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Paddy Leaf Disease Classification using ResNet-50 integrated with Canny Edge Detection Mechanism

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ABSTRACT

Agriculture is the primary source of income in India. Paddy is grown almost everywhere in the world but is most common in Asian nations where it serves as the main source of food to world's population. Various diseases attack at different stages of plant growth. The biotic & abiotic stresses that affected plant growth are temperature, viruses, bacteria, fungi & various environmental issues. Brown spot, Sheath rot, bacterial blight and Leaf blast are all important paddy leaf diseases that destroy rice and drastically reduce yield. By using various image processing techniques farmers can identify leaf diseases. In this research paper by integrating CNN with edge detection mechanism paddy leaf disease cab be identified. Various images can be captured from farm using camera. These images include disease like brown spot, bacterial blight, blast diseases and sheath rot. During preprocessing RGB images can be converted into HSV images. Then various color and texture features have been extracted using GLCM. After this edge-based CNN have been applied to improve the accuracy of the model. To train the model 70% images have been categorized as training set, 20% images as testing set and remaining 10% have been considered for validation set. The accuracy of the proposed model is 98%.

1. INTRODUCTION

Rice is an important crop in India. It is largest cultivated crop because rice is rich source of carbohydrates and proteins. In India for most of the small-scale farmers rice cultivation is the main source of income. Their crop has been suffered from various diseases like brown spot, Leaf Blast, sheath rot, Bacterial Leaf Blight etc. Manually detecting these disease takes lot of manual processing time. Several issues have been minimized by using technical facilities that have been carried out in order to restrict disease. Studies of recognition of plant diseases consider the diseases as pattern that are observed on plants [6]. Image processing involves the recognition of diseases by using various pattern recognition techniques. Various features are extracted from leaves and then classification have been done. It is observed that in several plants' leaves are significant source to find the disease. Sheath rot, brown spot, leaf blast, bacterial blight and leaf smut have been considered as diseases that are common in case of rice plants [10]. Symptoms of plant diseases are varied in case of various plants. Observations conclude that plant diseases have been found in variety of color, size and shape. There different disease associated to different features of plant leaves. Researchers have found that some plant diseases have yellow while some have brown color [11]. Many diseases are found same in shapes but different in colors. But some are of same color but different in shapes. Normal part of characteristics that is related to disease might be fetch after segmentation [12]. Because of the unawareness of suitable management to rectify rice plant leaf diseases, the rice production is being reduced in recent years [37]. Research is considering on four most common rice plant diseases. The names of these diseases are brown spot, Leaf blast, Bacterial blight and Sheath rot.

2. LITERATURE REVIEW

There has been existing research to recognize and classify paddy leaf diseases. Existing research focuses on improvement of rice production [2]. Some researches are based on Deep Neural network with Jaya algorithm [1]. Automated leaf disease detection has been performed using various image features [3]. Several AI based expert system [5], [10], nanotechnology bases system [6] have been proposed by researchers. Image processing [7], [9], [12] has been frequently used to detect and analyze the rice plant diseases [11]. Deep neural network [13], [17] is also integrated to image processing-based mechanism to detect and classify the plant disease that has provided accurate and reliable approach. However, some researchers have made used of support vector machine [15], [28].

The given literature review in table 1 is based on the crop types studied by the researchers & methodology they have used in their research. Some researchers are using their own datasets, but some are using open-source datasets. Different performance metrics they have used in their research work.

TABLE 1. Review of Literature

Crop	Methods used	Performance metrics	Dataset	Accuracy (%)	Reference
Paddy Leaf	Optimized Deep Neural Network with Jaya Optimization Algorithm (DNN_JOA)	Accuracy, precision, F1-score, TNR, TPR, FPR, FNR, FDR and NPV	(own)	97%	[1]
Tomato plant	Moth-flame optimization & genetic algorithm	Recall, precision, Accuracy, F1-score	UCI machine learning repository	86	[4]
Rice plant	InceptionResNetV2, Xception, ResNet50, MobileNet and InceptionV3	Accuracy	own	98.9%	[8]
Sunflower, Apple, Mango, Alstonia Scholaris, Jamun, Pongamia pinnata, Pomegranate,	multi-level deep information feature fusion extraction network (DFN-PSAN)	Accuracy and F1-core	PlantVillage open-source plant	95.27%	[14]

ISSN: 00845841
Volume 54, Issue 12, December, 2023

Chinar, Guava, Arjun, Jatropha, Lemon Bael, and Basil			disease dataset		
Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Ras pberry, Soybean, Squash, Strawberry, Tomat o	CNN (AlexNet, GoogLeNet)	Accuracy	PlantVill age	99.35%	[16]
Apple, Banana, Blueberry, Cabbage, Cantaloupe, Cassava, Celery, Cherry, Corn, Cucumber, Eggplant, Gourd, Grape, Onion, Orange	AlexNetOWTBn, VGG	Accuracy	Plant Village dataset	99.53%	[17]
Tomato	EfficientNet-B7, EfficientNet-B4		Plant Village dataset	99.95%	[18]
Banana	CNN (LeNet architecture)	Accuracy, precision, recall, and F1-score	Plant Village dataset	92%–99%	[19]
Tomato	CNN (AlexNet, GoogLeNet)	Accuracy	Plant Village dataset	99%	[20]
Olive tree images (	CNN (Modified LeNet)	Accuracy, Matthew's Correlation Coefficient (MCC), F1-Score, Precision and Recall	(own)	99%	[21]
Corn images	CNN (Pipeline)	Precision, recall, and an F1 score, ROC	(own)	97%	[22]
Tomato images	VGG net and Residual Network (ResNet)	Intersection-over-Union (IoU), and the Average Precision (AP)	(own)	83%	[23]
Apple images	CNN (AlexNet)	Accuracy	(own)	98%	[24]
Rice images	CNN (AlexNet inspired)	Accuracy	(own)	95%	[25]
Potato images	CNN (VGG)	Accuracy	(own)	96%	[26]

Apple & cucumber plant	-means clustering and PHOG	Recognition rate	Real-field images	90.43 & 92.15	[27]
Plant leaves (like rose, lemon, mango, and banana)	-means clustering, genetic algorithm, SVM	Accuracy	Real conditioned capture images	95.71	[29]
Rice plant	Radial basis function neural network	Accuracy, precision, recall	Real-field images	95.0	[30]
Cucumber plant	-means clustering, SVM	Accuracy	Real-field images	86	[31]
Rice crop	KNN, ANN	Accuracy	Real-field images	86 & 99	[32]
Tomato plant	Extreme Learning Machine (ELM)	Accuracy, AUC	Tomato powdery mildew dataset (TPMD)	89.19	[33]
Potato leaves	Capsule networks (CapsNet)	Accuracy	Plant village dataset	91.83	[34]
Tomato plant	SVM & logistic regression (SVM-LR)	Accuracy, AUC, F1-score	Real-time data of tomato powdery mildew disease dataset	92.73	[35]
Rice plant	SVM	Accuracy, sensitivity, specificity, AUC, ROC, F1-score	Real-field images	94.65	[36]

3. ROLE OF CNN IN CLASSIFICATION

Image processing techniques are frequently used to scale, resize, compare, transformation of graphical contents. The detection of pattern from image set could be frequently made using CNN model. Several issues have been observed when CNN based classification is used. There has been limited work to improve the performance of detection. However, there are many research in field of image processing but it has been observed that the time taken for prediction need to be reduced. Moreover, there is issue of space consumption by graphical content. Proposed research is supposed to minimize the prediction time and space consumption. Research has focused on study of existing image processing research and techniques and eliminating their limitation. Research proposes a methodology for detection using edge-based convolution neural network algorithm. The elimination of useless content from graphical image before applying Conventional Neural Network has reduced time consumption. Moreover, it has also reduced the storage requirement for the graphical dataset. As the number of data set increases every comparison makes a huge gap in size and comparison time. Proposed work is supposed to implement the proposed methodology using MATLAB. Comparison of proposed methodology and algorithm with the traditional algorithm is made during simulation. The proposed work is found more efficient as compared to traditional techniques used in detection of pattern.

ISSN: 00845841
Volume 54, Issue 12, December, 2023

The use of proposed work in paddy leaf disease detection is supposed to improve capability of convolution neural networking at the time of decision making. Proposed work is supposed to be more accurate as compared to traditional mode. The proposed work would integrate the CNN approach with edge detection mechanisms in order to improve performance of face mask detection mechanism.

Therefore, the performance of traditional CNN model needs to be improved.
1. Traditional research proved SVM best according to textual data but works well for image analysis and image classification. Thus, there is need to do more work on pattern detection model considering the benefits of CNN.
2. If the dataset is overlapping to some extent, then SVM is not best. In such cases Random Forest may give better results as compared to SVM. Thus, there is need to introduce the performance comparison of Random Forest with SVM.
3. PSO has been known as the computational technique. It has been used to optimize a challenge. It has been used to make improvement in a candidate solution as per the given measure of quality. PSO has been referred as a met heuristic. The reason is that it does not make any assumptions about any challenges. It can make search of large spaces of candidate solutions. Thus, PSO can be applied to optimize the solution of challenges faced during its uses. Such challenges may be partially irregular, change, over time noisy, etc.

4. PERFORMANCE PARAMETERS

Performance matrix used for evaluation purpose is confusion matrix. In it true positive (TP), true negative (TN), false positive(FP), false negative(FN) can be represented. The parameters utilized for verifying results are accuracy, precision, recall and f1 score that are discussed below:
Accuracy - Accuracy is most intuitive performance measure and it is simply a ratio of correctly predicted observation to total observations.
Accuracy = TP+TN/TP+FP+FN+TN
Precision - Precision is ratio of correctly predicted positive observations to total predicted positive observations.
Precision = TP/TP+FP
Recall (Sensitivity) - Recall is ratio of correctly predicted positive observations to all observations in actual class - yes.
Recall = TP/TP+FN

5. PROPOSED WORK

In this research paper existing image processing techniques have been studied. Here canny edge detection is integrated with Resnet50 CNN model for detecting disease in paddy leaves. Firstly, Resnet50 is applied on the dataset for classifying disease into Sheath rot, brown spot, leaf blast and bacterial blight. Then canny edge detection is integrated with Resnet50 model for improving the accuracy of the model. MATLAB is used to implement the proposed work. Then comparison of between Resnet50 & canny edge with Resnet50 have been done.

1. The image base of data set captured by camera would be created. The graphical content captured from camera is preprocessed using image resize function.
2. Apply tradition Resnet50 CNN classifier in order to check the space and time consumption after getting the image dataset. The time and space variable are stored in order to compare it with Resnet50 CNN classifier results after applying Canny Edge detection.
3. Apply the edge detection mechanism on the image data set. The edge detector would be detecting the edges of the image. The edge detection reduces the file size as well as the feature extraction time.
4. Apply the proposed CNN classifier in order to check the space and time consumption.

5. Compare the accuracy time and space consumption Resnet50 model and canny edge detection with Resnet50 model.

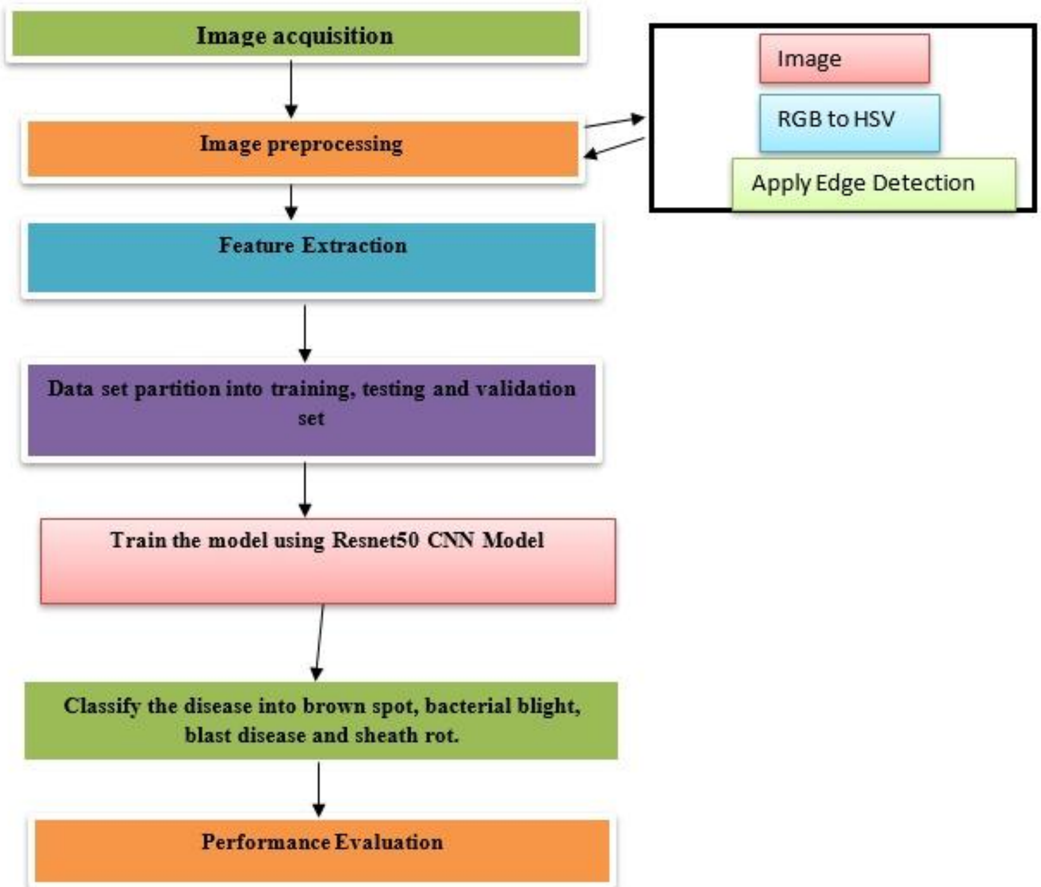

Fig. 1. Process Flow of Work

In figure 1 process flow of proposed work have been shown. Here in table 2 comparison between previous work & proposed work have been given.

TABLE 2. Comparison Chart for Previous and Proposed Research

Feature	**Previous Research**	**Proposed Research**
Detection time	Comparatively high	Comparatively low
Space	More storage space is required	Comparatively less space required
Accuracy	Relatively less accuracy	Relatively high accuracy
Edge Detection mechanism	Not applied	Canny edge detection is applied
Neural Network	Not applied	Convolution Neural Network
Flexibility	Lack of flexibility	High flexibility as it could be applied in another application
Scalability	Limited scalability	Work could be implemented at huge scale
Performance	Relatively low	Relatively high
Mechanism	DNN	CNN

6. EXPERIMENTAL RESULTS

ISSN: 00845841
Volume 54, Issue 12, December, 2023

Acquisition of images

Images acquisition have been done using high resolution digital camera from farm field. In order to perform recognition of diseases, all captured images are stored in computer. The dataset is consisting of images of different diseases as shown in figure 2. Dataset is prepared with 650 images that are consisting of 95 normal images,125 bacterial blight images, 170 blast images, 110 sheath rot images and 150 brown spot images.

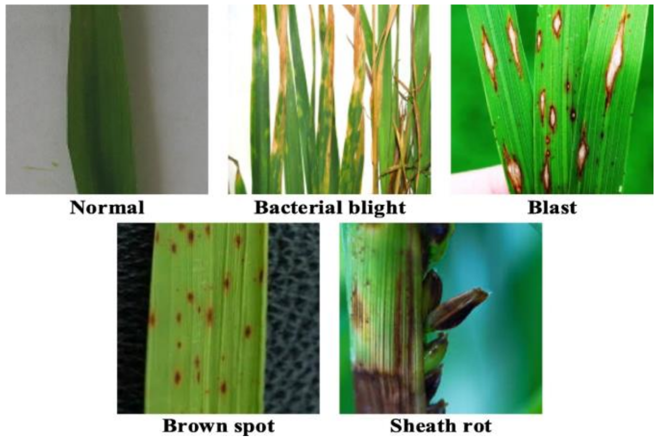

Fig. 2. Sample images of normal and diseased leaves

Pre-processing

During preprocessing dimension of the images have been set to 300 × 450 pixels. Then to remove image background hue values-based fusion with edge detection mechanism. Image in RGB model is converted into HSV at initial stage. From the HSV model S value is considered for process as it overs the whiteness. Considering threshold value to 90, image is modified to binary image. Then this binary image is fused with original RGB image in order to create a mask. Threshold value is chosen considering many trials. Fusion process is helps in removing background by assigning pixel values to 0. Pixel value 0 is showing black color in the RGB model. Figure 3 & 4 is showing preprocessing steps.

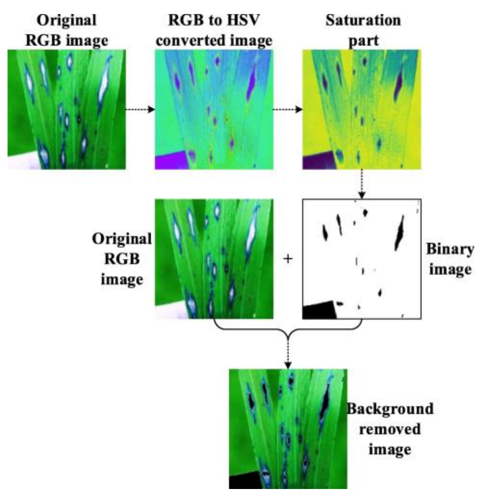

Fig. 3. Pre-processing steps for background elimination

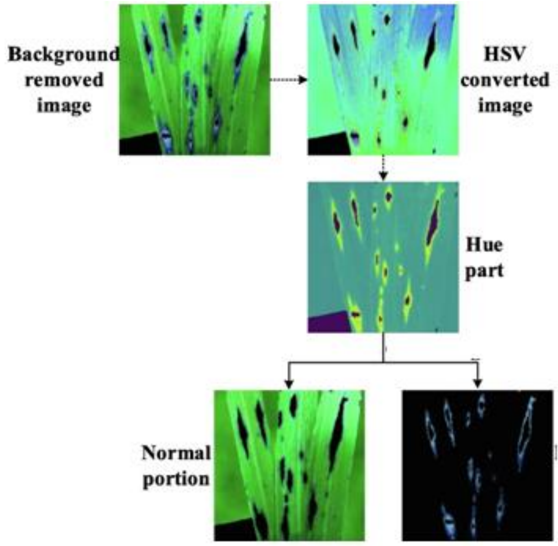

Fig. 4. Edge detection from the hue part

Feature Extraction

In this work we extracted both the texture features and color features. The color features include extracting the mean values and standard deviation values whereas the texture features include the GLCM features such as homogeneity, contrast correlation and energy. Finally, edge detection mechanism is applied to improve the accuracy during classification.

Color features

1. Initial R, G and B components have been fetched for diseased portion. Mean value and standard deviation have been evaluated.
2. In case of HSV model, H, S and V components are considered. Then mean value has been calculated.
3. In case of LAB color model, L, A and B components are taken in account. Then mean value is calculated.

The mean and standard deviation are calculated by using the formulas given below.

$$M_y = \frac{1}{n}\sum_{x=1}^{n} P_{yx} \ldots\ldots (1)$$

$$S_y = \sqrt{\frac{1}{n}\sum_{x=1}^{n}\left(P_{yx} - M_y\right)^2} \ldots\ldots (2)$$

Here n is showing total number of pixels. $P_{yx}$is meant for pixel values.

Texture Features

Considering spatial relationship among pairs of gray value intensity pixels, the GLCM is getting texture of image. For the specified displacements homogeneity, correlation, energy and contrast are characteristics got from GLCMs. Formulas for such characteristics have been shown as.

$$H_y = \sum_{x-0}^{n} \frac{P_{yx}}{1+(y-x)^2} \ldots\ldots (3)$$

$$Ct_y = \sum_{x=0}^{n} P_{yx}(y-x)^2 \ldots\ldots (4)$$

$$Cn_y = \sum_{x-0}^{n} P_{yx}\frac{(y-M)(x-M)}{S_y} \ldots\ldots (5)$$

$$E_y = \sum_{x=0}^{n}\left(P_{yx}\right)^2 \ldots\ldots (6)$$

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Volume 54, Issue 12, December, 2023

where, H_y shows homogeneity, Ct_y is meant for contrast, Cn_y indicates correlation, E_y shows energy, n is considered for total number of pixels, P_{yx} is presenting pixel values, $M_y$is showing mean and S_y is showing standard deviation.

After extracting the color features and texture features, normalization is performed to normalize the feature values. For this normalization process Min-Max method is employed to normalize the values in the range of 0 to 1.

Classification using ResNet-50

ResNet-50 is a sophisticated deep neural network that excelled in the classification challenge. Convolution, pooling, activation, and fully-connected layers are all stacked one on top of the other in a Deep Residual Network. The identity link between the layers is the only construction that turns a simple network into a residual network. ResNet-50 follows a four-stage architecture. The architecture of ResNet-50 is shown in figure 5.

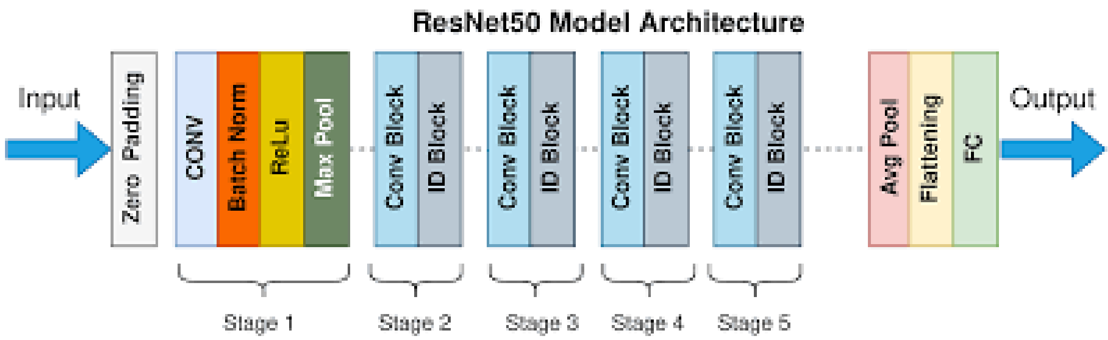

Fig. 5. Architecture of Resnet50

Simulation of Previous model

Existing methodology that is using DNN_JOA was estimated and compared with performance of existing classifiers such as ANN, DAE and DNN. The results were compared based on the disease classes which includes normal, bacterial blight, brown spot, sheath rot and blast disease. From dataset 70% of images were used for training, 20% were used for testing and remaining 10% are used for validation.

TABLE 3. Confusion Matrix of DNN-JOA

	Blast	**Bacterial blight**	**Brown spot**	**Sheath Rot**	**Normal**
Blast	29	1	0	0	0
Bacterial blight	1	26	0	0	1
Brown spot	0	0	25	2	0
Sheath Rot	1	1	1	22	0
Normal	0	1	0	0	19

Table 3 shows the confusion matrix obtained for previous method. From this confusion matrix the True Positive, True Negative, False Positive and False Negative values are predicted.

TABLE 4. Precision & Recall in Previous research

	Blast	Bacterial blight	Brown spot	Sheath Rot	Normal	Classification overall	Precision Accuracy
Blast	29	1	0	0	0	30	96.67%
Bacterial blight	1	26	0	0	1	28	92.58%
Brown spot	0	0	25	2	0	27	92.59%
Sheath Rot	1	1	1	22	0	25	88%
Normal	0	1	0	0	19	20	95%
Truth overall	31	29	26	24	20	130	
Recall accuracy	93.548%	89.655%	96.154%	91.667%	95%		

In case of previous work that is using DNN_JOA algorithm the overall accuracy 93.077 as shown in table 4.

Simulation of Proposed model

In Proposed methodology Resnet50 with canny edge detection have been used. Here results are also compared depending on disease classes which includes normal, bacterial blight, brown spot, sheath rot and blast disease. From dataset 70% of images have been used for training, 20% is considered for testing and remaining 10% have been considered for validation.

TABLE 5. Confusion Matrix of Proposed work

	Blast	Bacterial blight	Brown spot	Sheath Rot	Normal
Blast	30	0	0	0	0
Bacterial blight	0	28	0	0	0
Brown spot	0	0	26	1	0
Sheath Rot	1	0	0	23	0
Normal	0	1	0	0	20

Above table 5 is showing confusion matrix obtained for previous method. From this confusion matrix the True Positive, True Negative, False Positive and False Negative values have been predicted.

TABLE 6. Confusion Matrix of Proposed work

	Blast	Bacterial blight	Brown spot	Sheath Rot	Normal	Classification overall	Precision Accuracy
Blast	30	0	0	0	0	30	100%
Bacterial blight	0	28	0	0	0	28	100%
Brown spot	0	0	26	1	0	27	96.296%
Sheath Rot	1	0	0	23	0	24	95.833%
Healthy	0	1	0	0	20	21	95.238%
Truth overall	31	29	26	24	20	130	
Recall accuracy	96.774%	96.552%	100%	95.833%	100%		

In case of proposed work precision is 100% in Blast, 100% in Bacterial blight, 96.296% in Brown spot, 95.833% in Sheath Rot and 95.238% in Healthy leaf. The Recall accuracy is 96.774% in Blast, 96.552% in Bacterial blight, 100% in Brown spot, 95.833% in Sheath rot and 100% in Healthy leaf. The overall accuracy is 97.692% as shown in table 6.

ISSN: 00845841
Volume 54, Issue 12, December, 2023

7. COMPARATIVE ANALYSIS

It has been observed that the overall accuracy is more in case proposed model where CNN has been used with canny edge detection mechanism as compared to previous model. In proposed model overall accuracy is 98% but in case of previous research it was 93.077% as shown in table 7 & figure 6.

TABLE 7. Comparison of Previous & Proposed Methodology

	Previous research	Proposed research
Overall accuracy	**93.077%**	**98%**

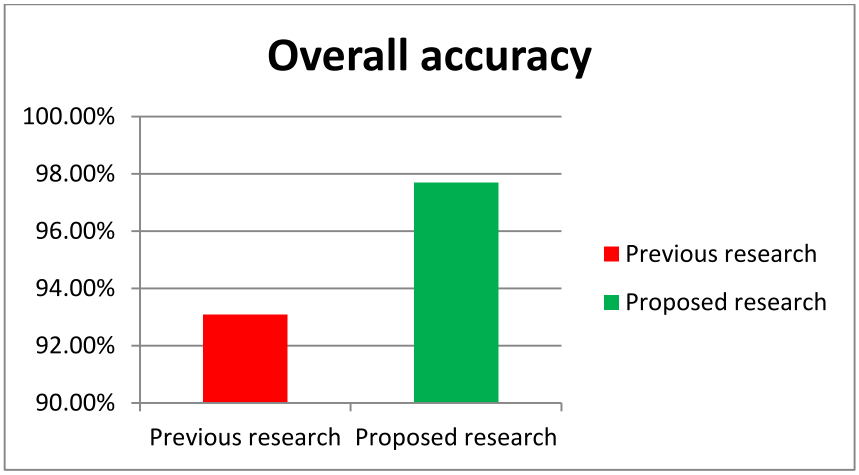

Fig. 6. Comparison of overall accuracy

Comparison of Precision of previous and proposed model

It has been observed that the precision is more in case proposed model where CNN has been used with canny edge detection mechanism as compare previous model as shown in table 8 & figure 7.

TABLE 8. Comparison of Precision

Class	Previous research	Proposed research
Blast	96.67%	100%
Bacterial blight	92.58%	100%
Brown spot	92.59%	96.296%
Sheath Rot	88%	95.833%
Normal	95%	95.238%

Considering above table, the comparison chart has been generated as shown in figure 7.

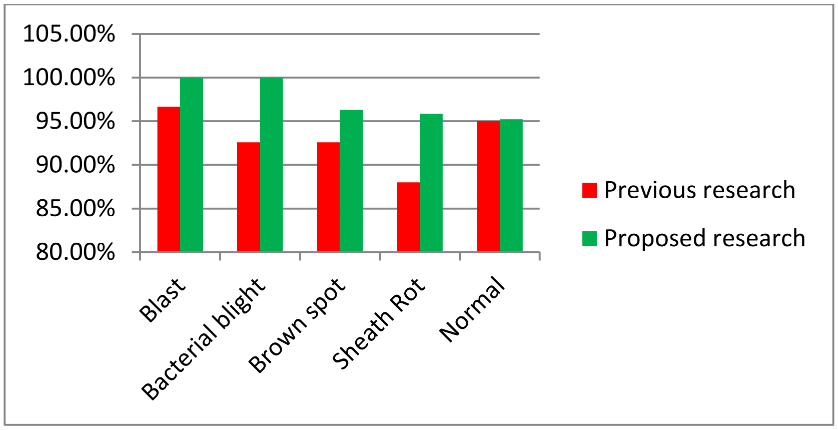

Fig. 7. Comparison of Precision

Comparison of Recall of previous and proposed model

It has been observed that the recall is more in case proposed model where CNN has been used with canny edge detection mechanism as compare previous model as shown in table 9.

TABLE 9. Comparison of Recall accuracy

Class	Previous research	Proposed research
Blast	93.548%	96.774%
Bacterial blight	89.655%	96.552%
Brown spot	96.154%	100%
Sheath Rot	91.667%	95.833%
Normal	95%	100%

Considering table 9, the comparison chart has been generated as shown in figure 8.

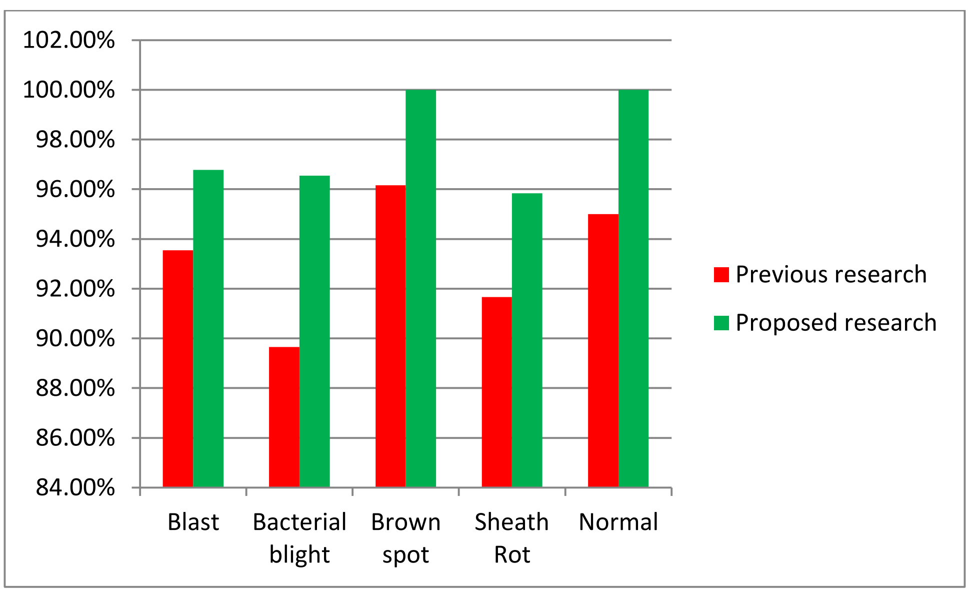

Fig. 8. Comparison of Recall

8. CONCLUSION

It has been concluded that the proposed methodology that is using ResNet-50 with canny edge detection is providing more accuracy as compared to previous research. Here results have been compared considering disease classes that are consisting normal, bacterial blight, brown spot, sheath rot and blast disease. In proposed model overall accuracy is 98% but in case of previous research it was 93.077%. Moreover, it has been observed that the precision and recall accuracy for blast, bacterial blight, brown spot and shealth rot is more in case proposed model where CNN has been used with canny edge detection mechanism as compare previous model. Finally, it is concluded that proposed model is providing more accurate, flexible, scalable solution as compared to previous model.

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