Semiconductor Optoelectronics
ISSN: 1001-5868

PREDICTION OF PLANT DISEASES USING OPTIMIZATION BASED MACHINE LEARNING TECHNIQUES

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Abstract
Plant diseases are unfavorable factors that severely lower the quality of crops and the yield they produce. It is a widespread practice among experienced farmers and biologists to visually inspect plants for signs of illness, despite the fact that this method can be unreliable and takes a significant amount of time. The objective of this project is to design and construct an intelligent classification system for plant diseases that makes use of machine learning methodologies. The various plant features are classified by utilizing a Naive Bayes classifier, a K-nearest neighbor classifier, a Logistic regression classifier, and an Ensemble classifier, and the results are obtained in terms of precision, sensitivity, f-score, and accuracy. The approaches described above will make it possible for farmers all over the world to take early action to protect their crops from suffering irreparable harm, which will save both the world as a whole as well as the farmers themselves from the possibility of an economic disaster.
Keywords: Plant diseases, optimization, Machine Learning, GWO

1. Introduction

Productivity in agricultural endeavors is something that has a significant impact on the economy. Because the presence of diseases in plants is a natural occurrence, disease detection in plants is an essential part of the agriculture industry [1]. This is one of the reasons that disease detection in plants plays such a significant role in this sector. If sufficient care is not given in this region, then it produces major impacts on plants, and as a result, the quality, quantity, or

productivity of the corresponding products is compromised. For example, the pine trees in the United States are susceptible to a disease known as small leaf disease, which is a dangerous disease. It is helpful to identify plant illnesses using some kind of automatic technology since it cuts down on the amount of work that has to be done to monitor huge farms of crops, and it detects the symptoms of diseases at a very early stage itself, such as when they emerge on plant leaves.

Visual detection of plant diseases is a time-consuming process that also yields less reliable results. Additionally, this method is only applicable in constrained environments. On the other hand, if an automatic detection technique is utilized, it will necessitate fewer efforts, take less time, and result in increased precision. Brown and yellow spots, early and late scorch, and other diseases caused by fungi, viruses, and bacteria can all be found on plants. Other common plant diseases include brown and yellow spots. As a result, the entire procedure might take a significant amount of time, which not only makes it more difficult to eradicate the disease but also makes it a highly laborious operation in the case of vast areas [1]. Methods of data analysis and optimization are utilized in the process of evaluating plant disease and classifying the many different kinds of illnesses that can affect a variety of crops. Advanced techniques such as similarity identification and machine learning based classification techniques are available for cotton crop disease predication [2]. These techniques are superior to the traditional methods in terms of the amount of time saved and the level of accuracy they provide. These techniques will help farmers improve the quality of their crops while also bringing about a reduction in the occurrence of diseases through early detection and timely treatment of any problems that arise.

The primary focus of this effort will be on classification algorithms that are beneficial for accurate disease prediction in plant systems. Because an accurate method of prediction has the potential to dramatically boost agricultural output, this subject area is of the utmost significance. Machine learning methods, such as Naive Bayes, K-nearest neighbor, Logistic regression, and Ensemble Algorithms, are used to classify the numerous plant variables in order to forecast plant illnesses [2]. These algorithms are utilized in the process of predicting plant diseases. In addition, this research evaluated numerous measures using the data that was provided in order to predict a priori the expected performance of the various classifiers that were compared for plant disease datasets.

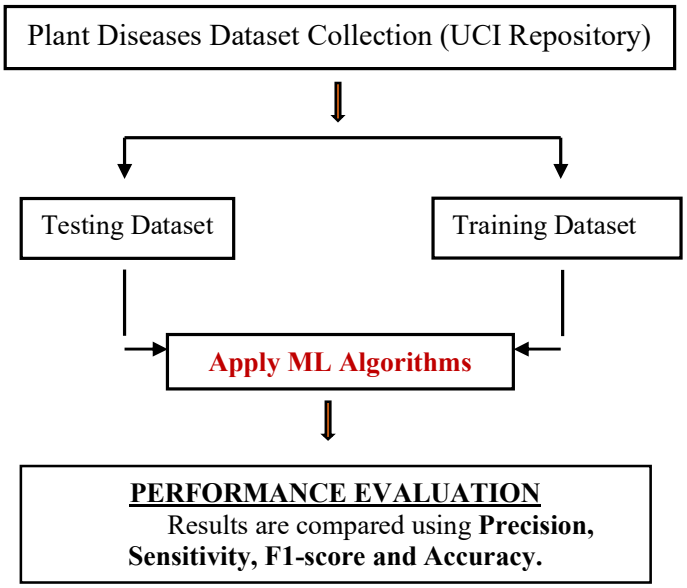


Fig.1. System Architecture

The experiment that is being presented has a block diagram, which may be seen in the figure above. Dataset collection, data partitioning into a testing dataset and a training dataset, and a classification model make up the components of the architecture that has been presented. The primary objective of this study is to investigate ML models and to highlight the significance of their application in the agriculture sector. Machine learning algorithms have a vast variety of characteristics, and the performance of the model is affected by these attributes.

2. Literature Review

The process of programming digital computers to comprehend datasets is quite challenging. (Agrawal, A., et al., 2019) [3] An advanced computer-aided system accomplishes this by finding a solution to the problem using a variety of methods, one of which is machine learning. Other methods include data mining. It is extremely challenging to diagnose the illness in cotton crops in its early stages due to the complex and multi-factoral character of the disease. A computer-aided prediction system that not only contributes to a better understanding of the progression of disease but also has the potential to assist in the disease's early diagnosis. Approaches including data mining and classification have been created as part of this research in order to get a diagnosis that is more reliable and accurate.

The automated Vision-Based Diagnosis of Banana Bacterial Wilt Disease and Black Sigatoka Disease was created by Godliver Owomugisha and his colleagues (2018). "The RGB colour space is converted to the HSV colour space, and then the RGB colour space is converted to the L*a*b colour space. In order to generate the max tree, peak components are utilised. Additionally, five shape features are utilised, and area under the curve analysis is utilised for categorization. They utilised SVM classifier, nearest neighbours, decision tree, random forest, very randomised tree, Naive bayes, and random forest. Randomized trees produce an extraordinarily high score in seven different classifiers, offer real-time information, and make the programme more flexible [6].

A model was proposed by Benos et al., (2021) to determine whether the crops are affected or not, and if they are, then the specific disease can be recognised based on the crop. The VGG16 algorithm has a 97.53% accuracy, which is the highest that could be achieved. We have developed a Content-based filtering strategy on the dataset so that it may be used for the crops recommendation system. when we offer suggestions for crops taking into account a variety of characteristics. They were able to recommend crops by using a training model that was based on their collected data and took into account the user's location as well as the season for production as inputs [7].

Bhagat et al. (2021) suggested a method for identifying diseases that affect the leaves of plants. SVM is an algorithm for machine learning that is now being applied in the process of developing a system for the classification and identification of plant diseases. Farmers would have an easier time acquiring a valuable method for accurate disease identification if they used this strategy because it requires less computational effort. The SVM classifier had a precision of 80% before it was paired with Grid Search hyperparameter tweaking, at which point it rose to 84%. [8].

3. Methodology

In supervised learning, one learns a mapping between a set of input variables (X) and an output variable (Y), and then uses this mapping to make predictions about outputs for data that has not yet been observed. Supervised learning is utilised in the bulk of practical machine learning approaches. Every piece of data is given a label, and the algorithms learn how to predict the output based on the input. This study utilises a variety of machine learning classification methods, including NB, KNN, and LR, and illustrates the effectiveness of each classification technique on a selection of features.

3.1 Classification

a. Naive Bayes

Naive Bayes [9] is a statistical method that is derived from Bayesian theory that bases decision-making on the probability that is highest in a given situation. The Bayesian theory of probability makes use of values that are already known in order to estimate probabilities that are not known. In this, reasoning and experience are utilised to analyse claims that contain a degree of ambiguity. This method operates under the assumption that the features in the data are conditionally independent of one another. The naive Bayes classifier makes use of the conditional probabilities of plant diseases, such as disease and non-disease classes.

$$P(c_i|f_k) = \frac{P(f_k|c_i) * P(c_i)}{P(f_k)}$$

$$P(f_k|c_i) = \prod_{i=1}^{n} P(f_k|c_i), k = 1, 2, \ldots, n$$

Where n is the maximum number of features, $P(f_k|c_i)$ is the probability of generating feature value f_k given class c_i, $P(c_i|f_k)$ is the probability of feature value f_k being in class ci, $P(c_i)$ and

P(f_k) are the probability of occurrence of class ci and the probability of feature value f_k occurring respectively, and f_k is the maximum number of features that can be generated. The classifier makes use of the following classification rules in the process of performing binary classification.

- The classification is C_1 if $P(c_1|f_k) > P(c_2|f_k)$
- The classification is C_2 if $P(c_1|f_k) < P(c_2|f_k)$

b. K-Nearest Neighbors

The K-nearest neighbours classifier is an instance-based learning method that makes use of similarity metrics such as Euclidean, Minkowski, or Manhattan distance. Additionally, it is a learning technique. The Minkowski distance works well with categorical variables, whereas the Euclidean distance and the Manhattan distance are more effective when applied to continuous variables [10]. Within the context of this paper, the k-nearest neighbor's classifier makes use of Euclidean distance. The following equation can be used to determine the Euclidean distance (D_{ij}) between two input vectors (X_i, X_j):

$$D_{ij} = \sqrt{\sum_{k=1}^{n} (X_{ik} - X_{jk})^2} \text{ k=1,2,. . . ,n}$$

Calculations are performed on every data point in the dataset to determine the Euclidean distance between the current input and an input data point. The Euclidean distances that were calculated are placed in ascending order, and then k items are chosen based on which ones have the smallest distance to the data that was input. The classifier delivers the majority class among these k data points as the categorization for the input point.

c. Logistic Regression

Logistic regression is a method that makes use of an approach that is functional in order to determine the probability of a binary response based on a variety of characteristics. In order to choose the parameters that provide the greatest fit, it makes use of a nonlinear function known as the sigmoid function [11]. The sigmoid function, denoted by sigma, and the variable that serves as its input, x, are presented in the following table:

$$\sigma(x) = \frac{1}{(1 + l^{-x})}$$

$$x = w_0 z_0 + w_1 z_1 + \cdots + w_n z_n$$

The best coefficients, w, along with the input data, which is a vector z, are multiplied jointly, followed by multiplying each element individually. When all of these are added together, the resulting number is what ultimately determines a target class's classification score. If the sigmoid value that is calculated comes out to be less than 0.5, then we consider it to be 0;

otherwise, we consider it to be 1.

3.2 Feature Selection

The number of features in the retrieved features was reduced by deleting unnecessary and superfluous features to obtain acceptable classification accuracy using the feature selection approach [13]. In order to attain better accuracy and faster convergence, feature selection is a common and important method in classification problems. This section covers optimizers for selecting the finest features from an obtained dataset. PSO and whale feature selection methods are exposed here to compare the suggested optimizer's performance. The optimizers for successful feature selection are discussed in this section. The preliminary backdrop of the PSO, whale, and the working mechanism of the suggested optimizer is discussed using GWO approaches.

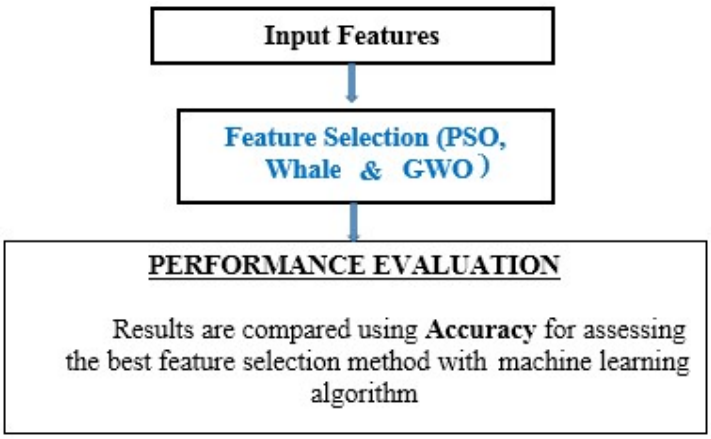


Fig.3. Feature Selection system

Feature selection will be transformed into a more reliable and appropriate form of input for the classifier to classify the various feature categories. The chaotic based GWO optimized characteristics for machine algorithms to categories human activities were introduced in this research. Meanwhile, the suggested method has been compared to the machine learning algorithms PSO, GWO, and Whale in terms of accuracy.

i. PSO

It is an optimization method inspired by groups of birds. Respectively, every bird in the swarm regulates the search model depending on their newly acquired information [10]. The PSO algorithm is a hybrid of evolutionary algorithms and swarm system.The particles (Birds) of the swarm are free to fly across the multidimensional search space. Each particle acquires its own velocity and location throughout the voyage. The entire population is updated by updating each particle. The particles gradually concentrate around the upper goal function value as the swarm arrangement forces itself toward it. The steps in particle swarm optimization are as follows:

Step 1: Initialization – The swarm particles are within the velocity and location ranges

that have been pre-defined.

Step 2: Velocity Updating – The velocity of the swarm particles are determined at the end of each cycle by:

$$\vec{V_i} = W\vec{V_i} + c_1R_1(\vec{P}_{i,best} - \vec{P_i}) + c_2R_2(\vec{g}_{i,best} - \vec{P_i})$$

Where $\vec{P_i}$ = position of particle 'i'
$\vec{V_i}$ = velocity of particle 'i'
$\vec{P}_{i,best}$ = finest position reached by the particle
$\vec{g}_{i,best}$ =best location remembered by the particle individual
'W' = parameter controlling the flying elements

R_1, R_2 =random numbers among 0 and 1
c_1, c_2 =cognitive learning factor and social learning factor

The PSO, or correctness in searching facility, is created by including variables from each particle. The weighting aspects c1, c2 prevent particle collision (individuals). To avoid collision, the velocity v and random number r are proven to be protected within the range supplied after updating particle I.

Step 3: Position updating - Because there is a time interval between repetitions, the positions of the particles change.

$$\vec{P_i} = \vec{P_i} + \vec{V_i}$$

$\vec{P_i}$ Must be checked and within the permitted range after refreshing.

Step 4: Memory updating – Using the formula, update $\vec{P}_{i,best}$ and $\vec{g}_{i,best}$

$$\vec{P}_{i,best} = \vec{P_i}\ if\ f(\vec{P_i}) > f(\vec{P}_{i,best})$$

$$\vec{g}_{i,best} = \vec{g_i}\ if\ f(\vec{g_i}) > f(\vec{g}_{i,best})$$

Where ($\vec{x}$) is the point function that has been extended.

Step 5: Checking of Destination – Once completed, the technique repeats steps 2 through 4 until definitive end states are attained, for a predetermined number of iterations. Estimating $\vec{g}_{i,best}$ and and $\vec{P}_{i,best}$yields the result.

PSO algorithms do not take fitness values into account. When the population is large, this is a significant computational benefit over GA. The real-number arithmetic operation is used to calculate velocity and position. The PSO is based on the ideas of altering velocity (accelerating) toward pbest (Personal Best) and lbest (Global Best) locations (local form

of PSO) and accelerating toward pbest and lbest locations [14].

Personal Best: The best solution (fitness value) is effectively achieved when individual particle maintains the path of its coordinates in feature space. This value is called pbest.

Global Best: Particle, while maintaining all the features as its topological neighbor, this value is the gbest (global best). When a particle locates with reference to its neighbor it is called lbest.

ii. WHALE Optimization Algorithm

WOA, which was proposed in [15], has recently sparked a spike of attention. This hunt and progress estimate is based on a scientific model of humpback whale behaviour and development as they sustained their search for foodstuff and accommodations. The Bubble-net-Assaulting technique, in which whales attack fish by twisting air pockets around them down to 12 metres below the surface, then swimming back up to grasp and catch their victim, was the inspiration for this method.

In this computation, the inquiry technique is employed to address the unpredictable pursuit of food, which can be scientifically evaluated by recreating historical arrangements rather than randomly choosing unique configurations. Despite this peculiar behaviour, WOA differs from other improvement estimates in that it just requires the modification of two parameters. These traits make switching between the abuse and inquiry forms a breeze. In the next section, we'll go over the mathematical models of surrounding prey, pursuing prey, and spiral bubble-net foraging. Prey found nearby: Humpback whales update their position as they circle their prey by increasing the number of repeats from zero to maximum. This behaviour can be mathematically stated as:

$$\text{If } (p<0.5 \text{ and } \operatorname{mod}(U) <1)$$

The following equations then update the location of the candidate position X (t+1).

$$D= \operatorname{mod} \{(C.X)-X(t)\}$$

$$X(t+1) = [X(t) - \{U.D\}]$$

Where X (t+1) is the optimal location in the current scenario and p =0.1 (constant). The following equations are used to compute U and D.

$$U= \operatorname{mod} \{2.a.r-a\}$$

$$C=2.r$$

Where r is a randomly selected vector and a decreases linearly from 2 to 0.

Searching of Prey: The random variables replace X in the prey search method. The following are the Xrandom and mathematical equations:

$$D= \text{mod } \{(C.X_{random})-X(t)\}$$

$$X(t+1) = [X_{random}(t) - \{U.D\}]$$

In the whale optimization algorithm's exploring phase [12], the prey was encircled and spiral updates were performed. The following equation gives the mathematical phrase for updating a new position throughout the spiral process.

$$X(t+1) = D^{l}.e^{bl}.\cos(2\pi l) + X^{*}(t)$$

The distance between the new and updated positions in the new generation is D, and b is a constant ranging from 0 to 1.

iii. Grey Wolf Optimization algorithm

In the basic GWO algorithm, we set the population size of the wolf is N and the search space is d
Dimension, the position of the i^{th} wolf in the space is the global optimal solution. According to [16], the position of the grey wolf surrounding the prey is updated as follows:

$$D = | C.X_p(t) - X(t)|,$$
$$X(t+1) = X_p(t) - A \cdot D,$$

Where the t is the current number of iterations, $X_p = (x_1, x_2, x_3, \ldots, x_d)$ is the prey position, $A \cdot D$ is the bounding step, and the vector A and C are defined as

$$A = 2(r_1 - E) \cdot a,$$
$$C = 2r_2,$$

Where r_1 and r_2 are the 1 row d column random vectors between interval [0, 1], and each element is 1 row d column vector of 1 in the E. a is the convergence factor vector, decreasing linearly from 2 to 0 as the number of iterations increases, the equal of a is as follows:

$$a= 2(1-t/t_{max}) \cdot E^{T},$$

According to the above formulas, the predation position of other grey wolf individuals guided by the first three levels of wolves in the predation process is updated as below,

$$D\alpha = |C_1 \cdot X\alpha - X|, D_\beta = |C_2 \cdot X_\beta - X|,$$
$$D_\delta = |C_3 \cdot X_\delta - X|,$$
$$X_1 = X\alpha - A_1 \cdot D\alpha, X_2 = X_\beta - A_2 \cdot D_\beta,$$
$$X_3 = X_\delta - A_3 \cdot D_\delta,$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3}$$

4. Result and Discussion

Calculations are made using all of the system's features to determine how accurately the proposed classification works. We carry out the duty of disease identification on a wide range of plants with a variety of characteristics (features). The effectiveness of the proposed algorithms was measured using a variety of test cases, all of which are shown in the following section. The characteristics that were tested in these tests can be seen in the following:

1. ***Weed Management***
2. ***Nutrient Management***
3. ***Right Variety***
4. ***Right Season***
5. ***Tolerance Nature***
6. ***Climatic Factors***
7. ***Physiological Factors***
8. ***Management Factors***
9. ***Nature of Variety***
10. ***Temperature***
11. ***Moisture***
12. ***Wind***
13. ***Rainfall***
14. ***Dew***
15. ***Leaf Wetness***
16. ***Plant Healthiness***
17. ***Crop Geometry***
18. ***Seed Treatment***
19. ***Irrigation System***

This dataset is a collection of distinct features that were taken from leaf specimens that came from a total of forty different species of plants. It was obtained from the UCI repository.

4.1 Experimentation details:

The test is carried out on a machine that uses a 64-bit version of macOS and has an Intel 2.6GHz 8-core i7 processor, 16GB of DDR4 RAM, and a Radeon Pro 560X 4GB GPU. Python 3.8 is utilized by each of the programmes, and they are all executed on the MATLAB 2019a platform.

4.2 Performance Metrics and Evaluation:

Evaluation of the various methods is performed using the parameters listed below, including precision, recall, F1 score, and classification accuracy [11]. These parameters include TP, FP, TN, FN, and TP, FP, respectively. False positive and false negative values are denoted by the letters FP and FN, respectively. True positive and true negative values are denoted by the letters TP and TN, respectively.

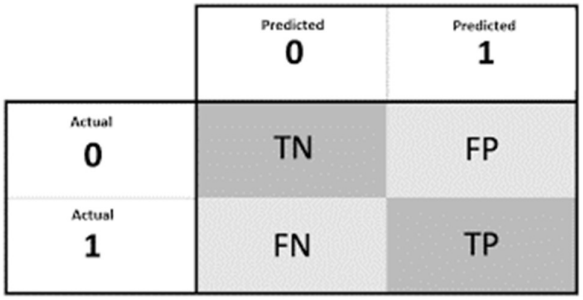


Fig.5. Confusion Matrix Format

Calculations are made to evaluate the performance of the suggested architecture using the

metrics, which are presented in the table below.

Table.2. Performance Metrics

SL.NO	Performance Metrics	Mathematical Expression
01	Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
02	Sensitivity or recall	$\frac{TP}{TP+FN}$ x100
03	Specificity	$\frac{TN}{TN+FP}$
04	Precision	$\frac{TN}{TP+FP}$
05	F1-Score	$2.\frac{Precison * Recall}{Precision + Recall}$

4.3 Results and Findings:

Several different machine learning and feature selection strategies are integrated into the proposed architecture. Calculations are made to evaluate the performance of the suggested architecture using the metrics, which are presented in the table below.

Table.3. Performance Analysis with Feature selection Algorithms

Algorithm Details	Performance Metrics				
	Accuracy	Sensitivity	Specificity	Precision	F1-Score
NB	81.5	80.4	81.0	79.6	80.4
KNN	84.5	82.5	80.5	82.3	82.7
LR	85.56	83.67	81.89	83.37	83
NB-PSO	82.6	82.45	82.74	80.46	81.78
KNN-PSO	85.14	83.5	81.78	83.67	83.23
LR-PSO	86.13	84.1	82.87	84.51	84.15

NB-WOA	83.76	83.9	83.61	81.78	82.67
KNN-WOA	86.22	84.55	82.0	84.6	84.78
LR-WOA	87.8	85.85	83.86	85.89	85.88
NB-GWO	88.89	86.85	86.86	85.89	85.88
KNN-GWO	89.5	88.56	87.5	86.56	86.45
LR-GWO	92.9	91.8	92.23	91. 89	91.88

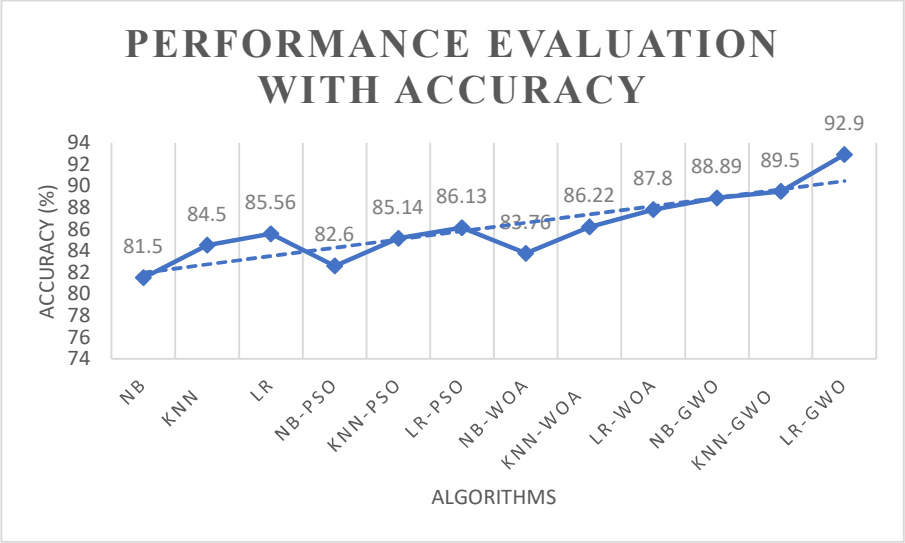
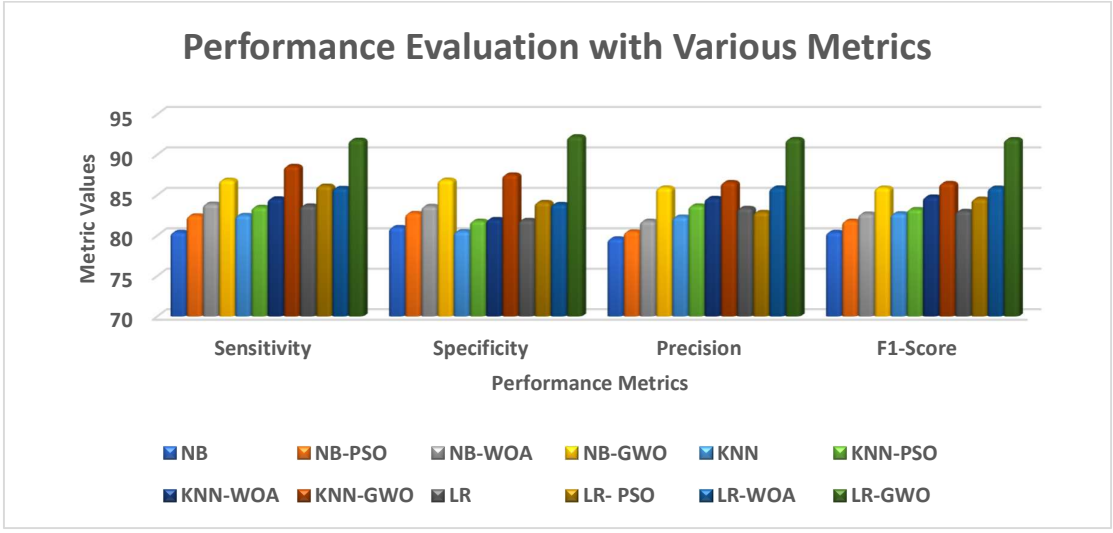


Fig.6. Performance Analysis with FS-ML Algorithms



According to the data, it is very clear that the LR-GWO approach has a greater detection ratio than any of the other algorithms that are now available. As can be seen from the graph, the recommended approach easily outperformed all of the other algorithms that were already in use.

5. Conclusion

The results of the experiments reveal that the LR-GWO feature optimization strategy achieves better results than any of the other algorithms. Several machine learning techniques are applied on the features that have been picked in order to evaluate the performance of the feature selection methods. According to the findings, a wide variety of machine learning techniques perform admirably in the bulk of the classification problems for this dataset. As a direct consequence of this, the following stage of this investigation will consist of analysing how well novel machine learning algorithms function. According to the findings of this study, the LR-GWO algorithm has the potential to achieve satisfactory results with appropriate feature tuning and statistical testing to determine the applicability of the findings. As a consequence of this, machine learning algorithms are an essential component in the creation of intelligent expert systems, which can consequently enhance accuracy and detection while simultaneously reducing the number of false positives. The several machine learning strategies that are used for the plant disease detection system, such as SVM, KNN, and NB, amongst others. The size of the dataset is increased for this particular study. Work therefore has to be enhanced by building more accurate models using cutting-edge machine learning techniques.

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