

Progressive Regional Spatial Mechanism With Convolutional Neural Network For Cotton Leaf Disease Classification

E.D. Pavana Kumar¹ * S. Malathi¹ , C. Siva Balaji Yadav²

¹ Department of Computer Science and Engineering, Annamalai University, Chidambaram, Tamil Nadu, India

² Department of Artificial Intelligence, Annamacharya Institute of Technology, Tirupathi, Andhra Pradesh, India

* Corresponding author's : E.D. Pavana Kumar

Abstract

Cotton leaf disease is the infections affected cotton plant leaves produced though bacteria, fungi and viruses are leads to symptoms like discoloration and spots in the cotton leaves. The cotton leaf disease classification is procedure of recognizing and classifying the diseases from the leaf images based on leaf shapes and visual patterns. However, intra class similarities among diseases, complex background images and overlapping disease symptoms are leads to misclassification which reduce the model classification accuracy. To overcome these challenges, Progressive Regional Spatial Mechanism - Convolutional Neural Network (PRSM-CNN) is proposed to increase the spatial feature discrimination and efficiently classify the visual similarity among diseases which increases the model classification accuracy. The proposed PRSM-CNN increases classification accuracy though efficiently highlighting disease relevant regions while suppressing complex background noise and allowed reliable performance under noisy data augmentation conditions. The cotton leave disease and cotton disease datasets are used in this research, the proposed PRSM-CNN model attains the high level of accuracies of 99.12 % and 99.58% in cotton leaf disease and cotton disease datasets respectively.

Keywords: Background Images, Bacteria, Convolutional Neural Network, Cotton Leaf Disease, Intra Class Similarities, Progressive Regional Spatial Mechanism.

1.Introduction

Crop disease is a vital problem in agriculture which is affecting and damaging the crops, the challenge of crop disease in agriculture shows the output like low yields and low level of food quantity and quality [1]. The cotton is called as economic crop that contribute to a production of natural fiber, production of clothing is cotton crops contribution which enhances the textile sector [2]. The leaf disease is one the necessary problem of affecting the crop, farmers inspections is required for to check the quality of the crops [3]. Farmers daily inspections are time consumed, very expensive and failed to shows the accurate state of leaf [4]. Cotton is called as white gold is one of fiber crops across the world, in India cotton ranks between a top socioeconomic crop with huge harvesting area [5]. The cotton plant displays exposure a viral and bacterial infections, examples of infections like leaf curl disease, bacteria blight and fusarium wilt [6]. In textile sector the main source is cotton which is main in cellulose which has concern in global economy and medical sector also [7]. The purpose of crop management is yielding estimation, exact data for a sizeable area of cotton is necessary, the cultivation of cotton plant is called as *Gossypium herbaceum* [8].

Cotton serves as a primary source of natural fiber and plays a key role in clothing production. Its cultivation supports the growth of the textile industry and contributes significantly to the agricultural and industrial economies [9]. The cotton leaf disease classification and detection are difficult because of contrast among two leaves like environmental conditions, shadow light and back ground soil [10]. The difficulties are happened because of pests' control, water usage and sustainability [11]. However, cotton leaf disease is vital difficulty for cotton farmers in country, the world population consumes cotton related materials [12]. Because of damaging diseases effects, affecting the cotton quality which are necessary that continuous analysis and enhancement of cotton crop [13]. Nevertheless, cotton production faces various difficulties among cotton like leaf blight, leaf spot, gray mold, leaf curl and fusarium wilt are impact and affected the cotton yield and quality [14]. The Artificial Intelligence (AI) based method such as Machine Learning (ML) and Deep Learning (DL), specifically DL models are performed well in cotton leaf disease classification. The DL approaches is extracting an inherent features and contextual data from a huge image dataset which are combining into a feature learning process for building the procedure for cotton leaf disease classification [15].

1.1 Problem statement and objectives

To accurately classifying the cotton leaf disease is difficult because of high inter class similarity, complex backgrounds and overlapping visual symptoms between various disease classes. Diseased and healthy cotton leaves are looking and sharing similar color texture patterns and color distributions while disease symptoms like curls, spots and discoloration appear only in localized regions. To solve this issue, Progressive Regional Spatial Mechanism - Convolutional Neural Network (PRSM-CNN) is proposed to focused on localized disease symptoms such as curls, spots, discoloration rather than global color similarities. Though suppressing background noise and increasing the spatial regions by PRSM while the model efficiently reduces an inter class confusion and enhances a classification accuracy even under complex backgrounds and limited training data.

1.2 Contributions

The main contributions of this research are described in below:

- The proposed PRSM-CNN enhances semantic feature representation by grouping convolutional feature maps based on intra group similarities allowing increased spatial localization and noise suppression in cotton leaf disease classification.
- The PRSM is associated into the CNN as layer modification to strength spatial feature discrimination and minimize background noise this mechanism operates a convolutional output though highlight informative regions and suppressing irrelevant features.
- The integration of PRSM and CNN permits the model to learn discriminative spatial features by various augmented samples without affected the noise variations which spatial mechanism suppress random pixel noise while preserving discriminative lesion regions.

The research paper is organised as follows: Section 2 represents the related works, Section 3 illustrates a proposed methodology. Section 4 shows the experimental results and discussion of this research. Section 5 concludes a conclusion of a research paper.

2. Related Works

In this section denotes the advantages and limitations of existing approaches for cotton leaf disease classification based on cotton disease and cotton leaf datasets.

V. Pandiyaraju et al. [16] developed transfer learning based automated framework was proposed which contains two key phases such as feature extraction and detection. The convolutional Neural Network by Visual Geometry Group (VGG16) was applied in the feature extraction stage for attained a deep feature from a cotton leaf images with difficult background. An extracted optimal feature was input to Random Forest (RF) and Support Vector Machine (SVM) while the hybrid models were utilized to enhanced a detection accuracy.

Chitranjan Kumar Rai and Roop Pahuja [17] implemented Improved Deep Convolutional Neural Network (IDCNN) for classified the diseased cotton leaves and plants. In the preprocessing stage data augmentation techniques were used such as rescaling, rotation and horizontal flipping were performed. A DCNN model was utilized to classify the diseases automatically in cotton leaves and plants though altering a parameter of the AlexNet architecture.

Chitranjan Kumar Rai and Roop Pahuja [18] introduced supervised bagging ensemble technique involved of five transfer models like InceptionV3, InceptionResNetV2, VGG16, MobileNet and Xception named ETL-NET. The ensemble ETL-NET model was approved to enhance a performance of every individual model, the transformations like height shift, zoom range, rotation a shear range were performed in preprocessing stage. The ETL-NET model was utilized while the five neural networks were ensemble for detected a cotton leave diseases and plants.

Md.Manowarul Islam et al. [19] developed DL based cotton leaf disease detection model by fine tuning Transfer Learning (TL) were used though layer tuning and parameters with web application in agriculture. The web application-based detection system though associating an DL approaches to recognize a disease affected leaves accurately which allowed to make exact diagnosis and increasing a harvest output.

Hirenkumar Kukadiya et al. [20] implemented Ensemble VGG16 with Inspection V3 for automatic classification of cotton leave disease. An objective of this ensemble based DCNN method relies on two pretrained approach like VGG16 with Inspection V3 for early detection of cotton leave diseases. The hyperparameter Stochastic Gradient Descent (SGD) Optimizer was increased an ensemble model to classify a cotton leave disease.

3. Proposed Methodology

In the proposed methodology section, the proposed PRSM-CNN is utilized for cotton leaf disease classification, the model classified the diseases into two classes such as binary and multiclass disease. The binary classes are classified into based on cotton disease dataset and multiclass is categorized into based on cotton leaf disease dataset. The PRSM as a layer

modification module with CNN to enhance spatial feature discrimination for cotton leaf disease classification. The PRSM efficiently address and overcome the issues like inter class similarity, background complexity, augmentation induced noise and overlapping disease symptoms allowing robust learning from the limited training samples. Figure 1 shows the block diagram of proposed PRSM-CNN for cotton leaf disease classification.

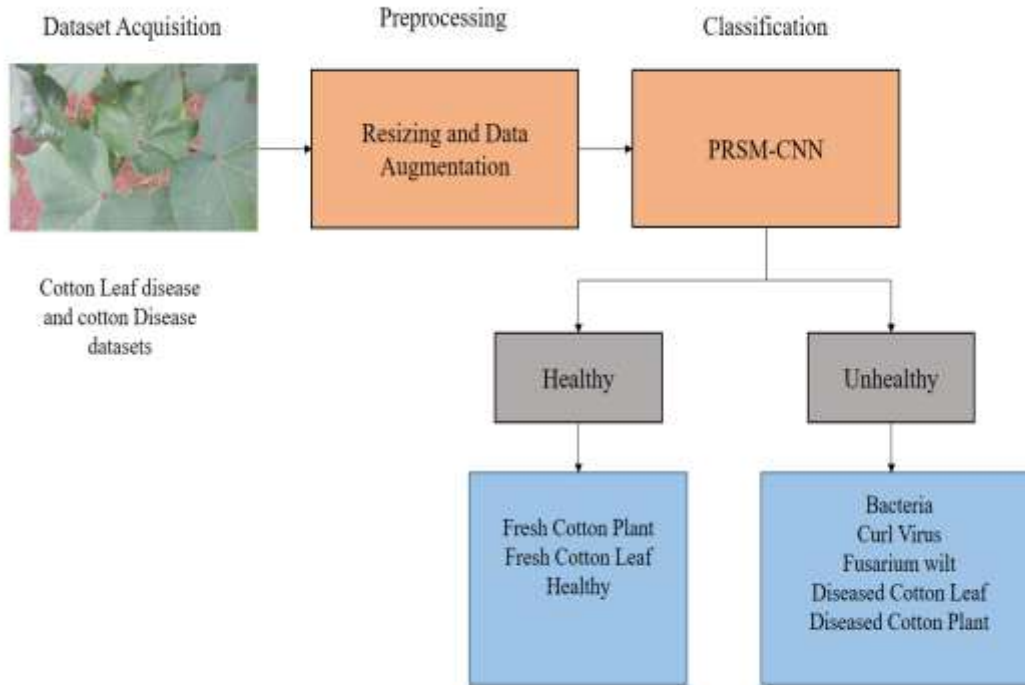


Figure 1. Block diagram of proposed PRSM-CNN for cotton leaf disease classification

3.1 Dataset Acquisition

In this research, the cotton leaf disease [21] and cotton disease [22] dataset is utilized to evaluate and estimate the model performance which are described in below: The dataset description of cotton leaf disease and cotton disease dataset are presented in table 1.

Table 1. Dataset descriptions of Cotton leaf disease and cotton disease, number of classes and image count

Datasets	Number of classes	Image Count
Cotton Leaf Disease Dataset	Bacteria Blight	448
	Curl virus	418
	Fusarium wilt	419
	Healthy	426
Cotton Disease dataset	Diseased Cotton Leaf (DCL)	346

	Diseased Cotton Plant (DCP)	922
	Fresh Cotton Leaf (FCL)	511
	Fresh Cotton Plant (FCP)	514

The cotton disease dataset contains 4 classes like DCL, DCP, FCL and FCP, in this research the 4 classes are categorized into 2 classes. The DCL and DCP considered as diseased classes and FCL and FCP called as healthy classes.

3.2 Preprocessing

In the preprocessing stage, to handle an size of cotton leaf, height and width of each of an cotton leaf images the resizing is used. The procedure of modifying a size of image while keeping the number of pixels constant for each image in the dataset. The input image is reshaped into size of 256×256 which enhanced a quality of resized of cotton leaf images. In preprocessing stage, data augmentation is performed to address the limited size of cotton leaf disease datasets and to enhance model generalization, data augmentation approaches like horizontal, vertical and rotation are used to enhance the image count and augmented produces noisy variations like background inconsistencies, illumination changes and geometric distortions. The proposed PRSM-CNN overcome the noisy augmented images by PRS features that emphasize consistent disease patterns across augmented samples while preserving discriminative lesion regions. Data augmentation increases generalization ability but which produces the noisy samples such as blurred, incomplete misaligned features, slight geometric distortions which minimized the model performance while model lacks robust feature discrimination mechanisms. Data augmentation performed as regularization technique, the proposed PRSM-CNN overcome the noisy images though highlights reliable spatial patterns across augmented samples, increasing invariant disease related features and suppressing random pixel level disturbances which permits the CNN to learn noise representations tuning augmentations noise into a regularization advantage rather than a limitation.

3.3 Classification

In the classification stage CNN is used to classify the cotton diseases and convolutional layers and CNN is a supervised class for better performance in cotton disease classification. The CNN as feedforward neural networks automatically extracted features from data by convolution layers, CNN contains convolutional, pooling, activation and pooling layers are described in below:

Convolution Layer

The convolutional layer extracted a feature though operating a scalar product among input image information and filter weights integrating a bias term. In the convolution a filter kernel size across an input features and for every position which operates a sum of weights values in a small region of an input. The procedure is based on each input channel and outputs

are integrated to generate an output feature maps, the convolution operation is mentioned in equation (1):

$$y_i = \sum_{i=1}^n W_{ij} X_i + \beta_i \quad (1)$$

Where, X_i is input parameter, W_{ij} presents weight integrating input parameter X_i to j , β_i is based to a bias term integrated with an input parameter.

Progressive Regional Spatial Mechanism

The cotton leaf disease shows the challenges like localized and overlapping disease symptoms, complex backgrounds, limited training samples, high visual similarity among the classes to overcome this problem PRSM is used in this research to classify the cotton leaf disease accurately. When classifying the binary and multiple classes of cotton leaf disease, the model disturbed though irrelevant features like background led to inaccurate classification output. The proposed PRSM is performed well in cotton leaf disease which localized the spatial patterns like spots, curls, lesions compared to global texture modifications which enhances a localized region while minimizing background images. The PRSM groups the feature maps and contains each classes denoting asemantic feature which produces attention masks relies on similarity among local and global features while increasing spatial distribution of semantic features. The PRSM enhances spatial discrimination which is suitable for cotton leaf disease classification where cues and subtle spatially recognized. Through associating parallel GAP channels and presenting modifiable parameters to balance an effect of GAP and Global Max Pooling (GMP) based on that only PRSM generated, his modifications aims to increase a model ability to denote image information efficiently. The PRSM operates a GAP to capture global data by the group feature maps, in primarily, the PRSM split the input feature map $X \in R^{C \times H \times W}$ into G groups and each group feature map undertakes both GAP and GMP operations and p_1 and p_2 are learnable parameters presented to update an weights of an parallel channels. An element wise multiplication of each group input feature map with feature matrices attained by output of an initial attention mask c is mentioned in equations (2) and (3):

$$n = p_1 \cdot F_{GAP}(X_g) + p_2 \cdot F_{GMP}(X_g) \quad (2)$$

$$c = n \cdot X_i \quad (3)$$

Then attention mask c is normalized and learnable scaling and shifting parameters γ and β are produced based on equations (4) and (5):

$$c_i = \frac{c_i - \mu_c}{\sigma_c + \epsilon}, \mu_c = \frac{1}{m} \sum_j^m c_j, \sigma_c^2 = \frac{1}{m} \sum_j^m (c_j - \mu_c)^2 \quad (4)$$

$$a_i = \gamma c_i + \beta \quad (5)$$

The PRSM employs though split the feature maps into groups and adaptively highlighting spatial locations that shows a semantic importance of features which is suited for cotton leaf disease classification. The proposed PRSM-CNN increases the fine-grained spatial features with group allowed the CNN model to capture subtle variations in shape, textures and color this group wise increasement minimizes a confusion among visual similar disease classes. In the data augmentation produce a slight noise differentiation like blurring, geometric distortions affect the model performance CNN is constructed to learn spatially

invariant and discriminative features permit them to focused on disease related patterns rather than noise artifacts. In the training stages the convolutional layers learn local receptive field-based features which minimizes sensitivity to random pixel level noise. Early layers capture structures of cotton leaf like texture gradients, edges while deeper layers highlight high level of disease characteristics, in output noise produced by augmentation does not dominate a learned representation. To enhance spatial feature representation and robustness against background noise the PRSM is associated into CNN as layer modification, while PRSM is positioned after a convolutional layer to adaptively increase spatially necessary feature groups while suppressing irrelevant regions.

Pooling Layer

The pooling layer minimize spatial dimension though down sampling feature maps by max or average pooling functions. This pooling operation reduces a computational demand and mitigates overfitting via retaining necessary features while removing a redundant information. A pooling layer is chosen to pool all feature maps, when operating pooling layers to handle a window size and chosen a pooling approach to attain a best output. This pooling approach summarizes a feature maps though averaging a value which preserve key data while simplifying a data.

Fully connected layer

The output of pooling layer feature maps is then procedure though an flatten layer which transforms them into an 1dimensional vector to produce an information for a fully connected layer. Fully connected features utilized extracted features for classification of cotton leaf disease, softmax activation functions operates a multiclass task allowing precise classifications relies on learned representations.

Pseudocode for proposed PRSM-CNN for cotton leaf diseases classification

Initialize CNN architecture and PRSM parameters

Load cotton leaf disease and cotton disease datasets

Resize input images to fixed dimension

Perform data augmentation (rotation, horizontal flip, vertical flip)

For each training epoch Do

For each input image X_i in training batch Do

Feature extraction phase

Apply convolution operation to X_i to obtain feature maps F

Progressive Regional Spatial Mechanism (PRSM)

Split feature maps F into G groups $\{F_1, F_2, \dots, F_G\}$

For each group F_j Do

Apply Global Average Pooling (GAP)

Apply Global Max Pooling (GMP)
 Combine GAP and GMP using learnable weights α and β
 Generate attention mask A_j
 Multiply F_j with A_j to enhance disease-relevant regions
 End For
 Concatenate all enhanced group feature maps
 Apply pooling operation to reduce spatial dimension
 Classification phase
 Flatten pooled feature maps
 Pass features through fully connected layers
 Apply Softmax activation to obtain class probabilities
 Compute loss using predicted and true labels
 Update network weights using backpropagation
 End For
 End For
 Evaluate trained PRSM-CNN on test dataset
 Output predicted disease classes and performance metrics

4. Experimental Results

The performance of proposed PRSM-CNN is evaluated and estimated based on Cotton Leaf Disease and Cotton Disease datasets. proposed approach is evaluated on python 3.4 and system specifications windows10, 128-bit OS, Intel Core i7. The proposed PRSM-CNN method is estimated through various evaluation metrics such are F1-score, accuracy, recall and precision are described in table 2.

Table 2. Description of performance metrics like accuracy, recall, precision and F1-score

Metrics	Formula	Description
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	The amount of accurately determined and rejected images based on the total amount of images.
Precision	$\frac{TP}{TP + FP}$	It shows the number of accurately classified images related to total number of classified images.

Recall	$\frac{TP}{TP + FN}$	Recall is the classified the cotton leaf image accurately.
F1-score	$2 \times \frac{\text{Precision} * \text{recall}}{\text{Precision} + \text{recall}}$	Harmonic mean of the classes that shows balance among precision and recall

Where, TP - True Positive, TN - True Negative, FP - False Positive, FN - False Negative.

4.1 Performance Analysis

In the performance analysis section, the proposed PRSM-CNN is compared with various DL models like VGG 16, ResNet 50, CNN are compared. The performance estimation of proposed CSLCL-CNN is estimated and evaluate across two datasets are Cotton Leaf disease and Cotton Disease datasets which performance is analyzed though different metrics like recall, precision, F1-Score and accuracy. Table 3 shows the proposed PRSM-CNN model attains better results for cotton leaf disease classification while compared with other existing approaches.

Table 3. Performance analysis of proposed PRSM-CNN is compared with other DL based approaches for cotton leaf disease classification

Datasets	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cotton Leaf disease	VGG 16	94.32	93.85	93.12	93.48
	ResNet 50	96.74	96.12	95.84	95.98
	CNN	97.86	97.34	97.12	97.23
	Proposed PRSM-CNN	99.12	98.65	98.71	98.68
Cotton Disease dataset	VGG 16	95.48	94.92	94.36	94.64
	ResNet 50	97.12	96.84	96.53	96.68
	CNN	98.26	97.98	97.65	97.82
	Proposed PRSM-CNN	99.58	99.12	99.14	99.13

Table 3 demonstrates that the proposed PRSM-CNN achieves accuracy, precision, recall and F1-score compared to VGG16, ResNet50, and conventional CNN across both datasets. This improvement is mainly due to the PRSM which highlights disease specific localized regions such as spots, curls and lesions while suppressing background noise. Unlike traditional CNNs that rely on global feature learning, PRSM-CNN enhances fine-grained spatial discrimination which reducing inter class confusion caused by visually similar disease patterns. Table 4 illustrates the computational complexity analysis of proposed PRSM-CNN for cotton leaf disease classification.

Table 4. Performance of computational complexity analysis of proposed PRSM-CNN for cotton leaf disease classification

Datasets	Methods	Inference Time (s)	Training Time (s)	Memory Usage (KB)	Flops (G)	Parameters (s)
Cotton Leaf disease	VGG 16	0.214	520	3680	15.3	138
	ResNet 50	0.148	385	2540	9.6	121
	CNN	0.121	310	2120	7.8	106
	Proposed PRSM-CNN	0.085	246	1580	5.4	94
Cotton Disease dataset	VGG 16	0.226	545	3820	15.9	129
	ResNet 50	0.156	402	2680	10.2	124
	CNN	0.129	328	2240	9.8	109
	Proposed PRSM-CNN	0.112	192	1980	8.4	97

Table 4 highlights that PRSM-CNN achieves better computational efficiency with reduced inference time, training time, memory usage, FLOPs and parameter compared to other approaches. This efficiency is attained by grouping feature maps and selectively enhancing informative spatial regions, which avoids redundant feature learning. The pretrained networks that process irrelevant background information, PRSM-CNN focuses computation on disease-relevant regions enabling low level of time and reduced memory usage. Table 5 shows the Cross generalization analysis, training dataset is plant village dataset as training and testing as Cotton Disease dataset.

Table 5. Cross generalization analysis, training dataset is plant village dataset as training and testing as Cotton Disease dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG 16	90.84	89.76	88.92	89.34
ResNet 50	93.68	92.85	92.14	92.49
CNN	95.42	94.63	93.98	94.30
Proposed PRSM-CNN	97.24	95.47	94.67	95.07

The cross-dataset evaluation in Table 5 confirms that PRSM-CNN generalizes more effectively when trained on the Plant Village dataset and tested on the Cotton Disease dataset. The results are achieved because PRSM learns spatially invariant disease patterns rather than dataset-specific textures. By suppressing background dependency and emphasizing consistent lesion structures. The PRSM-CNN maintains high accuracy and F1-score than conventional CNN and other models in unseen environments. Table 6 depicts the Ablation study of proposed PRSM-CNN is compared with other DL models across two datasets.

Table 6. Ablation study of proposed PRSM-CNN is compared with other DL models across two datasets

Datasets	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cotton Leaf disease	PRSM+ VGG 16	95.64	94.24	93.15	93.69
	PRSM+ ResNet 50	96.97	95.48	93.58	94.52
	PRSM	97.58	96.87	95.87	96.37
	Proposed PRSM-CNN	99.12	98.65	98.71	98.68
Cotton Disease dataset	PRSM+ VGG 16	96.57	95.49	94.87	95.18
	PRSM+ ResNet 50	97.84	96.75	95.19	95.87
	PRSM	98.01	97.67	96.67	97.17
	Proposed PRSM-CNN	99.58	99.12	99.14	99.13

Table 6 validates the individual and combined contribution of PRSM and CNN architecture. While PRSM integrated with VGG16 or ResNet50 improves performance the proposed PRSM-CNN configuration achieves the high level of output confirming effective interaction between spatial grouping and convolutional feature extraction. The PRSM enhances attention to disease regions, but its integration with CNN enables better feature representation, lead to attain high level of performance across both datasets. Table 7 determines the K-fold analysis of proposed PRSM-CNN using Cotton Leaf disease and Cotton Disease dataset across various k-folds.

Table 7. K-fold analysis of proposed PRSM-CNN using Cotton Leaf disease and Cotton Disease dataset across various k-folds

Datasets	K-Fold values	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cotton Leaf disease	K=2	96.48	95.92	95.36	95.64
	K=3	97.62	97.14	96.85	96.99
	K=4	98.46	97.98	97.65	97.82
	K=5	99.12	98.65	98.71	98.68
	K=6	98.94	98.32	98.26	98.29
Cotton Disease dataset	K=2	96.92	96.35	96.08	96.21
	K=3	97.98	97.42	97.18	97.30
	K=4	98.86	98.35	98.12	98.24
	K=5	99.58	99.12	99.14	99.13
	K=6	99.21	98.74	98.68	98.71

The K-fold results in Table 7 demonstrate stable and consistent performance of PRSM-CNN across different data partitions, with peak performance observed at K=5. This consistency

indicates that the proposed model is not biased toward specific training samples. The progressive spatial grouping mechanism ensures robust feature learning even with varied training distributions, preventing overfitting and confirming the statistical reliability of the achieved results.

4.2 Comparative Analysis

In the comparative analysis section, the proposed PRSM-CNN is compared with existing approaches such as Hybrid VGG SVM [16], IDCNN [17], Ensemble learning based DCNN [18] and Ensemble VGG 16+Inception V3 [20]. The table 8 illustrates the comparative analysis of proposed PRSM-CNN is compared with existing approaches.

Table 8. Comparative analysis of proposed PRSM-CNN with existing approaches

Datasets	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Cotton Leaf disease	Hybrid VGG SVM [16]	98.33	98.17	98.29	98.29
	Ensemble VGG 16+Inception V3 [20]	98.13	NA	NA	NA
	Proposed PRSM-CNN	99.12	98.65	98.71	98.68
Cotton Disease dataset	IDCNN [17]	97.98	NA	NA	NA
	Ensemble learning based DCNN [18]	99.48	99	99	99
	Proposed PRSM-CNN	99.58	99.12	99.14	99.13

Table 9 presents a comparative evaluation of the proposed PRSM-CNN with existing state-of-the-art methods such as Hybrid VGG-SVM, IDCNN and ensemble-based DCNN models. The proposed PRSM-CNN achieves the highest accuracy on both Cotton Leaf Disease and Cotton Disease datasets due to its ability to explicitly model spatially localized disease symptoms. The proposed PRSM-CNN enhances discriminative learning by progressively highlighting disease-relevant regions and suppressing background interference enabling better classification accuracy with improved efficiency in under complex visual conditions.

5. Conclusion

In this research the proposed PRSM-CNN enhances semantic feature representation by grouping convolutional feature maps based on intra group similarities allowing increased spatial localization and noise suppression in cotton leaf disease classification. The proposed ASGE improves spatial discrimination making it well suited for cotton leaf disease recognition tasks where disease cues are subtle and spatially constrained. Although data augmentation introduces minor noise variations the CNN effectively suppresses such perturbations through

convolutional feature extraction, pooling operations, and regularization techniques, thereby learning noise-invariant disease representations. The PRSM efficiently address and overcome the issues like inter class similarity, background complexity, augmentation induced noise and overlapping disease symptoms allowing robust learning from the limited training samples. The proposed PRSM-CNN increases classification accuracy though efficiently highlighting disease relevant regions while suppressing complex background noise and allowed reliable performance under noisy data augmentation conditions. The proposed PRSM-CNN model attains the high level of accuracies of 99.12 % and 99.58% in cotton leaf disease and cotton disease datasets respectively.

References

- [1]. Nazeer, R., Ali, S., Hu, Z., Ansari, G.J., Al-Razgan, M., Awwad, E.M. and Ghadi, Y.Y., 2024. Detection of cotton leaf curl disease's susceptibility scale level based on deep learning. *Journal of Cloud Computing*, 13(1), p.50.
- [2]. Kaur, A., Singla, G., Singh, M., Mittal, A., Mittal, R. and Malik, V., 2024. Cotton crop classification using satellite images with score level fusion-based hybrid model. *Pattern Analysis and Applications*, 27(2), p.43.
- [3]. Askr, H., El-dosuky, M., Darwish, A. and Hassanien, A.E., 2024. Explainable ResNet50 learning model based on copula entropy for cotton plant disease prediction. *Applied Soft Computing*, 164, p.112009.
- [4]. Sharma, V., Tripathi, A.K., Mittal, H., Parmar, A., Soni, A. and Amarwal, R., 2023. Weedgan: a novel generative adversarial network for cotton weed identification. *The Visual Computer*, 39(12), pp.6503-6519.
- [5]. Kumari, S., Marwaha, S., Haque, M.A., Sachan, H., Deb, C.K., Dahiya, S., Arora, A. and Shashank, P.R., 2025. A lightweight densely connected network for insect-pest identification in cotton crop. *Neural Computing and Applications*, 37(26), pp.21459-21472.
- [6]. Patil, B.M. and Burkpalli, V., 2022. Segmentation of cotton leaf images using a modified chan vese method. *Multimedia Tools and Applications*, 81(11), pp.15419-15437.
- [7]. Ali, T., Zakir, R., Ayaz, M., Murtaza, M., Hijji, M. and Hadi Aggoune, E.M., 2025. Cotton crop disease detection and classification using statistical prediction model in deep learning approach. *Multimedia Tools and Applications*, 84(41), pp.49503-49525.
- [8]. Mo, H. and Wei, L., 2025. Lightweight detection of cotton leaf diseases using StyleGAN2-ADA and decoupled focused self-attention. *Journal of King Saud University Computer and Information Sciences*, 37(4), p.41.
- [9]. Kumar, R., Kumar, A., Bhatia, K., Nisar, K.S., Chouhan, S.S., Maratha, P. and Tiwari, A.K., 2024. Hybrid approach of cotton disease detection for enhanced crop health and yield. *IEEE Access*.
- [10]. Shao, M., He, P., Zhang, Y., Zhou, S., Zhang, N. and Zhang, J., 2022. Identification method of cotton leaf diseases based on bilinear coordinate attention enhancement module. *Agronomy*, 13(1), p.88.
- [11]. Govindasamy, S. and Jayaraj, D., 2023. Collaborative ant colony optimization-assisted support vector machine for accurate cotton leaf disease classification and yield prediction. *Journal of Theoretical and Applied Information Technology*, 101(15).
- [12]. Nikith, B.V., Keerthan, N.K.S., Praneeth, M.S. and Amrita, T., 2023. Leaf disease detection and classification. *Procedia Computer Science*, 218, pp.291-300.

- [13]. Biju, G., Khan, A., Walker, D., Qadri, S., Hssan, Q., Mahmood, K. and Hanan, A., 2023, September. Identification of Cotton Leaf Curl Disease Using CNN and Vision Transformer. In *Proceedings of SAI Intelligent Systems Conference* (pp. 670-688). Cham: Springer Nature Switzerland.
- [14]. Ripon, S., Gani, R., Niha, N.M., Rahat, W.B., Toufiq, S.H., Maisha, M.F. and Ahmed, J., 2025. Cotton leaf image dataset for disease classification and health monitoring. *Data in Brief*, p.112142.
- [15]. Jashim, F.B., Refat, F.R., Karim, M.H., Mahmud, F.U. and Ashrafi, F., 2025. A web-based application for cotton leaf disease classification using vision transformer.
- [16]. Pandiyaraju, V., Anusha, B., Senthil Kumar, A.M., Jaspin, K., Venkatraman, S. and Kannan, A., 2025. Spatial attention-based hybrid VGG-SVM and VGG-RF frameworks for improved cotton leaf disease detection. *Neural Computing and Applications*, 37(14), pp.8309-8329.
- [17]. Rai, C.K. and Pahuja, R., 2023. Classification of diseased cotton leaves and plants using improved deep convolutional neural network. *Multimedia Tools and Applications*, 82(16), pp.25307-25325.
- [18]. Rai, C.K. and Pahuja, R., 2024. An ensemble transfer learning-based deep convolution neural network for the detection and classification of diseased cotton leaves and plants. *Multimedia Tools and Applications*, 83(36), pp.83991-84024.
- [19]. Islam, M.M., Talukder, M.A., Sarker, M.R.A., Uddin, M.A., Akhter, A., Sharmin, S., Al Mamun, M.S. and Debnath, S.K., 2023. A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture. *Intelligent Systems with Applications*, 20, p.200278.
- [20]. Kukadiya, H., Arora, N., Meva, D. and Srivastava, S., 2024. An ensemble deep learning model for automatic classification of cotton leaves diseases. *Indonesian Journal of Electrical Engineering and Computer Science*, 33(3), pp.1942-1949.
- [21]. Cotton Leaf Disease Dataset access link:
<https://www.kaggle.com/datasets/seroshkarim/cotton-leaf-disease-dataset> (Accessed on January 2025)
- [22]. Cotton Disease dataset access link:
<https://www.kaggle.com/datasets/janmejybhoy/cotton-disease-dataset> (Accessed on January 2025)