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Reliable and Automatic Recognition of Leaf Disease Detection using Optimal Monarch Ant Lion Recurrent Learning

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Abstract—Around 7.5 billion people worldwide depend on agriculture production for their livelihood, making it an essential component in keeping life alive on the planet. Negative impacts are being caused on the agroecosystem due to the rapid increase in the use of chemicals to combat plant diseases. These chemicals include fungicides, bactericides, and insecticides. Both the quantity and quality of the output are impacted when there is a high-scale prevalence of diseases in crops. Plant diseases provide a significant obstacle for the agricultural industry, which has a negative impact on the growth of plants and the output of crops. The problem of early detection and diagnosis of diseases can be solved for the benefit of the farming community by employing a method that is both quick and reliable regularly. This article proposes a model for the detection and diagnosis of leaf infection called the Automatic Optimal Monarch AntLion Recurrent Learning (MALRL) model, which attains a greater authenticity. The design of a hybrid version of the Monarch Butter Fly optimization algorithm and the AntLion Optimization Algorithm is incorporated into the MALRL technique that has been proposed. In the leaf image, it is used to determine acceptable aspects of impacted regions. After that, the optimal characteristics are used to aid the Long Short Term Neural Network (LSTM) classifier to speed up the process of lung disease categorization. The experiment's findings are analyzed and compared to those of ANN, CNN, and DNN. The proposed method was successful in achieving a high level of accuracy when detecting leaf disease for images of healthy leaves in comparison to other conventional methods.

Keywords-Monarch Butterfly Optimization (MBO); AntLion Optimization (ALO)Algorithm; Feature selection; Diagonition; Leaf Disease; Recurrent Neural Network (LSTM).

I. INTRODUCTION

Agriculture is the mainstay of India's initial growth as a rapidly evolving nation. Agricultural fields, however, face numerous obstacles, like significant crop yield losses. Diagnosing plant leaf infection is indeed a daunting task in the agricultural sector [1]. Plant leaf diseases are one of the most significant factors contributing to yield loss. The conventional "naked eye" approach of infection identification requires many people, is misleading, takes a long time, and cannot be used in broader fields. Additionally, it costs a lot because experts must constantly monitor it. Thus, machine learning is efficient, a trustworthy projection methodology for sensing numerous plant leaf infections provoked by fungi, bacteria, and viruses. Classification algorithm-based illness forecasting, however, seems to be a challenging task because the reliability fluctuates depending on the input data. Nowadays, the world's farmland is a vital economic and social resource. The Indian economy is heavily reliant on crop yields. The importance of plants cannot be overstated compared to the other forms of life in this world. As a result, it is crucial to identify plant diseases in the agricultural sector [2]. Agriculture must perform the integral factor of initial plant leaf infection sensing. Numerous techniques, including thermography, fluorescence imaging, and affinity biosensors predicated on DNA/RNA, chain reactions, natural gas chromatography, etc., have been regularly utilized to

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evaluate the quality of leaves. Automated disease detection methodologies are useful for spotting plant diseases at their earliest stages [3]. The majority of plant diseases are typically first discovered on plant leaves. Using effective image processing techniques, yellow and brown spots, early and late blisters, and other bacterial, viral, and fungal diseases are automatedly identified.

Accurately diagnosing and identifying leaf infections at the initial phase enables producers to exert more control over the severity of the disease [4]. These diseases have a variety of symptoms. Diseases can be seen in some crops in the early stages, while in others, they won't be seen until later because there won't be a chance to save the crop. Consistent plant monitoring reduces yield loss while maintaining plant quality and assisting in the early detection of pests and diseases. Many farmers are unaware of how to identify a disease based on the way its symptoms appear on leaves. For this reason, the use of diagnostic support services offered by organizations like agricultural research institutions and state farm advisory services is becoming obligatory for the detection of leaf diseases in plants [5]. Farm owners must establish an automated system to mitigate these annoyances and have user-friendly recommendations [6]. The farmers can benefit from automation using cutting-edge computer technologies like machine vision, computer vision, and image processing [7]. The agricultural industry has extensively used computer vision and machine vision systems for various tasks, including grading and sorting fruits and vegetables, the detection of weeds, and more [8]. Another area that will eventually need automated computer vision or machine vision systems built around image processing is automatic leaf disease identification and classification. Various combinations of image acquirement, enrichment, categorization, and feature selection techniques have been tried in the past few decades for the purpose of detecting leaf disease.

II. LITERATURE REVIEW

Velandia et al., [9] evaluated four fuzzy inference system-based optimization frameworks that utilise Quasi-Newton and genetic algorithms to evaluate bean leaves for Xanthomonascampestris disease. For the purpose of analysing the application of frameworks, the RGB colour scale's colour concentration is employed to identify the plant's condition as either healthy or unhealthy. The best model's accuracy in detecting Xanthomonas campestrisin in an image of a bean leaf is 94%, and its achievement against training data is at 99.68%. These findings would therefore enable producers to take quick action to lessen the disease's effects on the appearance and productivity of green bean crops.

Chen et al., [10] the fully automated identification and categorization of plant leaf infections are handled in a novel way in this paper. The feature engineering assessment was carried out predicated on the image processing technologies, and the index system for the estimation methodologies was built. The GMDH-Logistic model is then fed with the chosen features, and comparison experiments are run. The results show that the approach is successful in determining whether a plant is infected or not. Image processing and computer vision rely on feature extraction for plant disease detection by leaf images. This paper used GIWA filtering, image segmentation, a grey-level co-occurrence matrix, and other techniques to extract the crucial features of leaf images. The paper uncovered a total of 15 features, such as Pct, Num, Contrast1, etc.; on the premise of these, an indexing system was established for model prediction. Additionally, we presented self-organizing data mining techniques in the domain of image recognition. We postulated an innovative GMDH-Logistic approach for the fully automated sensing and categorization of plant leaf infections based on the findings of feature assessment. This algorithm conquers the drawbacks of other methodologies by instantaneously choosing the vital elements to include in the framework and typically making the defined variables comprehensible.

Sumithra and Saranya [11] the leaf images of some therapeutic plants are used in this paper to propose a fully automated categorization approach. The work's main objective is to present a novel technique for predicting leaf disease. This research offers a novel methodology to segregating images, obtaining features, and categorizing plant leaf diseases. The recommended method preprocesses leaf images of plants and then segments infected parts using Particle Swarm Optimization (PSO)–based fuzzy c means segmentation (PSO-FCM) and Gaussian Mixture Model (GMM)–based background subtraction. Vein, shape, edge-based feature extraction, and texture characteristics (T.F.) are calculated. Using a classifier known as the Multiple Kernel Parallel Support Vector Machine (MK-PSVM), this approach sorts the leaves of medicinal plants into different categories. The performance was measured by precision, responsiveness, selectivity, reliability, and F-measure. As per experimental findings, the classifiers that have been suggested here have a higher categorization precision, facilitating leaf detection.

Chouhan et al., [12] developed Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) to identify and classify plant leaf diseases instantaneously. Bacterial foraging optimization (BFO) is

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utilized to allocate optimal weight to Radial Basis Function Neural Network (RBFNN) to boost its velocity and precision in identifying and classifying plant leaf disease regions. The author studied fungal infections like common and cedar apple rust, late blight, leaf curl, leaf spot, and early blight. The results demonstrate that the proposed approach accomplishes better than other methodologies in identifying and categorizing plant leaf diseases.

Waheed et al., [13] to recognize and categories corn leaf diseases, this paper propose a dense convolutional neural network (DenseNet). One of the most widely grown grains worldwide is corn. Corn crops are particularly prone to the occurrence of a number of leaf infections, the most common of which are common corn rust, corn grey leaf spot, and northern corn leaf blight. The reliability of the mentioned optimized DenseNet model is 98.06%. The system has a 98.06% success rate in detecting three distinct corn leaf diseases. To boost relevant data, data augmentation was used. As a result, it assisted in making the proposed framework more general.

Deenan et al., [14] created an automated system that uses image processing to identify leaf diseases, saves time, and money, and primarily aids in raising banana fruit productivity. Image segmentation is a crucial step in this automated process to examine the image and extract data from it. A low-level image processing module called image segmentation is used to separate the necessary object from an image for further analysis. Therefore, various segmentation methods, including adaptive thresholding, canny, color segmentation, fuzzy C-means, geodesic, global thresholding, K-means, log, multithresholding, Prewitt, region growing, Robert, Sobel, and zero crossing are analyzed and compared in this paper to choose an appropriate segmentation method for leaf analysis. The findings revealed that, compared to all other methods, the geodesic method had significantly lower MSE values (6610), higher PSNR values (6608), and lower SSIM values (0.196). It has been determined that the geodesic method is superior for image segmentation of the banana leaf disease.

Kabir et al., [15] introduce an effective leaf diagnostic model that extracts discriminant features from disease-segmented leaf images using optimal segmentation algorithms. This study uses segmentation techniques to distinguish between the diseased and healthy leaf portions. Following that, various distinguishable features are extracted from the leaf image based on the color and intensity values of the image pixels. In order to identify and diagnose the leaf disease, the Multiclass Support Vector Machine (MC-SVM) with RBF Gaussian kernel is used. This paper extracts useful features from the disease segmented images in the proposed model, such as the healthy ratio, disease ratio, red diseases mean, green diseases mean, and blue diseases mean. An online benchmarked leaf image dataset is used to assess the proposed model. The experimental results indicate that the suggested model performs better in classifying leaf disease.

Aasha Nandhini et al., [16] this paper proposes a compressed sensing-based web-enabled disease detection system (WEDDS) to detect and classify leaf diseases. The segmentation of the diseased leaf is advised using a statistically-based thresholding strategy. The accuracy of the WEDDS' performance has been assessed, and its results are contrasted with existing methods. Additionally, the WEDDS was experimentally evaluated using a Raspberry Pi 3 board. The findings demonstrate that the proposed technique offers an overall detection accuracy of 98.5% and a classification accuracy of 98.4%.

Filev et al., [17] using an image processing technique, this article present a method for detecting and identifying unhealthy tomato leaves. Since texture is one of the essential features of tomato leaf, the proposed system uses the Gray-Level Co-occurrence Matrix (GLCM) to detect and identify tomato leaf states, whether healthy or infected. The classification phase uses the Support Vector Machine (SVM) algorithm with various kernel functions. According to experimental findings, the suggested classification method used a linear kernel function to achieve a classification accuracy of 99.83%.

Kan et al., [18] to address the difficulty of manually classifying medicinal plants, this paper proposes an automatic classification method based on images of their leaves. In our method, the leaf images of medicinal plants are first preprocessed; next, the ten shape features (S.F.) and five texture characteristics (T.F.) are computed; and finally, the leaves of medicinal plants are classified using a support vector machine (SVM) classifier. The outcome suggests that using multi-feature Extraction from leaf images combined with SVM makes it possible to classify medicinal plants automatically. The suggested SVM classification algorithm based on both shape and texture features is successful and practical for the image classification of medicinal plant leaves. The disadvantage is that medicinal plant leaves are not classified according to their edge and leaf vein characteristics.

III. PROPOSED METHODOLOGY

The methodology that is being suggested is established using a total of five phases, the first three of which are preprocessing, picture fragmentation, feature extraction, and optimal categorization. The database stores close to 174,000 photos, including sick and healthy examples of leaves from various plants. In this instance, we decided to select the

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maize leaf dataset to identify the diseased leaf automatically. During the preprocessing procedure, the dimensions of the photographs are shrunk, and the backdrop is removed. The subsequent process is known as image segmentation, and it involves using threshold-based masking to separate the good component from the infected section of the image. After that, as a consequence, the ideal features are chosen, and a hybrid algorithm that combines the Monarch Butterfly Algorithm and the Ant Lion Optimization Algorithm is employed to categorise the leaf illness. After that, the chosen characteristics are used to assist in the classification process carried out by a recurrent neural network. In the final step, the effectiveness of the suggested automatic methodology is assessed using the evaluation metrics. The proposed methodology is shown in Figure 1 as follows,

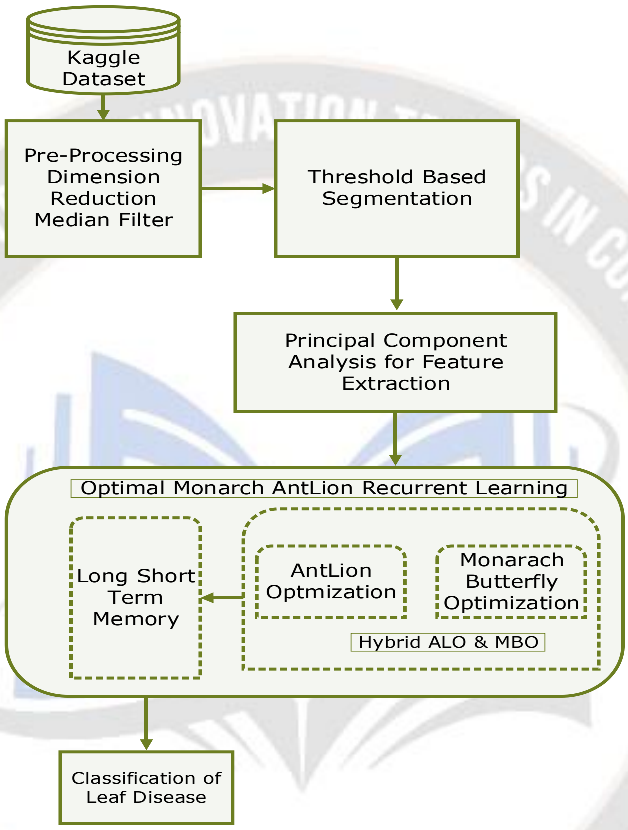

Figure 1. Proposed Methodology

A. *Pre-processing*

Some noise may be introduced into the image collection process due to the flash of the camera. This cacophony can make it more difficult to diagnose diseases. Image smoothing technique is required so that unwanted spots can be removed. The median filter is applied for this purpose throughout this paper.

Median Filter

The median filter is a type of statistics filter of a higher order. The nature of the median filter is nonlinear, and it works by substituting the value of the center pixel with the median of the grey levels in the portion of the image encompassed by the filter [19, 20]. The median of a numerical collection is the value at which half of the values in the collection are equal to or lower than the median, and the other half of the values in the collection are equal to or higher than the median. The initial step in performing median filtering involves moving the window and shorting all of the pixels contained within the relocated window. After that, the median is computed, and this value is given to the pixel that is in the middle. The middle value is selected as the median value if the number of items in the K*K window is odd; otherwise, the average of the two middle values is selected as the median value.

B. *Segmentation*

The objective of segmentation is to alter the representation of a picture into something that is easier to understand, has greater significance, and can be analysed more straightforwardly.

There are many different applications for the many different types of segmentation techniques. The majority of the time, threshold techniques [21] is used to diagnose illnesses that affect leaf tissue. Because it calculates the threshold value without requiring any input from the user, Otsu's thresholding is very helpful for thresholding in general.

Image segmentation based on a local threshold is employed to locate and isolate probable hotspots for disease. A brownish rim surrounds the reddish core that can be seen in areas damaged by the disease [24]. The images were then put through a thresholding procedure, considering how bright the red and blue channels were compared to one another. Pixels in infected areas were recognised as having a significantly higher red plane value than the green plane value and the blue plane value. Following the threshold application, we saw that the bulk of the diseased areas had white pixel values, whereas the remaining areas had black pixel values. Nevertheless, there were still blank places that couldn't be identified as disease hotspots due to a lack of data. These linkages to the regions afflicted by the disease needed to be built with extreme caution. Inverting the photographs and then clipping out any areas of the binary images that had an area of 200 pixels or less allowed us to achieve our goal. These approaches made it possible to acquire disease-affected spot patches that were too small to be discovered utilizing the threshold method. Following that, a median filter was employed to eliminate the noise, and the images were turned upside down. By proceeding in this manner, a segmented binary picture of the sick areas has been obtained. In the end, the diseased image that had been segmented was brought back to its original form by changing the pixel values of the areas that were harmed by the disease.

C. Feature Extraction

Principal components analysis (PCA) is a quantitative method that employs orthogonal transformation to reshape a data set containing observational data of variables that may be correlated into a data set containing values for linearly uncorrelated variables. There are more original variables than there is P.C.s. It reacts differently depending on how the initial variables were scaled. The true eigenvector-based multivariate analysis known as PCA [22] is the simplest of them all. PCA is closely related to factor analysis. Consequently, the dimensions of the feature data have been decreased, and accurate feature extraction has been accomplished.

D. Proposed Optimal Monarch AntLion Fly Optimization (MALRL) model

The movement patterns of monarch butterflies can be simplified into the basic guidelines to enable them to handle different optimization issues.

1. Lands 1 and 2 are the only places where monarch butterflies can be found. The whole population of monarch butterflies resides in Lands 1 and 2, in other words.
2. The migration operator creates each young monarch butterfly from a monarch butterfly in either Land 1 or Land 2.
3. Once a youngster is produced, an old monarch butterfly will die, maintaining the population at its current level. If the newly generated parent has a higher fitness than the parent, this can be accomplished using the MBO approach by replacing the parent. However, if the freshly created one does not show greater fitness compared to its parent, it may be discarded. In this case, the parent is preserved and unharmed.
4. The fittest monarch butterfly individuals are automatically transferred to the following generation; no operators can alter them. This can ensure that the monarch butterfly quality of population or efficacy will never decline with the passage of time. An overview of the migration and the butterfly adjusting operator will be provided in the next subsections.

E. Migration operator

Monarch butterfly populations in Lands 1 and 2 are referred to as Subpopulations 1 and 2, respectively, for the sake of clarity. This migration procedure can be described in the manner below.

$$a_{n,b}^{d+1} = a_{w_{1,b}}^{d} \tag{1}$$

And the *b-th* element of $a_n$at generation t + 1, which displays the locale of the monarch butterfly *n*, is denoted by a$a_{n,b}^{d+1}$. Similar to the previous example, $a_{w_{1,b}}^{d}$denotes the *b-th* element of a_{w1}that is the freshly produced position of the monarch butterfly in w_1 . The generational number is *d*. From Subpopulation 1, Monarch Butterfly w_1 is randomly chosen. When, $w \leq z$, Equation produces the element b in the freshly formed monarch butterfly (1). In this case, *w* is calculable as

$$w = rand * Migperi \tag{2}$$

The value of migperi, which stands for migration period, is 1.2 at work. A random number is chosen from a uniform dispersion called *w* and. Besides, if $w > z$, the freshly created monarch butterfly is produced using the following equation:

$$a_{n,b}^{d+1} = a_{w_{2,b}}^{d} \tag{3}$$

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here the freshly created position of the monarch butterfly $w_2$is indicated by the *b-th* element of the expression a of $a^d_{w_{2,b}}$the expression a a_{w2}. From Subpopulation 2, Monarch butterfly$w_2$is randomly chosen.

Mirjalili recently put forth the optimization approach known as Antlion optimization. The ALO algorithm imitates an natural hunting strategy of antlions. The two subsections that follow go through the artificial algorithm's sources of inspiration and its operators.

F. AntLion Inspiration

The Myrmeleontidae family and Neuroptera order are home to antlions. The adult stage is used for breeding, and they mostly hunt in larval stages [23]. A larval antlion excavates a cone-shaped hole in the soil by shifting in a circle and expelling sand with its powerful jaw. Once created the hole for the trap, the larvae conceals beneath the base of cone and awaits for pests especially ants to fall into it. The antlion seeks to capture its prey after it learns there is a prey in the trap. Insects attempt to escape the trap but typically are not caught right away. In this instance, antlions cleverly toss grains toward the rim of the hole to help the prey slip towards the base of pit. A prey that is captured in the jaw is dragged under the ground and eaten. Antlions discard the leftover prey outside the hole after eating it and prepare the hole for the subsequent hunt. The relationship between the magnitude of the trap, level of hunger, and the structure of the moon is another intriguing behaviour that has been noticed in antlions way of life.

During optimization, Mirjalili specified the following requirement formulated on the aforementioned specification of antlions:

- Ants, who serve as prey, roam about the search area utilizing various random walks.
- Antlion traps have an impact on random walks.
- Antlions can create holes based on their physical condition.
- Larger holes on antlions increase the likelihood that they will capture ants.
- In every iteration and the elite, an antlion can seizureeach ant.
- In order to simulate ants sliding toward antlions, the span of the random walk is compatibly reduced.
- •If an ant grows sturdier than an antlion, the antlion will catch it and tug it beneath the soil.
- •After each hunt, an antlion shifts to the location of the most recent prey caught and digs a hole to increase its chances of trapping another one.

Building trap:

A roulette wheel is employed to replicate an capacity of antlion for hunting. One particular antlion is thought to have the only imprisoned ants. When choosing ants based on fitness throughout refinement, the ALO algorithm should employ a roulette wheel operator. The fitter antlions have a greater feasibility of capturing ants thanks to this technique.

Catching prey and re-building the hole:

The antlion eats the ant at this point in the hunting procedure. It is presumed that collecting prey happens when ants get healthier than their matching antlion in order to replicate this process. To boost its possibilities of snagging fresh prey, an antlion must then adjust its position to match the latest locale of the hunted ant. Considering this, the respective equation (4) is posited.

$$AL_{S_n}^x = A_{t_m}^x\ If\ \left(A_{t_m}^x\right)\ is\ better\ than\ E\left(AL_{S_n}^x\right) \quad (4)$$

where *x* represents the current iteration, $AL_{S_n}^x$ depicts the stance of the *m*-th antlion that was chosen at iteration *x*, and $A_{t_m}^x$points the stance of the *n*-th ant at iteration *x*.

Sliding ants towards antlion:

Once they detect an ant inside the trap, antlions blast sands outward from the centre of the opening. Trying to escape the trapped ant slides down due to this behaviour. The hyper-sphere of ants' random radius of walk is adaptively reduced when modelling this behaviour mathematically; see equations (5), (6), and (7).

$$G^x = \frac{G^x}{I_1} \quad (5)$$

where$I_1$is a ratio and $G^x$is the minimum value of all variables at iteration *x*.

$$K^x = \frac{K^x}{I_1} \quad (6)$$

whereK^x is the highest value achieved by all variables at iteration *x* and I_1 is a ratio with the following definition:

$$I_1 = 10^{\varphi}\,\frac{x}{H} \quad (7)$$

where*x* is the present iteration, H is the maximal count of iterations, and is a constant delineated formulated on the present iteration. In essence, the constant *w* allows for exploitation accuracy level adjustment.

Trapping in holes of anlion:

The slide ant is imprisoned in the chosen antlion's burrow by simulating the sliding of prey towards it. In other words, the position of the chosen antlion serves as a boundary for the walk of ant, which may be described by adapting the random of ant range of walk to the stance of antlion as in equations (8) and (9).

$$G_m^x = G^x + AL_{S_n}^{\ x} \quad (8)$$

$$K_m^x = K^x + AL_{S_n}^{\ x} \quad (9)$$

where G^x is the minimal and K^x is the maximal value of all variables at iteration *x*, G_m^x is the minimal and K_m^x is the maximal value of all variables for ant *n*, and $AL_{S_n}^{\ x}$ is the stance of the chosen antlion *m* at iteration *x*.

Random walks of ants:

All random walks are built using this equation (7)

$$Z(x) = [0, CSUM(2y(x\_1\ ) - 1); CSUM(2y(x\_2\ ) - 1); \ldots\ldots; CSUM(2y(x\_H\ ) - 1)\ ] \quad (10)$$

where *H* is the maximum count of iterations, *CSUM* computes the cumulative total, *x* displays the random walk step , and y(x) is a stochastic function described in equation (11).

$$y(x) \begin{cases} 1\ if\ yand > 0.5 \\ 0\ if\ yand\ \leq 0.5 \end{cases} \quad (11)$$

where *x* is a random walk step and rand is a evenly dispersed random number engendered in the range [0, 1].

The random walks are normalized employing the equation to remain within the search space (12)

$$Z_m^x = \frac{(Z_m^x - O_m) \times (K_m - G_m^x)}{(P_m^x - O_m)} + G_m \quad (12)$$

If G_m^x is the minimal of the *m*-th variable at the *x*-th iteration and K_m^x indicates the maximal of the *m*-th variable at the *x*-th iteration, *Oi* is the minimal of the random walk in the *m*-th variable, *pi* is the maximal of the random walk in the *x*-th variable, and so on.

Elitism:

Elitism should be used to sustain the best solution(s) during iterations. Here, the elite and chosen antlions lead the random walk of the ant, and as a result, the relocating of a particular ant takes the form of the average of both random walks; see equation (13).

$$A_{t_m}^{\ x} = \frac{Q^x L + Q^x V}{2} \quad (13)$$

where $Q^x V$ and $Q^x L$ is the random walk around the elite antlion and the antlion that was chosen at random by the roulette wheel.

G. *Long Short-Term Memory (LSTM)*

It's crucial to note that Long Short-Term Memory (LSTM) [24]networks are a subset of RNNs that can learn long-term dependencies. For many NLP and machine learning tasks in recent years, vanilla LSTM has been considered the gold standard (NLP). Of particular, it is used to bypass the difficulty in achieving high precision in estimates. Learning these dependencies, which are essentially permanent, is beyond its capabilities. In addition, time series learning is accounted for in the architecture's design. This section details a traditional LSTM architecture, highlighting a unique aspect of the basic cell unit.

Using the current time inputs, sigmoid function output, and previous time output, the cell state is intensified. By using the gate function, the previous state of the unit can be monitored. If the sigmoid function gives a value of 0, then some of the data should be forgotten; otherwise, it should be broadcast across the United States.

The gate's operational history allows us to monitor the state of the ageing unit. The gate layer actually implements the forget gate layer from before, thus that layer controls what data gets ignored and what gets inserted. The gate layer decides which pieces of data are forgotten and which ones are added. The gate, composed of the secondary sigmoid and the tanh function, specifies the inputs that the state should receive. Here, we break it up into two parts. For instance, the sigmoid layer dictates which numbers will be modified. Tanh layer, which functions similarly to the initial layer, is used to inject the latest data into the state. The subject state, for instance, could be changed in the previous sentence.

The purpose of the first two doors is mostly for monitoring the penetration line. Calculating past the third door requires information from the present input data computing module and familiarity with the penetration line. At time t, the gate control mechanism decides what percentage of the state value is broadcast. What has been updated and what needs to be added must be determined. Below is a diagram depicting the mathematical representation of an LSTM memory cell.

$$a_t = \sigma\ (S_a y_t + U_a h_{t-1} +\ b_a \quad (14)$$

$$d_t = \sigma\ (S_d y_t + U_d h_{t-1} +\ \ b_d \quad (15)$$

$$\tilde{C}_t = tanh\ (S_c y_t\ +\ [S_c h_{t-1}, y_t] +\ b_c \quad (16)$$

$$C_t = a_t * C_{t-1} + d_t * \tilde{C}_t \quad (17)$$

$$e_t = \sigma\ (S_e y_t + U_e y_t +\ b_e \quad (18)$$

$$n_t = e_t * tanh\ C_t \quad (19)$$

where

Weight of LSTM is depicted as S_a, S_d, S_c, S_e and U_a, U_d, U_c, U_e

Every cell bias is depicted as b_a, b_d , b_c, b_d

Cell state depicted as C_t

Forget gate depicted as d_t

Input gate and output gate as a_t, e_t: Memory cell output is depicted as h

In this way, the LSTM network will conduct a thorough analysis of the input data (a set of financial time-series of the cross currency selected to build a triangular arbitration) during the data processing phase, defining precisely which aspects of the input data to store in memory and which to throw away (forget gate).

The improved LSTM is built by doing away with the memory cell's output and input gate to reduce the amount of difficult computation required. In addition, the research uses a mix of the AntLion and Monarch Butterfly Optimization algorithms to improve the training data's selected attributes for accurate prediction. The enhanced memory cell regulates how much past state data is used to inform the current state of the cell. In contrast, it is more challenging to adjust to data in a concealed condition. Due of this, the attention gate is implemented by bringing the attention mechanism found within the memory cell out into the open. Long-term memory can be used to improve the precision of predictions.

$$d_t = \sigma\,(S_d y_t + U_d h_{t-1} + \ b_d \qquad (20)$$

$$\tilde{C}_t = tanh\,(S_c y_t \ + \ b_c \qquad (21)$$

$$a_t = \sigma\,(S_a y_t + U_a h_{t-1} + \ b_a \qquad (22)$$

$$d_t = \sigma\,(S_d y_t + U_d h_{t-1} + b_d \qquad (23)$$

$$\tilde{C}_t = tanh\,(S_c y_t \ + \ [S_c h_{t-1}, y_t] + \ b_c \qquad (24)$$

$$Ay_{t,}h_{t-1} \ = \ q^T\,tanh(S_a y_t + U_a h_{t-1}) \qquad (25)$$

$$\alpha_t = \frac{\exp(A\,(y_{t,h_{t-1}}))}{\sum_{i=1}^{n} \exp(A(y_t,h_{t-1}))} \qquad (26)$$

$$\tilde{C}_t = \tanh(\alpha_t) * (S_{\tilde{C}}\, y_t \ + \ U_{\tilde{c}} h_{t-1} + \ b_{\tilde{c}} \qquad (27)$$

$$C_t = d_t * C_{t-1} \ + (1 - d_t) * \tilde{C}_t/2 + (1 - d_t) * \tilde{C}_t/2 \qquad (28)$$

$$C_t = \ h_t \qquad (29)$$

vector of attention gate (q), weight matrices (S, U), and the critical vector (t). the update and attention gate, both of which aid in memory retention and play key supporting roles in making reliable predictions by way of distinct mechanisms. Update gates are carried out by bringing the cell's status up to date with the present moment. The result of an update gate is fed into the attention gate as an input. On the other hand, attention gate helps focus the relevant data by filtering out the irrelevant stuff. Improved network estimation and the ability to reliably anticipate outcomes are the fruits of the suggested method.

IV. RESULT AND DISCUSSION

This dataset is a subsection of the database that is featured at Kaggl, which was used for the research presented here. The database comprises close to 174,000 photos depicting the contaminated and good leaves of a variety of plants, including tomato, orange, and maize, among others. In this particular study, only photographs of corn plants were utilized. This subsection consists of been selected because it contains the most extensive variety of conditions while still containing an adequate amount of pictures in each category. As shown in Figure 3, the subset that was used contains photos from four distinct categories, for a total of 12,332 images that were used for the training set, and 3,076 images that were used for the test set. There are three categories that represent maize leaves that have been infected, and one group that represents healthy leaves. The number of pictures that fall within each classification is listed in Table 1.

TABLE 1 NUMBER OF LEAF DISEASE IMAGES IN DATASET

Leaf Conditions	Number of totals
Common Rust	3,780
Grey Leaf Spot	1,639
Northern Leaf Blight	3,456
Healthy	3,012

A. *Simulation Analysis*

MATLAB platform is setup and analysis the above said dataset to provide the experimental result. In this manner, the Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Deep Neural Network (DNN) and proposed classifier is analyzed to know the performance of leaf disease recognition.

B. *Confusion Matrix*

Multiple classes of equivalent structure can lead to uncertainty among classifiers. Greater sophistication of the patterns that are showcased in the same class, which causes lower efficiency, may also be caused by contaminated apple leaf images at various stages or against various backgrounds. A confusion matrix can be utilized to graphically guesstimate a model's categorization accurateness. Since all accurate prognostications are on the diagonal and all inaccurate projections are off the diagonal, it is simple and convenient to identify the classes that have confused the detecting system.

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C. Performance Evaluation Metrics

As efficiency assessment measures, we utilized F1-score, recall, accuracy, and precision. Since the basic confusion matrix can be misrepresentative, we utilized the initially described efficiency assessment methods.

D. Accuracy

Accuracy (A) embodies the fraction of presently categorized prognostications and is computed as the following:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{30}$$

Observe that, and depict true positive and negative, false positive and negative, respectively.

E. Precision

Precision symbolizes the fraction of favorable outputs that were genuinely accurate and is computed as follows:

$$Precision = \frac{TP}{TP+FP} \tag{31}$$

F. Recall

Recall (R) quantifies the fraction of true positives that were recognised accurately and is computed as follows:

$$Recall = \frac{TP}{TP+FN} \tag{32}$$

G. F1-Score

F1-score is outlined as the harmonic mean of accuracy and recollection and computed as follows:

$$F1 = 2.\frac{Precison.Recall}{Precison+Recall} \tag{33}$$

H. Sensitivity

$$Sen = \frac{TP}{TP+FN} \tag{34}$$

I. Performance of proposed model and Comparison Analysis

The effectiveness of numerous categorization methodologies, including ANN, CNN, DNN, and the presented classifier MALRL, is examined in this section on a data - set for the identification of maize diseases. It is discovered that the Automatic Monarch AntLion Recurrent Learning (MALRL) classification methodology outperforms the others. The data - set for maizeplant disease has four class labels and 3.823 total images. The information about the class label data about the maize disease dataset is as followed: Common Rust, Gray Leaf Spot, Northern Leaf Blight, and Healthy are 1639,3780, 3456, and 3012, respectively in automatic manner. The execution of these classification models is done by employing MATLAB. The performance analysis are shown in Table 2.

TABLE 2 PERFORMANCE ANALYSIS OF LEAF DISEASE PREDICTION

Methodologies	Leaf Conditions	Precision	Recall	F-measure	Sensitivity	Accuracy
Artificial Neural Network (ANN)	Common Rust	85.5	84.8	83.5.	86.8	89.6
	Gray Leaf Spot	74.6	78.56	72.67	76.8	78.23
	Northern Leaf Blight	82.1	79.3	80.2	78.5	83.6
	Healthy	88.6	85.6	89.78	86.7	90.5
Convolutional Neural Network (CNN)	Common Rust	95.5	96.8	95.5.	96.6	98.6
	Gray Leaf Spot	84.6	88.56	92.67	86.8	90.23
	Northern Leaf Blight	88.1	78.3	81.2	77.5	87.8
	Healthy	98.6	95.6	85.78	96.7	95.5
Deep Neural Network (DNN)	Common Rust	78.3	76.6	75.8	76.4	80.7
	Gray Leaf Spot	85.7	87.56	93.67	96.8	91.13
	Northern Leaf Blight	89.1	79.3	89.2	79.5	89.8
	Healthy	95.8	94.9	95.8	96.9	96.7
Monarch AntLion Recurrent Learning (MALRL)	Common Rust	98.3	96.6	95.8	97.4	97.7
	Gray Leaf Spot	95.7	97.56	95.67	96.8	97.13
	Northern Leaf Blight	99.1	99.2	98.2	93.5	99.8
	Healthy	96.8	97.9	98.8	97.9	99.7

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J. Common Rust Leaf Disease Analysis

The graphical representation of common Rust leaf Disease analysis are presented as graphical representation in Figure 2.

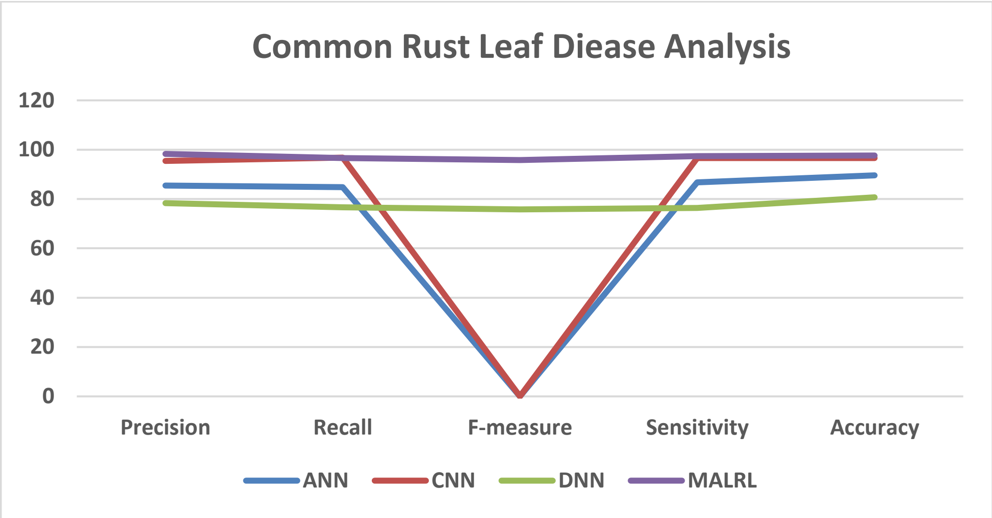

Figure 2. Common Rust Leaf Disease Analysis

According to Figure 2, the proposed classifier is provided the high values in term of precision, recall, F-measure, Sensitivity and Accuracy to classify the common rust disease identification. As the result, the proposed classifier (MALRL) on maize disease detection is superior one than other exiting approaches such as ANN, CNN and DNN

K. .Leaf Spot Leaf Analysis

The leaf spot disease analysis is provided in Figure3 as below,

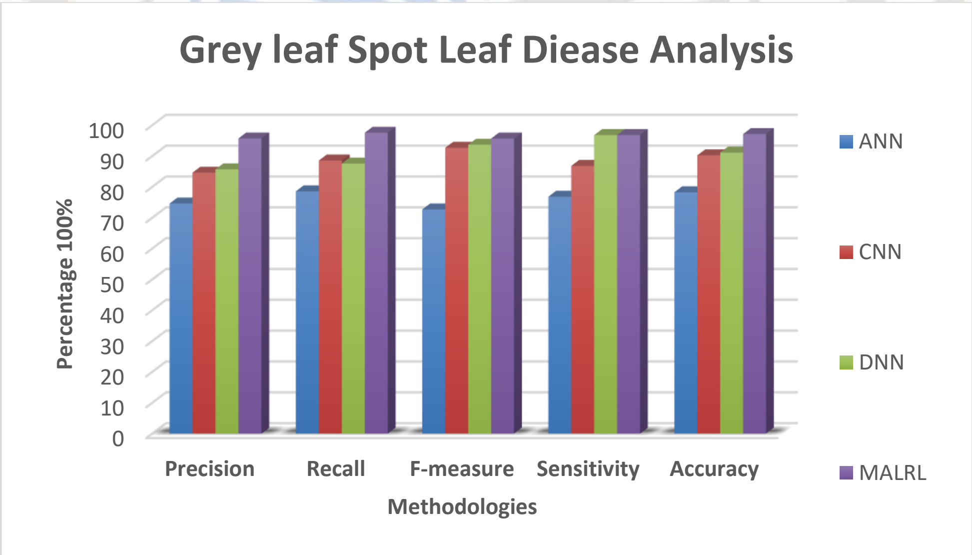

Figure 3. Grey Leaf Spot Disease Analysis

From Figure 3, shows that, the high accuracy is provided by proposed classifier. The yellow color chat represents the proposed classifier performance. It is indicating that proposed classifier is obtained high values among the whole metrics.

L. Northen Leaf Blight Leaf Disease Analysis

The disease of northen leaf blight is identified and recognized in Figure 4. It depicts that the proposed classifier attained great effectiveness in terms of precision, recall, sensitivity, F1-measure and Accuracy to recognize the Northan Leaf Blight Disease.

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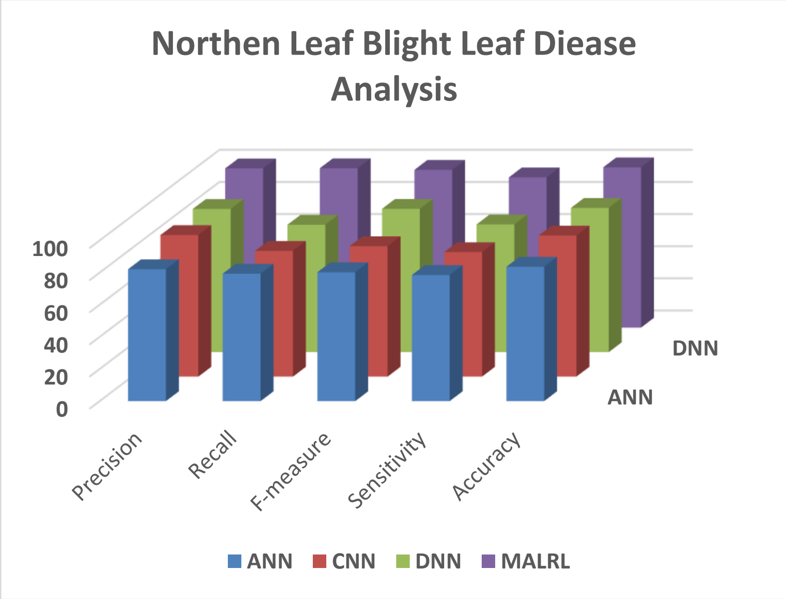

Figure 4. Northan Leaf Blight disease analysis

M. Healthy Leaf Analysis

Healthy leaf is analyzed using ANN, CNN, DNN and Proposal Classifier and shown in Figure 5. According to that, the Convolutional network has high precision value. However, proposed classifier is provided the high accuracy. The reduce the error also significant manner compared than other conventional approaches.

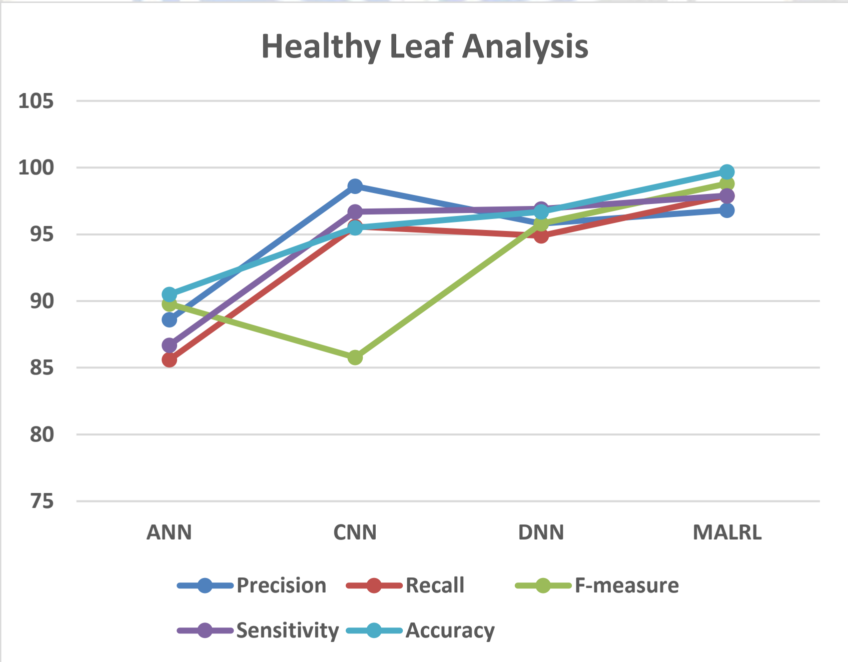

Figure 5. Healthy Disease Analysis

N. Overall Accuracy

The overall classifiers accuracy is calculated using below formula,

$$Overall\ Accuracy = \frac{\sum Classifer\ Accuracy}{Average} * 100 \qquad (35)$$

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Thus, the ANN, CNN, DNN classifier's overall accuracy is classified and recognize the maize leaf diseases and healthy leaves. Accordingly, existing approaches are achieved the accuracy as 85%, 91%, 90% respectively ANN, CNN and DNN. Besides, the proposed classifier has 98% and proved that it is superior outcome compared than others. The outcomes are provided in Table 3 and Figure 6

TABLE 3 OVERALL ACCURACY EVALUATIONS

Methodologies	Accuracy
ANN	85
CNN	91
DNN	90
MALRL	98

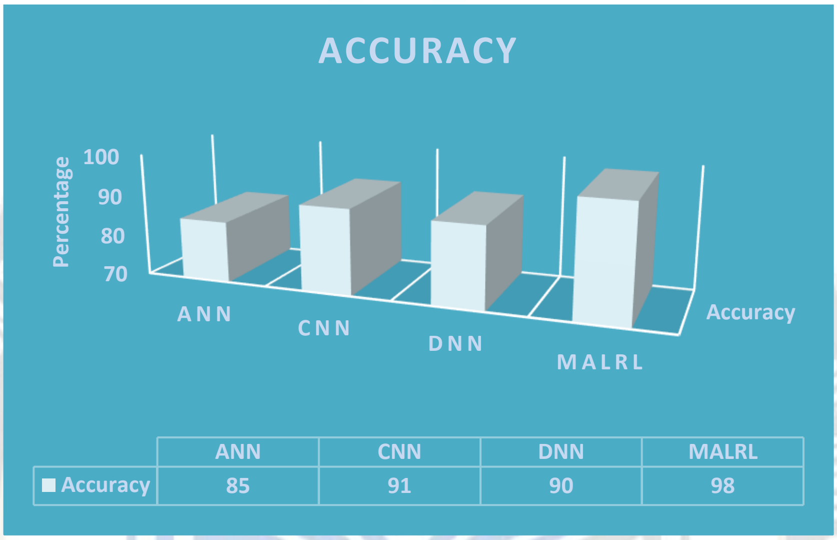

Figure 6. Graphical Representation of accuracy of all classifier

The proffered model is proved that it effectively classifies the disease and healthy leaf of maize from Figure 6. comparison result.

V. CONCLUSION

Even though there are a lot of different approaches to the automated plant disease detection and classification process, this field of study still has possibilities for development. In addition, there are currently no commercial solutions available on the market, with the exception of those that deal with the detection of plant species utilizing pictures of their leaves. In this study, an innovative method that makes use of the Automatic Optimal Monarch AntLion Recurrent Learning (MALRL) model was investigated with the goal of automatically classifying and detecting plant illnesses based on images of leaf lesions. A novel hybrid optimization is integrated to promote the Recurrent Neural Network classifier. The recent findings offer cause for optimism; hence, this body of work can be extended upon by determining more subtypes of maize leaf infection and making a more optimized framework that requires significantly less time and effort to compute. The model that was constructed was able to detect the presence of leaves and differentiate between healthy leaves and the leaves of four different diseases that can be identified in automatic manner. The effectiveness of the newly proposed MALRL model has been evaluated by contrasting its findings with those of previously developed ANN,CNN and DNN structures. The results of experiments indicate that performs better in term of accuracy, precision, recall, F-measure and sensitivity. In the near future, one of our objectives is to create a smart phone app for identifying maize leaf diseases. Additionally, while this is going on, the trained framework can be integrated with mobile devices in a flexible way to provide crop producers with the ability to make instant and logical judgments regarding information regarding plant diseases.

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