ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IDENTIFICATION AND CLASSIFICATION OF MANGO LEAVES DISEASE ON GREY WOLF OPTIMIZATION OF MULTIVARIATE GATED RECURRENT NETWORK

AMIRTHA PREEYA V[1], DR.S.PRAVINTH RAJA[2]

[1]Research Scholar, Presidency University, Department of CSE, Bangalore, India
[2]Associate Professor, Presidency University, Department of CSE, Bangalore, India E-mail: [1]
[1]amirtha.20213cse0011@presidencyuniversity.in, [2] pravinth.raja@presidencyuniversity.in

ABSTRACT

Plant provides essential nutrients and energy for daily life on reducing sickness, stress and anxiety through its process of cleaning air. Further it provides many medicinal and health benefits to the society to treat various degenerative disease. Especially mango leaves are potential source of minerals like nitrogen, potassium, calcium, magnesium and vitamins. In Particular, these most beneficial plant were exposed to various disease in its growing regions due to several environment changes. Hence it becomes mandatory to protect and prevent the plant against the disease using precautionary measures. Even though there exist large solutions to combat these issues still it requires a strong solutions to examine those disease and categorize it into various forms to establish a effective countermeasures. Many researches has been initiated using machine learning and deep learning to detect the disease and its types but those approaches fails to discriminate diseases effectively in early stages. In this work, a new deep learning model entitled as Multivariate Gated Recurrent Network composed of Input layer, hidden layer , abstract layer and output layer contains various state like hidden state, forgot state, update state and Reset state is employed to analyze the disease region of the image in detail towards effective discrimination in early stages. In particular abstraction layer has been combined with graph cut segmentation algorithm to improves the efficiency of the network by searching and grouping of seed points which represents the infected region of leafs has common attributes. Those common attributes generate the best features for classification. Further optimization of gated recurrent network is carried out using grey wolf optimization to eliminate the network over fitting issues on increasing the speed and accuracy of the network to identify and classify the regions infected of different diseases on the plant leafs on different diseases perspectives. Experimental analysis of proposed architecture on cross fold validation of plant village dataset explains the model accuracy and efficiency with respect to execution performance in terms of training accuracy and validation accuracy respectively for disease identification. GWO and multivariate GRU work together to automate disease diagnosis with low computing overhead, advancing accurate, real-time agricultural disease management. This research advances our understanding of plant disease detection while providing a scalable, reliable, and optimal approach that may be modified for comparable horticultural and agricultural uses.

Keywords: *Mango Leaf Disease, Deep learning, Recurrent Neural Network, Multivariate Gated Recurrent Network, Grey Wolf Optimization algorithm.*

1. INTRODUCTION

Plant has many botanical benefits which provides essential nutrients and energy for daily life on reducing sickness, stress and anxiety due to its antioxidant and anti-inflammatory properties. Further it treat various degenerative disease like skin disease, diabetics, tumors and heart disease. In Particular , mango fruit has potential source of minerals like nitrogen, potassium , calcium, magnesium and vitamins. and it is considered as most beneficial plant to treat various disease due to chemical compound like polyphenols and terpenoids[1]. These chemical compound will be easily infected by various diseases occurring due to climatic changes and several environment changes. It causes as severe threat to the growing human well being on basis of nutrient deficiency. Hence it becomes mandatory to protect and prevent the plant against the disease using precautionary measures[2].

In order to provide adequate nutrient security of the plants species across the world, many scientific solutions have been employed in form of pesticides and insecticides but still it requires a strong solutions to monitor and examine those disease to categorize it into various forms on establishing a effective countermeasures in the plant growing region[3]. Many researcher has initiated the solutions to identify the plant disease and its varieties using machine learning[4] and deep learning approaches[5] but those approaches fails to discriminate diseases effectively in early stages.

In this work, a new deep learning model entitled as "Multivariate Gated Recurrent Network composed of Input layer, hidden layer , abstract layer and output layer contains various state like hidden state, forgot state, update state and Reset state is employed to analyze the disease region of the image in detail towards effective disease discrimination in early stages. In particular abstraction layer has been combined with graph cut segmentation algorithm to improves the efficiency of the network by searching and assembling seed points which represents the infected region of leafs has common attributes. These common attributes generates the best features for classification.

Further optimization of gated recurrent network is carried out using grey wolf optimization to eliminate the network over fitting issues on increasing the network's ability to quickly and accurately detect and categorize plant leaf disease-infected areas from several disease perspectives. The further-trained model boosts the computation speed to classify the infected region of mango leaves with small variance to represent disease types including bacterial, fungal, and viral on known mango leaf diseases when the plant village dataset is cross-fold validated.

Rest of the article is managed into following section as defined. Section 2 details the review of the literature towards identifying and classifying the mango leaf diseases on machine learning and deep learning architecture. Section 3 provides design of proposed multivariate gated recurrent Neural Network architecture along the image preprocessing using contrast enhancement, image segmentation using graph cut segmentation, feature extraction and selection approaches through Principle Component Analysis and grey wolf optimization algorithm. Section 4 mentions the experimental and performance analysis of the architectures on accuracy and efficiency towards identifying and categorizing diseases while analyzing the plant village dataset. The articles are finalized in Section 5 along with research suggestions.

The application of Grey Wolf Optimization in conjunction with GRU networks for the purpose of identifying and categorizing mango leaf diseases is the focus of this paper. The current scope and datasets are restricted to mango leaf diseases, while the suggested approach can be modified to other plant kinds. Additionally, the focus of this study is on using visual characteristics to classify diseases rather than exploring physiological or environmental aspects that could influence the course of the condition.

2. RELATED WORK

In this article, numerous conventional approaches incorporating the artificial intelligence approaches has analyzed towards detecting and classifying the mango plant leaf diseases on extracted features in disease regions. Detailed analysis of the architecture is as follows

2.1. Identification and Classification of Mango leaves Disease on Optimization of Deep Inception v5 Convolution Neural Network using Staged genetic Algorithm

In this literature, disease diagnosis of the mango leaf is carried out using Deep Inception V5 Convolution Neural Network on optimizing the feature using staged genetic algorithm. Initially preprocessing of the image through contrast enhancement [6] , segmentation[7] and feature extraction[8] is carried out . Finally extracted feature is applied to proposed network with metaheuristic optimization technique to generate the disease classes on disease types. The suggested trained model identifies and classifies the diseased area of plant leaves with little variation, improving computation speed and classification accuracy.

2.2. Optimization of the Convolutional Neutral Network through Crossover inclined levy flight feature generations towards Mango leaf disease detection and classification

In this literature, disease diagnosis of the mango leaf is carried out using optimization of crossover inclined levy flight feature generation on convolutional Neural Network. Particular optimization eliminates the computational complexity and overfitting issue on using multiple feature selection stages. Optimal feature extraction and selection on the levy flight distribution is projected to the convolutional neural network for classification of the plant diseases termed as anthracnose and bacterial black spot on setting the effective hyperparameter for the layers of the model [18].

2.3. Fully Resolution Convolutional Network for Mango Leaf Disease Detection and Classification

In this literature, deep learning model represented as fully resolution convolutional Neural Network is used to segment and identify the leaf diseases. Specified model learns the feature of the diseases pixels on basis of the intensity variation and segment it according intensity value. Further each disease segmented is classified in the convolutional neural network on basis of various disease to the features which extracted and selected using meta heuristic approaches like particle swarm optimization and ant colony optimization [19].

2.4. Perceptual Pigeon Galvanized optimization on Multiobjective Convolution Neural Network against detection and classification of Mango Leaf disease

Perceptual Pigeon Galvanized optimization is used in this literature to improve the Convolution Neural Network classifier's ability to accurately identify and categorize mango leaves. It initiate with preprocessing methods to enhance the image quality for disease classification through contrast enhancement technique and it propagates with segmentation approach to cluster the image into normal and disease cluster. Those cluster further processed using linear discriminant analysis and Perceptual Pigeon Galvanized optimization to extract and select optimal feature for disease classification .Finally disease is classified on processing the feature in the multiple layer of the convolution neural network [21].

2.5. Improved Yolo Model for detecting severity of the plant diseases

The Yolox model is used in this literature to determine how serious the plant diseases are. The revised Spatial Pyramid Pooling (SPP) layer is specifically used to collect similar information across various scales. Several features that have been gathered from smaller to bigger scales are concatenated with the extracted feature. Additionally, different skip connections are employed to generalize the illnesses. To decrease the over-fitting problems, the regression loss function was used to improve network convergence [12]. Because skip connections have been incorporated, it results in a high computation time.

3. PROPOSED MODEL

In this part, a Multivariate Gated Recurrent Network to identify and classify the mango leaf overlapping disease features with respect to bacterial, fungal and viral categories. Processing steps to accomplish the aforementioned goal are as follows

3.1. Image pre-processing- Sigmoid Stretching and Pixel Brightness transformation

Preprocessing of the image is to enhance the segmentation and classification accuracy of the mango leaves images containing various disease categories uses image normalization and pixel enhancement.

- **Image normalization – Sigmoid Stretching**

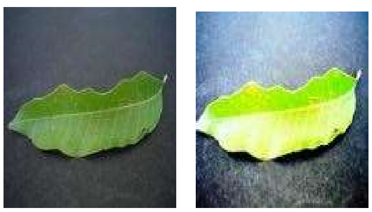
Image Normalization uses sigmoid stretching to elaborate the specified pixel which requires detail examinations. Sigmoid function is a non linear function to determine the image histogram each light and dark pixel elements. Those pixel elements is represented as separate Gaussian histogram. Cumulative distribution function is used to combine histogram distribution. Cumulative distribution function is represented as

Journal of Theoretical and Applied Information Technology
15th December 2024. Vol.102. No. 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$F(n) = \sum_{i=0}^{n} f(i)$ where n≥i ; n=0 to 255..Eq.1

Further Quartile of each cumulative distribution function represented in the color mapping curve. Quadratic curve fitting function calculates the mapping functions for restructure the pixel distribution of the image with support of lookup tables for dark pixel elements and light pixel elements respectively. Figure 1 represents the preprocessed image[9].



(a) (b)

Figure 1: Image Preprocessing

(a) Input Image (b) Pre-processed image (Contrast Enhancement Image)

- **Pixel brightness Transformation**

Pixel brightness transformation adjusts and corrects the brightness of pixels position in an image. Properties of the pixel is analyzed with respect to gamma correction using pigeonhole principle. Gamma Correction is model as continuous mapping function for intensity transformation on analyzing the pixel value histogram. Distribution of the pixel values creates the peaks and gaps in the shape of the output histogram. Specifically gamma correction function is represented on probability distribution over pixel value is as follows

$m_\gamma(j) = N(\frac{j}{N})^\gamma$ ...Eq.2

Where j represents the pixel value and m_γ is continuous transform with non parametric variable N . To normalize histogram of the image, image is transformed into matrix or vector to obtain the compact matrix on its smoothness operation of the vectors. Smoothness operations maps the multiple input pixel values to single output value. First order and second difference reveals the smoothness difference between the pixel represented in form of the histogram. Smooth operation of the pixel of the image with its neighbouring component is illustrated as

$P_{output}(i) = \sum_{j=0}^{N-1} \delta$ (i- matrix[m(j)]).$p_{input}(i)$ Eq.3

3.2. Image Segmentation -Graph Cut Segmentation

Graph cut segmentation is employed to segment the disease parts of the preprocessed plant village dataset containing mango leaves images. Segmentation technique changes the representation of the images with highlighting the boundaries of the diseased and non disease regions separately in order to make disease analysis more effective. However similarity, proximity and continuity were considered as significant factor of the segmentation[10]. In order to segment the image, image is transformed into weighted undirected graph with the set of image space points. It is depicted as

G= (V,E) ...Eq.4

V is vertices of the image space which is considered as node in the graph.

E is regarded as the edge connecting each pair of nodes.

Weight of edge w(i,j) is function of similarity between the nodes i and j

Partition the image's vertex set into distinct sets with a high degree of similarity within and a low degree of similarity between the sets. Partition is represented as cut in graph cut segmentation approach and it is defined as set of edges whose eliminations disconnects the graph. In another words, Edge connectivity is the minimum number of edges whose eliminations disconnects the graph which is mentioned as K(G). In weighted graph, cut is represented by minimum cut and normalized cut. In those types, Minimum Cut is mentioned as

C (E,F) = $\sum_{u \in E, u \in F} w(u,v)$...Eq.5

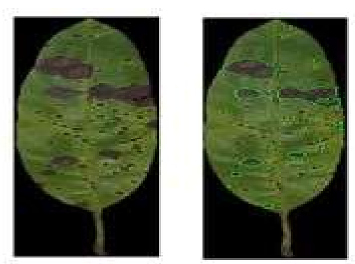
where E and F is considered as two partitioned disjoint sets. However Minimum Cut is a cut with a minimum number of edges and it partitions the graph into clusters using Highly Connected Sub graph technique where cluster considered as segments. Minimum cut separates Graph into subgraph H and H^1. Highly Connected Subgraph is a induced subgraph H in Graph G such that H is highly

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

connected. Condition for grouping the segments of the pixels in the image spaces is

Graph with vertices n>1 is likely to be connected if its edge connectivity K(G)>n/2

Single vertices are considered as segment and it is grouped into singleton set S using normalized cut on basis of association between the pixel values of two vertices. Figure 2 represent the disease region segmentation with boundary lines.



(a) (b)

Figure 2: Image Segmentation

(a) Pre-Processed Image (b) Segmentation Image

3.3. Feature extraction – Principle Component Analysis

In this section , feature extraction of the plant leaf's morphological characteristics based on its contour and shape. Morphological feature[11] includes invariable moment features and geometric features. Sphericity, circularity, aspect ratio, convexity, perimeter ratio, rectangularity, and form factor are some of the geometric characteristics of plant leaves. The angle code histogram and the regional moment of inertia are constant moment features. Further diameter, length, width , area and perimeter is obtained for each segment of the image.

Principle component analysis generate the most distinguishing morphological features of the leaf. It initiates with statistical calculation of the image segment matrix. Image segment matrix calculate the mean and variance for each element to identify pattern and express the features. It describes the feature of the image on basis of variance. Each principle component(feature) of the image segment describes with large variance. Variance Computation is represented as

$$\text{var}(x) = \frac{\sum_{i=1}^{n} a(xi - x)\ (xi - x)}{n-1} \text{...Eq.6}$$

However identifying the features in the image segment is highly complex. Hence principle component analysis identifies the significant features on reducing the irrelevant features in images using variance computation. Resultant feature is represented in the matrix for further processing. Feature Matrix containing uncorrelated variable is processed to obtain the correlation and covariance matrix. Those matrix output the Eigen vector with Eigen values[13].

Covariance is calculated for the E and F pixel elements in the image segment which changes together with mean is as follows

$$\text{Cov(E,F)} = \frac{\sum_{i=1}^{n} a(ei - e)\ (fi - f)}{n-1} \text{...Eq.7}$$

Covariance Matrix is a N*N Matrix, where each pixel element is represented by

$$M_{ij} = \text{Cov}(e,f) \text{..Eq.8}$$

Eigen Vector of M_{ij} is a vector represents of principle feature and its features values as Eigen value for classification or recognition. Definition of features obtained from the principle component analysis is as follows

- Aspect Ratio: The aspect ratio, which is the ratio of the minimal bounding rectangle's maximum length (L_max) to its minimum length (L_min), is thought of as the proportionality relationship between each pixel element's height and width.
  $AR = \frac{L_{max}}{L_{min}}$..Eq.9
- Rectangularity(R) : Rectangularity is defined as the ratio of the ROI area to the MBR area and is a measure of how similar the leaf is to a rectangle. $R = \frac{A_{ROI}}{\frac{L_{Max}}{L_{min}}}$..Eq.10
- Circularity : Circularity is based on the bounding points of the ROI and is the ratio of the mean distance between centre of ROI and all the bounding points (μR) and the quadratic mean deviation of the mean distance (sR)
  $C = \frac{\mu R}{sR} .. Eq.11$
- Convex Ratio: Convex ratio is the ratio of the pixel element's ROI to convex hull area (AC).
  $CAR = \frac{A_{ROI}}{AC}$..Eq.12

- Perimeter Ratio: Perimeter Ratio of the ROI perimeter and convex hull perimeter(PC) of the pixel element

  CPR = $\frac{P_{ROI}}{PC}$..Eq.13
- Sphericity(S) : The ratio between the segment's ROI's incircle radius (ri) and its encircle radius (rc)

  S= $\frac{r_i}{r_c}$..Eq.14
- Form factor : Form factor is considered shape description characteristic of the pixel element.

  FF= $\frac{4\pi A_{ROI}}{P^2{}_{ROI}}$..Eq.15

Morphological feature Vector of the segment = { diameter, length , width , area and perimeter sphericity, circularity, aspect ratio, convex ratio, perimeter ratio, rectangularity and form factor }

3.4. Feature Selection – Grey Wolf Optimization Algorithm

Feature selection approach using Grey Wolf Optimization algorithm[14] is to select the optimal feature for the plant disease classification of mango leaf on the morphological feature vector which is considered as search space. It searches the optimal feature from feature vector of all the segments in the image. Figure 3 illustrates the proposed architecture of the multivariate gated recurrent network.

Grey wolf optimization algorithm selects subset of the morphological feature on the feature set from the multiple segment of the image with objective that correlation between the selected feature should be minimum[15]. Optimal selection process is as follows

- Initially, grey wolf population I_i is generated using morphological features by dividing it into three categories such as α,β,γ
- Set leader any among three categories to make the decision related to other feature to be selected(prey)
- Feature(prey) in the population is evaluated using fitness function. It identifies the behaviour of wolf(optimal feature set) towards prey(normal features).It is represented as coefficient vector J and K with I representing the position vector of the grey wolf and I_p indicating position vector of prey and t refer the current iteration

Feature selection computation is represented in form of Hunting behavior of the wolf

A = $|xI_p(t)-I(t)|$..Eq.16

Position of feature leader is represented as Position Vector of the Wolf

$I(t+1)=I_p(t)-J*A$...Eq.17

Coefficient Vector is represented as

J= $2a*r_1-a$ & X=$2r_2$..Eq.18

Updated position of wolf which provides optimal features selection is represented by

$I(t+1) = \frac{I_1+I_2+I_3}{3}$ ..Eq.19

Position of wolfs is considered as feature is represented as I_α , I_β, I_γ . Optimal feature is selected on basis of best position of wolfs. The objective function of the GWO is minimization of correlation between the two morphological features.

I(E,F) =min(correlation)

Correlation = $\frac{n\sum ab-\sum a\sum b}{\sqrt{(n\sum a^2-(\sum a)^2-(n\sum b^2-(\sum b)^2}}$..Eq.20

Optimal feature from different segments = {feature 1, feature 2, feature 3, feature 4,…feature n}

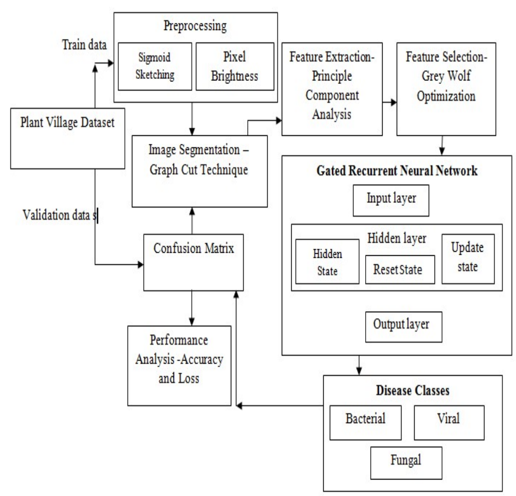


Figure 3: Proposed Architecture

3.5. Disease classification using Multivariate Gated Recurrent Neural Network

Multivariate Gated Recurrent Neural Network is evolution of the Recurrent neural network to solve the vanishing gradient challenges occurs during recurrent determination

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and it becomes simple through associating gating mechanism. Gating mechanism is a simple long term short memory process the feature with reduced network parameters. Gated Neural Network uses candidate activation feature vector through reset gate and update gate. Between the two gates, the update gate defines how many activation vectors should be added to hidden states, while the reset gate determines how many hidden states with feature vectors should be forgotten. Gated recurrent Neural Network composed of the following layer

- **Input layer :**

Input layer obtains the optimal feature vector and it is processed further in the various layer of the Gated recurrent Network. It constructs the hidden states to hidden layer to process the optimal feature of the disease segments. Hidden state is represented through following equation

Hidden state $h_t = (1-z_t)*h_{t-1} + z_t *h_{t}$...Eq.21

where ht-1 is the previous hidden state, ht is the current hidden state, Wr is learnable weight matrices, and xt is the input feature to the hidden state at each time step.

- **Hidden Layer**

In this layer, Recurrent computation of the features is carried out. The current input and past hidden states are used to update the hidden state for each computation. Hidden state is considered as vector which represents the memory of previous inputs. Gating mechanism is used to update the hidden states at each time step to model the classifier to the optimal feature vector. Further it applies respective activation function to each gate to process the parameterized vectors.

- **Reset gate**

Reset gate is used to compute the no of the hidden state to be forgotten on obtaining the previous hidden states and current feature vector. It generates a vector between 0 and 1 that determines how much the prior concealed state is reset during the current iteration. It takes current input and previous hidden states as vectors through feature wise multiplications. It process on basis of respective weight of the feature. It is computed using following equation

$r_t = \text{sigmoid}(w_r * h_{t-1}, x_t)$..Eq.22

Table 1: Model Parameter of Gated Recurrent Neural Network

Parameter	Value
Window Size	30
No of neurons in the hidden state	50
Batch size	50
Epoch size	50
Learning rate	10^{-2}
Loss Function	Mean Square Error

- **Update gate**

Update gate is used to compute the no of activation vector to be incorporated into the new hidden state on obtaining the previous hidden states and current feature vector. It produces the vector between 0 to 1 which controls the degree to which activation vector is incorporated into new hidden state. It uses the back propagation for differential chain formation to train network. It is computed using following equation

$Z_t = \text{sigmoid}(w_z * h_{t-1}, x_t)$...Eq.23

- **Candidate Activation Vector**

Candidate Activation Vector is a modified vector of representing the prior hidden state that is combined with the current feature vector after being reset by the reset gate. It uses the activation function such as Rectified Liner unit and sigmoid function which obtains the output between -1 and 1. Training parameter of the gated recurrent neural network is mentioned in the table 1. Further vector is computed using following equation

$h_t = \tanh(w_h *(r_t * h_{t-1}, x_t)$..Eq.24

- **Output layer**

Output layer utilizes the final hidden state as input and produce the classification output on incorporating the support vector machine or K-nearest neighbour classifier functions . It can be single disease class or sequence of disease classes. Predicted class y_t to the disease features. Further error function is used to reduce the classification error on the summation of the gradients at each time step. Error function of the derivates is represented as mean square function

Classification Error $E_t = y_t \log(y_t)$...Eq.25

Mean Square Function $= \frac{1}{N}\sum_{i=1}^{N}(y_n - f_n)^2$ ..Eq.26

Algorithm 1: Gated Recurrent Neural Network

Input: Mango leaf Disease Features

Output: Disease Classes
Process
Image Preprocess _ Image Normalization Method ()
Set bounding = 256*256
Sigmoid Sketching ()
Compute Histogram to dark and light pixel elements of the image()
Gaussian Histogram (Image)
Apply Cumulative Distribution Function()
Histogram Aggregation (Gh1,Gh2,Gh3)
Color mapping Curve()
Restructure the pixel Distribution on specified histogram
Pixel Brightness Transformation_Pigeonhole()
Gamma Correction ()
Continuous Mapping Function ()
Smoothness operation (Non parametric variables of the pixel)
Adjust and corrects the brightness of the image pixel positions
Calculate mean brightness of the image = Pixel Brightness
Segmentation _Graph Cut ()
Compute Undirected Weighted Graph ()
G=(V,E)
Determines vertices and Edges
Partition set of vertices into disjoint sets
Determine Edge Connectivity()
If (Graph with Vertices > 1)
Connect the similar vertices to form segment
Feature Extraction_ Principle Component Analysis ()
Morphological feature (Disease Segment)
Compute Covariance and Correlation Matrix
Eigen vector = { diameter, length , width , area and perimeter sphericity, circularity, aspect ratio, convex ratio, perimeter ratio, rectangularity and form factor}
Feature Selection ()
Grey Wolf optimization Algorithm ()
Initialization (feature as population)
Set as α ,β ,γ as best features on weighted operations
Select the leader among best features
Coefficient vector ()
update the position of the features
Fitness = Objective Function (correlated features)
Optimal features = {Feature 1, Feature 2, Feature 3}
Multivariate Gated Recurrent Neural Network ()
Input layer ()
Initialize the hidden state with features
Hidden layer ()
Process the feature into groups with hidden states
Reset State ()
Compute no of the previous hidden state to be forgotten
update state ()
Compute no of the activation feature vector to be incorporated to the hidden states
Candidate activation vector()
Vector of hidden state with current feature()
Output layer ()
Classifies the hidden state feature on basis of classification function.
Classifier = SVM(hidden State feature maps)
Class labeling = { Viral, Bacterial, Fungal }
Loss layer ()
Loss Function _Mean Square Error (Disease Class features)

4. EXPERIMENTAL RESULTS

Experimental analysis is carried out in the Tensorflow and keras framework using plant village dataset[17],a model which helps to identify the mango leaf disease into various disease classes on multiple disease types. Model tuned with hyper parameter of the different layer of the inception modules generates effective disease classes to the validation images. Multivariate gated recurrent neural network designed in the Google colab as it provides

Journal of Theoretical and Applied Information Technology
15th December 2024. Vol.102. No. 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

online python environment for model training and testing. In this environment configuration of proposed architecture, 20 percent of the image dataset is used for validation, while the remaining 80 percent is used for training.

Further, to prevent overfitting problems, additional batch size, learning rate, and epoch value have been set to stop the mechanism. Confusion matrices for cross-fold validations have been used to access the illness feature's classification and detection performance on the segmented region [16].To enhance the precision of identifying mango leaf disease in the segmented areas of mango plant leaves are classified as bacterial, fungal, viral, etc.. This work uses a multivariate gated recurrent neural network architecture. The current methodology provides the improved outcomes on determining the varied size diseased region using cross over and mutation process of the new generation to the population and its characteristics using staged genetic algorithm

4.1. Performance Evaluation metrics

Based on training and validation accuracy and training and validation loss, the model's performance has been evaluated. The precision and recall values have been calculated using the confusion matrix for the detection and classification of mango plant leaves at different stages of growth. Confusion Matrix is provided as figure 4.

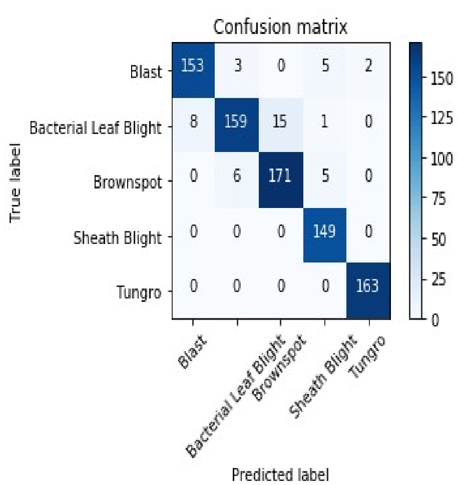


Figure 4: Confusion Matrix

- **Precision**

It is computed as the variation between the segment features' classification results. In other words, it can be computed using the classification findings true positive, false positive, and false negative values. It is represented as

$$\text{Precision} = \frac{2TP}{2TP+F\quad +FN} \quad ...\text{Eq.27}$$

- **Recall**

It is computed as the proportion of True Positives that correctly identify the disease features among a variety of features. It is represented as

$$\text{Recall} = \frac{TP}{TP+FN} ..\text{Eq.28}$$

Table 2: Performance Evaluation of Mango Leaf Disease Classification Techniques on different disease

Disease	Technique	Training Accuracy	Validation Accuracy	Training loss	Validation Loss
Brown spot	Deep Inception V5 Convolutional Neural Network-Existing model	0.9999	0.9919	0.689	0.612
	Multivariate Gated Recurrent Neural Network-Proposed model	0.9999	0.9947	0.601	0.589
Bacterial Leaf Blight	Deep Inception V5 Convolutional Neural Network-Existing model	0.9998	0.9902	0.691	0.628
	Multivariate Gated Recurrent	0.9999	0.9942	0.615	0.549

	Neural Network-Proposed model				
Blast	Deep Inception V5 Convolutional Neural Network-Existing model	0.9999	0.9921	0.689	0.629
	Multivariate Gated Recurrent Neural Network-Proposed model	0.9999	0.9987	0.623	0.574
Tungro	Deep Inception V5 Convolutional Neural Network-Existing model	0.9995	0.9925	0.689	0.678
	Multivariate Gated Recurrent Neural Network-Existing model	0.9998	0.9987	0.622	0.631
Sheath Blight	Deep Inception V5 Convolutional Neural Network-Existing model	0.9998	0.9965	0.671	0.689
	Multivariate Gated Recurrent Neural Network-Proposed model	0.9999	0.9978	0.615	0.628

- **Accuracy**

It is an estimate of the True Negative percentage that precisely computes the non-disease attributes based on image features.. It is represented as

$$\text{Accuracy} = \frac{\text{TP}}{TP+FN} \text{..Eq.29}$$

Several mango disease samples from the Plant Village dataset were studied in order to determine the type of disease and classify it using the current method, which has been evaluated for accuracy in both training and validation.is shown in Table 2. It demonstrates that current architecture classifies leaf disease of mango plant accurately. Gated Recurrent Neural Network with grey wolf optimization provides increased efficiency on compared with state of art Recurrent Neural Network. The current model produces the enhanced performance with hyper parameter modification [17].

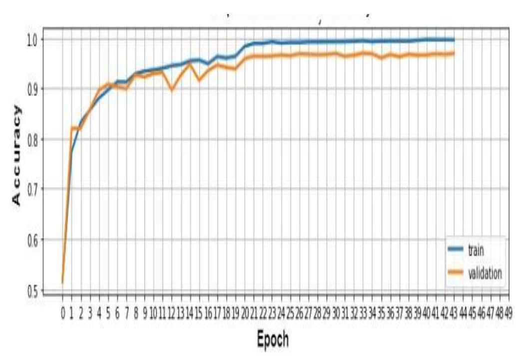


Figure 5: Accuracy of the current Architecture

The performance of the current design in terms of training and validation accuracy of the training and testing data for detecting leaf disease and categorizing it using the recommended deep learning architecture is demonstrated in Figure 5. The current architecture's training and validation losses are depicted in Figure 6 on the identification and classification of disease types.

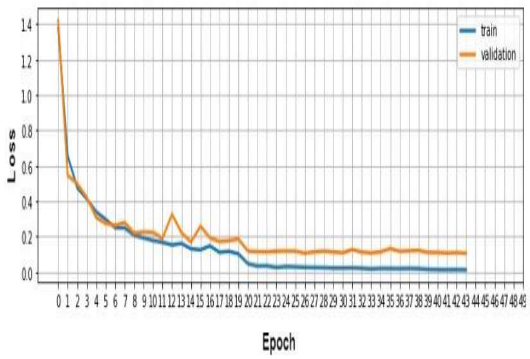


Figure 6: Loss Computation of the Current Architecture

The performance of proposed network is high suitable to other horticulture plant diseases. Instead, optimal features to plant types during training can be carried out using any metaheuristic approaches.

CONCLUSION

In this article, design and development of multivariate gated recurrent neural network on optimization using grey wolf optimization algorithm is used to identify and categorize the mango leaf disease. Initially, the plant village dataset is preprocessed using pixel brightness transformation and sigmoid sketching techniques. The preprocessed image is applied to graph cut segmentation technique to segment preprocessed image into several disease segments containing infected mango leaves parts. Next, Segmented region is applied to principle component analysis technique to extract the morphological feature. Further optimal feature were selected towards classification using grey wolf optimization algorithm. Finally, a model of a gated recurrent neural network architecture is created in order to choose the best feature based on reset and update states. Anthracnose, powdery mildew, phoma blight, algal leaf spot, and other common mango leaf diseases can be represented by a specific trained model that increases computation speed and classification accuracy in identifying and classifying the affected plant leaf region with little variance. This work creates new knowledge in the domain by illustrating the effectiveness of bio-inspired optimization techniques with advanced recurrent networks for high-precision plant disease diagnostics, supporting the broader aim of sustainable agriculture through technology. The GWO-optimized GRU model may be extended to other crops in future research, even though current study concentrates on mango leaf disease. Validating the applicability and efficacy of this method across a range of agricultural domains would involve testing it on diseases that impact other plants, such as wheat, tomatoes, or apples.

REFERENCES:

[1] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM pp: 84–90,2017.
[2] Smita Naikwadi, Niket Amoda, Advances in image processing for detection of plant diseases, Int. J. App. Innov. Eng. Manage. Vol.2, 2013
[3] Prakash M. Mainkar, Shreekant Ghorpade, Mayur Adawadkar, Plant leaf disease detection and classification using image processing techniques, Int. J. Innov. Emerg. Res. Eng. Vol.2 issue .4, pp: 139–144, 2015.
[4] Sammy V. Militante, Bobby D. Gerardo, Nanette V. Dionisio, Plant leaf detection and disease recognition using deep learning, 2019 IEEE Eurasia Conference on IoT, Communication and Engineering (ECICE). IEEE, 2019.
[5] Sunayana Arya, Rajeev Singh, A comparative study of CNN and AlexNet for detection of disease in potato and mango leaf, 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), 1, IEEE, 2019.
[6] Shivali Amit Wagle, Harikrishnan R "Comparison of Plant Leaf Classification Using Modified AlexNet and Support Vector Machine" Department of E&TC, Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University) (SIU), Lavale, Pune 412115, India
[7] Md Rasel Mia, et al., Mango leaf disease recognition using neural network and support vector machine, Iran Journal of Computer Science 3 (3) (2020) 185–193.
[8] Junde Chena, Jinxiu Chena, Defu Zhanga, Yuandong Sunb, Y.A. Nanehkarana, in: Using Deep Transfer Learning for Image-Based Plant Disease Identification, Elsevier B.V., 2020, pp. 0168–1699. /Published by.
[9] F. Islam, M.N. Hoq, C.M. Rahman, Application of transfer learning to detect potato disease from leaf image, in: 2019

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IEEE International Conference on Robotics, Automation, Artificial-intelligence and Internet- of-Things (RAAICON), Dhaka, Bangladesh, 2019, pp. 127–130,

[10] Siddharth Singh Chouhan, Ajay Kaul, Uday Pratap Singh, Sanjeev Jain "Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology"IEEE Access, Vol.6,2018.

[11] Khalid M. Hosny, Walaa M. El-Hady, Farid M. Samy, Eleni Vrochidou, George A. Papakostas "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern" IEEE Access, Vol.11, 2023.

[12] Serosh Karim Noon, Muhammad Amjad, Muhammad Ali Qureshi, Abdul Mannan" Handling Severity Levels of Multiple Co-Occurring Cotton Plant Diseases Using Improved YOLOX Model" IEEE Access, Vol.10,2022.

[13] Tan Nhat Pham, Ly Van Tran, Son Vu Truong Dao"Early Disease Classification of Mango Leaves Using Feed-Forward Neural Network and Hybrid Metaheuristic Feature Selection" IEEE access, vol.8, 2022.

[14] K. P. Ferentinos, ''Deep learning models for plant disease detection and diagnosis,'' Comput. Electron. Agricult., vol. 145, pp. 311–318, Feb. 2018.

[15] B. Liu, Y. Zhang, D. He, and Y. Li, ''Identification of apple leaf diseases based on deep convolutional neural networks,'' Symmetry, vol. 10, no. 1, p. 11, Dec. 2017.

[16] A. Fuentes, S. Yoon, S. Kim, and D. Park, ''A robust deep-learningbased detector for real-time tomato plant diseases and pests recognition,'' Sensors, vol. 17, no. 9, p. 2022, Sep. 2017.

[17] J. Lu, J. Hu, G. Zhao, F. Mei, and C. Zhang,''An in-field automatic wheat disease diagnosis s system,'' Comput. Electron. Agricult., vol. 142, pp. 369–379, Nov. 2017.

[18].M.Prabu and Balika J.Chelliah "Mango leaf disease identification and classification using a CNN architecture optimized by crossover-based levy flight distribution algorithm" Neural Computing and Applications, Springer, Vol.34, PP: 7311-7324, 2022

[19]. Rabia Saleem , Jammal Hussain Shah, Muhammed Sharif "Mango Leaf Disease Identification Using Fully Resolution Convolutional Network", Computer, Materials and Continua , Tech science press publisher, 2021

[20].Rama Koteswara Rao and Swathi" mango leaf disease detection using modified multi support vector machine "palarch journal of archaeology of egypt"Vol.17, 2020.

[21]. Amirtha Preeya V,S.Pravinth Raja, B K Dhanalakshmi, HL Gururaj,Vinayakumar Ravi,Pradeep Ravi, "Perceptual Pigeon Galvanized Optimization of Multi-objective CNN on the Identification and Classification of Mango Leaves Disease",The Open Agriculture Journal,Vol.18, 2024.