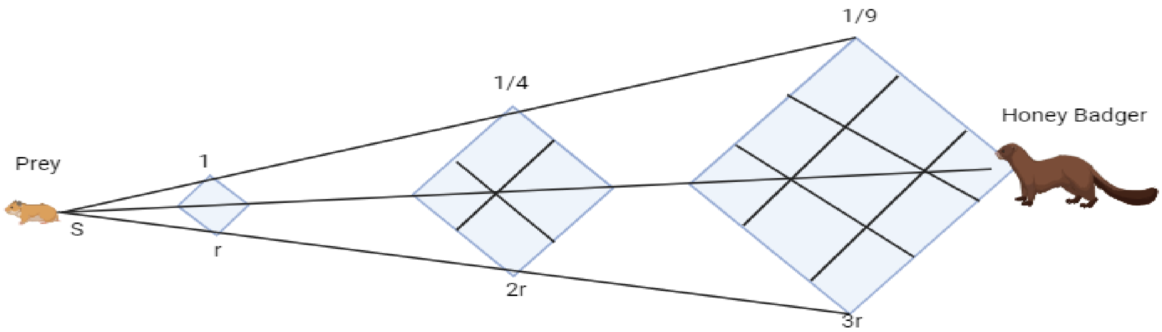

Figure 6. Digging Finding Phase of Honey Badge

Step 1: based on Equation (1), initialise the population's total amount of honey badgers (N) and their physical locations.

$$P_i = lb_i + r_1 * (ub_i - lb_i) \qquad (1)$$

Step 2:

$$I_i = r_2 \cdot \frac{S}{4\,\pi d_i^2} \qquad (2)$$
$$S = (x_i - x_{i+1})^2$$
$$d_i = x_{prey} - x_i$$

In this case, R2 can have any value from 0 to 1. S denotes the concentration or intensity of the source. Equation (2) shows the distance between the badger and its prey.

Step 3: one technique that effectively manages the presence of time-varying randomness is the density factor, which helps to ensure a seamless transition between the exploration and exploitation phases.

$$\alpha = C \cdot \exp\left(\frac{-t}{t_{max}}\right) \qquad (3)$$
$$t_{max} = \text{numberofiterations}$$
$$\text{where C is a constant} \geq 1(\text{default} = 2)$$

Step 4: evade Suboptimal Convergence Points. This step, together with the previous tactics, is essential to successfully avoid the pitfalls of local optima. The method uses a directional flag ('F') to deliberately change the direction of the search path. This modification is intended to augment the agents' exploratory powers, guaranteeing a comprehensive exploration of the search space and averting premature convergence on less-than-ideal solutions.

Step 5: the locations of the agents are updated. Two distinct stages comprise the process of revising the agents' locations within the Honey Badger Algorithm (HBA): the 'excavation stage', wherein the agents adjust their positions to search for promising areas, and the 'foraging stage' (referred to as Xnew), wherein the agents refine their positions to exploit the resources more effectively they find.

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

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Step 6: equation (2) can be used to determine the distance that separates the honey badger from its prey during the excavating phase. Three unique random numbers, denoted as r3, r4, and r5, are selected at random from a uniform distribution of values between 0 and 1. The flag that was shown in F.

$$F=\begin{cases} 1, & \text{if } r6 < 0.5 \\ -1, & \text{else} \end{cases} \quad (5)$$

Modified HBA

This fitness function generates reliable outcomes by integrating all the computational formulas inherent in the current Honey Badger Algorithm framework. The threshold number is set to 5 because it is impossible to achieve ideal outcomes in every cycle. Antlion optimization has been employed to determine a new coordinate value if the optimal value cannot be found by the fifth iteration. This is the modification has made to the HBA fitness function.

Steps of Modified algorithm

The variables Xprey, Food Score, and CNVG.

Perform feature selection using the Honey badger algorithm (HBA) with a custom objective function (objfunc).

Algorithm: honey badger fusion algorithm for feature selection

function HBA (objfunc, dim, lb, ub, tmax1, N1)

Input: objfunc, m1, lb, ub, tmax1, N1

Output: Xprey, Food Score, CNVG

Initialization: beta = 6; C1 = 2; vec_flag = [1,-1];

```
for i ←1 to N11
        temp ← randperm(ub);
        X (i, :) ← temp (1: dim);
End For
 for i ← 1to N
        fitness(i) ← objfunction (objfunc, X (i, :));
  End For
[GYbest, gbest] ← min(fitness);
Xprey ← X (gbest, :)
Idx←0;
Thresh←5
for t ← 1 to tmax1
        Alpha1 ← C1*exp (-(t^2)/(tmax1^2));
          I ← Intensity (N1, Xprey, X);
          for l ←1 to N1
              r ← rand ();
              F ← vec_flag (floor (2*rand () +1));
              for j=1:1 to m1
                   di← ((Xprey(j)-X(i, j)));
                     if r<.5 then
                          r3 ← rand;
                          r4← rand;
                          r5← rand;
```

```
                    Xnew(i,j) ← Xprey(j) +F*beta*I(i)*Xpre
                    y(j)+F*r3*alpha*(di)*abs(cos(2*pi*r4)*(1-
                    cos(2*pi*r5)));
                End If
                r7← rand
            Xnew (i, j) ← Xprey(j)+F*r7*alpha*di;

        End For
      End For
    FU←Xnew(i,:)>ub;
    FL=Xnew(i,:)<lb;
    Xnew(i,:)=(Xnew(i,:).*(~(FU+FL)))+ub.*FU+lb.*FL;
    Xnew (i, :) ← Check Limit (Xnew (i, :), [lb ub], m1)
        tempFitness ← objfunction (objfunc, Xnew (i, :))

        if tempFitness<fitness(i) then
                fitness(i) ← tempFitness;
                X(i,:) ←  Xnew(i,:);
         Endif
       if Idx>Thresh then
                Idx ← 1;
                xRW ← Random_walk_around_antlion (m1,
                tmax1, lb, ub, Xprey,t);
                Xnew ← xRW (1: N1, :);
        End if
    FU=X>ub;
    FL=X<lb;
    X=(X.*(~(FU+FL)))+ub.*FU+lb.*FL
     [Ybest, index] ←  min(fitness);
    CNVG(t) ← min (Ybest)

    if Ybest<GYbest then
          GYbest ← Ybest;
           Xprey ← X(index,:)
    End If
End For
Food_Score = GYbest;
```

.

The Honey Badger Algorithm has been augmented by incorporating a feature selection mechanism derived from the Antlion Optimization (ALO) algorithm. Feature sets can occasionally contain dependent, correlated, and duplicate attributes. These characteristics may significantly impact classification algorithm performance and increase training time. Feature selection is thus pivotal for discarding superfluous features and enhancing the model’s ability to generalize. The goal of wrapper-based feature selection is to identify an optimal combination of features that maximizes the effectiveness of a classifier. Using a strong search strategy is necessary to identify the optimal feature combinations during this process. The antlion optimisation method is a swarm optimisation methodology that has gained popularity recently due to its effective search capabilities. The Antlion Optimization (ALO) algorithm has been used as a search strategy to pinpoint the optimal set of features that enhances classifier performance.

The suggested method takes its cue from the clever hunting techniques of the honey badger to formulate a more practical search strategy for solving optimization problems through mathematics. The honey badger's dynamic search behaviour Digging and looking for honey are classified as exploration and exploitation phases

RESULTS AND DISCUSSION

Dataset

Table 2. Dataset table

Plant	Disease Name	Number of Images
Apple	healthy	2008
	scab	2016
	black-rot	1987
	cedar apple	1760
Corn	Healthy	1859
	Cercosporin	1642
	leafspot	1907
	Common-rust	1908
	Northern-Leaf	
	Blight	
Tomato	Healthy	1926
	Bacterial-spot	1702
	Early-blight	1920
	Late-blight	1851
	Leaf-Mold	1882
	Septorial-leafspot	1745
	Two-spotted	1741
	spider-mite	1827
	Target-Spot	1961
	Yellow	1790
	Leaf-Curl-Virus	
	Tomato	
	Mosaicvirus	
Potato	Healthy	1824
	Early-blight	1939
	Late-blight	1939
Grapes	Healthy	1692
	Black-rot	1888
	Black-Measles	1920
	Leaf-blight	1722

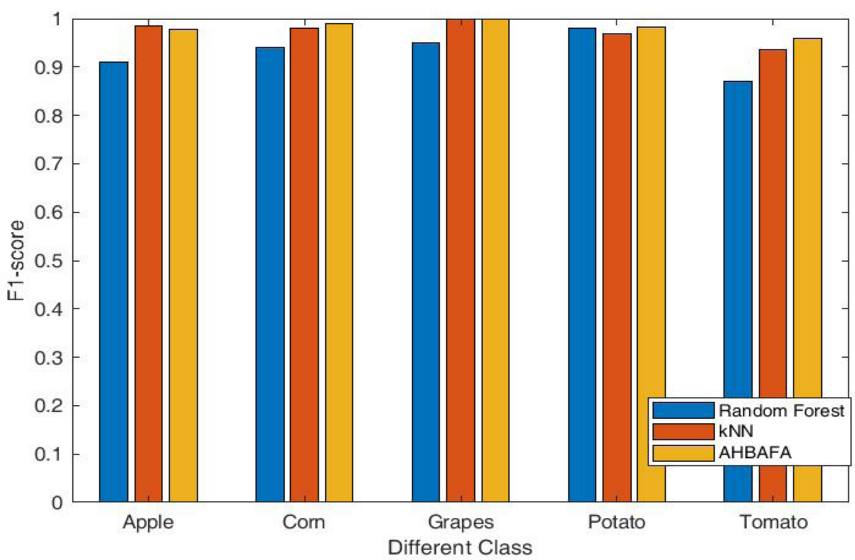

Figure 6. Competitive F1-score of Different Crops Class

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Various statistical primary goal is to explain Analysing a given dataset entails looking at its dispersion and central tendency. It is also necessary to consider the data's skewness and kurtosis when analysing it. A statistical metric called skewness is used to assess how much symmetry—or lack thereof—exists within a certain distribution.

The collection contains 87 000 RGB images of plant leaves in both healthy and unhealthy states that have been divided into 38 different categories. Table 2 shows more than 25 classes were chosen to serve as test cases for our methodology.

The Antlion algorithm implemented for selecting the best features from the feature set. Once the code was put into practice, the intended output was obtained. It is considering class 1 to be healthy, class 2 to be black rot, class 3 to be black measles, and class 4 to be leaf blight in the confusion matrix.

In figure 6, Alex-net Honey badger fusion algorithm showing satisfactory f1 scores of all classes of diseases.

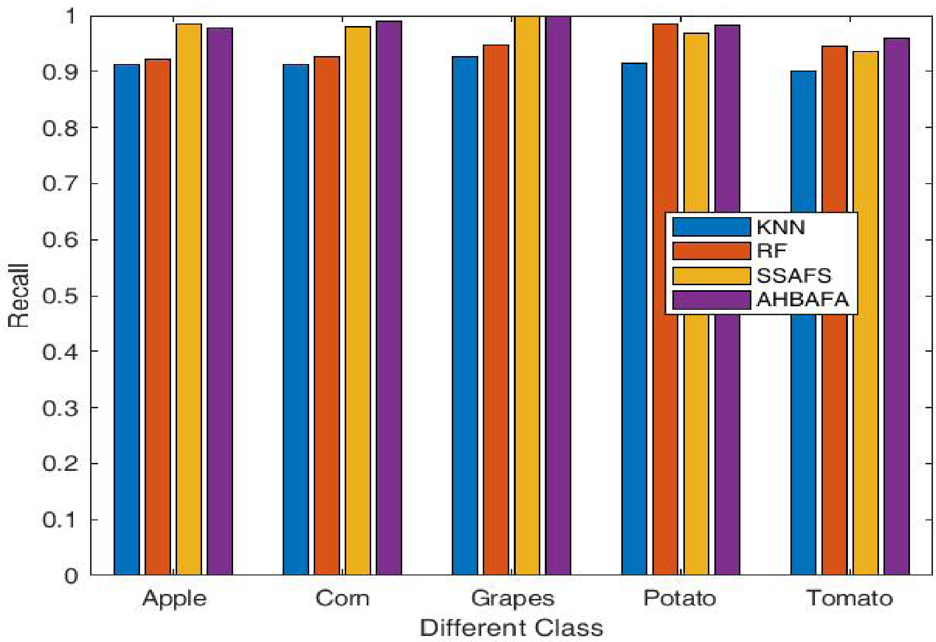


Figure 7. Competitive Recall Value of Different Crops Class

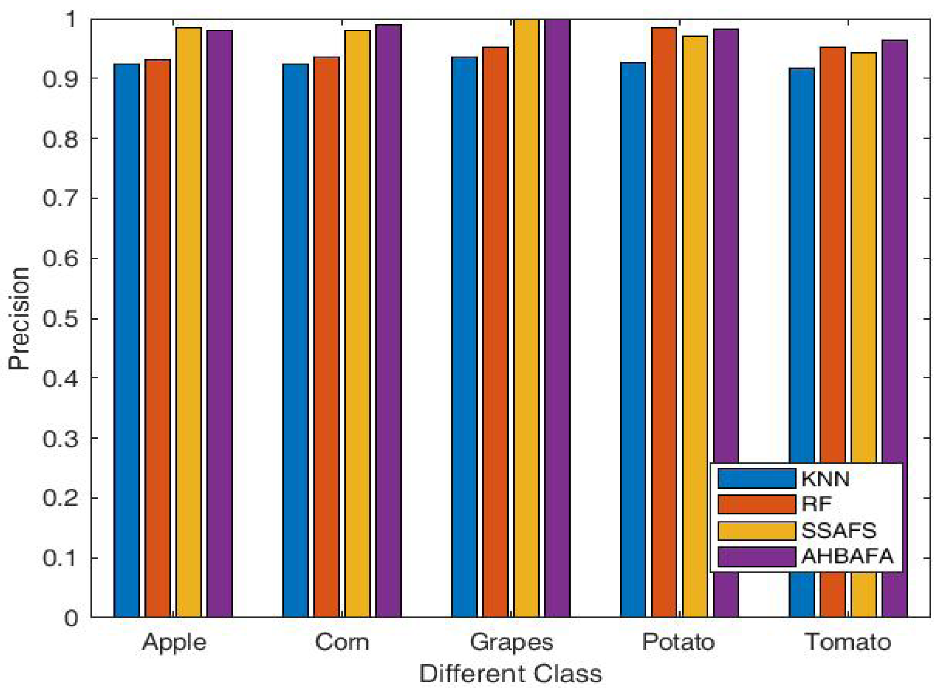


Figure 8. Competitive Precision Value of Different Crops Class between KNN, RF and Proposed Algorithm

In figures 7 and 8, the precision performance metric also shows satisfactory values for all classes of diseases. The proposed algorithm (Alex-Net honey badger fusion algorithm) found good compared to all existing algorithms.

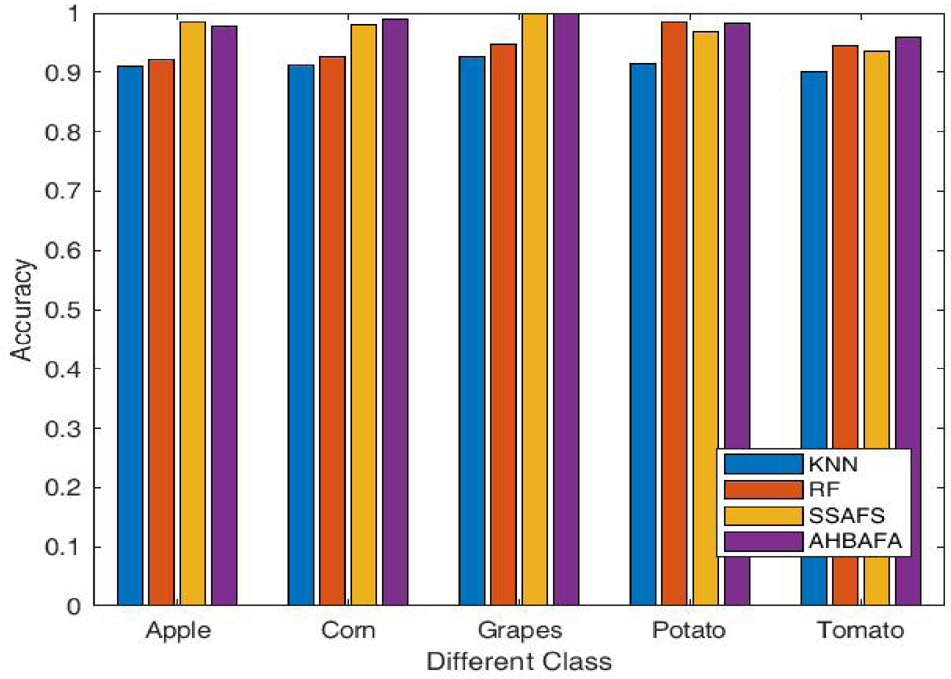


Figure 9. Competitive Accuracy Value of Different Crops Class between KNN, RF and Proposed Algorithm

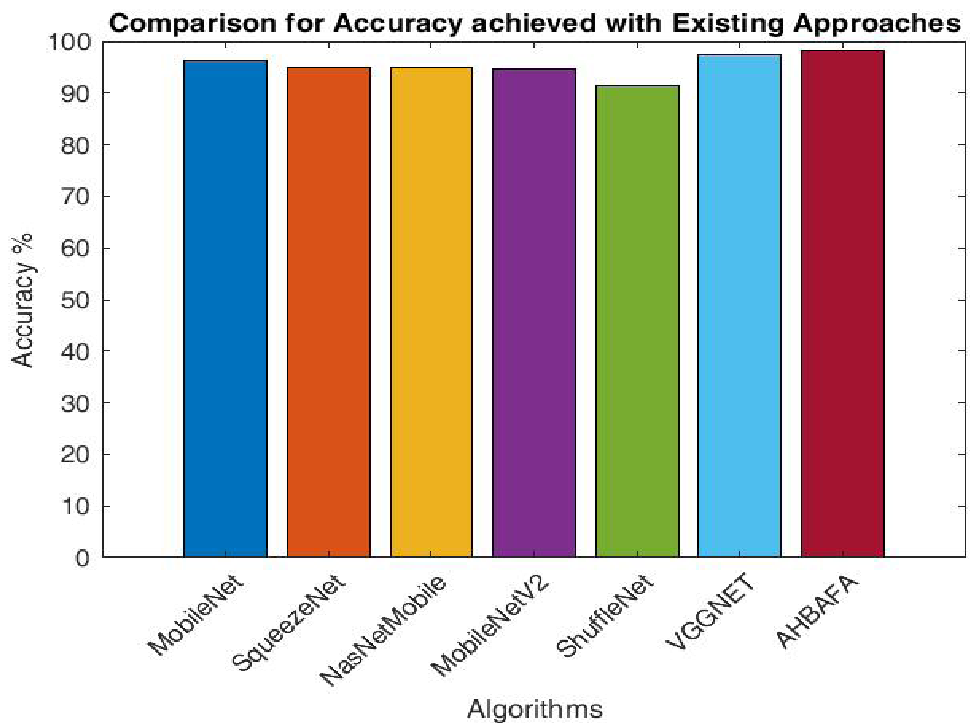


Figure 10. Competitive Accuracy of Pre-trained model and Proposed Algorithm

The precision, accuracy, F1-Score, recall, and figures 9–13 show the results of the proposed method. This section details the process of implementing and optimising the new technique in MATLAB. Several pre-trained models are evaluated against the suggested method using f1 score, recall, and precision as performance metrics. Figures 11, 12, and 13 further demonstrate improved outcomes.

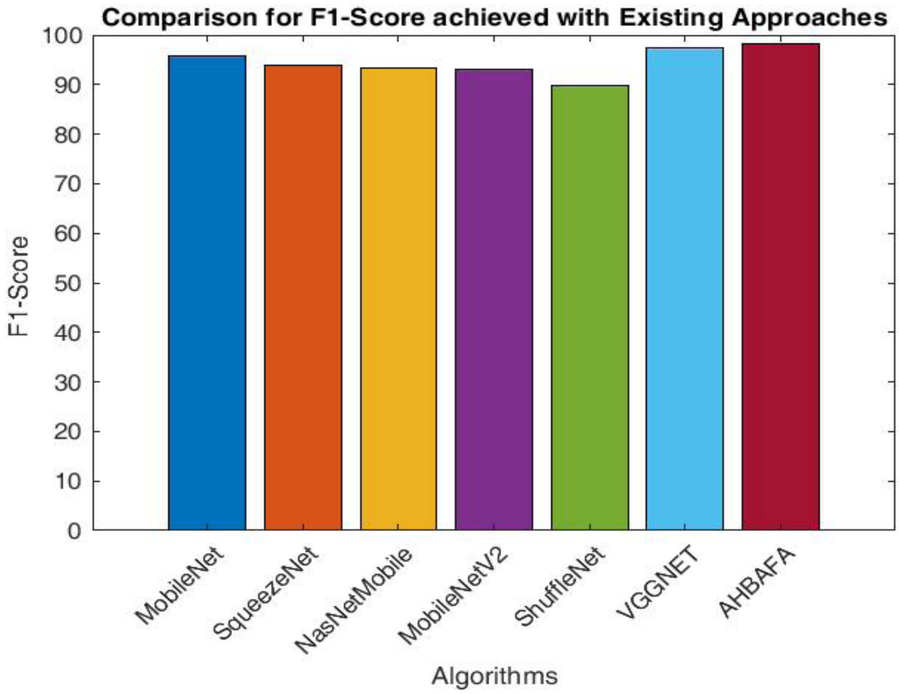


Figure 11. Competitive F1-score of pre-trained model and Proposed Algorithm

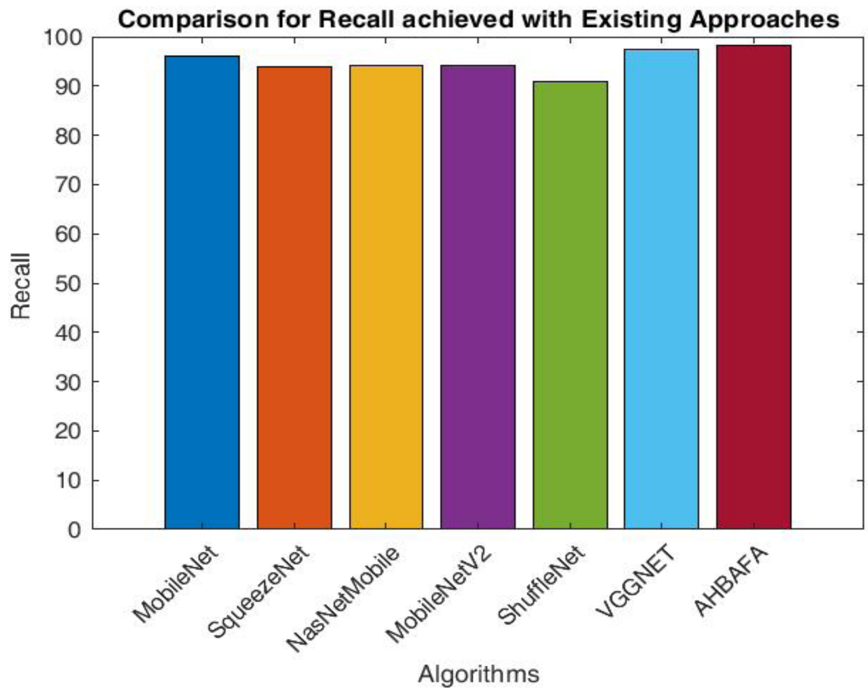


Figure 12. Recall Percentage of Pre-trained model and Proposed Algorithm

Figure 14 shows that the proposed method has a higher accuracy rate than the model given in, where the top-performing models were Mobile Net (96,31 %), Squeeze Net (95,05 %), Nas net Mobile, Mobile Net v2, and Shuffle Net. Then, to determine whether plant diseases are present, the data were analyzed using precision and recall measures. However, after applying the suggested technique, every performance indicator showed positive results.

A convergence graph is a graphical representation of the evolution of an algorithm or metric. Looking at the convergence graphs may tell you whether a measure has converged successfully. Figure 15 show the fitness vs. iteration graph and here, AHBAFA showed better convergence than SSAF (swarm method for feature selection). Two sets of data were generated from the same dataset: one set served as a training set and the other as a test set. The model was trained using the train set, and then verified using the test set.

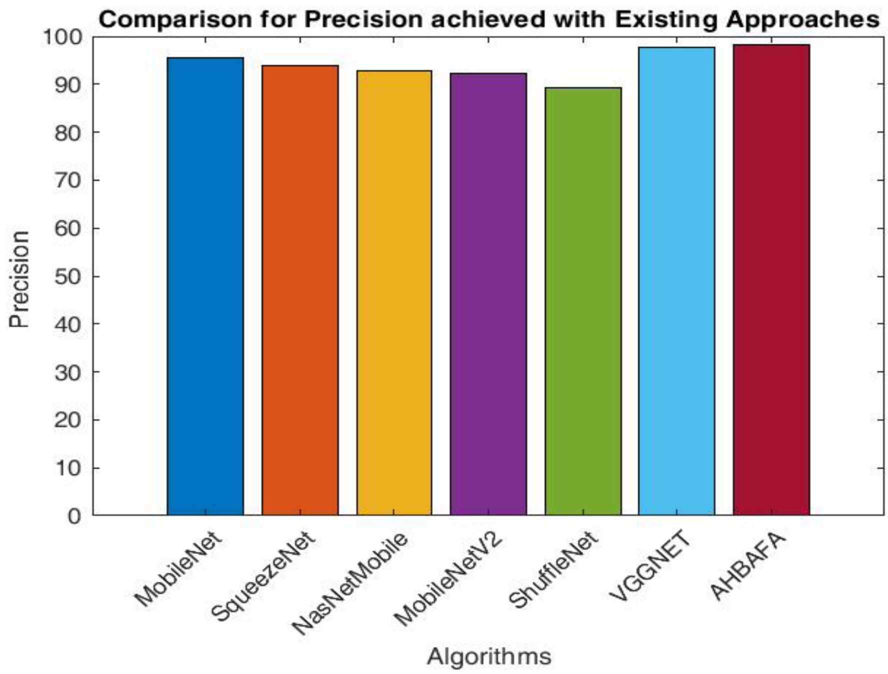
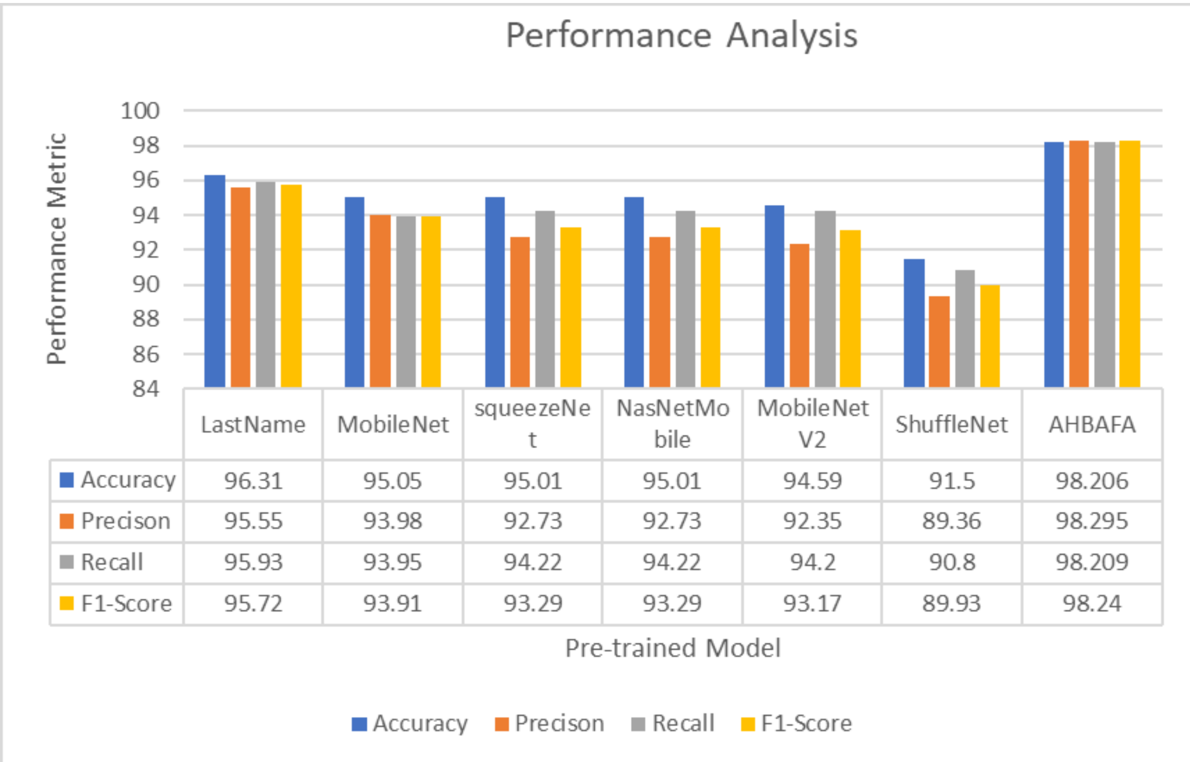


Figure 13. Precision Percentage of Pre-trained model and Proposed Algorithm



	LastName	MobileNet	squeezeNet	NasNetMobile	MobileNet V2	ShuffleNet	AHBAFA
Accuracy	96.31	95.05	95.01	95.01	94.59	91.5	98.206
Precison	95.55	93.98	92.73	92.73	92.35	89.36	98.295
Recall	95.93	93.95	94.22	94.22	94.2	90.8	98.209
F1-Score	95.72	93.91	93.29	93.29	93.17	89.93	98.24

Figure 14. Comparative Analysis with respect to Performance Metric

Figure 16 shows the training, validation, and test datasets labelled by the error histogram. When training a feed forward neural network, an error histogram shows the distribution of values that differ from the target and predicted values. Since these error statistics reveal the extent to which the target values deviate from the anticipated values, they could even be negative. In this case, thirty smaller bins are used to partition the whole error range. The Y-axis displays the total number of data points that fall into a certain bin within the dataset. In the centre of the figure, where the error of 0,6578 is fitted, the bin heights of the validation and test datasets range from 600 to 900, in contrast to the training dataset's bin heights, which are below 600. It seems that many datasets contribute to a high number of samples that fall inside the following range of error. On the X-axis, which represents the error dimension, the zero-error line represents the zero-error value. Within the 0,6578-centered bin is the zero error point in this case.

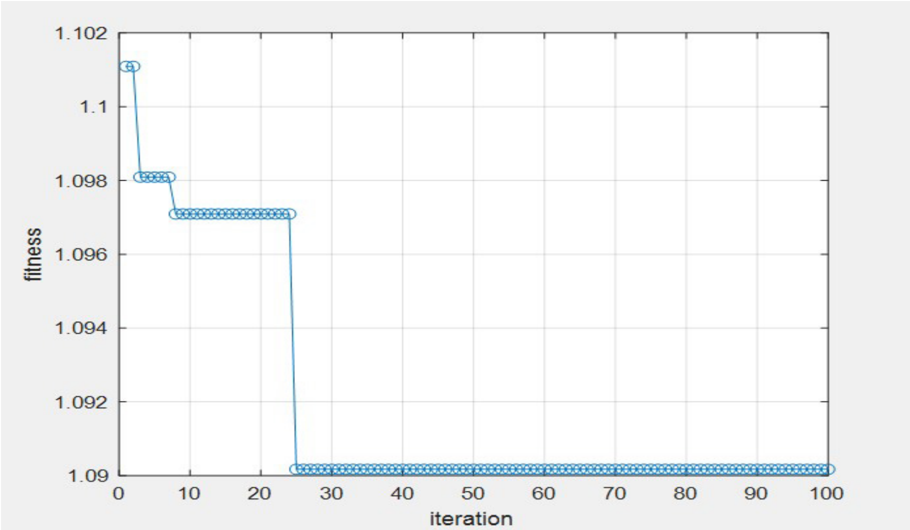


Figure 15. convergence of fitness function using proposed algorithm

Classifier Performance

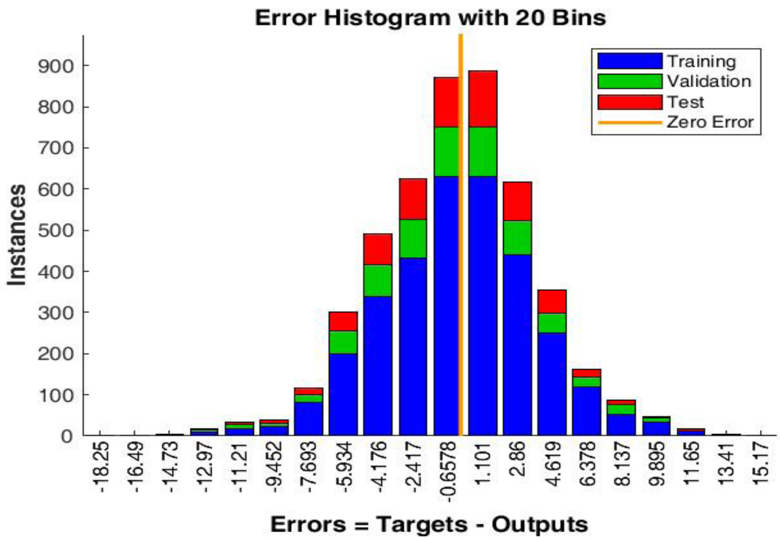


Figure 16. Error Histogram

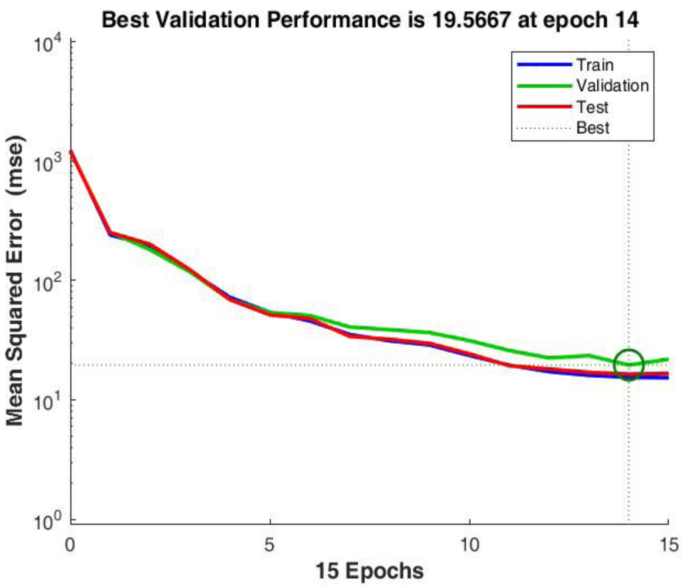


Figure 17. Validation performance of proposed classifier

The disparity between the recommended minimum performance epoch and the optimal validation performance epoch shown in the plot is likely caused by the way epochs are indexed. According to this standard, 0 denotes the first epoch, 1 the second, and so on. Thus, in agreement with this finding, the “15th” epoch is represented by the number 14 of the “best epoch” variable.

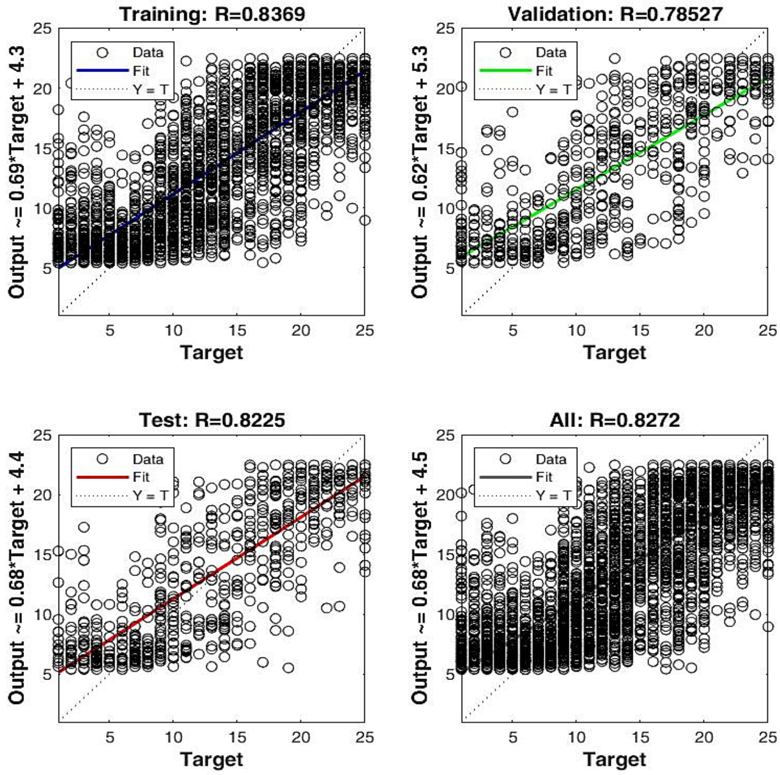


Figure 18. Regression values obtained for training, testing, validation

According to MathWorks (2016), the line that fits the aims and outputs the best is the solid line. The equations are also illustrated in the figure 19 Results for training, validation, and testing all show a strong correlation with the goal value, with a value near to 1, as shown in the regression plots (figure 18).

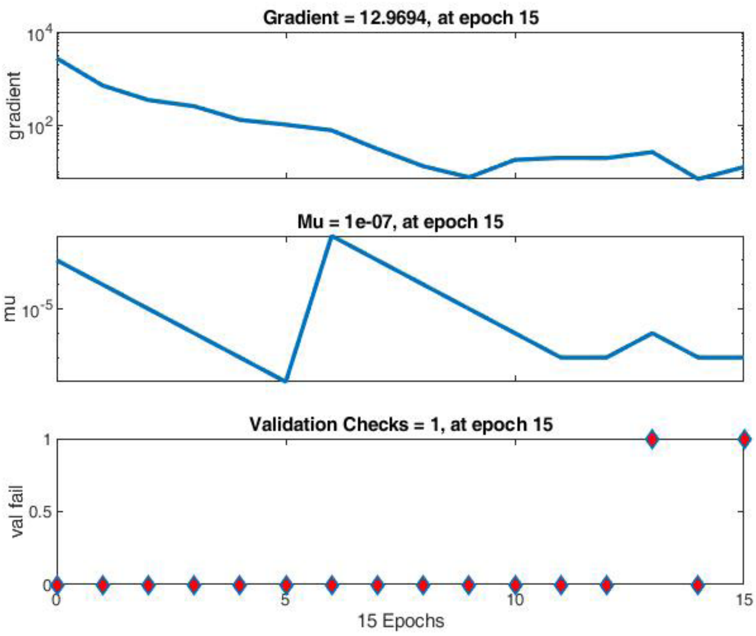


Figure 19. Variation of gradient during training

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To decrease the value of the performance function, i.e. MSE, ANN continually modifies the weight throughout 15 iterations, as shown in figure 19. At least 19,5667 is the minimum value of MSE. At 15 iterations, the validation fails and the gradient and mu (in TRAINLM) develop according to the principles shown in figure. Further, it shows that the validation never reaches its maximum value and that ANN eventually stops training. Figure 18 displays the dings, with the anticipated deviation value shown on the y-axis and the known deviation value represented on the x-axis. The training outcomes are improved when the little circles in figure 18 are placed closer to the diagonal. The findings of various data divisions are shown in four subfigures labelled "Training Set," "Validation Set," "Test Set," and "ALL Data," respectively.

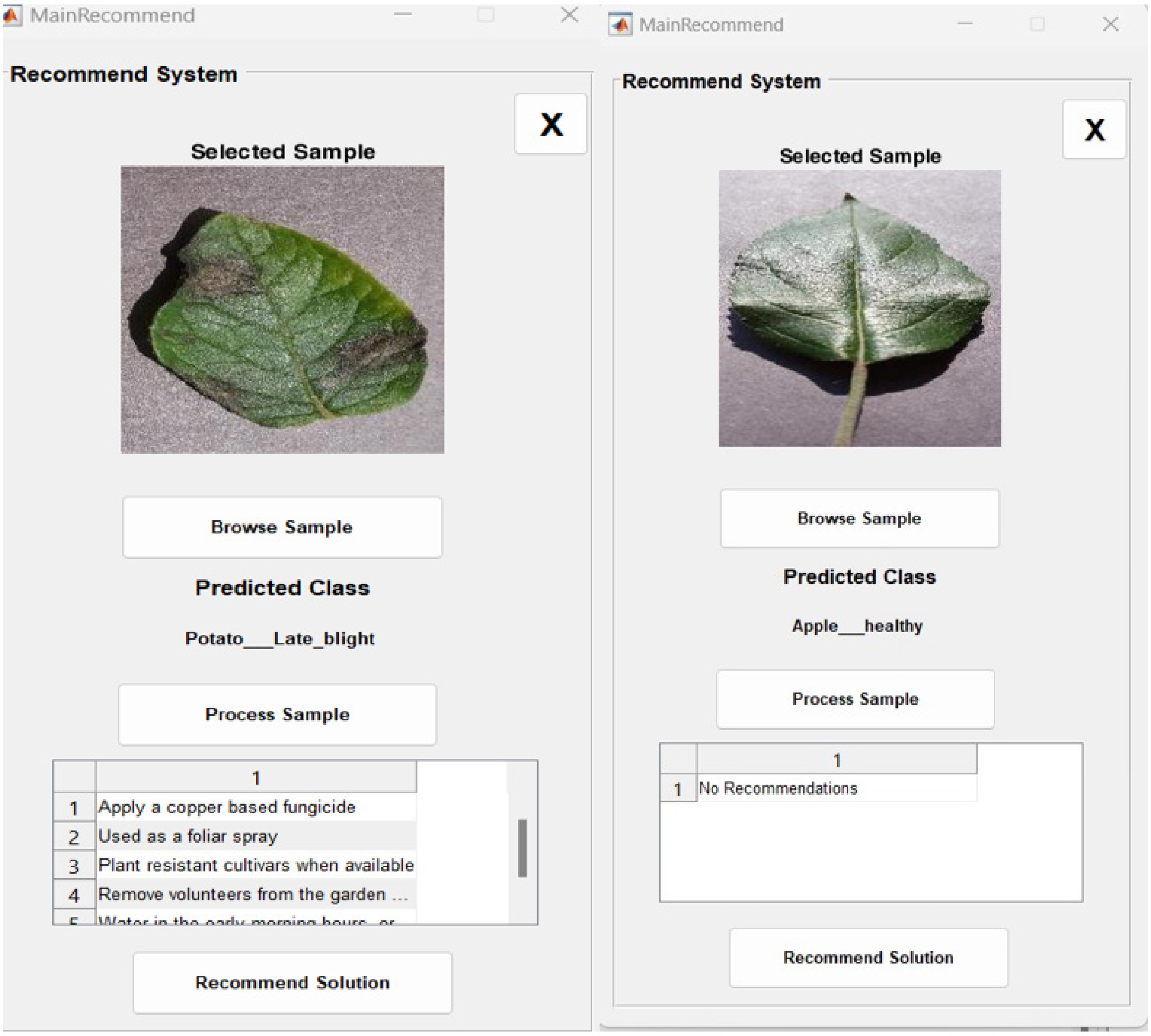

Figure 20. Recommended system using Proposed algorithm

In figure 20, the potato leaf was selected, and upon hitting the process sample, it showed the predicted class is potato late blight. After pressing the recommended button, it showed all the recommendations required to protect the leaf from late blight.

With the help of the proposed algorithm, a recommended system has been created. The agriculturist can input any real-time corrupted leaf image and process the same through the GUI. They will get the solution instantly, and accordingly, they will motivate the farmers to take the necessary precautions to protect the crop from the disease. Hence, food insecurity is required to be managed to some extent.

CONCLUSIONS

Through meticulous exploration and implementation, our proposed algorithm, enriched by advanced learning frameworks and genetic optimization, demonstrates unparalleled accuracy and efficiency in identifying diverse plant diseases across multiple crops. Our technique is shown to be better by a thorough comparison with prominent algorithms such as Support Vector Machines (SVM), k-Nearest Neighbours (KNN), Random Forest (RF), Convolutional Neural Networks (CNNs), Random Forest (RF) and Salp Swarm Algorithm for Feature Selection(SSAFS). The broad dataset, carefully selected to mimic actual agricultural settings, guarantees the suggested algorithm's flexibility and adaptability. This research, which promises improved plant health and sustainable farming, represents a paradigm shift in agricultural operations by utilising state-of-the-art artificial intelligence techniques. The integration of theoretical foundations and empirical results strengthens our work at the nexus of plant disease management and artificial intelligence. Despite not using the honey-budger optimisation technique, the experimental results demonstrated good performance when the HBA optimisation strategy was implemented, in contrast to the preceding work. The proposed method has a 98 % accuracy rate. As a result, it might be applied once more with improved outcomes. As a result, a suggested technique is given, offering a speedy fix to shield crop leaves from pesticides and global warming. Future plant leaf diseases will be easier for farmers to spot because of a suggestion system based on the suggested algorithm.

Future scopes

Integration of Multimodal Data: The work primarily focuses on optimising algorithms for plant disease identification and treatment suggestion, thereby laying the groundwork for future investigations into the integration of multimodal data. The technique consists of merging image data with drone data, hyperspectral imaging, and measurements of environmental variables including humidity and temperature. Future algorithms may provide a more thorough picture of plant health by incorporating information from a variety of sources and taking into account different contributing factors. Advancements in Deep Learning Architectures: It is encouraging to investigate deeper and more intricate deep learning architectures. Subsequent studies may explore the amalgamation of Transformer-oriented models, attention processes, and sophisticated recurrent neural networks to apprehend complex patterns and interdependencies in images of plant leaves. This development is consistent with the thesis's focus on artificial intelligence approach optimisation, guaranteeing that the algorithms remain at the forefront of technological innovation. Transfer Learning and Pre-trained Models: Subsequent investigations could expand upon the optimisation work conducted for the thesis and investigate the use of pre-trained models and transfer learning.

Availability of data and materials: The datasets used in this research are publicly available and properly cited in our dataset section for transparency and ease of replication.

BIBLIOGRAPHIC REFERENCES

1. Bisht IS, Rana JC, Pal Ahlawat S. The future of smallholder farming in India: Some sustainability considerations. Sustainability. 2020;12(9):3751.

2. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Comput Electron Agric. 2018;145:311–8.

3. Pu M, Zhong Y. Rising concerns over agricultural production as COVID-19 spreads: Lessons from China. Glob Food Sec. 2020;26:100409.

4. Haque A, Haque S, Rahman M, Kumar K, Zeba S. Potential Applications of the Internet of Things in Sustainable Rural Development in India. In: Proceedings of Third International Conference on Sustainable Computing. Springer; 2022. p. 455–67.

5. MITRA D, GOYAL A, GUPTA S, KANYAL HS, KAUSHIK S, KUMAR K. Automated tomato leaf disease detection technique using deep learning. J Theor Appl Inf Technol. 2023;101(14).

6. Sharma R, Singh A, Jhanjhi NZ, Masud M, Jaha ES, Verma S. Plant Disease Diagnosis and Image Classification Using Deep Learning. Comput Mater Contin. 2022;71(2).

7. Alimul Haque M., Haque S., Rahman M., Kumar K. ZS. Potential Applications of the Internet of Things in Sustainable Rural Development in India. In: Proceedings of Third International Conference on Sustainable Computing [Internet]. Springer, Singapore; 2022. p. 455-67. Available from: https://link.springer.com/chapter/10.1007%2F978-981-16-4538-9_45#citeas

8. Oppenheim D, Shani G, Erlich O, Tsror L. Using deep learning for image-based potato tuber disease detection. Phytopathology. 2019;109(6):1083–7.

9. Yadav SS, Jadhav SM. Deep convolutional neural network based medical image classification for disease diagnosis. J Big data. 2019;6(1):1–18.

10. Zeba S, Haque MA, Alhazmi S, Haque S. Advanced Topics in Machine Learning. Mach Learn Methods Eng Appl Dev. 2022;197.

11. Di X, Shi R. A survey on autonomous vehicle control in the era of mixed-autonomy: From physics-based to AI-guided driving policy learning. Transp Res part C Emerg Technol. 2021;125:103008.

12. Brahimi M, Boukhalfa K, Moussaoui A. Deep learning for tomato diseases: classification and symptoms visualization. Appl Artif Intell. 2017;31(4):299–315.

13. Kasinathan T, Singaraju D, Uyyala SR. Insect classification and detection in field crops using modern machine learning techniques. Inf Process Agric. 2021;8(3):446–57.

14. Risnumawan A, Sulistijono IA, Abawajy J. Text detection in low resolution scene images using convolutional neural network. In: Recent Advances on Soft Computing and Data Mining: The Second International Conference on Soft Computing and Data Mining (SCDM-2016), Bandung, Indonesia, August 18-20, 2016 Proceedings Second. Springer; 2017. p. 366–75.

15. Da Costa AZ, Figueroa HEH, Fracarolli JA. Computer vision based detection of external defects on tomatoes using deep learning. Biosyst Eng. 2020;190:131–44.

16. Kaur P, Harnal S, Tiwari R, Upadhyay S, Bhatia S, Mashat A, et al. Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction. Sensors. 2022;22(2):575.

17. Kebapci H, Yanikoglu B, Unal G. Plant image retrieval using color, shape and texture features. Comput J. 2011;54(9):1475–90.

18. Singh KP, Kumar J. Current status of apple scab disease and management strategies in Uttaranchal Himalayas. In: Diseases of Horticultural Crops: Diagnosis and Management. Apple Academic Press; 2022. p. 1–29.

19. Zhang X, Wu T, Wang L, Liu S, Gao Y, Zhang P, et al. Pesticide-Fertilizer Synergistic Spray Hydrogel for Enhanced Pesticide Retention and Nutrient Optimization Against Apple Valsa Canker. Available SSRN 4884828.

20. Turechek WW. Apple diseases and their management. Dis Fruits Veg Vol I Diagnosis Manag. 2004;1-108.

21. Ward JMJ, Nowell DC. Integrated management practices for the control of maize grey leaf spot. Integr Pest Manag Rev. 1998;3(3):177–88.

22. Cooke LR, Schepers H, Hermansen A, Bain RA, Bradshaw NJ, Ritchie F, et al. Epidemiology and integrated control of potato late blight in Europe. Potato Res. 2011;54:183–222.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CONFLICT OF INTEREST
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