Deep Convolutional Neural Networks Fusion with Support Vector Machines and K-Nearest Neighbors for Precise Crop Leaf Disease Classification

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***Abstract*—Maize and Paddy are pivotal crops in India, playing a vital role in ensuring food security. Timely detection of diseases and the implementation of remedial measures are crucial for securing optimal crop yield and profitability for farmers. This study utilizes a dataset encompassing images of diseased maize and paddy leaves, addressing various conditions such as corn blight, common rust, gray leaf spot, brown spot, hispa, and leaf blast, alongside images of healthy leaves. The dataset used here is a combination of online repository as well as manually collected samples from neighborhood farmlands at different growth stages. A machine vision approach that is accessible, quick, robust and cost effective to determine crop leaf diseases is need of the hour. In the proposed work, using transfer-learning approach, many Deep Convolutional Neural Networks (DCNN) and hybrid DCNNs have been developed, trained, validated and tested. To achieve better accuracy, integration of DCNNs and machine learning classifiers like multiclass Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms is carried out. The research is carried out in four stages, in the first stage, DCNNs have been used as classifiers. Subsequently, these same DCNNs are repurposed as feature extractors, and the extracted features are input into classifiers such as multiclass SVM and KNN. In the third stage, an ensemble of DCNNs is performed for networks exhibiting excellent performance during first stage. At a fourth stage, features extracted from these ensemble networks are fed into the same multiclass SVM and KNN classifiers to assess accuracy. A total of 1600 images for training and 400 images for testing are used. For maize data set, we achieved a 100% accuracy in AlexNet plus VGG-16 hybrid network for multiclass SVM with 75:25 split ratio and for paddy dataset 99.51% accuracy is achieved in ResNet-50 plus Darknet-53 hybrid network for multiclass SVM with 75:25 split ratio. In the proposed study a comprehensive analysis is conducted, exploring features from various layers and adjusting data split ratios.**

Keywords*—Deep Convolutional Neural Network (DCNN); multiclass Support Vector Machine (SVM); K-Nearest Neighbor (KNN); ensemble; features; accuracy

I. Introduction

In India, agriculture is the primary source of livelihood for nearly 55% of the population. At current prices, agriculture and allied sectors account for 18.3% of India's GDP [1]. Maize and Paddy being major crops cultivated across Karnataka state, India, in various seasons, face several challenges of diseases impacting crop growth and subsequently diminishing yield and food quality [2-3]. The primary culprits behind these issues are bacteria, viruses and fungi, necessitating continuous monitoring of the leaves, stem and fruits of the crops. Some disease manifest with similar features, demanding expert level knowledge for accurate identification and preventive measures. Often, farmers struggle to pinpoint the causes through naked eye observation [4], resorting to suggestions from pesticide vendors. This, unfortunately, may lead to the excessive and unwarranted use of hazardous pesticides, causing harm to both crops and the environment. Simultaneously, engaging experts to visit farmlands is a cumbersome and time-consuming task. In addressing these challenges, automatic disease detection and crop monitoring emerge as crucial areas, where early identification of crop diseases allows for prompt intervention and effective damage control is possible [5].

Over the last decade, the Convolutional Neural Network (CNN) has produced groundbreaking outcomes in various domains associated with pattern recognition, spanning from image processing to voice recognition. In recent decades, it has been acknowledged as one of the most potent tools, gaining widespread popularity in literature due to its capability to manage vast amounts of data [6]. The success of CNN can be attributed to its exceptional ability to create high-level image representations across multiple scales, contrasting with the manual crafting of low-level features [7]. CNN automatically extracts features from the provided training data and conducts classification through its output layer. Various advantages of CNN architectures, such as weight sharing, the inclusion of a pool layer, and local connections, contribute to minimizing the number of parameters requiring training and reducing the overall complexity of the network [8]. Ecological agriculture requires the advancement of nondestructive intelligent methods capable of early detection of crop diseases [9]. In the current scenario, several modifications are made to CNN based architectures and proposed in this regard. Many plant leaves from open database and manually processed dataset have been used in many works. A simple CNN can be modified by applying hybrid combination of activation functions for agriculture crop leaf disease detection, where activation functions like Rectified Linear Unit (ReLU), Gaussian Exponential Linear Unit (GeLU), Scaled Exponential Linear Unit (SeLU) can be used [10]. In some studies, a combination of VGG-16 and MobileNet deep learning models with stacking ensemble learning techniques are introduced to obtain 89% accuracy on sunflower leaves

[11]. A novel activation function which is sum of Parametric ReLU (PReLU) and multiple Mexican hat functions called as Mexican ReLU (MeLU) are introduced for VGG16 and ResNet-50 to enhance the accuracy of disease detection [12]. In another work, a novel hybrid approach work was proposed in three phases. First phase includes improved histogram equalization to enhance contrast. In second phase features are extracted using Gray Level Co-occurrence matrix (GLCM), Gabor feature and curvelet feature extraction methods. In third phase Neuro-Fuzzy logic classifier is trained with features extracted from second phase. PlantVillage data base is used and obtained 90% accuracy [13].

Another report shows AlexNet plus SVM [14] hybrid approach used to obtain a massive 99.98% accuracy on 12 crop species with 38 different leaf diseases. A hybrid approach VGG16 with dropout operation and attention module was also introduced to have better accuracy of classification [15] on tomato leaves. A hybrid model based on CNN and Convolutional Auto Encoder (CAE) was built for automatic plant disease detection. CAE was used to reduce the training parameters of the hybrid model. The proposed hybrid model used only 9914 training parameters. The model was tested on peach plants to identify Bacterial Spot disease achieving 99.35% training accuracy and 98.38% testing accuracy[16]. A novel deep neural network using Caffe framework to recognize plant leaf diseases was proposed. In their work 14 different plants are considered and used 30880 images for training and 2589 images for validation. For accuracy test, 10-fold cross validation techniques used. 15 different classes were made and a precision of 91% to 98% accuracy was achieved [17]. A high-performance attention-based dilated CNN logistic regression (ADCLR) was used to claim 100% accuracy on tomato leaves. Similarly CNN based AlexNet, GoogLeNet, VGG-16, DenseNet-121, Inception V4 and ResNet-50 have been implemented in many studies on plant village dataset as shown in the works [18-19].

Deshapande et al. [2] conducted a research with the goal of distinguishing various Maize diseases, including corn rust, northern leaf blight, other fungal diseases, and healthy leaves. They employed Decrement, KNN, and SVM classifiers. To achieve accuracies of 85% and 88% on the KNN and SVM classifiers, respectively, Haar wavelet features and first-order histogram features on GLCM were utilized. Chowdhury R et al. [20] conducted a study on eight different types of paddy leaf diseases, analyzing approximately 1426 images for disease and pest detection. Their work introduced a simple two-stage CNN designed for mobile application development, considering limited memory and resources. The model underwent training using baseline training, fine-tuning, and transfer learning methods gave 93.3% accuracy. S. Ramesh and D. Vydeki [21] applied a deep neural network and the jaya algorithm for the recognition and classification of various paddy leaf diseases. They achieved an accuracy of more than 92% for different diseases. A DenseNet based model was also proposed for identifying and recognizing Maize leaf diseases, yielding an accuracy of 96% [22]. A modified LeNet architecture, [23] utilizing a DCNN, is employed for the classification of maize leaf diseases. The study involves experimenting with maize leaf images sourced from the PlantVillage dataset. The developed CNNs are specifically trained to distinguish among four distinct classes, including three disease categories and one representing a healthy state. The trained model demonstrates an impressive accuracy rate of 97.89%. In the work proposed by Poornima K M and Sunilkumar H R [24], ten different modified DCNN were studied and implemented on maize leaf data set addressing four diseases. Different activation functions, epochs, learning rate were introduced on trial-and-error basis. They claim ResNet-50 outperforms others with 98.5% accuracy.

Another CNN based model was introduced to classify diseases on Maize data set claiming 97% accuracy [25]. Utkarha N Fulari et al. [26] proposed an AlexNet based plant leaf disease identification and classification in which about 12949 open database images were used. An accuracy of 95% achieved for Maize leaf data. Md. A. Haque et al. [27] experimented with inception-V3 model and used baseline training approach on maize leaves. The trained model out performs other CNN based transfer learning approaches giving out an accuracy of 95.99%. M. Micheni et al. [28] carried out an experiment on maize data set using AlexNet and ResNet-50 with the help of transfer learning along with SVM, amounting accuracies of 98.3%, 96.6% and 88.5% respectively. Paddy leaves were used by Naware et al. [29] to classify diseases using KNN and SVM giving 96.2% and 98.56% accuracies respectively. A. Nigam et al. [30] proposed a new method for paddy leaf images classification using Principal Component Analysis (PCA) and Bacterial Foraging Optimization Algorithm (BFOA) with cost function for feature extraction and deep neural network used for classification to get an accuracy of 98%. Another [31] CNN based paddy leaf disease classification is done using about 2239 training and 168 testing data set. An accuracy of 91% is achieved.

X. Qian et al. [32] introduced a novel model distinct from CNN, the approach relies on transformers and self-attention. It captures visual details of image localities through tokens, computes the correlation (referred to as attention) among these local regions utilizing an attention mechanism, and ultimately consolidates global information to facilitate the classification process. Later the proposed model outperforms various existing models. Using maize data set an accuracy of 98.7% is achieved. A work carried out [33] on Paddy leaves of 800 data set. CNN was applied and compared with logistic regression, decision tree. CNN model was giving around 80.25% accuracy. K. Saminathan et al. [34] used multiple classifiers like Logistic Regression (LR), Random Forest Classifier (RFC), Decision Tree Classifier, K-Nearest Neighbor (KNN) Classifier, Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Gaussian Naive Bayes (NB). The accuracy of the RFC model gained 92.84% after validation and 97.62% after testing using paddy disordered samples. B Sowmiya et al. [35] proposed a classification of paddy leaf diseases with extended Huber loss using CNN to minimize the loss. The model has achieved 96.63% training and 86.61% validation accuracies respectively. Another CNN based approach for maize dataset achieving 96.53% accuracy [36]. M. Syarief and W. Setiawan have proposed a fusion method where seven different CNNs are used to extract the features and fed to three classifiers namely k-NN, SVM and decision tree. Maize data set is used where AlexNet with SVM is giving maximum accuracy of 95.83% [37].

A. Gap Identification

Given the current landscape, there is a pressing need for a machine vision –based technique that is easily accessible, swift, robust and cost effective. Deep learning techniques have the potential to meet these requirements when carefully designed. Very less work has been progressed in creating hybrid DCNN and fusion of DCNN with machine learning classifiers like SVM and KNN.

Having this motivation, the study explored several advanced DCNN frameworks to classify three maize diseases, three paddy leaf diseases, and healthy leaves. Adjustment of various parameters to train the networks using a transfer learning approach on the given dataset is carried out. Subsequently, the features extracted from these trained networks were input into classifiers such as multiclass SVM and KNN to improve the overall results. This process was iterated for an ensemble of diverse DCNNs. Additionally, comparative analysis with methods proposed in the existing literature is carried out.

The study makes several notable contributions: firstly, an image database has been created by collecting images from both open-source repositories and visiting nearby farmlands at various stages of growth in a nondestructive manner. The same database was utilized for training, validating, and testing the developed DCNN models. Secondly, we extracted features from both shallow and deep layers of the trained DCNNs for testing with SVM and KNN along with different split ratio of training and testing. Thirdly, an ensemble of DCNNs was created to assess performance enhancement. The proposed study demonstrates a substantial improvement in the classification performance of maize and paddy diseased leaves. The paper is structured as follows. Section II presents methods and materials; Section III presents results and discussion; and Section IV presents the Conclusion.

II. METHODS AND MATERIALS

The envisaged system aims to establish an efficient mechanism for detecting diseases in maize and paddy plant leaves by employing a combination of DCNNs, multiclass SVM, KNN and image processing techniques. This section offers a comprehensive elucidation of the proposed system. Fig. 1 illustrates the entire workflow of the proposed system.

A. Dataset Collection

An image database is created by collecting images from both open-source [38] repositories and visiting nearby farmlands at various stages of growth in a nondestructive manner. In the proposed work, we have taken maize and paddy leaf diseases like corn blight, corn common rust, corn gray leaf spot, brown spot, hispa, leaf blast along with healthy leaves. A total of 11322 images have been collected. Out of which 2000 images have been used for the experimentation as shown in the Table I.

Fig. 2 gives a glimpse on the various maize and paddy diseased leaves considered for the experiment.

B. Preprocessing the Dataset

Since dataset is image, we need to do some preprocessing like, resizing, noise removal etc. usually grayscale versions of images and background removal does not work well for classification performance of neural networks [8]. The networks we are using in proposed work shall take images of different size. For example, AlexNet can take images of size 227x227x3 but SqueezeNet would consider only 224x224x3 size images and DarkNet-53 considers 256x256x3 as shown in Table II.

C. Splitting of Dataset

A total of 2000 images have been considered, in that 400 images are used for testing and 1600 images are used for training purpose, 80:20 ratio is being followed. While training, 30% of the total training data have been split and used randomly for validation purpose as shown in the Table I.

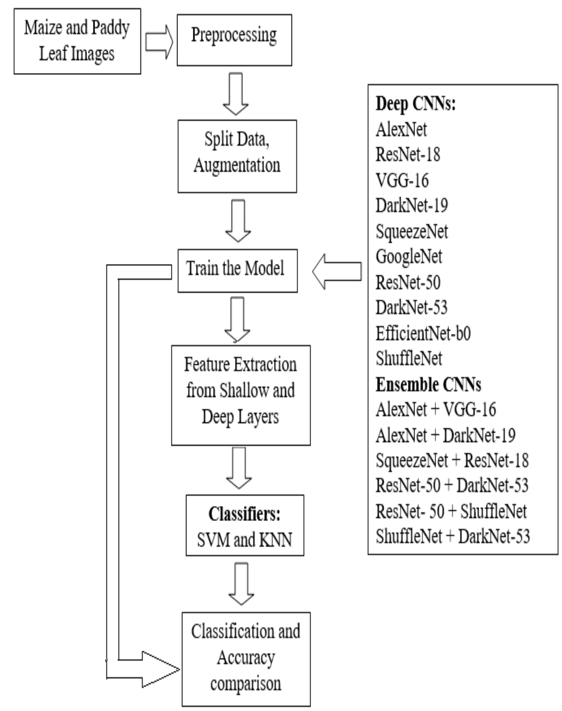

Fig. 1. The proposed methodology.

TABLE I. DATA SET COLLECTION

Disease Name	Data set from open database [38]	Manually collected dataset	No. of images for training and validation (70:30)	No. of images for testing
Corn Blight	1146	1354	200	50
Corn Gray Spot	574	355	200	50
Corn Common Rust	1306	313	200	50
Healthy Corn	1162	547	200	50
Paddy Brown Spot	418	399	200	50
Paddy Hispa	764	365	200	50
Paddy Leaf Blast	623	411	200	50
Paddy Healthy	1100	485	200	50
Total	7093	4229	1600	400

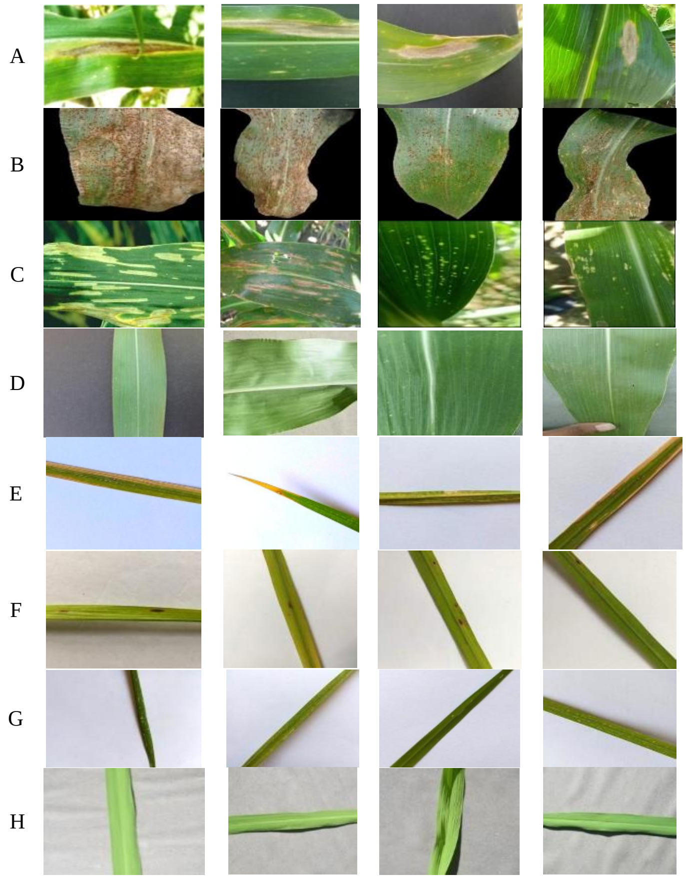

Fig. 2. Maize leaves diseases: A. Blight, B. Common rust, C. Gray leaf spot D. Healthy maize, Paddy leaves diseases: E. Blast, F. Brown spot, G. Hispa H. healthy paddy.

TABLE II. DCNNS WITH LAYERS, INPUT IMAGE SIZE, ACTIVATION FUNCTIONS, LEARNING RATE

DCNNs	Layers / Connections	Size of input image	Activation function	Learning Rate
AlexNet	23/24	227-by-227	ReLU	.0001
DarkNet-19	63/24	256-by-256	Leaky-ReLU	.0001
VGG-16	41/40	224-by-224	ReLU	.0001
Squeeze Net	68/75	227-by-227	ReLU	.0001
Resnet-18	71/78	224-by-224	ReLU	.0001
Shuffle Net	172/186	224-by-224	ReLU	.001
DarkNet-53	184/206	256-by-256	Leaky-ReLU	.0001
ResNet-50	177/192	224-by-224	ReLU	.0001
GoogleNet	144/170	224-by-224	ReLU	.0001
EfficienNet-b0	290/363	224-by-224	Sigmoid	.0001

D. Data Augmentation

Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using an existing one. In the proposed work various augmentation techniques like Random reflection axes, random rotation, random rescaling and random horizontal and vertical translations have been applied. The images were not duplicated but augmented during the training process, so the physical copies of the augmented images were not stored but were temporarily used in the process. This augmentation technique not only prevents the model from overfitting and model loss but also increases the robustness of the model so that, when the model is used to classify leaf disease images, it can classify them with better accuracy [39].

E. Train the Model

Models are trained using the data set as shown in the Table I. Transfer learning [3] approach is applied to train each and every network considered. Activation functions used and learning rates applied on various DCNNs have been shown in the Table II and various training properties are used as shown in the Table III.

TABLE III. TRAINING PROPERTIES AND PARAMETERS USED FOR TRAINING

Properties	Parameters
Solver	Stochastic Gradient Descent with Momentum (SGDM)
Initial learning rate	0.001- 0.0001
Validation frequency	10-20
Max Epochs	30-50
Mini Batch size	15-20
Execution momentum	auto
Sequence Length	longest
Sequence padding value	0
Sequence padding direction	right
Gradient threshold method	L2norm
L2reularization	.0001
Shuffle	Every epoch
Learn rate schedule	Piecewise
Learn rate drop facto	0.1
Learn rate drop period	10
Reset Input normalization	1
Momentum	0.9

F. Feature Extraction

Feature extraction in Convolutional Neural Networks (CNNs) is a crucial step in image processing and computer vision tasks. CNNs are designed to automatically learn and extract relevant features from input images to facilitate accurate classification, detection, or other tasks [9].

1) Train classifier on shallower features: Extract features from an earlier layer in the network and train a classifier on those features. Earlier layers typically extract fewer, shallower features, have higher spatial resolution, and a larger total number of activations.

2) Train classifier on deeper features: Deeper layers contain higher-level features, constructed using lower-level features of earlier layers. To get the feature representations of the training and test images, activations on the global pooling layer is used. The global pooling layer pools the input features over all special locations, giving maximum features in total. Features extracted from the training images as predictor variable and fit them to classifier like multiclass SVM and KNN. Later classify the test images using trained classifiers using features extracted from the test images [40]. Same thing is repeated for hybrid DCNNs with multiclass SVM and KNN. The detailed results are shown in Section III.

G. Multiclass Support Vector Machine

Multiclass Support Vector Machine (SVM) is a machine learning algorithm used for classification tasks involving more than two classes. The primary objective of multiclass SVM is to create decision boundaries in a high-dimensional space that effectively separate and categorize data points into multiple classes. Unlike binary SVM, which is designed for two-class problems, multiclass SVM extends its capabilities to handle scenarios where there are three or more distinct classes [26]. In our study, we opt for a linear kernel [34] due to the increased number of features and the characteristic of our classification problems being linearly separable, as articulated in Eq. (1).

$$f(X) = W^T * X + b \tag{1}$$

H. K-Nearest Neighbor

K-Nearest Neighbors (KNN) stands out as a straightforward, instance-based, and nonparametric machine-learning algorithm applicable to both classification and regression tasks. Its predictions rely on either the majority class (in classification) or the average value (in regression) derived from the k-nearest neighbors within the feature space. In classification, the anticipated class is typically determined through a majority vote among the k-nearest neighbors, with the class possessing the highest frequency within this group being assigned to the new data point [37]. While KNN demonstrates accuracy, it operates at a slower pace [34]. The mathematical expression for determining the Euclidean distance between any two points is provided in Eq. (2), and this process is reiterated accordingly.

$$d = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \tag{2}$$

I. Classification and Accuracy Comparison

Leaf disease classification from various methods and their corresponding accuracies are collected and compared for the analysis purpose.

III. Results and Discussion

The results are analyzed as follows. The proposed model was trained and tested on combination of images from online repository and manually collected data. For every diseased leaf including healthier one, we hand picked randomly to make a dataset of 2000 images from both the sources. Out of which, 80:20 ratio is maintained for training and testing purpose. The same dataset is used to train the individual DCNNs using transfer learning approach by giving suitable learning rate, epochs and parameters as shown in the Tables II and III. Later results were noted and compared as shown in the following sections.

A. Results with respect to Maize Data

1) Results with individual DCNN and DCNNs with k-NN, SVM: The Table IV depicts the results of maize leaf diseases classification with accuracies. Initially classification accuracy using individual DCCNs is taken and compared with the accuracies achieved from the extracted features from both shallow and deep layers, which were later used for KNN and SVM classifiers. Classifiers are tried with 50:50, 60:40, 70:30, 80:20 training and test ratio of the features extracted.

One very important observation made here is, SVM giving better results on deep layers compared to KNN, which is good at shallow layers as indicated in the Table IV. Best accuracy values with corresponding split ratio are considered for the analysis purpose.

TABLE IV. Features are Extracted from Pre-Trained Network and Used for Classification Through Multiclass SVM and KNN for Maize Dataset

Pre-T	Clas	Bes	Spl	Be	Spl	Acc
AlexNet	Multiclass SVM	94.37	60:40	97.1	80:20	95.6
	KNN	94.37	60:40	95	80:20	
ResNet-18	Multiclass SVM	95	80:20	94.37	60:40	94.8
	KNN	92.5	70:30	88.12	60:40	
VGG16	Multiclass SVM	96.25	80:20	98.21	80:20	95.5
	KNN	95.83	70:30	87.5	70:30	
Darknet-19	Multiclass SVM	95	70:30	94.17	70:30	96.5
	KNN	93.75	80:20	87.50	70:30	
Squeeze Net	Multiclass SVM	91.25	60:40	95	70:30	95.8
	KNN	93.50	50:50	90	80:20	
GoogleNet	Multiclass SVM	93.75	80:20	95	50:50	96
	KNN	95	80:20	71.67	70:30	
ResNet-50	Multiclass SVM	94.17	70:30	97.4	80:20	94.7
	KNN	94.37	60:40	97.5	60:40	
DarkNet-53	Multiclass SVM	93.75	80:20	96.25	80:20	94
	KNN	94.17	70:30	78.75	80:20	
Shuffle-Net	Multiclass SVM	94.1	60:40	95	80:20	96
	KNN	93.7	80:20	93.11	70:30	
EfficientNet-b0	Multiclass SVM	96.67	70:30	92.5	80:20	91.5
	KNN	95.50	50:50	61.67	70:30	

Fig. 3 representing the comparison between accuracies obtained by individual DCNNs and best possible results when features from DCNNs are used to feed k-NN and multiclass SVM with different split ratio. The graphs show significant improvements in the results of EfficientNet-bo, ResNet-50 and VGG-16 when features from these models are fed to the k-NN and SVM.

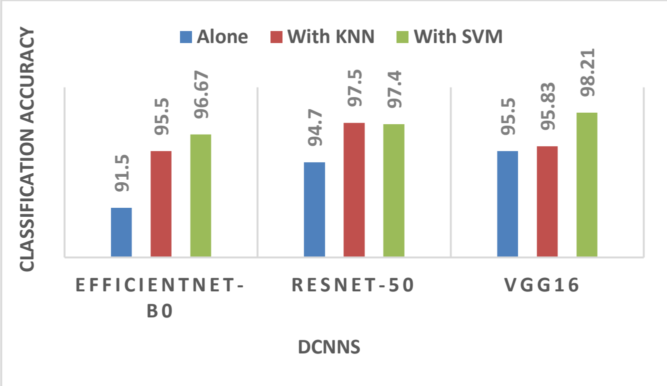

Fig. 3. Comparison of accuracies with DCNNs, k-NN and SVM for Maize data set.

2) Results with hybrid DCNNs and hybrid DCNNs with k-NN, SVM: Three network ensembles are made and tried with the dataset. Accuracy is significantly improved compared with individual DCCNs. As a final step, hybrid networks created are used for feature extraction to feed KNN and SVM classifiers with different training and testing ratio of dataset features. Again, an overwhelming improvement in the accuracies as evidenced in the Table V is achieved.

TABLE V. FEATURES ARE EXTRACTED FROM HYBRID PRE-TRAINED NETWORK AND USED FOR CLASSIFICATION THROUGH MULTICLASS SVM AND KNN FOR MAIZE DATASET

Hybrid Pre trained network for feature extraction	**Classifier**	**Best Accuracy**	**Data split ratio (Training: Testing)**	**Accuracy when Hybrid Pre trained networks considered alone**
AlexNet + VGG16	Multiclass SVM	**100**	75:25	97.83
	KNN	96.25	80:20	
AlexNet+DarkNet-19	Multiclass SVM	98.33	70:30	**97.99**
	KNN	97.5	70:30	
SqueezeNet+ResNet-18	Multiclass SVM	97.50	70:30	93.17
	KNN	**98.5**	80:20	

A 100% accuracy achieved in AlexNet plus VGG-16 hybrid network for multiclass SVM with 75:25 split ratio. And a whopping accuracy of 98.5% is achieved in the SqueezeNet plus ResNet-18 for k-NN with 80:20 split ratio.

The graphs in Fig. 4 show that the proposed work significantly improves the performance when features are extracted from hybrid network and used for classification through multiclass SVM and KNN.

B. Results with Paddy Data

1) Results with individual DCNN and DCNNs with k-NN, SVM: The Table VI depicts the results of paddy leaf diseases classification with accuracies. Initially classification accuracy using individual DCCN is taken and compared with the accuracies taken from the extracted features from both shallow and deep layers to be used for KNN and SVM classifiers. Classifiers are tried with 50:50, 60:40, 70:30, 80:20 training and test ratio of extracted features from both train and test images. Best accuracy values with corresponding split ratio are considered for the analysis purpose.

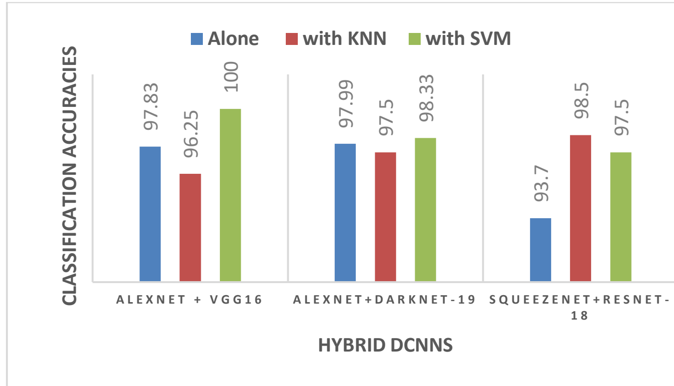

Fig. 4. Comparison of accuracies with hybrid DCNNs, with k-NN and with SVM Maize data set.

TABLE VI. FEATURES ARE EXTRACTED FROM PRE-TRAINED NETWORK AND USED FOR CLASSIFICATION THROUGH MULTICLASS SVM AND KNN USING PADDY DATASET

Pre-Trained Network to Extract Features	**Classifier**	**Best Accuracy for shallow layers**	**Split Ratio**	**Best Accuracy for deep Layers**	**Split Ratio**	**Accuracy from individual DCNN**
AlexNet	Multiclass SVM	76.60	60:40	74.49	70:30	94.11
	KNN	74.07	70:30	53.99	80:20	
ResNet-18	Multiclass SVM	72.39	80:20	80.66	70:30	94.14
	KNN	73.62	80:20	79.31	50:50	
VGG16	Multiclass SVM	82.76	50:50	75.31	70:30	93.13
	KNN	84/05	80:20	61.35	80:20	
Darknet-19	Multiclass SVM	78.6	70:30	84.66	80:20	70.08
	KNN	80.25	70:30	68.72	70:30	
Squeeze Net	Multiclass SVM	78.22	60:40	80.67	60:40	85.75
	KNN	78.53	80:20	74.84	80:20	
GoogleNet	Multiclass SVM	77.3	80:20	77.49	70:30	92.35
	KNN	77.91	80:20	55.83	60:40	
ResNet-50	Multiclass SVM	81.6	60:40	84.66	80:20	97.53
	KNN	81.6	80:20	70.55	80:20	
DarkNet-53	Multiclass SVM	74.85	80:20	82.30	70:30	98
	KNN	74.85	80:20	63.37	70:30	
Shuffle-Net	Multiclass SVM	78.3	80:20	74.49	70:30	97.29
	KNN	77.91	80:20	55.83	60:40	
fficientNet-b0	Multiclass SVM	90.80	80:20	65.03	80:20	92.13
	KNN	89.57	**80:20**	49.38	70:30	

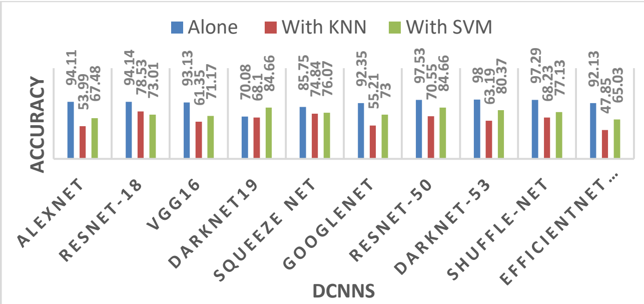

Fig. 5. Comparison of accuracies with DCNNs, k-NN and SVM for Paddy data set.

The graphs in Fig. 5 show accuracy variation of DCNNs with k-NN and SVM. The observation made here is, accuracies when pretrained networks considered alone are giving better results compared to the features extracted and fed to the k-NN and SVM classifiers.

2) Results with hybrid DCNNs and hybrid DCNNs with k-NN, SVM: Three network ensembles are made and tried with paddy dataset. Accuracy is significantly improved compared with individual DCCNs. As a final step, hybrid networks created are used for feature extraction to feed KNN and SVM classifiers with different training and testing ratio show an improvement in the accuracy as shown in the Table VII.

A 99.51% accuracy achieved in ResNet-50 plus Darknet-53 for multiclass SVM and 96.06% accuracy can be seen for k-NN, maintaining 75:25 split ratio for both. A detailed comparison is shown in the Fig. 6.

As a final remark, utilizing features extracted from DCNNs and subsequently feeding them into SVM and k-NN has demonstrated enhanced accuracy in the precise classification of Maize and Paddy diseased leaves, as depicted in Fig. 7.

A detailed comparison analysis is done as shown in the Table VIII for Maize data. The proposed work is giving a maximum accuracy of 100%, which is quite impressive compared to the results from the literature.

A detailed comparison analysis is done as shown in the Table IX and 99.51% for paddy leaf images obtained which is better compared to other studies in the literature.

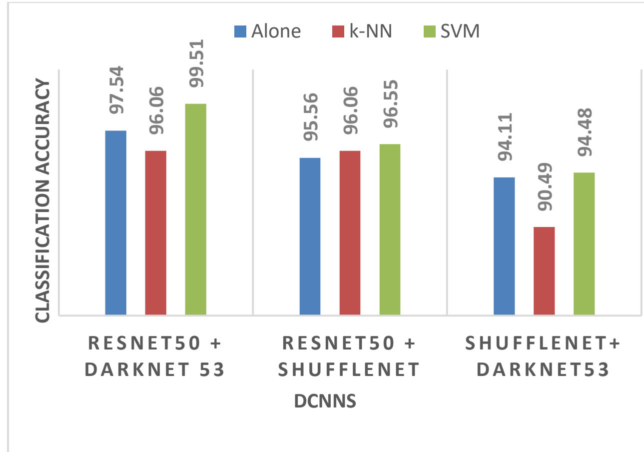

Fig. 6. Comparison of accuracies with hybrid DCNNs, k-NN and SVM.

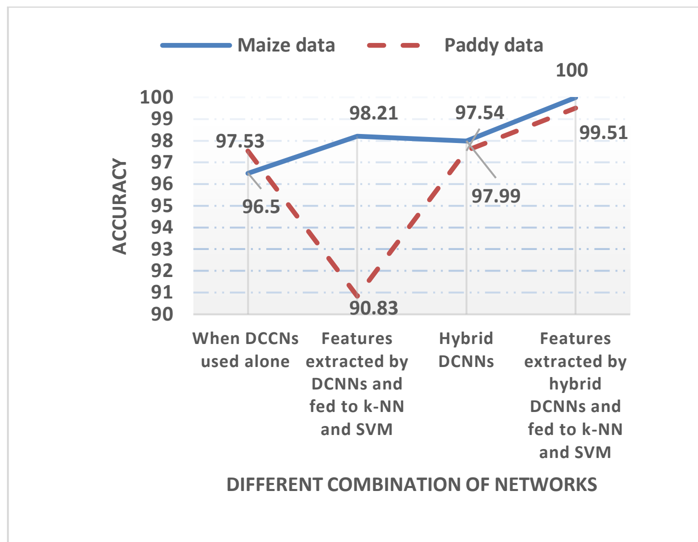

Fig. 7. Comparison of various approaches used in the proposed work.

TABLE VII. FEATURES ARE EXTRACTED FROM HYBRID PRE-TRAINED NETWORK AND USED FOR CLASSIFICATION THROUGH MULTICLASS SVM AND KNN FOR PADDY DATASET

Hybrid Pre trained network for feature extraction	Classifier	Accuracy with various split ratio	Data split ratio (Training: Testing)	Accuracy when Hybrid Pre trained networks considered alone
RESNET50 + Darknet 53	Multiclass SVM	**99.51**	75:25	**97.54**
	KNN	**96.06**	75:25	
RESNET50 + ShuffleNet	Multiclass SVM	96.55	70:30	95.56
	KNN	96.06	70:30	
ShuffleNet + Darknet53	Multiclass SVM	94.48	60:40	94.11
	KNN	90.49	60:40	

TABLE VIII. COMPARISON OF THE PROPOSED METHOD WITH OTHER RESULTS (MAIZE)

Reference	Classes	Dataset	Data-source	Models	Classification Accuracy
[2]	4	Own collected	In-field condition	KNN and SVM	85% and 88%
[22]	4	Open-source	Lab condition	DenseNet model	96%
[23]	4	Open-source	Lab condition	Modified LeNet	97.89%
[24]	4	Open-source dataset	Lab condition	ResNet-50 based model	98.5%
[27]	4	Own collected	In-field condition	Inception V3	95.99%
[28]	4	Own collected	In-field condition	ResNet-50, AlexNet, SVM	98.3%, 96.6%, 88.5%
[32]	4	Open-source	Lab condition	Author defined CNN	98.7%
[36]	4	Open-source	Lab condition	Author defined CNN	96.53%
[37]	7	Own collected	In-field condition	AlexNet plus SVM	95.83&
Proposed work	4	Open-source / Manually collected	Lab condition / field condition	AlexNet plus VGG-16 hybrid network for multiclass SVM with 75:25 split ratio.	**100%**
				SqueezeNet plus ResNet-18 hybrid network for k-NN with 80:20 split ratio	**98.5%**

TABLE IX. COMPARISON OF THE PROPOSED METHOD WITH OTHER RESULTS (PADDY)

Reference	Classes	Dataset	Data-source	Models	Classification Accuracy
[20]	8	Own collected	In-field condition	Author defined CNN	93.3%
[21]	5	Own collected	In-field condition	DNN with JOA	92%
[29]	3	Open-source	Lab condition	KNN, SVM	96.2%, 98.6%
[30]	3	Open-source	Lab condition	Hybrid BFOA-DNN, DNN-JAO, DNN	98%, 97%, 93.5%
[31]	4	Open-source	Lab condition	Author defined CNN	91%
[33]	2	Own collected	In-field condition	Author defined CNN	80.25%
[34]	4	Open-source	Lab condition	LR, LDA, KNN, CART, RF, NB, SVM	94.05%, 76.79%, 81.55%, 94.05%, 97.62%, 66.07%, 96.43%
[35]	4	Open-source	Lab condition	Author defined CNN	96.63%
Proposed work	4	Open-source / Manually collected	Lab condition / field condition	ResNet-50 plus Darknet-53 for multiclass SVM with 75:25 split ratio	**99.51%**

IV. CONCLUSION

This research focuses on the successful experimentation of identifying and classifying diseases in Maize and Paddy leaves. The dataset comprises both online repository data and manually collected images from neighboring farmlands. Employing transfer-learning approach, many DCNNs and hybrid DCNNs have been developed, trained, validated and tested successfully. Features from various layers of the developed DCNNs have been used to feed the multiclass SVM and KNN for higher accuracies in identification and classification of the Maize and paddy leaf diseases.

The conclusion is presented in four key parts. Firstly, diverse Deep Convolutional Neural Networks (DCNNs) were developed, trained, validated and tested using our own dataset. Initially these DCNNs served as classifiers, achieving an accuracy range of 70% to 98%. In the subsequent stage, the same DCNNs were repurposed as feature extractors from deep and shallow layers. These extracted features were then input into traditional machine learning classifiers such as multiclass SVM and KNN, yielding promising improvements in results. Further enhancing the experimentation, selected superior DCNNs are combined for ensemble purposes from the first stage.

Combinations like AlexNet with VGG-16, AlexNet with DarkNet-19, and SqueezNet with ResNet-18 were utilized for the maize dataset, resulting in a classification accuracy ranging from 93.166% to 98%. For paddy leaves, hybrid approaches involving ResNet-50 with DarkNet-53, ResNet-50 with ShuffleNet, and ShuffleNet with DarkNet-53 are used and achieved an accuracy of 94.11% to 97.54%.

In the final phase, features from these hybrid DCNNs were fed into multiclass SVM and KNN classifiers, demonstrating exceptional accuracy of 100% and 99.51% for Maize and paddy leaves respectively for various data split ratios. Overall, this research highlights the effectiveness of employing both DCNNs and traditional ML classifiers for accurate disease identification and classification in Maize and Paddy leaves with variable data split ratio.

The investigation could extend to obtaining real-time data sets, where leaf images are acquired directly from farmlands in a non-destructive manner and processed simultaneously. This processing aims to enhance the accuracy of disease identification and severity assessment, facilitating the recommendation of remedial measures for farmers. A smartphone application could effectively fulfill this purpose.

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