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An Enhanced Precise and Severity Evaluation of Multi Class Plant Disease Prediction Using Epistemic Neural Network with Spike-Driven Transformer

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ABSTRACT
One of the primary issues in the agricultural sector is Multiclass Plant Diseases (MPDs). For automatically identifying them is essential for keeping an eye on the plants. Plants' leaves display the majority of disease signs, however leaf diagnosis by specialists in labs is expensive and time-consuming. Numerous techniques are used for predicting Multiclass Plant Diseases. However, there are numerous drawbacks to the existing approaches, including a high error rate and low accuracy. To overcome the before mentioned problem, Epistemic Neural Network with Spike-Driven Transformer using Atomic Orbital Search Algorithm (EcNN-SeDTr-AOSA) is proposed for predict the multiclass plant diseases with high accuracy. In this input data is taken from Groundnut dataset. To reduce noise in the input data, Iterative Self-Guided Image Filtering (ISGIF) is proposed. Following that, the pre-processed images undergo feature extraction using Modified ResNet-152 (M-ReNt-152). After that classification is done by using Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) and optimized using Atomic Orbital Search Algorithm (AOSA) for forecasting the multiclass plant diseases with outstanding accuracy and effectiveness. The efficiency of the proposed EcNN-SeDTr-AOSA is analyzed using Groundnut dataset and attains 99.5% accuracy, 99.3 % recall and attains better results in comparison with the existing techniques. The outcomes of the proposed technique showed that it could improve the crop yield, reduced losses and early disease detection of the Multi Class Plant Disease Prediction method.

Keywords: Multiclass Plant Diseases (MPDs), Iterative Self-Guided Image Filtering (ISGIF), Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr), Atomic Orbital Search Algorithm (AOSA)

1. INTRODUCTION

One of the main causes of plant extinction is plant diseases. Accurately identifying plant illnesses can aid in the recommendation of a timely treatment plan and significantly stop the spread of disease, both of which are critical to minimizing financial losses [1-3]. In the last twenty years, there has been a lot of focus on agriculture related to automatic plant disease detection and severity estimation using visible range photos. One significant contributing cause to crop loss is plant diseases. They could have a negative impact on crop quality and lower crop yield. It could lead to famines and a rise in unemployment in the agricultural sector [4-6]. Agriculture is one of the primary industries in developing countries like India. Crop losses could have a detrimental effect on the economy of the country. Farmers' ignorance is one of the main barriers to detecting plant diseases and implementing the appropriate measures to prevent crop loss. Many diseases affect crops, particularly in the world's moderate, tropical, and subtropical climates. Plant infections can also result from specific viruses, fungus, microbes, molds, and occasionally environmental factors including temperature, humidity, and precipitation. These substances could potentially act as a conduit for infections caused by infectious agents, epidemics, and other pathogens. These diseases may have a detrimental effect on farmers' livelihoods and cause considerable financial losses [7-9]. Increasing crop quantity and quality can be beneficial for agricultural development if plant diseases are adequately handled. Plant diseases pose a threat to human food safety and sustainability because they severely damage crops and lower the amount of food available. Therefore, it is essential to identify plant diseases early for crop administration and control [10-12]. Human expertise is frequently used to detect plant diseases, but in remote locations and rural populations of developing countries, this expertise is infrequent and difficult to come by. Moreover, the traditional methods that farmers and field experts use to detect plant illnesses are expensive, time-consuming, and error-prone [14][19-20]. For this reason, artificial intelligence-based methods can be crucial for accurately and quickly diagnosing plant diseases. Recent developments in computational image processing and algorithms for pattern identification have revealed some methods for illness recognition, which will help farmers and agriculture specialists. A variety of artificial intelligence-based techniques can be automatically applied to photographs to determine the quality of agricultural and aquaculture products. It is possible to capture pictures of different plant components and use those photographs to infect a plant detection system. Plant leaves are thought to be the most often used component for plant disease detection [16][21-22].

Novelty and Contribution

- Iterative Self-Guided Image Filtering (ISGIF) is to enhance data quality by reducing noise in input images through iterative filtering, leading to improved accuracy in subsequent image analysis tasks.
- The objective of using Modified ResNet-152 (M-ReNt-152) for feature extraction is to accurately capture and represent critical image features, enhancing the performance of subsequent image analysis and classification tasks.
- To achieve outstanding accuracy and effectiveness in forecasting multiclass plant diseases by employing Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) for classification, and optimizing the model using the Atomic Orbital Search Algorithm (AOSA), enhancing the predictive performance and reliability of plant disease diagnosis.

2. LITERATURE SURVEY

In 2021, Tiwari, et al [13] has introduced a DenseNet-201 method for classifying and detecting plant diseases using photos of plant leaves. The method makes use of an architecture for deep convolutional neural networks that has been extensively trained on plant leaves from many nations. With unseen photos with complicated backdrop conditions, the model achieves a standard cross-validations accuracy of 99.58% and a mean test accuracy of 99.199%, demonstrating its ability to accurately categorize a variety of plant leaves with efficiency and precision.

In 2022, Kundu, et al [15] has developed a deep learning-based "MaizeNet" approach. It extracts the region of interest using the K-Means clustering algorithm. They then use the tailored deep learning model "MaizeNet" to estimate crop loss, predict illness severity, and detect diseases. 98.50% is the maximum accuracy reported by the model. Additionally, the Grad-CAM is used by the authors to visualize the features. Currently, a web application and the suggested model are combined to create an interface that is easy to use. The model's effectiveness in extracting pertinent features, reduced parameter count, short training duration, and excellent accuracy support its significance as a supporting tool for pathology of plants specialists.

In 2023, Hosny, et al [17] has introduced a unique lightweight Deep Convolutional Neural Network (DCNN) model. Then, deep characteristics are fused with traditional local binary pattern features to obtain local textural data from plant leaf pictures. The proposed model is trained and evaluated on three publicly available datasets: the Apple Leaf, Tomato Leaf, and Grape Leaf datasets. On the three datasets, the recommended approach achieves 99%, 96.6%, and 98.5% validation accuracy levels and 98.8%, 96.5%, and 98.3% test accuracies. The results of the experiment show that the recommended approach may provide a more efficient way to manage plant diseases.

In 2023, Shovon, et al [18] has suggests a Deep Ensemble Model named PlantDet, which is derived from Xception, EfficientNetV2L, and InceptionResNetV2. The model utilizes nourished performance for a sparse dataset and resolves underfitting issues. In datasets containing rice and betel leaves, PlantDet performs better than earlier models thanks to its great accuracy and precision. Additionally, the study shows how well Deep Learning models work with complicated datasets, with Score-CAM marginally surpassing Grad-CAM++ in projected area localization.

Problem Statement

The existing multiclass plant disease prediction methods suffer from high error rate and low accuracy. To solve these issues Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) is proposed. By employing multiclass plant disease prediction from groundnut dataset, it enhances detection through Iterative Self-Guided Image Filtering (ISGIF) for noise reduction, and M-ReNt-152 for feature extraction. Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) for classification and Optimized with AOSA, the method achieves 99.5% accuracy and 99.3% recall, outperforming current practices and maybe improving multiclass plant disease prediction.

3. PROPOSED METHODOLOGY

The working principle of EcNN-SeDTr is illustrated in Fig 1. The proposed method consists of four process (1) data collection, (2) pre-processing and (3) feature extraction and (4) classification.

3.1 Data Collection

The suggested model gathers input data and conducts research. We obtained all of our data's from the Groundnut dataset.

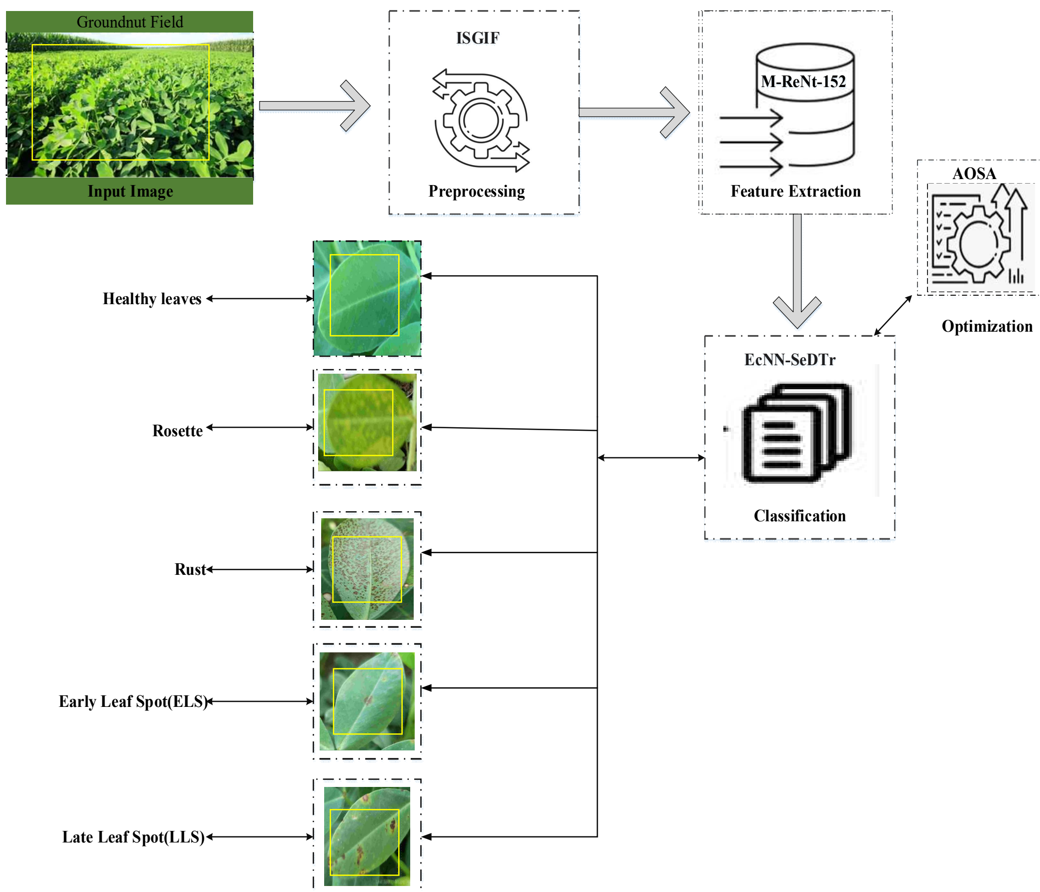

Figure 1: Workflow diagram of proposed EcNN-SeDTr method

3.2. Iterative Self-Guided Image Filtering (ISGIF) Based Pre-processing

Pre-processing is the initial step of data enhancement in computer processes. The input data is full of noise, so Iterative Self-Guided Image Filtering (ISGIF) is used to remove the noise. The Iterative Self-Guided Image Filtering (ISGIF) method is a sophisticated image processing technique designed to preserve sharp edges while smoothing non-edge areas, making it particularly suitable for preprocessing images in tasks like plant disease prediction. In the context of plant disease prediction, ISGIF-based preprocessing offers several benefits. By preserving sharp edges, ISGIF helps maintain the integrity of important features such as leaf edges and disease spots, which are crucial for accurate disease identification. ISGIF effectively smooth out noise in non-edge areas, enhancing the clarity of the image and improving the performance of machine learning models. The filtered output image R is assumed by the Guided Image Filter (GIF) to be a linear transform of the guiding image D at a window v_h centered at pixel h is given by equation (1):

$$R_j = b_h D_j + a_h, \quad \forall j \in v_h \tag{1}$$

where , b_h and a_h denotes the two constants. v_h represents a square window centered on pixel h of a radius l .The gradient of the filtered image R is proportional to the gradient of the guidance image D is given by equation (2):

$$\nabla R_j = b_h \nabla D_i \qquad \forall j \in v_h \tag{2}$$

When applied in the image domain Ψ , with the input image K as the guidance image, this relationship becomes given by equation (3):

$$\nabla R_h = b_h \nabla K_h \qquad \forall h \in \Psi \tag{3}$$

Therefore, by solving the following optimization problem, the smoothed image R can be obtained. Initially, the objective is to minimize the difference between the filtered image R and the input image K while maintaining the gradient constraint. It's given by equation (4):

$$\min_{r} \|R - K\|^2 r.l. \|\nabla R_h - b_h \nabla K_h\|^2 \leq \lambda \tag{4}$$

where, λ is a sufficient small. The following objective function has been established by the GIF in order to ascertain the linear coefficient b_h illustrate in equation (5):

$$\min_{b_h, a_h} F(b_h, a_h) = \min_{b_h, a_h} \sum_{j \in v_h} ((b_h D_j + a_h - K_j)^2 + \varepsilon b_h^2) \tag{5}$$

where , ε denotes the regularization parameter penalizing large values for $b_h . a_h$ represents the coefficient. By integrating ISGIF into the preprocessing pipeline, the overall precision and reliability of multi-class plant disease prediction models are significantly improved, ultimately aiding in better crop management and yield improvement. The following section describes the process of feature extraction.

3.2 Feature Extraction Using Modified ResNet-152 (M-ReNt-152)

The modified ResNet-152 model is leveraged for feature extraction in the context of multi-class plant disease prediction. This involves using a pre trained ResNet-152, originally trained on the Image Net dataset, and adapting it to analyze plant disease images to predict the type and severity of diseases affecting crops. The primary goal is to enhance precision and improve crop yield by accurately diagnosing plant health issues. The architecture of ResNet-152 is shown in Figure 2.

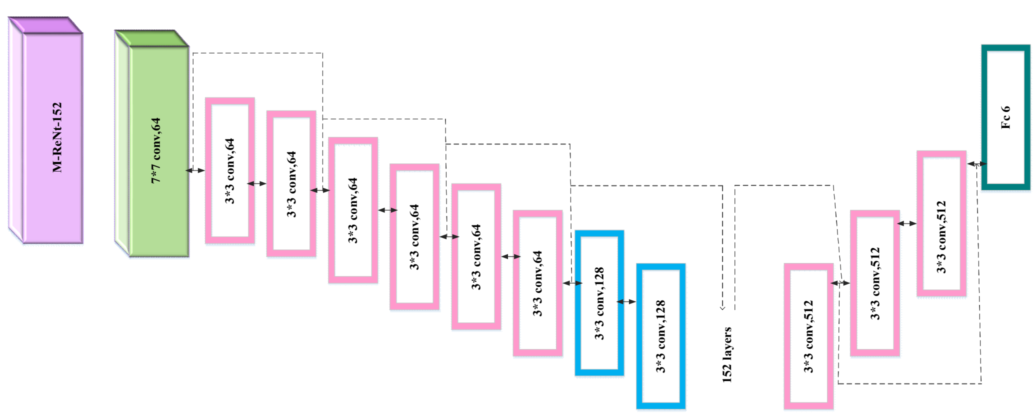

Figure2: Architecture of M-ReNt-152

ResNet is designed to counteract vanishing gradient issue that has been observed in deeper networks such as VGG-16. This it does through the use of "identity shortcut connections" which helps to bypass some layers, which in effect allow the training of very deep networks without any compromised performances. Identity Shortcut Connections are enabling the network to short circuit, which is effective in retaining the gradient during the back propagation process. This mechanism helps gradients not decrease, or increase as they pass through the network which is very important when it comes to training deeper structures. The ResNet-152 model is then pre trained on the large-scale image Net dataset this gives the model a large set of learned features that can be transferred to the task of plant disease prediction. These plant images, which may be infected with one or several diseases, are input and transformed by the ResNet-152 model and analysed with a comprehensive dataset. This involves scaling down and normalizing the images and some may even involve performing data augmentation to feed to the ResNet-152 model. In this paper, pre trained ResNet-152 network is used in order to extract the features of a given plant images. In this step, the pictures are passed through the network, and the features are obtained from a particular layer of the neural network usually the layers before the output layer is taken as the features. Specifically for the plant disease prediction task, more layers like dropout and batch normalization are included to modify the ResNet-152.[23]

- **Dropout Layer**

Dropout layer helps reduce over fitting by randomly disabling a fraction of the neurons during training, which forces the network to learn more robust features.

- **Batch Normalization Layer**

Batch normalization layer stabilizes the learning process and accelerates training by normalizing the input to each layer.

By leveraging the powerful feature extraction capabilities of the modified ResNet-152, the approach significantly improves the precision and reliability of plant disease predictions, ultimately aiding in better crop management and yield optimization. After that, the feature-extracted data is given to classification.

3.3 Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) Based Classification

In the classification stage, the extracted features are fed as input to the EcNN-SeDTr. For Multiclass Plant Diseases prediction we suggest Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) based classification. An epistemic neural network with spike-driven transformer-based classification for evaluating multi-class plant disease prediction to improve crop yield is an advanced machine learning framework designed to enhance agricultural productivity by accurately diagnosing plant diseases.

3.3.1 Epistemic Neural Network (ENN)

Epistemic Neural Networks (ENN) can enhance the evaluation of multi-class plant disease prediction by incorporating a mechanism to model and address uncertainty, thus potentially improving the accuracy and reliability of predictions.

- **Conventional Neural Networks**

A conventional neural network uses a parameterized function l to produce an output vector $l_{\vartheta}(y)$ given input y and parameters ϑ. The class probabilities are obtained via a softmax function, yielding a predictive distribution $\hat{R}(x) = \exp((l_{\vartheta}(y))_x)) / \sum_{x'} \exp((l_{\vartheta}(y))_{x'})$.

- **Epistemic Neural Networks(ENN)**

An ENN extends this architecture by introducing an additional variable, the epistemic index v, which represents uncertainty in the model. The function now becomes $l_{\vartheta}(y, v)$, where v is drawn from a reference distribution R_v (e.g., uniform or Gaussian distribution). This additional dimension allows the model to account for uncertainties that can be resolved with more data (epistemic uncertainty). A joint prediction, given input $y_1, ..., y_\eta$, gives each class combination $x_1, ..., x_\eta$ a probability $\hat{R}_{1:\eta}(x_{1:\eta})$. Although joint predictions are not intended by typical neural networks, joint predictions can be generated by multiplying marginal predictions is given by equation (6):

$$\hat{R}_{1:\eta}^{MM}(x_{1:\eta}) = \prod_{i=1}^{\eta} soft\max(l_{\vartheta}(y_i))_{xi} \tag{6}$$

where, $x_{1:\eta}$ denotes the independent data, l represents the class of functions. This approach allows the model to capture dependencies and provide a more informed joint prediction, distinguishing between reducible and irreducible uncertainties. Epistemic Neural Networks offer a powerful approach for multi-class plant disease prediction by effectively modeling uncertainty and producing more reliable joint predictions. This can lead to better crop management strategies and ultimately improve crop yield.

3.3.2 Spike-Driven Transformer

Spike-driven transformer-based classification is an emerging method applied for the classification of multiple plant diseases for enhancing crop productivity. This method combines aspects of SNNs and transformers to make the disease diagnosis in plants quicker and more precise. Spiking Neuron models all mimic biological neuron but the one which is used to process the information is spiking neurons. Particularly, the Leaky Integrate-and-Fire (LIF) model is widely used because of its simplicity and possibilities of simulation. There are varied approaches followed with equal importance being given to Leaky Integrate and-Fire spiking neurons as they are biologically realistic and easier to implement in a computer. The process is given by equation (7, 8 and 9):

$$V[l] = K[l-1] + Y[l], \tag{7}$$

$$R[l] = Hea(V[L] - v_{th}), \tag{8}$$

$$K[l] = U_{reset}R[l] + (\lambda V[l])(1 - R[l]), \tag{9}$$

where, l represents the time step, $V[l]$ denotes the membrane potential which produced by coupling the spatial input information $Y[l]$, $K[l-1]$ denotes the temporal input. v_{th} is the threshold value. $\lambda < 1$ denotes the delay factor. $Hea(x)$ is the Heaviside step function. V_{reset} is the reset potential which is set after activating the output spiking.

In this research work, the proposed Spike-Driven Transformer architecture has successfully used spiking neurons and also, optimized self-attention for precisely identifying several plant diseases. Such an approach, along with the energy-use feature that was mentioned earlier, has great potential in raising crop productivity due to the possibility of timely and targeted intervention against diseases. The integration of epistemic neural network along with spike driven transformer classification is a novel method towards multi-class plant diseases prediction. This strengthens the diagnosing of disease making it better for the farmers to be informed and thus helping in increasing crop yield and agricultural productivity. The aims of the following networks are used after the classification is done. Subsequently to increase the classification accuracy and to minimize the error rate, processing time, complexity, and cost related to EcNN-SeDTr, these parameters are optimized with the help of AOSA for the accurate Prediction of Multi-Class Plant Disease for Improving Crop Yield from groundnut dataset. The optimizing process of the presented EcNN-SeDTr is described flowchart below.

3.4 Optimization Using Atomic Orbital Search Algorithm (AOSA)

The Atomic Orbital Search Algorithm (AOSA) is based on the quantum mechanics and atomic orbital theory for solving the problems of optimization. In the following part of the paper, the authors would like to describe what kind of fitness function, exploration, and exploitation have been implemented in the AOSA when solving the problem of multi-class plant disease prediction to help increase the yield of crops.

Step1: Initialization

Create an initial population of Atomic Orbital Search Algorithm solutions, each representing a set of EcNN-SeDTr hyper parameters.

Step 2: Generation of Random Variables

Generate at random the optimization variables of Atomic Orbital Search Algorithm to attain the best solution.

Step 3: Evaluation of Fitness Function

The fitness function in the context of the AOSA is designed to evaluate how well each solution performs relative to the desired outcome. For the multi-class plant disease prediction problem, the fitness function can be defined to measure the accuracy and precision of the predictions made by a model is given by equation (10):

$$R = T_j \times l \tag{10}$$

where, R is the fitness value (objective function value) of the j-th solution candidate T_j. The goal is to maximize this fitness value, which represents the model's ability to correctly predict plant diseases.

Step 4: Mutation (Exploration) for improving accuracy
Exploration refers to the algorithm's ability to search through the global search space effectively to find diverse and potentially optimal solutions. Therefore, the position of the solution candidate is updated accordingly using Equation (11):

$$Y_h^{j+1} = Y_j^h + s_j \tag{11}$$

where, s_j denotes the random vector promoting exploration. Y_h^{j+1} *and* Y_j^h are the current position and next position for the j-th candidate solution of the h-th layer.

Step 5: Selection (Exploitation) for reducing error rate, processing time, computational complexity and cost
Exploitation refers to the algorithm's capability to intensively search around the promising areas in the search space to refine solutions. This step ensures that only the most promising solutions are carried forward. By sorting candidates and positioning them in layers based on their fitness, the algorithm ensures that better candidates influence the search more, thereby exploiting known good regions of the search space. The following mathematical expression is then used to update the position. It's given by equation (12):

$$Y_j^{h+1} = Y_j^h + \rho_j \times (\mu_j \times TF^h - \phi_j \times AC^h) \tag{12}$$

where, Y_j^{h+1} denotes the next position and Y_j^h is a current position. TF^h is the lower energy level. AC^h denotes the binding state .The randomly created vectors ρ_j, μ_j *and* ϕ_j which are uniformly distributed in the interval (0, 1), are utilized to calculate the quantity of energy emitted or absorbed.

Step 6: Termination
When a termination requirement is satisfied at this phase, the algorithm comes to an end. Once the best answers are obtained using equations (10-11), end the operation. Additionally, equation (12) yields the most accurate answer, and minimizes error rates, processing times, computing complexity, and cost. This iteration is remaining until the tentative criteria $j = j + 1$ is met. Lastly, the suggested EcNN-SeDTr-AOSA accurately evaluates the Multi Class Plant Disease Prediction to Improve Crop Yield.Hence, EcNN-SeDTr detailed and explained. It pre-processed data using ISGIF, feature extraction using M-ReNt-152, Classification using EcNN-SeDTr optimization using AOSA method for evaluation of multiclass plant disease prediction to improve crop yield demonstrating superior efficiency and accuracy. In the next section the results and discussions are discussed.

4. RESULT AND DISCUSSIONS
The experimental results and comments for the proposed approach applied to the Python platform are shown in this section.

4.1Dataset description
Groundnut dataset collected the leaves from the farmland. Five groups of samples were gathered, they are Healthy leaves, Rosette, Rust, Early leaf spot (ELS), and Late leaf spot (LLS). This dataset contained 600 photos of leaves in total. Smartphones and high-resolution digital cameras to capture images of groundnut leaves. The 80% is utilized for training and 20% is for testing. Figure3 shows the groundnut dataset Image of proposed method.

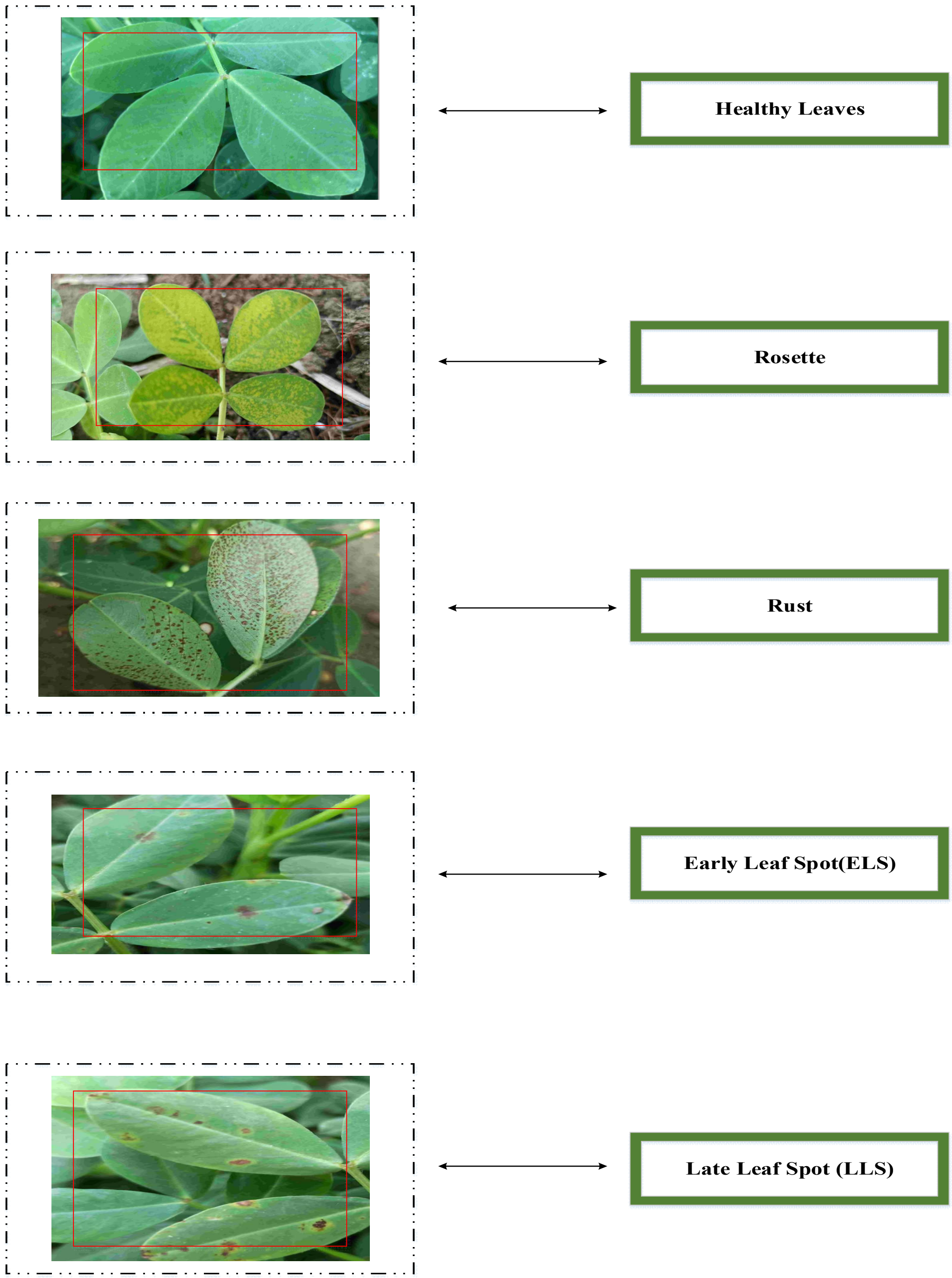

Figure3: Groundnut Dataset Image of proposed method

Table1: Groundnut Leaf Classes and Labels.

Class Name	Class Label
Healthy Leaves	0
Rosette	1
Rust	2
Early Leaf Spot (ELS)	3
Late Leaf Spot(LLS)	4

The table 1 shows groundnut leaf classes and their corresponding labels used for classification. There are five classes: Healthy Leaves (0), Rosette (1), Rust (2), Early Leaf Spot (ELS) (3), and Late Leaf Spot (LLS) (4). These labels help in categorizing the condition of the groundnut leaves for disease prediction. The table 2 shows the distribution of original images across different groundnut leaf classes

Table 2: Distribution of original images across different Groundnut Leaf Classes

Class Name	Number of original images
Healthy Leaves	200
Rosette	80
Rust	50
Early Leaf Spot (ELS)	150
Late Leaf Spot(LLS)	120
Total	600

The table 2 shows the distribution of original images across different groundnut leaf classes. There are 200 images of Healthy Leaves, 80 of Rosette, 50 of Rust, 150 of Early Leaf Spot (ELS), and 120 of Late Leaf Spot (LLS). The total number of images is 600, used for analysis.

4.2 Performance metrics

The efficiency of the proposed method is evaluated based on various performance metrics such as Accuracy, Sensitivity, Recall, Precision, F1 Score and Error rate. The experimental outcomes are shown in the following table3:

Table 3: Performance comparison of Groundnut Dataset

Methods	Accuracy (%)	Sensitivity (%)	Recall (%)	Precision (%)	F1 Score (%)	Error rate (%)
DenseNet-201	54.93	72.12	42.00	76.00	79.66	1.9
MaizeNet	40.71	72.16	53.00	85.00	58.20	1.0
LDCNN	80.	70.20	44.00	67.00	68.18	1.0
PlantDet	95.45	77.25	54.00	78.59	58.25	3.6
EcNN-SeDTr (proposed)	99.5	88.70	66.00	82.00	80.68	0.1

The table 3 compares the performance of various methods on the groundnut dataset. It includes sensitivity, precision, F1 score, accuracy, recall, and error rate. The proposed EcNN-SeDTr method shows the highest accuracy (99.5%) and lowest error rate (0.1%), outperforming other methods like DenseNet-201, MaizeNet, LDCNN, and PlantDet in most metrics. Figure 3 shows the Training VS Testing Accuracy and Loss.

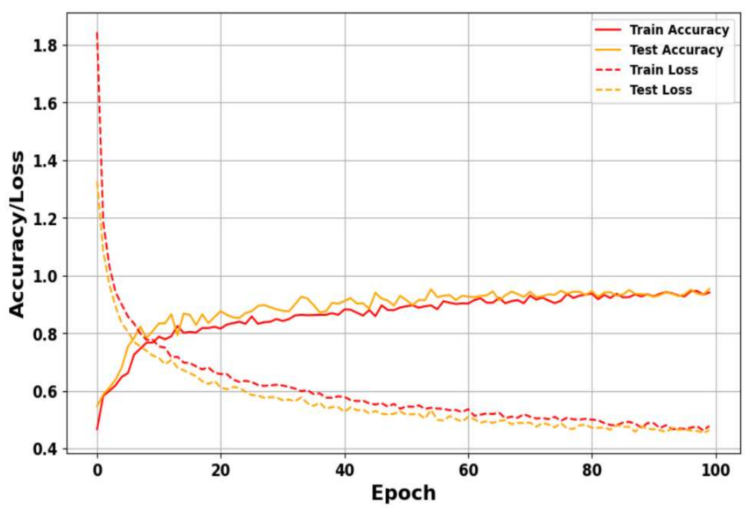

Figure 4: Training VS Testing Accuracy and Loss

The figure 4 shows the training and testing accuracy and loss over 100 epochs. Initially, training and testing loss decrease rapidly, indicating learning. Training accuracy steadily increases and stabilizes, while testing accuracy fluctuates but shows a slight increase. The divergence between training and testing metrics suggests potential over fitting.

5. CONCLUSION

In this manuscript, EcNN-SeDTr-AOSA is successfully manipulated. The input data is taken from Groundnut dataset. Then these data are pre-processed using ISGIF method. Following that, preprocessed data's are feature extracted using M-ReNt-152 method .Then the classification is done using Epistemic Neural Network with Spike-Driven Transformer (EcNN-SeDTr) for evaluating the multiclass plant disease prediction to improve crop yield. The introduced system is executed in python. The efficiency of the proposed EcNN-SeDTr-AOSA is analyzed using groundnut dataset and attains 99.5% accuracy and 0.1% error rate, compared with the existing methods. This demonstrates the method's increased effectiveness and possible advancement in the industry. By increasing the dataset, incorporating real-time processing, and developing a simple interface, further work will improve the robustness and generalizability of the model for evaluating the multi class plant disease prediction to improve crop yield.

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