International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
***Article Received**: 26 March 2023 **Revised**: 29 April 2023 **Accepted**: 17 June 2023*

A Novel Paddy Leaf Disease Detection Framework using Optimal Leaf Disease Features in Adaptive Deep Temporal Context Network

Rongali Divya Kanti[1], G.Sasibhusana Rao[2], S.Aruna[3], Rajkumar Goswami[4]
[1]Research Scholar,
Department Of ECE,
AU College of Engineering ,Andhra University
Visakhapatnam,
Andhra Pradessh, India.
divya.kanti74@gmail.com
[2]Senior Professor & Principal
Department Of ECE,
AU College of Engineering,Andhra University
Visakhapatnam, pin code:530003
Andhra Pradesh, India
sasi_gps@yahoo.co.in
[3]Assistant Professor & HOD
Department Of ECE
AU College of Engg. for women,Andhra University
Visakhapatnam, pin code:530003
Andhra Pradesh, India
dr.saruna@andhrauniversity.edu.in
[4]Professor & Principal,
Department of ECE,Gayatri Vidya Parishad College of Engineering for Women (GVPCEW),
Visakhapatnam,Pin Code :530048,
Andhra Pradesh,India,
rajkumargoswami@gmail.com

Abstract— Since paddy has become the staple food for all human beings, crop productivity is highly demanded. Nowadays, the agriculture industry faces the leaf disease issue as the insect or pests affects the plant leaves to hinder further growth. Owing to this, the productivity gets affected that makes the farmers have economic loss. In earlier time, several methods have been explored to detect the disease significantly. However, such methods become more time consuming, structure complexity and other issues. To alleviate such complex, a new paddy leaf disease detection model is proposed using adaptive methodology. Initially, images related with paddy leaf are gathered from standard resources and offered as the input to segmentation region. Here, segmentation is performed by Fuzzy C-Means (FCM) to get the abnormal regions. Then, the segmented images are fed to ensemble feature extraction region to attain different features like deep, textural, morphological, and color features. Further, the acquired ensemble features are provided to concatenation phase to obtain the concatenate features and the optimal features are selected by the Fire Hawk Optimizer (FHO). Finally, the optimal features are subjected to paddy leaf detection phase, where leaf disease will be detected by Adaptive Deep Temporal Context Network (ADTCN), where the parameters are tuned by the FHO. Hence, the developed model secures efficient leaf disease detection rate than the classical techniques in the experiential analysis.

Keywords- Paddy Leaf Disease Detection; Fuzzy C-Means; Ensemble Feaures; Optimal Feature Selection; Fire Hawk Optimizer; Adaptive Deep Temporal Context Network.

I. INTRODUCTION

In the agriculture world, paddy is the most significant crop that is grown in most of the states in India. Rather than other food crops, paddy satisfies the human appetite in many scenarios [6]. However, environmental damage affects food production and causes economic loss. Nevertheless, the pests or insects are placed over the leaf, affecting the crop yield, resulting in leaf disease. The two major insects such as “cnaphalocrocis medinalis and Scirpophaga incertulas” worsen to yield the huge loss [7]. Hence, detecting leaf disease is a highly demanded job that evades the crop damage. When the disease is spread all over the leaf, the disease detection or identification is cumbersome [8]. Some manual methods did not give the proper results to forecast the disease, as it may incur human error, more time consuming and so on. Henceforth, the computerized automated detection model is suggested to discover the disease earlier [9]. Also, the manual process becomes inconsistent that degrades the system efficiency.

When it comes to the disease detection method, segmentation is a significant part that aids to extract the abnormal regions of paddy leaf images. Further, the noteworthy features are extracted from the segmented image to improve the performance [10]. However, these methods are facing the limitation that hinders to develop the effective model. As the raw image is considered, it contains noisy, artifacts or blur regions. This may affect the image quality and cannot be able to provide the appropriate abnormal parts [11]. Due to such factors, the accuracy and precision level gets reduced and also it mitigates the system robustness. Machine learning methods are used to classify the leaf disease; still, it cannot provide the proper results [12]. Though it contains the advantages of expertise in the classification task, the downside factors get pulled down in detecting the disease [13]. Hence, a limited works have done in the leaf disease detection field with the help of machine learning, it becomes too far from the desired value.

Contrary to the machine learning methods, deep learning approach is implemented in recent years to detect the leaf disease significantly. It has the ability to address the existing issues of detection model [14]. In general, the deep learning models are constructed with multiple layers that train the model to estimate the classified outcome as either normal or abnormal state. " Convolutional Neural Network (CNN)" [15] is the most common method while design the automated model, where the features have been learnt. Yet, these approaches have also contained disadvantage like computation burden, time complexity and over fitting issue. Thus, all these issues motivate to frame the new deep learning model for paddy leaf disease detection.

The main contributions of the model are summarized as below.

- To develop the novel paddy leaf disease detection method using heuristic-assisted deep learning model for identifying the leaf disease to improve the crop productivity.
- To utilize the FCM clustering for segmenting the abnormal regions of leaf images that helps to classify the diseases accurately.
- To extract the deep, temporal, color and morphological features and concatenate with each other, which is then used to select the optimum features using FHO to maximize the correlation coefficient and variance.
- To develop the classification model named ADTCN for predicting the various types of disease, in which the parameters are tuned using FHO to increase the accuracy level.
- To examine the efficacy of the system using diverse metrics and compared among other traditional approaches.

The introduction is followed by the literature on paddy leaf disease detection mentioned in Part II. Part III depicts the architectural depiction of proposed methodology. Ensemble features and optimal feature selection is illustrated in Part IV. Part V describes the suggested detection methodology of paddy leaf diseases. Finally, the simulation results are discussed in Part VI. Also, the conclusion of work is shown in Part VII.

II. LITERATURE SURVEY

A. Existing Works

In 2022, Amin *et al.* [1] have considered the different learning methods for identifying the leaf disease in corn plants. The enhanced model has structured with two CNNs as "EfficientNetB0, and DenseNet121". The deep features were extracted from each CNN from the input images, which was then taken to feature fusion. Finally, the classification was done to found the disease affected leaves. Performance was examined and the results were computed using different metrics. When compared with existing works, the proposed methodology has attained the higher results to maximize the efficiency.

In 2021, Khattak *et al.* [2] have suggested the CNN for leaf disease classification. The source images were taken from "Citrus and Plant Village". It was followed by feature extraction phase, where the most discriminative features were obtained. The efficacy of the system has been evaluated and compared among conventional methods. Hence, the suggested method has outperformed with the classification process for increasing the farmer economic value.

In 2020, Nigam *et al.* [3] have utilized the heuristic-based deep learning model for disease classification. The foremost step was the image acquisition using standard data sources. The abnormal regions were segmented by "k means clustering". Further, the relevant features were determined using "Principal Component Analysis (PCA), " fed into the BFO-DNN model. This mode was classified the images into either healthy or unhealthy images. Finally, the simulation outcome has illustrated that it has increased the system efficiency.

In 2020, Ramesh and Vydeki [4] have proposed the Jaya Algorithm (JA) along with DNN for paddy leaf disease detection. The leaf images of rice plant was gathered and fed into the pre-processing stage. Subsequently, the abnormal

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
***Article Received**: 26 March 2023 **Revised**: 29 April 2023 **Accepted**: 17 June 2023*

segmentation was done by clustering mechanism. Finally, the segmented image was given to JA-based DNN model for detecting the leaf disease. Thus, divergent measures have taken to analyze the model and compared with baseline methods to ensure the system effectiveness.

In 2021, Abed *et al.* [5] have explored the intelligent detection model of bean leaf diseases. Initially, the U-Net based ResNet 34 model has been employed to capture the abnormal regions. Further, the five classifiers like “ResNet34, Densenet121, VGG-16, ResNet50 and VGG-19” were considered. Amongst, the Densenet 121 has provided the better classification results that became easier to avoid the crop damage.

B. *Problem Statement*

One of the most prominent research topics in agriculture relies on the accurate detection of paddy leaf diseases for the early prevention of productivity loss. It may also cause high environmental losses. Deep learning methods have recently obtained promising results leads to apply them to the challenge of recognizing paddy leaf diseases. Many researchers have developed many techniques to solve the problems on association between rule patterns; few techniques are described in Table 1. CNN [1] reduces the time for training the model and it increases the detection rate with high accuracy. But it requires more processing power and also it acquires large parameter size in the models to get better results.CNN [2] extracts complementary discriminative features and tackles the problem of classifying diseases. But the performance becomes less prominent if the number of hidden layer is more than 2 and the images used in leaf disease dataset is smaller, which is also a limitation.DNN[3] reduces the entropy loss as well as it consumes minimum effort and time. However, the regular monitoring of specialists in the huge farm probably will be expensive and requires huge amount of data. DNN-JOA [4] process results in low computational complexity and the testing accuracy increases with the increase in the samples. But, it is a time consuming process and sometimes the false classifications may occur during the classification of plant diseases. Deep learning in Robotic vision [5] helps in solving the problem to identify the healthiness status of plants in addition to this there is no need for user interventions. But, the number of images within the dataset for each class was relatively small to reveal the performance and to prove the reliability large datasets will be needed which is a disadvantage in some cases. These drawbacks associated with the classical paddy leaf disease detection approaches are need to resolve, and thus a novel paddy leaf disease detection framework is designed based on deep learning approaches.

III. PRESENTING THE NOVEL PADDY LEAF DISEASE DETECTION FRAMEWORK: ADAPTIVE DEEP LEARNING

A. *System Model of Proposed Paddy Leaf Disease Detection*

Paddy is the most important crop in the agriculture industry that improves the economic value. In recent years, the crops get affected due to the presence of insects or pests in the leaf. Owing to this, the farmer may lose crop production, affecting their financial crisis. Hence, the classification of paddy leaf disease is requisite. Former methods are used to detect the disease, still it holds some lacking points to estimate the accurate value. Therefore, the recent developed model as deep learning classifier is used to facilitate the impressive results. To accomplish this, an adaptive model is proposed. At the initial stage, the raw images are fetched from standard sources. It is then followed by the abnormality segmentation using FCM. Subsequently, the texture, morphological and color features are extracted from the segmented images. Similarly, the deep features are also acquired using CNN. Further, all the resultant features are fused together, where the optimal features are also selected using FHO. Finally, the optimal features are subjected into ADTCN for classifying the leaf disease. Therefore, the empirical results are obtained that can be able to improve the system efficiency. Fig. 1 shows the diagrammatic representation of proposed disease detection model.

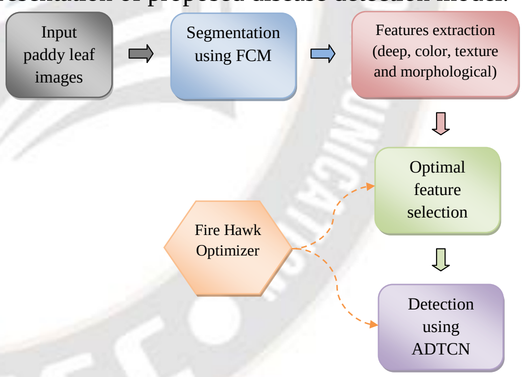


Fig.1. Diagram of proposed novel paddy leaf disease detection using adaptive deep learning

B. *Collection of Raw Leaf Images*

The paddy leaf images are fetched from the link as “https://www.kaggle.com/competitions/paddy-disease-classification/data: Access Date: 2023-04-06”. The dataset is named as “Paddy Doctor: Paddy Disease Classification”. The dataset contains 10 classes, in which 9 classes are belongs to disease and one class for healthy leaf. It comprises of 75% of training data corresponds to 10,407 images and 25% of testing data corresponds to 3,469 images. Hence, the input leaf image is noted as L_u, where the term u varies from 1 to total number of paddy leaf images.

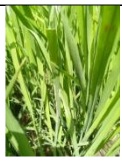
Sample images	1	2	3	4	5
Disease name	"blast"	"brown spot"	"hispa"	"normal"	"tungro"
Leaf images					

Fig.2 .Sample images of different leaf images with disease names

C. *FCM-based Abnormal Segmentation*

The FCM [22] is a unique clustering process to segment the abnormal regions of raw leaf images. It is mainly processed by considering the fuzzy membership function. Here, the input image L_u is taken used for generating the different cluster groups. Consider the image as L that constitutes M number of pixels, which is represented by $L = (l_1, l_2, \ldots l_M)$. Hence, the total pixels in images are distinguished into create the T clusters. The objective function of FCM is derived using Eq. (1).

$$F = \sum_{x=1}^{M} \sum_{y=1}^{T} \lambda_{xy}^{n} \left\| l_x - r_y \right\|^2 \tag{1}$$

Here, λ_{xy} means the membership function of x^{th} pixel of y^{th} cluster, the norm metric is identified by $\|\cdot\|$ and n is the fuzziness parameter. The membership function is determined using Eq. (2) and cluster center is calculated by Eq. (3).

$$\lambda_{xy} = \frac{1}{\sum_{z=1}^{T} \left(\frac{\left\| l_x - r_y \right\|}{\left\| l_x - r_z \right\|} \right) 2/(n-1)} \tag{2}$$

$$r_y = \frac{\sum_{x=1}^{M} \lambda_{xy}^{n} l_x}{\sum_{x=1}^{M} \lambda_{xy}^{n}} \tag{3}$$

Therefore, the abnormal regions are segmented and it is denoted by L_u^{ab}.

IV. ENSEMBLE FEATURE EXTRACTION AND OPTIMAL FEATURE SELECTION FOR DETECTING THE LEAF DISEASE

A. *Ensemble Feature Extraction*

After the segmented image is obtained, the different feature extraction technique is used to find the relevant features. Here, the deep feature, morphological features, texture features and color features are extracted. The description of such methods is given below.

CNN: Firstly, the deep features are extracted using CNN model. Here, the segmented image L_u^{ab} is considered as input. CNN [23] is normally processed with multiple layers as "input, convolution, pooling and fully connected layer". Rather than other models, the CNN is so simple in nature to do the extracted process.

Convolution layer: Once the input is given, it forwards to the convolution layer, which performs the convolution operation with weights and bias term. It is also processed with filter, where the feature map is generated. Thus, the convolution operation is mathematically given in Eq. (4).

$$con = af\left[\left(w_j^t * L_u^{ab} \right) + bi_j^r \right] \tag{4}$$

Term, af specifies the activation function as "Rectified Linear Unit (ReLU)", r and j refers the layer and feature map.

Pooling layer: It helps to decrease the dimension of the convolution layer and is processed by the pooling operation. It is implemented on the image pixel values. Here, the max pooling is taken for providing the features. Thus, the extracted features are denoted by DF_a.

Morphological features [24]: Similarly, the morphological features are also determined from segmented image as L_u^{ab}. Rather extracting the features of raw image, the features of segmented image is significant. Due to this features, it emphasizes the visual representation. Since it becomes effective, it aids to increase the classification accuracy value. Conversely, different disease occurs in leaves, it affects the morphological traits. Thus, the extraction of morphological features is required and obtained in this section, which is indicated by MF_b.

Texture features: Image texture features are achieved via Grey Level Co-occurrence Matrix (GLCM) [25]. It mainly focuses on image texture characteristics by estimating the connection between the image pixels. In order to achieve this, the GLCM matrix is computed with multiple blocks, in which

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
Article Received: 26 March 2023 Revised: 29 April 2023 Accepted: 17 June 2023

different statistics are taken to extract the significant features. Hence it is marked by TF_c.

Color features: In general, the color image pixel is represented by the intensity value, which assists to visualize the abnormal parts of affected leaf images. The color features are commonly identified by using the histogram value. Therefore, the acquired features are signified by CF_c.

B. Feature Concatenation and Optimal Feature Selection

Through different methods, four feature sets are acquired, which are then concatenated together. The feature fusion is marked by $CF_f = \{DF_m, MF_m, TF_m, CF_m\}$. But, the feature is represented by large dimension manner and contains some non-optimum features, resulting in performance degradation. To overcome that, the optimal features are determined using the utilized FHO algorithm from the concatenated features. Hence, the selected optimal features are indicated as OF_m fitness function of the optimal feature selection is formulated using Eq. (5).

$$Obj(1) = \underset{\{OF_m\}}{\arg\max}\,[Crr + Vrce] \tag{5}$$

Here, the term Crr annotates the "correlation coefficient that defines the degree of relation between the features". Then, the variance is represented by $Vrce$ that refers as the "statistical measurement of the spread between features". The two measures are expressed in Eq. (6) and Eq. (7).

$$Crr = \frac{\sum(a-\bar{a})(b-\bar{b})}{\sqrt{\sum(a-\bar{a})^2 \sum(b-\bar{b})^2}} \tag{6}$$

$$Vrce = \frac{\sum(a-\bar{a})^2}{c-1} \tag{7}$$

V. Novel Detection Method using Adaptive Deep Temporal Context Network and Heuristic Algorithm

A. Fire Hawk Optimizer

FHO [16] is a heuristic algorithm for determining the optimal solution. It inspires by the natural behavior of fire hawk birds. It is intentionally create and spread the fire over the searching space. Further, the fire hawks can take the burnt sticks put on the other space to set the small fires. Due to this fire, it makes the attention to get the prey easily. When it tries to come near to fire, the search agents can easily to get the food sources. In order to perform the process, the fire hawk agents are initialized at random places in searching region. The position of FH is initialized using the maximum and minimum boundary level. The subsequent process is explained as below.

Over the selected foraging space, the bird gathers the burnt stick and placed in other non-fired places. To achieve this, the position is to be updated by flying the bird in the searching region. Thus, the new position is updated using Eq. (8).

$$H_i^{nw} = H_i + (rn_1 \times gb - rn_2 \times H_{nr}) \tag{8}$$

Here, the new position of i^{th} FH (H_i) is noted by H_i^{nw} and the global value is represented as gb. Further, the near FH is indicated by H_{nr} and the random value lies among 0 and 1 that is given in rn_1 and rn_2, respectively.

Inside the territory region, the prey gets moved from one place to another. When the stick is dropped, the prey easily moved away or near to the stick. Hence, the position updating is shown in Eq. (9).

$$P_j^{nw} = P_j + (rn_3 \times H_i - rn_4 \times sf_i) \tag{9}$$

Here, the new position of prey with respect to i^{th} FH is given as P_j^{nw}. Then, the term rn_3 and rn_4 is the random parameter lies between 0 and 1.

Similarly in outside of the territory, the new position is generated and it is formulated using Eq. (10).

$$P_j^{nw} = P_j + (rn_5 \times H_{alt} - rn_6 \times sf_i) \tag{10}$$

Terms rn_5 and rn_6 are the random number that ranges of [0, 1] and the other FH is mentioned by H_{alt}. Thus, the best optimum value is attained.

B. Adaptive DTCN with Parameter Optimization

The ADTCN is newly developed that is inferred from the concept of DTCN for classifying the plant leaf diseases. Normally, DTCN [26] is one kind of deep learning models entail with multiple layers for processing the classification task. When learning the model, "Temporal Context Learning (TCL)" aids to train the features by sequential as well as temporal with its context for prediction. Rather than other models, DTCN is adaptive in nature to represent the contextual information in time series manner, which is then correlated with trained data or features.

In this method, the two factors are taken as "Periodic Temporal Context (PTC) and Neighboring Temporal Context (NTC)". Here, the optimal features as OF_m are given as input. The former PTC is processed with preceding data sequence that provides the periodic pattern of long-term ranges. The latter NTC entails neighboring features of classification job, which is

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
Article Received: 26 March 2023 Revised: 29 April 2023 Accepted: 17 June 2023

inferred from the previous data series. All the data is representing the optimal features of abnormal segmented images. Hence, the discriminative function of both PTC and NTC is expressed using Eq. (11) and Eq.(12).

$$F_{PTC}(st_a, st_b) = \delta\left(mod\left(\frac{st_a - st_b}{\Delta st_{unit}} = 0\right)\right) \quad (11)$$

$$F_{NTC}(st_a, st_b) = \delta\left(\frac{st_a - st_b}{\Delta st_{unit}} < m\right) \quad (12)$$

As the model contains more layers and parameters, it needs more processing time. But, it affects the system efficiency and deduces the detection results. To sort out such complexity, certain parameters are optimized using FHO approach. Hence, the fitness function of ADTCN for disease detection is formulated using Eq. (13).

$$obj(2) = \underset{\{Hn,Ep,Af\}}{\arg\max}\left[Accy + Snty + maCc + \frac{1}{faPr}\right] \quad (13)$$

Here, the hidden neuron and activation function varies from 5 to 255, which is denoted as Hn and Af, correspondingly. Further, the epoch is indicated by Ep contains the range of [5, 50]. Similarly, the term "accuracy, sensitivity, Mathews Correlation Coefficient (maCc) and False Positive Rate (FPR)" is formulated using the below mentioned equations.

$$Accy = \frac{p^{te} + n^{te}}{p^{te} + n^{te} + p^{fa} + n^{fa}} \quad (14)$$

$$Snty = \frac{p^{te}}{p^{te} + n^{fa}} \quad (15)$$

$$maCc = \frac{p^{te} \times n^{te} - p^{fa} \times n^{fa}}{\sqrt{(p^{te} + p^{fa})(p^{te} + n^{fa})(n^{te} + p^{fa})(n^{te} + n^{fa})}} \quad (16)$$

$$faPr = \frac{p^{fa}}{p^{fa} + n^{te}} \quad (17)$$

Here, the "true positive, true negative, false positive and false negative" is specified by p^{te}, n^{te}, p^{fa} and n^{fa}, respectively. Fig. 3 illustrates the ADTCN for paddy leaf disease detection.

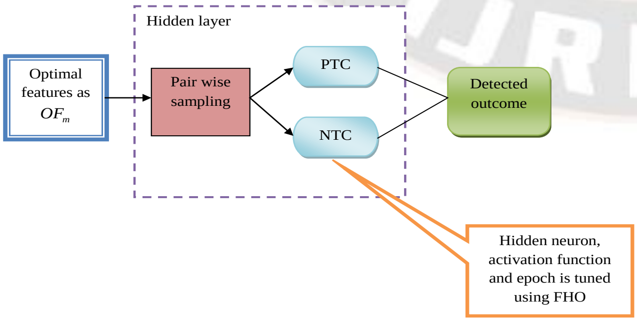


Fig.3. Schematic representation of ADTCN for disease classification model with parameter optimization of FHO.

VI. EXPERIMENTAL RESULTS ANALYSIS

A. *Simulation Setup*

Matlab R2019b tool was taken to execute the recommended paddy leaf disease detection model. The heuristic algorithm has considered the population size as 10 and total iteration count as 50. Existing algorithms such as Eurasian Oystercatcher Optimizer (EOO) [17], Rain Optimization Algorithm (ROA) [18], Tuna Swarm Optimization (TSO) [19] and Ageist Spider Monkey Optimization (ASMO) [20] were taken. Also, traditional classifier models were assumed as DNN [3], CNN [2], RNN [21] and DTCN [26].

B. *Different feature extraction technique analysis*

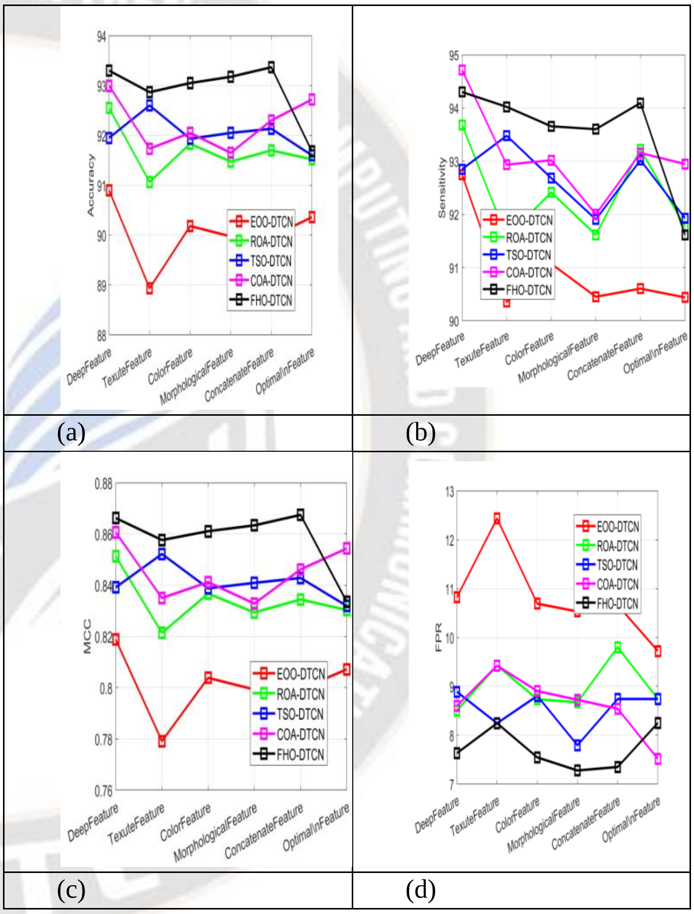


Fig. 4. Feature extraction analysis of the proposed paddy leaf disease detection model compared over heuristic algorithms concerning "(a)Accuracy, (b) Sensitivity, (c) MCC and (d) FPR"

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
***Article Received**: 26 March 2023 **Revised**: 29 April 2023 **Accepted**: 17 June 2023*

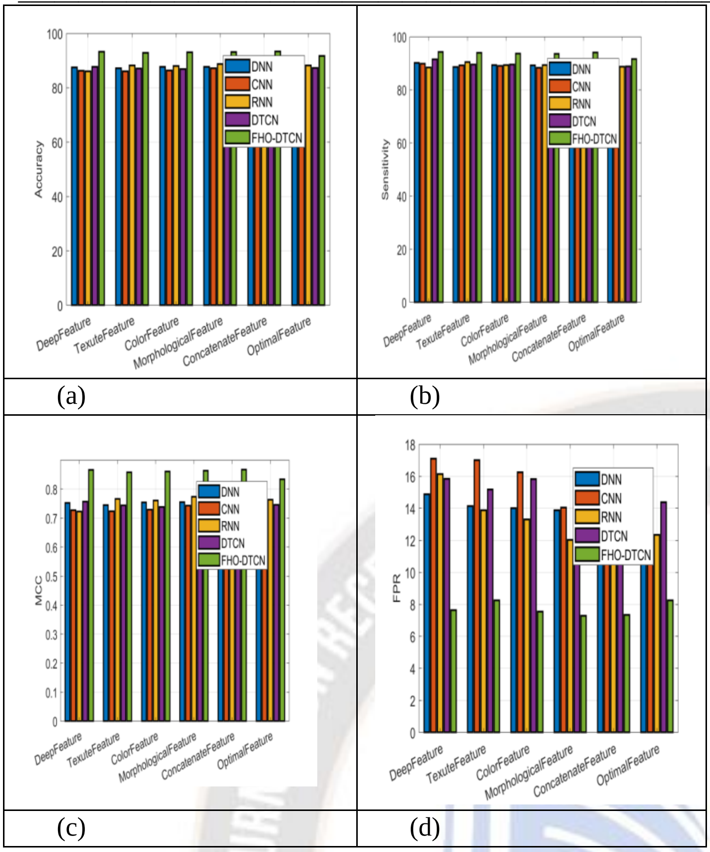


Fig.5 Feature extraction analysis of the proposed paddy leaf disease detection model compared over different classifiers concerning "(a)Accuracy, (b) Sensitivity, (c) MCC and (d) FPR"

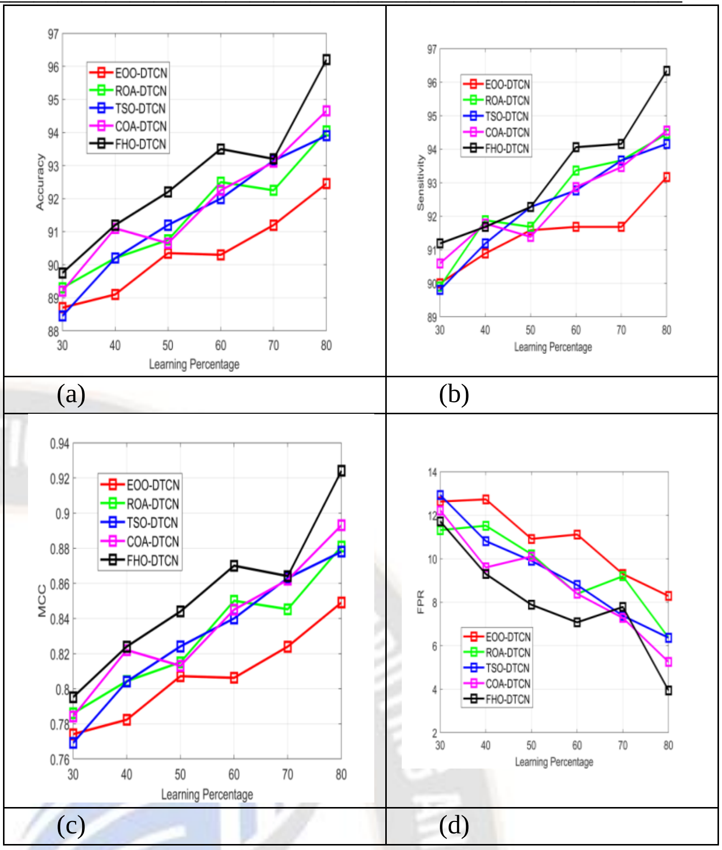


Fig.6. Performance analysis of the recommended paddy leaf disease detection model compared over heuristic algorithms concerning "(a)Accuracy, (b) Sensitivity, (c) MCC and (d) FPR"

Fig. 4 and Fig. 5 represent the feature extraction analysis of the proposed model and compared among traditional optimization and classifier model. Here, the performance is validated by different feature extraction and our proposed optimal feature selection. Fig. 5 (b) shows the specificity analysis of the proposed framework. While using concatenated features, the specificity of FHO-DTCN acquires as maximum value than 3.9% of EOO-DTCN, 2.69% of ROA-DTCN, 1.51% of TSO-DTCN, 1.29% of COA-DTCN, respectively. Hence, the suggested method helps to improve the desired results in detecting the different leaf diseases.

C. Performance evaluation of the proposed paddy leaf disease detection model

Fig. 6 demonstrates the performance analysis of the suggested method compared with distinct heuristic algorithms by varying the learning percentage. Similarly, the comparative analysis among diverse classifier models is shown in Fig. 7. Like, Fig. 7 (d) elucidates the sensitivity analysis of the new method. When the learning percentage is 50, the sensitivity of FHO-DTCN achieves sensitivity than 5.43%, 6.52%, 4.89% and 3.26% of DNN, CNN, RNN and DTCN, correspondingly. Hence, the more results assist to improve the system efficiency in detecting the different diseases.

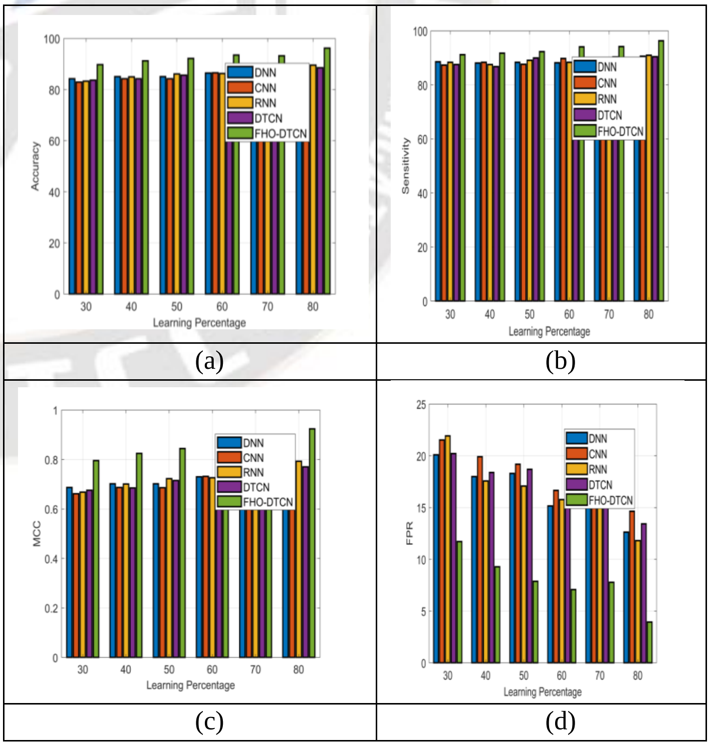


Fig.7. Performance analysis of the recommended paddy leaf disease detection model compared over different classifiers concerning "(a)Accuracy, (b) Sensitivity, (c) MCC and (d) FPR"

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
***Article Received**: 26 March 2023 **Revised**: 29 April 2023 **Accepted**: 17 June 2023*

VII. CONCLUSION

This work has demonstrated the detection of paddy leaf disease using adaptive network. Initially, the images were collected and fed into the segmentation stage done by FCM. Further, the segmented image was given to extract the different features. Then, the features were fused together that was given to determine the optimal features. Finally, the resultant features were subjected into the ADTCN for identifying the leaf disease, in which some of the hyper parameters were also tuned by FHO. The performance of the model was evaluated using different measures. Compared to traditional methods, the enhanced method has provided the promising results that have helped earlier crop damage prevention.

REFERENCES

[1] H. Amin, A. Darwish, A. E. Hassanien and M. Soliman, "End-to-End Deep Learning Model for Corn Leaf Disease Classification," IEEE Access, vol. 10, pp. 31103-31115, 2022.

[2] Asad Khattaki , Muhammad Usama Asghar, Ulfat Batool , Muhammad Zubair Asghar, Hayat ullah , Mabrook Al-rakhami, and Abdu Gumaei,"Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model," IEEE Access, vol. 9, pp. 112942-112954, 2021.

[3] Aakrati Nigam, Avdhesh Kumar Tiwari and Akhilesh Pandey,"Paddy leaf diseases recognition and classification using PCA and BFO-DNN algorithm by image processing," Materials today: Proceedings, vol.33, pp.4856-4862, 2020.

[4] S. Ramesh and D. Vodka," Recognition and classaification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm," Information Processing in Agriculture, vol.7, pp. 249-260, 2020.

[5] Sudad H.Abed, Alaa S.Al-Waisy,Hussam J.Mohammed and Shumoos Al-Fahdawi, "A modern deep learning framework in robot vision for automated bean leaves diseases detection," International Journal of Intelligent Robotics and Applications, vol. 5, pp. 235–251, 2021.

[6] Junde Chen, Defu Zhang and Y.A. Nanehkaran, "Identifying plant diseases using deep transfer learning and enhanced lightweight network," Multimedia Tools and Applications, vol.79, pp.31497-31515, 2020.

[7] Chiranjeevi Muppala and Velmathi Guruviah,"Detection of leaf folder and yellow stemborer moths in the paddy field using deep neural network with search and rescue optimization,"Information Processing in Agriculture,vol.8,pp.350-358,2021.

[8] Krishnamoorthy N , L.V. Narasimha Prasad , C.S. Pavan Kumar, Bharat Subedi, Haftom Baraki Abraha and Sathishkumar V E,"Rice leaf diseases prediction using deep neural networks with transfer learning,"Environmental Research,vol.198,pp.111275,2021.

[9] M. Yogeshwari and G. Thailambal,"Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks,"materialstoday:Proceedings,2021.

[10] Adem Tuncer,"Cost-optimized hybrid convolutional neural networks for detection of plant leaf diseases,"Journal of Ambient Intelligence and Humanized Computing,vol.12,pp.8625-8636,2021.

[11] Lucas M. Tassis , João E. Tozzi de Souza and Renato A. Krohling,"A deep learning approach combining instance and semantic segmentation to identify diseases and pests of coffee leaves from in-field images,"Computers and Electronics in Agriculture,vol.186,pp.106191,2021.

[12] Ani Brown Mary N , Robert Singh A. and Suganya Athisayamani,"Banana leaf diseased image classification using novel HEAP auto encoder (HAE) deep learning,"Multimedia Tools and Applications,vol.79,pp.30601-30613,2020.

[13] Sinan Uğuz and Nese Uysal,"Classification of olive leaf diseases using deep convolutional neural networks,"Neural Computing and Applications,vol.33,pp.4133-4149,2021.

[14] Koushik Nagasubramanian, Sarah Jones, Asheesh K. Singh, Soumik Sarkar, Arti Singh and Baskar Ganapathysubramanian,"Plant disease identification using explainable 3D deep learning on hyperspectral images,"Plant Methods,vol.15,no.98,2019.

[15] Trong-Yen Lee, I-An Lin, Jui-Yuan Yu, Jing-min Yang and Yu-Chun Chang,"High Efficiency Disease Detection for Potato Leaf with Convolutional Neural Network,"SN Computer Science,vol.2,no.297,2021.

[16] Mahdi Azizi, Siamak Talatahari & Amir H. Gandomi, "Fire Hawk Optimizer: a novel metaheuristic algorithm," Artificial Intelligence Review, 2022.

[17] Salim, Ahmad, Jummar, Wisam K., Jasim, Farah Maath and Yousif, Mohammed. "Eurasian oystercatcher optimiser: New meta-heuristic algorithm" Journal of Intelligent Systems, vol. 31, no. 1, pp. 332-344, 2022.

[18] Ali Reza Moazzeni and Ehsan Khamehchi, "Rain optimization algorithm (ROA): A new metaheuristic method for drilling optimization solutions", Journal of Petroleum Science and Engineering, Vol. 195, 2020.

[19] Lei Xie, Tong Han, Huan Zhou, Zhuo-Ran Zhang, Bo Han, Andi Tang, "Tuna Swarm Optimization: A Novel Swarm-Based Metaheuristic Algorithm for Global Optimization", Computational Intelligence and Neuroscience, Vol. 2021, No. 22, 2021.

[20] Avinash Sharma, Akshay Sharma, B.K. Panigrahi, Deep Kiran and Rajesh Kumar, "Ageist Spider Monkey Optimization algorithm", Swarm and Evolutionary Computation, Vol. 28, pp. 58-77, 2016.

[21] Toran Verma and Sipi Dubey, "Prediction of diseased rice plant using video processing and LSTM-simple recurrent neural network with comparative study", Multimedia Tools and Applications, Vol. 80, pp. 29267–29298, 2021.

[22] G. Zhou, W. Zhang, A. Chen, M. He and X. Ma, "Rapid Detection of Rice Disease Based on FCM-KM and Faster R-CNN Fusion," IEEE Access, vol. 7, pp. 143190-143206, 2019.

[23] S. Ghosal and K. Sarkar, "Rice Leaf Diseases Classification Using CNN With Transfer Learning," 2020 IEEE Calcutta Conference (CALCON), Kolkata, India, 2020, pp. 230-236, 2020.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 6
DOI: https://doi.org/10.17762/ijritcc.v11i6.7293
***Article Received**: 26 March 2023 **Revised**: 29 April 2023 **Accepted**: 17 June 2023*

[24] S. Phadikar, J. Sil, and A. K. Das, "Classification of Rice Leaf Diseases Based on Morphological Changes", International Journal of Information and Electronics Engineering, Vol. 2, No. 3, 2012.
[25] M. Yogeshwari and G. Thailambal, "Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks", Materials Today: Proceedings, 2021.
[26] Xiyang Dai, Bharat Singh, Guyue Zhang, Larry S. Davis, Yan Qiu Chen, "Temporal Context Network for Activity Localization in Videos", Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 5793-5802, 2017.