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RESEARCH ARTICLE

SEGMENTATION AND CLASSIFICATION OF PADDY LEAF DISEASE VIA DEEP LEARNING NETWORKS

Santhiya Govindapillai[1, *], and Radhakrishnan Ayyapazham[2]

[1]Assistant Professor/ (Senior Grade), Department of Information Technology, SRM valliammai Engineering College, SRM Nagar, Kattankulathur, Tamil Nadu 603203, India.
[2]Assistant Professor, Department of Information Technology, University College of Engineering-Nagercoil, Anna University Constituent College Konam, Nagercoil, India.

Corresponding e-mail: Santhiyag.it@srmvalliammai.ac.in

Abstract – Detection of paddy leaf disease is crucial for the agriculture industry since rice provides sustenance for over 50% of the global populace. In this paper, a novel YOLO-DBN framework has been proposed to identify the leaf diseases like blight, smut and spot in paddy crops. The paddy leaf images are pre-processed using CLAHE (Contrast Limited Adaptive Histogram Equalization) to increase the quality of the images. The pre-processed images are fed as input to YOLO Network to conduct instant segmentation of paddy leaves. The segmented images are fed as input to Deep Belief Network to classify the paddy leaves into blight, smut and spot diseases. The proposed YOLO-DBN achieves a high accuracy range of 97.68%, 96.71% and 98.76% for detecting Blight, smut and spot respectively. The proposed approach and the conventional deep learning techniques like DNN and Alex net. A clustering algorithm is utilized to segment the backdrop, normal section, and sick region. The proposed YOLO-DBN model improves the overall accuracy of 7.51%,1.18%, and 0.38 % better than CNN, DNN, Alex net respectively.

***Keywords** – Plant disease, segmentation, YOLO Network, Deep learning, Deep Belief Network.*

1. INTRODUCTION

One of the staple meals consumed worldwide is rice. But a number of paddy illnesses are a hindrance to rice production [1]. Due to the lack of expertise, it is typically exceedingly Paddy leaf infections are time-consuming and challenging for farmers in remote areas to diagnose [2]. Due to the ever-increasing population, there is a perpetual lack of water and food for everyone, and the situation may get worse in the future. Researchers are attempting to concentrate on these issues in order to develop a reliable and affordable solution [3]. For instance, plant water stress can increase leaf surface temperature, slow down photosynthesis, and decrease evapotranspiration. Other symptoms may be brought on by fungus, viruses, or bacteria [4].

Plant diseases and pest outbreaks have expanded in number in the past few years due to factors like changing climate and unstable environmental circumstances [5]. a few automatic classification tools, Plant identification requires pattern recognition and image processing diseases using current methods [6]. These are helping farmers increase the quality and output of their crop goods [7]. To identify the disease from the symptoms, plant disease leaf image segmentation is crucial on the leaves [8].

Computer Vision-based techniques for identifying pests and plant diseases usually make use of conventional image processing techniques or human feature creation in conjunction with classifiers [9]. Currently, it is challenging to produce superior detection results using the traditional classical methods because they frequently seem helpless. [10]. The automatic detection of crop diseases has been made possible as machine learning techniques advance. Numerous studies have been carried out to discover agricultural illnesses employing machine learning approaches [11].

The identification of Recognizing plant illnesses is crucial to avoiding drops in agricultural output and quantity. Monitoring plant health and diagnosing diseases are especially detrimental to agriculture that is sustainable. Plant illnesses are thought to be reflected by observable patterns based on research on plant disease on the plants identification [12]. When plant diseases are monitored manually, the process is more difficult. The manual process demands more time for processing, a substantial labor input as well as familiarity with plant disease. Therefore, image processing techniques are employed to detect diseases in plants. The following are the work's primary contributions:

- A novel YOLO-DBN framework has been proposed to identify the leaf diseases like blight, smut and spot in paddy crops.
- Initially, the paddy leaf images are pre-processed using CLAHE to increase the value of the images.
- The pre-processed images are fed as input to YOLO Network to conduct instant segmentation of paddy leaves.

- Consequently, the segmented images are fed as input to Deep Belief Network to classify the paddy leaves into blight, smut and spot diseases.
- The quantitative analysis of the proposed method is determined using the parameters like accuracy, specificity, recall, precision and F1-score.

The remainder of the paper is structured. In Section II, the literature review is explained in detail. Section III provides a description of the recommended procedure. Section IV covers the results and discussion section. Section V discusses the conclusion.

2. LITERATURE REVIEW

This section provide the basic theory in both modern and conventional methods for deep learning image analysis for plant disease diagnosis.

In 2022 Nuseir. A., et al., [13] proposed an analysis of insect attack and nutrient deficiency and disease in coconut leaves. Monitoring of coconut leaves after the application of pesticides and fertilizers has been performed using cutting-edge machine learning and image processing methods. SVM and CNN were selected as the best and most suitable classifiers with 93.54% and 93.72% accuracy, respectively. This system has the facility to fully monitor the plant from initial referral to complete recovery.

In 2020 Sakhamuri, and Kompalli [14] propose the correct solution regarding the disease, the identifiable source and the arrangement of the infection. Image processing approaches can automate a number of disease models and pest forecasts. Some types of problems can be identified at an early stage by human vision, while it takes some time to predict. If it concerns recognizing yellow rust and septoria, SVM classifier outperforms ANN with 95% and 70% accuracy, respectively.

In 2020 Khamparia, A., et al [15] proposed the network was trained to distinguish crop disease using leaf images. The network's several convolutional layers. The image's very basic attributes are extracted in the first few layers, but as we dig deeper, the complexity increases and it can be used to address more intricate issues. In 100 epochs, we were able to achieve 97.50% accuracy for 22 convolution filter sizes, and 33 filter sizes with 100% accuracy—better than other conventional approaches.

In 2020 Sharma, R., et al [16] proposed a foretelling model using CNN for rice crops to categorize disease predictive. Neural Networks are a collection of complex algorithms modelled following the human brain's ability to distinguish various patterns or images. 90.32% accuracy is observed on the test set and 93.58% accuracy on the training set.

In 2021 Adedoja, A., et al [17] proposed using the NASNet framework for Convolutional Neural Networks (CNNs). Artificial intelligence applications that use deep neural networks have proved effective. Among the primary problems, that endangers the availability of sufficient human food is plant diseases. We used different splits including 80%, 60%,50%, 40% and 20%. That is, for example, 80%, 60%, 50%, 40%, and 20% the entire collection of images are set aside for computer training while the other 40%, 50%, 60%, and 80% are used for validation purposes, respectively.

In 2019 Militante, S.V., et al [18] introduced Deep learning is a cutting-edge approach to machine learning that mimics the human brain works by using neural networks. The agriculture sector depends heavily on the early identification and treatment of chronic illnesses. While The accuracy rate of the trained model was 96.5%, and the system achieved up to 100% accuracy in categorizing and detecting various plant species and ailments.

In 2020 Tiwari, D., et al [19] proposed a model that have already been trained, like VGG19, that are being fine-tuned (transfer learning) to pull out pertinent features from the dataset. models that have already been trained, such as VGG19, are adjusting (transfer learning) in order to separate pertinent characteristics from the dataset. Huge amount of data to perform better than other techniques. Potato is a highly adaptable crop that makes up almost 28.9% of all agricultural crops produced in India.

In 2018 Zhang, K., et al [20] introduced a method for training deep neural Networks need a lot of information and expensive computing power. It is a high processing method. The maximum test accuracy of 96.51% is achieved by ResNet using the SGD optimization approach.

In 2021 Shrivastava, and Pradhan, [21] proposed various image-based CAD systems have been proposed using colour features in agriculture applications. In this work, we have concentrated particularly on the illness of the rice plant (Oryza Sativa). Every year the disease causes huge economic losses to formers. The proposed model can categorize rice diseases with 91.37% classified accuracy for 80%- 20% training-test distribution.

In 2019 Alruwaili, M., et al [22] proposed a state-of-the-art method recently developed result findings indicate that the strategy attains better metrics for memory, accuracy, precision, and F1 measure. Difficult to train and less efficient. The recommended method's overall accuracy is 99.11%, which is a good result.

The conventional techniques for identifying illnesses of the leaves depend on human vision. Seeking expert counsel in these circumstances is costly and time-consuming. The proposed YOLO-DBN method mainly focused on identifying various types of diseases present in the leaf of the plant.

3. PROPOSED METHODOLOGY

In this section, a novel YOLO-DBN technique for identifying and segmenting the blight and spot diseases of the paddy crops. In the pre-processing stage, CLAHE is used to increase the worth of image.

This dataset contains 120 jpg images of illness are included in rice leaves. Based on the type of disease, the images are divided into three categories. Every class contains 40 images.

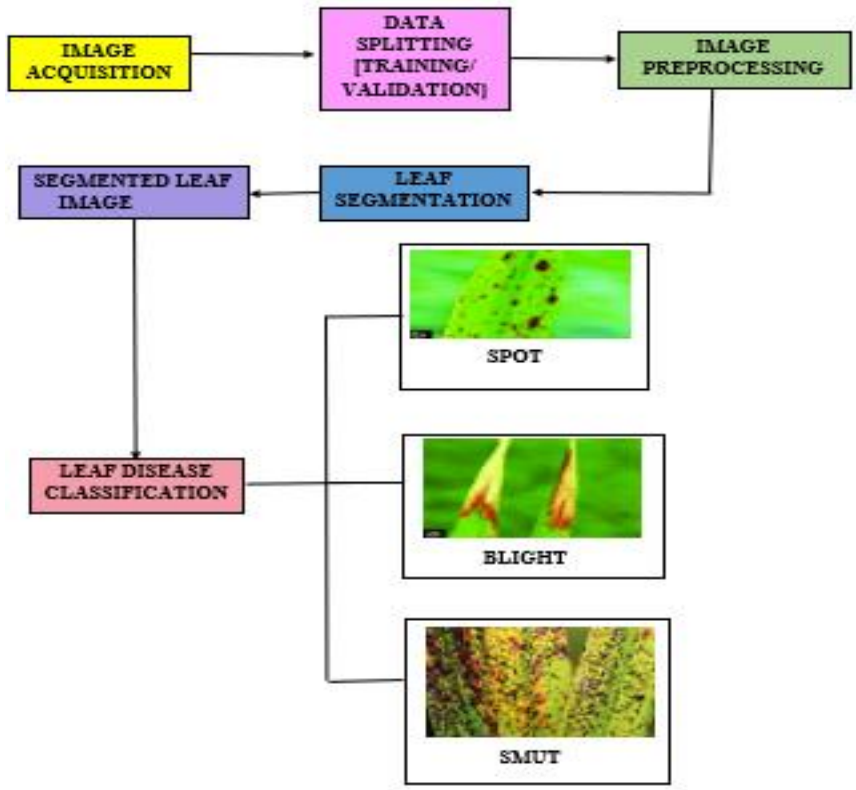

Figure 1. The overall process of the proposed methodology

3.1. Data Pre-Processing

The relative region of an image with adaptive histogram equalization (AHE) tends to have too much noise amplitude. CLAHE, a variation of Dynamic Histogram, tries to prevent over-amplification by restricting contrast. To produce the enhanced effect, CLAHE was applied. CLAHE was applied when the summary was a degree of decompression to the second-to-last in order to prevent a blocking effect. The high-frequency component at this time was improved by the low-frequency element. Finally, following the image restoration, CLAHE was employed.

The image contrast can be altered by the distribution is redistributed of the image histogram. Histogram equalization, which can increase The pixel grey value's dynamic range are thought of as a mapping modification of the original image's grey level. Thus, It is possible to enhance the image's contrast.

Suppose the greyscale of an image's size range is [0, m−1], with a grey condition of m. Let $q_s(s)$ be the grey-condition the probability density function (PDF). Then, the probability of the *k*th grey condition is,

$$q_s(s_t) = \frac{m_t}{m} \tag{1}$$

where t=0, 1, 2, …, n−1 and st stand for the t th greyscale. Then, the cumulative distribution function (CDF) K(st) can be revealed as:

$$f = K(st) = \sum_{x=0}^{t} q_s(s_x) = \sum_{x=0}^{t} \frac{m_x}{m}, \tag{2}$$

where 0≤f≤1

The stages of CLAHE are:

(1) Divide the input image into regions that are unceasing and don't overlap. The standard setting for the region size is 8×8.
(2) After obtaining the histogram for each region, apply the threshold to reduce the histogram. The CLAHE algorithm accomplishes the goal of limiting the data by first clipping the histogram with a preset threshold before calculating the CDF.

Magnification: It controls the slope of the transform function

(3) Reassign the pixel values, and then uniformly distribute the clipped pixel values below the histogram. The histogram distribution before and after clipping are shown in figures a and b, respectively.

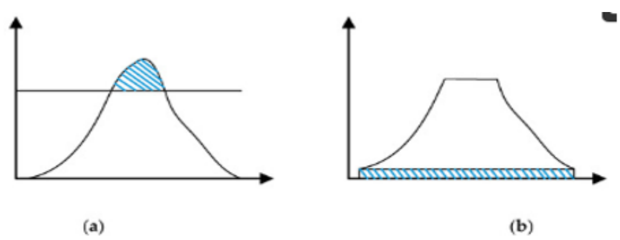

Figure 2. Histogram distribution: (a) Initial clipping (b) Final clipping

(4) On each region, carry out a local histogram equalization.
(5) When reconstructing pixel values, use a linear interpolation. Assume that the sample point q' r grey value is r, and that the new grey value obtained

using linear interpolation is r'. The surrounding areas' sample points are q1, q2, q3, and q4, and the corresponding r's grey-level mappings are fq1 (r), fq2 (r), fq3 (r), and fq4 (r). For pixels in the corners, the new gray value matches the region's r's grey-level mapping.

$$r' = f q_1(r) \tag{3}$$

The interpolation of the grey-condition mapping of r of the two samples of the surrounding areas creates a new grey value for the pixels at the boundaries. For example:

$$r' = (1-\alpha) f q_1(r) + \alpha\, f q_2(r) \tag{4}$$

The interpolation of the r-valued in the grey-condition mapping of the four models from the surrounding areas creates the new grey value for the pixels of the image's centre. For example,

$$r' = (1-\beta)\big((1-\alpha) f q_1\,(r) + \alpha\, f q_2(r)\big) + \beta\big((1-\alpha) f\, q_3\,(r) + \alpha f\, q_4(r)\big) \tag{5}$$

where α and β are the normalized distances from the location r_1.

3.2. YOLO-DBN model

In this section, a novel YOLO-DBN model has been introduced to classify the paddy leaf diseases. The YOLO-DBN model is an integration of YOLO network for segmenting the diseased paddy leaves and DBN is used for classifying the segmented leaves into blight, smut and spot. Fig. 3 depicts the YOLO-DBN structure.

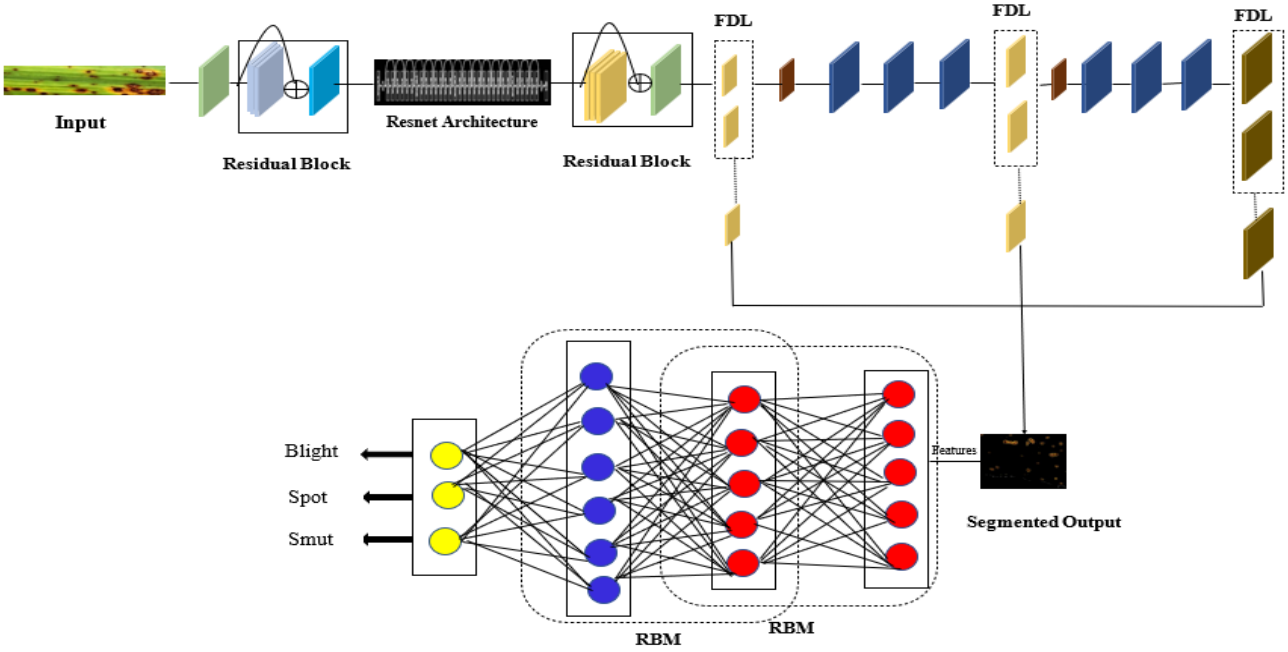

Figure 3. YOLO-DBN Architecture

3.3. YOLO Network

A YOLO (You Look Only Once) system is a real-time object detecting system. There are other ways to find objects, including as Regional Convolution Neural Network. The identification is extremely quick and accurate because YOLO formulates a single neural network predicts bounding box coordinates and class probabilities for example, in object detection tasks. An algorithm called YOLO is used to find objects of varied sizes. This model accepts using an image as input, sending it via a neural network, and then outputs bounding boxes. The bounding box here facilitates finding the things. YOLO will have versions like v1, v2, and v3 as it develops. Two groups of algorithms can be distinguished. Two steps make up the first group of algorithms.

The CNN-based classifiers are then used to run in the first stage once a specified In the image, several possible bounding boxes have been created. Following the classification process, bounding boxes are subjected to a post-processing step that makes some enhancements, such as improving bounding boxes, removing duplicate detections, and rearranging boxes in accordance with other items in the scene that have been identified. Due to the unique training required for each component, these complicated systems move relatively slowly, and it is exceedingly challenging to optimise any one component. The more complex versions of the most widely used of these methods is the RCNN, specifically Fast-RCNN and Faster-RCNN. The algorithms in the second category are based on the regression issue. They attempt forecast the enclosing boxes and classes over the entire image in a single run rather than picking out the most visually appealing areas of the image.

The detector finds the ROI's centre, and all images are cropped to 100 ×100 pixels in accordance with the central pixels. Utilizing convolutional layers, the characteristics are extracted of A; after that, they are used to lower the dimension and generate predictions for each pixel. The segmentation results' spatial accuracy is improved by merging combining coarse-grained, high-layer data combined with fine-grained, low-layer data. So, in order to effectively capture spatial information, merge the lower layers with the higher layers. A four-channel feature map is created by the final deconvolutional layer. The following method is used to determine the location at the channel x that corresponds to the pixel ca:

$$q(c_a = b_x) = \frac{1}{h} \times exp[U(b_x)] \tag{6}$$

where q ($j_l = b_l$)is the probability of b_l, U (b_l) is the rate of b_l,H is a term of normalization. The prediction of pixel j_l is executed as follows:

$$\hat{o}_l = \text{argmax}[\text{q}(j_l = b_x)] \tag{7}$$

The grid cell can detect many objects to the anchor box. For every anchor box, the YOLOv2 calculates bounding box coordinates corresponding to the grid cell position of the anchor box. To compute coordinates between 0 and 1, the YOLO v2 uses the logistic activation function. This study identifies the relevant grid cell for each prediction procedure to provide further information. The anchor size and cell belonging to (bj, bo) in the top left corner of the anchor box are first determined by the YOLOv2 (qf, qz). The study then forecasts offsets (kj, ko, kf, and kz) for this anchor box with a confidence score (ky). The predicted box was then tied to the corresponding grid cell by applying the sigma function to bind the coordinates of the box's centre to the location centre. The bounding box prediction offsets can be calculated as;

$$c_{j=6(k_j)+b_j} \tag{8}$$

$$c_{o=6(k_o)+b_o} \tag{9}$$

$$c_{f=}q_f e^{k_f} \tag{10}$$

$$c_{z=}\ q_z\ e^{k_z} \tag{11}$$

$$qs(object) * IoU\ (c, object) = \sigma\ (k_0\ ) \tag{12}$$

where (kj, ko, kf, kz) are predictions made by YOLO v2, (bj, bo) are grid cells in the anchor's top left corner, (qf, qz) are the width, height, and Є of the anchor (k0) is the box's confidence score. Additionally, (cj, co, cf, cz) are the bound box's projected value.

The distinction between the intended result and the neural network's projected output is measured using the loss or cost function. The loss function also helps the optimization algorithm change the weight in a way that minimises loss on the subsequent evaluation. The kind of problem that needs to be handled by CNN largely determines the loss function to be used. Some typical loss function types are employed for a variety of issues. First, we have the cross-entropy loss, the common loss function in deep learning. On the other side, cross-entropy compares the predictions (outputs) from the network with the desired outputs (true labels). It produces a probability value of 49, between 0 and 1. When the likelihood value of cross-entropy decreases, the network's accuracy improves, and predictions tend to be flawless when the probability value is zero. For image classification, the cross-entropy function is frequently employed as follows:

$$W(d, p) = -\sum d(j) logp(j) \tag{13}$$

Where d denotes the desired output and p denotes probability of the prediction output.

The Mean Squared Error (MSE), which is frequently employed as a default loss function in the evaluation detection in deep learning, is the second typical function. The MSE can be characterised as,

$$MSE = \frac{1}{M} \sum_{l=1}^{M} (o_l - \hat{o_l})^2 \tag{14}$$

o is the target output, $\hat{o}$ is the prediction output, where M is the training data's sample count. The MSE is ideal when there isn't an outlier in the dataset and it's also quite effective at achieving minima.

The loss function is defined as follows*:*

$$Loss = -\frac{1}{MN} \sum_l \sum_x o_{l_x} In[q(j_l - b_x) \tag{15}$$

The input considerably lowers the computational expense the model's potential for learning. It maintains excellent accuracy while delivering segmentation results at little computational cost.

3.4. Deep Belief Network

Deep Belief Network, a subclass of RBMs (restricted Boltzmann machines)-based deep neural networks. DBN used to accomplish Both supervised and using applications involving unsupervised learning, the feature space's dimensionality is reduced. and construct regression or classification models, respectively. Training and fine-tuning layer by layer are the two phases involved in training a DBN. The DBN's parameters are modified via error back-propagation mechanisms. After the unsupervised training is finished. The Layer-by-layer training refers to the unsupervised training of every RBM.

Greedy algorithm is a technique used to pretrain deep belief networks. The most significant generating weights are learned using a layer-by-layer method by this algorithm. The relationship between each variable in a layer and the other variables in the layer above is determined by the related weights. Gibbs sampling is performed in DBN in a number of steps on the top two hidden layers. The two hidden layers at the top are basically used to draw a sample from the RBM in this stage**.**

In DBN learning, there are two phases: preliminary training, final adjustment. While The inverse divergent nature of hierarchical stacked RBM training is the main reason of unsupervised learning; supervised learning is deduced by the BP method, This alters the initial and biased sample sets. Improving RBMs and extracting data characteristics are the two primary goals of unsupervised DBN training. The purpose of energy that is applied $E(v, h|\theta)$ and set of (v, h), is obtained.

$$E(v,\ h|\theta) = -\sum_{l=1}^{m} a_l v_{l-} \sum_{x=1}^{n} b_x h_{x-} \sum_{l=1}^{m} \sum_{x=1}^{n} v_l w_{lx} h_x \tag{16}$$

where $\theta = \{W_{lx}, a_l, b_x\}$ defines a parameter in RBM, where w denotes a weight and a and b, respectively, indicate the hidden and visible sides' bias layers associated with a layer;

$$q(v, \text{h}|\theta) = e^{\frac{-E(v,h|\theta)}{h(\theta)}}, h(\theta) = \sum_{v,h} e^{-E(v,h|\theta)} \tag{17}$$

In the case of Gibbs sampling, the probability distribution derived from the visible and hidden neurons:

$$q\ (h_l = 1|\text{v}, \theta) = sigmoid\ (b_x + \sum_l v_l w_{lx}) \tag{18}$$

$q\ (V_L = 1|\mathrm{h}, \theta) = sigmoid\ (a_l + \sum_x h_x\, w_{xl})$ (19)

The potential hx is what defines an active state. The equation above can be used to predict the potential for processing each neuron in a visible layer activation's hidden layer state, h, given that RBM is composed of uniform features.

By applying unsupervised learning from the DBN along with the preset learning technique, the RBM hierarchy is taught to attain W = w1, w2,...wl, the starting weights. Most often, supervised learning is used to refine linked weights obtained from unsupervised learning. As a result, the training dataset's gradient labels, which alter the networking variables, process the BP model.

4. RESULTS AND DISCUSSION

This study's creative setting was put into practice with the deep learning toolkit MATLAB 2019b. In this study of the results, the plant images from the selected datasets are classified as blight disease, smut disease, spot disease.

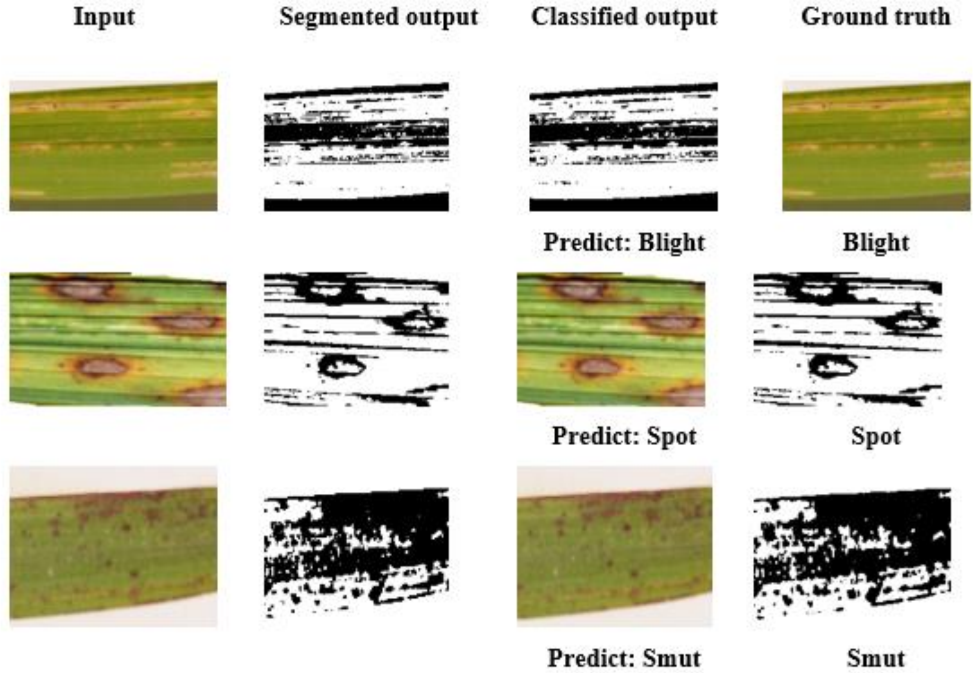

Figure 4. Results of the proposed YOLO-DBN model

For this work, it has chosen three paddy leaf diseases named Blight, spot and smut. The dataset contains 120 jpg images that was collected from Kaggle internet source. Fig.4 describes the visualization results of the proposed YOLO-DBN model. From fig.4, the diseased leaf is given as an input to YOLO network for segmentation and the DBN is predicted the output based on the segmented region.

4.1 Performance Analysis

In this study F1 score, specificity, accuracy, recall, precision, and correctness were used to generate the performance analysis.

$$accuracy\ = \frac{TP+TN}{TP+TN+FP+FN} \quad (19)$$

$$Specificity\ = \frac{TN}{TN+FP} \quad (20)$$

$$Precision\ = \frac{TP}{TP+FP} \quad (21)$$

$$recall\ = \frac{TP}{TP+FN} \quad (22)$$

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \quad (23)$$

where true positives, true negatives, false positives, and false negatives are denoted by the letters TP, TF, FP, and FN, respectively.

Table 1. Performance analysis of proposed method

Classes	Accuracy	Specificity	Precision	Recall	F1 Score
Blight	0.976	0.965	0.962	0.921	0.934
Spot	0.967	0.956	0.945	0.911	0.931
Smut	0.987	0.957	0.941	0.942	0.955

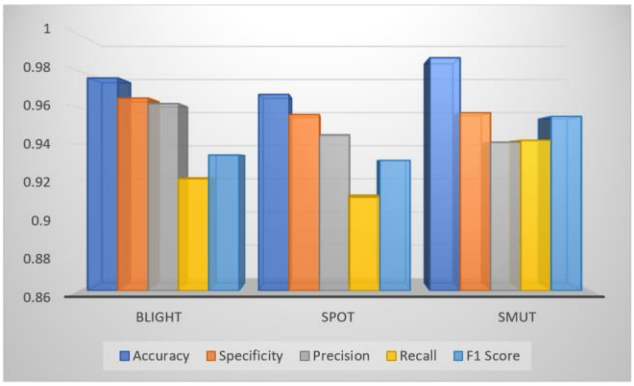

Figure 5. Performance metrics for three classes

Fig.5 depicts the suggested model's effectiveness for three groups, which comprise Blight, smut and spot. The proposed model's effectiveness for three groups, which comprise 0.976, 0.967 and 0.987 for the Blight, spot and smut. The suggested method produced greater results for blight, spot, and smut, with specificities of 0.965, 0.956, and 0.957 and precisions of 0.962, 0.945, and 0.941. The proposed approach produced better recall values (0.921, 0.911, and 0.942) and an F1 score (0.934, 0.931, and 0.955) for smut, blight, and spot—all of which are quantifiable using TPR and FPR metrics. The following is the sequence of accuracy, recall, and F1 score:0.949, 0.924, and 0.94. while the overall accuracy and specificity are 0.976 and 0.959, respectively.

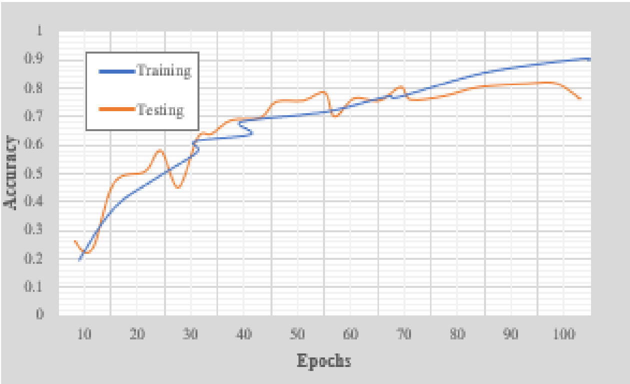

Figure 6. Training and Testing accuracy of proposed method

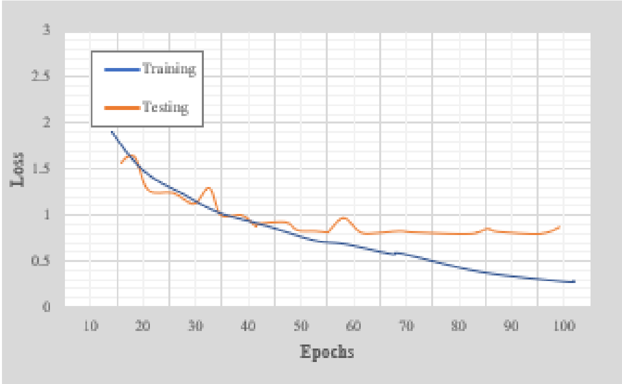

Figure 7. Training and Testing loss of proposed method

The proposed model Figure 6 and Figure 7 illustrate the model's excellent accuracy in training and testing, respectively, and loss. The recommended model achieves 97.66% accuracy. Performance is assessed using specificity, recall, accuracy, precision, and F1 score.

4.2. Comparative Analysis

In this section, a comparison is made between the proposed model and traditional neural networks. Depending on an instance of comparison with current methods, this tactic yields greater results than them. The F1 score, accuracy, precision, specificity, recall, and recall are used to evaluate performance. This comparison analysis compares the proposed model using the three most popular deep learning methods.

Table 2. Comparison between traditional deep neural networks

Networks	Accuracy	Specificity	Precision	Recall	F1 Score
SegNet	93.82	92.15	90.64	87.92	89.58
U-Net	92.67	91.87	89.67	89.45	92.34
Fast R-CNN	96.54	93.86	91.97	86.39	89.75
Faster R-CNN	96.70	92.32	94.65	93.67	94.76
YOLO net	97.66	94.23	95.34	96.72	95.76

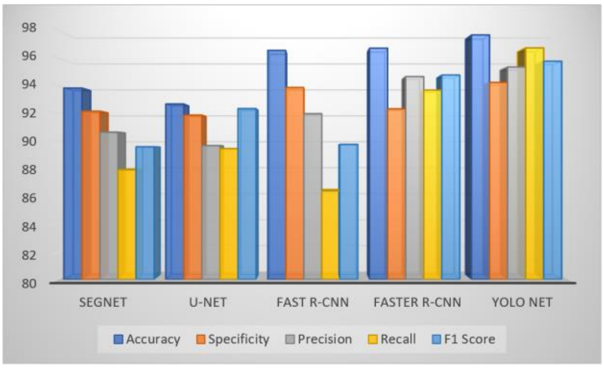

Figure 8. Comparison of traditional deep learning models

Table.2 present the result obtained in relation to the overall accuracy percentage. Table 2 shows that the YOLO net outperforms standard networks such as Seg net, U-net, Faster R-CNN, and Fast R-CNN concerning precision. YOLO preserves the high accuracy ranges of 97.66%. Figure 8 illustrates the accuracy that Seg net was able to achieve. U-net, Faster R-CNN and Fast R-CNN is 93.82%, 92.67%,96.70% and 96.54% respectively. The level of specificity attained by seg net, U-net, Faster R-CNN, Fast R-CNN and YOLO net is 92.15%,91.87%,92.32%.,93.86%, and 94.23%. Precision is obtained by Seg net, 89.67%, 91.97%, 94.65% and 95.34. Recall is obtained by seg net, U-net, Quick R-CNN, and Quicker R-CNN and YOLO net is 87.92%, 89.45%,86.38%,93.67% and 96.72%. F1 score is obtained by Seg net, U-net, Faster R-CNN, Fast R-CNN and YOLO net is89.58%, 92.34%, 94.76%, 89.75% and 95.76%. Compared to the current models, the accuracy rate obtained by the YOLO net is more efficient. This clearly shows that the YOLO-DBN model performs better than the alternative approaches.

Table 3. Comparison between proposed and the existing models

Author	Methods	Accuracy (%)
Sharma [12]	CNN	90.32
Militante.D [14]	DNN	96.5
Zhang[16]	AlexNet+ GoogLeNet, + ResNet	97.28
Proposed	YOLO-DBN	97.66

Table 3 present that the proposed YOLO-DBN model raises the accuracy overall. of 7.51%,1.18%and 0.38 % better than CNN, DNN, Alexnet respectively**.** The suggested YOLO-DBN model performs the current models in terms of accuracy, according to the comparison above. In order to accurately segment the diseases and advance the accuracy of the suggested model, the precision of the proposed approach will be improved in the future.

5. CONCLUSION

In this paper, a novel YOLO-DBN approach has been proposed for detecting the plant disease in leaves using YOLO-DBN model. From the kaggle dataset, we choose paddy plant diseases. These images were pre-processed using CLAHE for eliminating the distortions from the images. Finally, classification was performed using the DBN architecture. The proposed DBN net achieves the high classification accuracy rate of 97.68%, 96.71% and 98.76% for detecting Blight, Smut and spot respectively. The proposed YOLO-DBN model was contrasted with conventional models such as SegNet, U-net, and Fast R-CNN. The proposed YOLO-DBN model enhances the general correctness of 7.51%,1.18%, and 0.38 % better than CNN, DNN, Alexnet respectively. Future work, based on size and diversity, we intend to expand the training and testing datasets.

CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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AUTHORS

Santhiya Govindapillai received the B.E. degree in Computer Science and Engineering from Anna University, Chennai, India, in 2010, M.E degree in Software Engineering from Noorul Islam Centre for Higher Education, Kumaracoil, India in 2012. She is currently pursuing the Ph.D. degree with Anna University, Chennai, India. Currently, she is working as a Assistant Professor at SRM Valliammai Engineering College, Kattankulathur, Chennai with the Department of Information Technology, Anna University, Chennai, India. Her current research interests include machine learning, the Internet of Things (IoTs), and sensor networks.

Radhakrishnan Ayyapazham started his career as Lecturer at Bannari Amman Institute of Technology, Coimbatore. He has served as Head of the Department of Computer Application at Regional Centre of Anna University Tirunelveli. He has published book chapters and possess national and international publications. He has obtained 3 design applications granted from Indian Patent Office. His area of interests are Grid and Cloud Computing and IOT and Machine Learning. Now he is presently working as an Assistant Professor (Sr. Grade) in Department of Information Technology at University College of Engineering Nagercoil.

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