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A Hybrid Model for Crop Disease Detection Based on Deep Learning and Support Vector Machine

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Pakistan's agriculture sector is the backbone of its economy, contributing significantly to its gross domestic product (GDP). However, a key challenge in this sector is to counteract the crop diseases timely because these diseases result in reduced production, increased cost and eventually lead to economic loss. Traditional disease control methods are costly, time-consuming, and often lack technical support, resulting in poor disease management and harmful environmental consequences. This research harnesses the unmatched capability of Artificial Intelligence (AI) and deep learning for timely disease detection in crops. This research introduces a hybrid model that combines deep learning models with a machine learning classifier for disease detection. AlexNet, Vgg-16, ResNet50, and MobileNet are the deep learning models that have been employed for the detection of various diseases in crop leaves of rice, potato, and corn. These models have been trained by using healthy and diseased leaf images of the mentioned crops and then these models are combined with a Support Vector Machine (SVM) classifier to enhance the accuracy of detection. Experimental results show the outstanding performance of this hybrid approach for timely disease detection in crops. It is further observed that the combination of MobileNet and SVM results in an impressive accuracy of 95.68% in disease detection. This technological approach would be beneficial for farmers in the effective management and control of crop diseases thus improving the crop yield and ultimately contributing to economic growth.

Keywords: Crops Disease, Artificial Intelligence, Support Vector Machines, Deep Learning, Agriculture

Introduction:

Pakistan is an agricultural country, and a significant share of its population is dependent on the agricultural sector directly or indirectly. Pakistan's major exports are based on agricultural products which add a huge contribution to the country's gross domestic product.[1] [2] Considering the factors discussed above, it can be inferred that agriculture holds a crucial position in Pakistan's economy. To strengthen this sector and increase its contribution to national revenue, the country needs to adopt and integrate modern agricultural technologies. The agriculture sector is facing a significant reduction in production due to floods, diseases in crops, and old-fashioned technologies for cultivation [3] [4]. Therefore, there is an utmost need to take steps to enhance the annual yield by introducing advanced technologies and prevention of diseases.

Conventional agricultural techniques are a big hurdle in boosting the annual yield of crops; consequently, requiring modern tools and technologies in the agricultural sector. The integration of AI-based methods can significantly contribute to improving crop production. Recent studies, such as those by[5], have highlighted the effectiveness of AI not only in advancing agricultural practices but also in the broader development of smart systems. Their work on intelligent system architectures and the evaluation of machine learning models underscores the importance of real-time data analysis in optimizing operational efficiency and boosting productivity across various sectors. AI-based machines and equipment are revolutionizing the agricultural field around the globe and are going a long way in enhancing crop production, real-time monitoring, harvesting, processing, disease detection, diagnostics, and marketing[6] [7] [8] [9] [10]. For instance, [11] used a deep-learning model to classify four categories of wheat disease by taking images of various resolutions by camera for each category. They employed the Vgg-16 model for training and achieved an accuracy of 98% using this approach. In addition to that, [12] proposed a hybrid approach for disease detection of crop leaves by using a combination of autoencoders and convolutional neural networks. In their work, 5 different diseases of 3 crops were categorized by using different convolution filters of dimensions 2×2 and 3×3 over a dataset of 900-image where 600 constitute the training set and 300 test set. The proposed architecture demonstrated varying levels of accuracy depending on the number of epochs and filter sizes used. Specifically, it achieved an accuracy of 97.5% with a 2×2 filter size, while reaching a perfect accuracy of 100% when a 3×3 filter size was applied over 100 epochs.

Another study [13] has identified 8 different diseases of rice and maize by transfer learning of the deep convolutional neural networks. This study shows that VGGNet pre-trained on ImageNet is combined with the Inception module and the average accuracy of the proposed approach reaches 92.00% for rice and 80.38% for maize plant images. Authors in [14] have discussed crop disease detection methods using AI and the Internet of Things. They utilized machine learning, deep learning, and image analysis techniques to discuss crop disease detection. In [15], authors have surveyed different plant leaf disease detection methods over the past few years. These methods used artificial intelligence to detect the disease. In another study [16] deep learning architecture based on the convolutional neural network called EfficientNet was used to classify tomato leaf diseases. In this study, a modified U-Net method has been proposed for the segmentation of leaves which proves to be more efficient. For finding affected areas, Artificial intelligence algorithms for cloud-based image processing have been used in making the architecture and CNN is used for final classification. Authors in [17] have developed an automated leaf disease detection algorithm in different crop species through Local Binary Patterns (LBPs) feature extraction and one classifier and reported a significant success. In [18], authors have used deep learning and convolutional neural networks to identify 5 diseases in tomato leaves and have claimed an accuracy of 99.84. [19] reviewed several recent state-of-the-art machine-learning approaches for plant disease detection. Their review covers both traditional and deep learning techniques that utilize data collected through IoT devices, ground-based imaging, and satellite imagery. Additionally, the study highlights the significance of data fusion in enhancing the accuracy and effectiveness of disease detection research. In another work [20], machine learning approach has been discussed to detect plant disease using artificial intelligence.

The main objective of the study is to improve agricultural production by ensuring the timely detection of diseases using a hybrid model that combines deep learning with an SVM classifier. It aims to reduce economic loss by enabling early and accurate disease detection, offering a cost-effective and efficient alternative to traditional methods, and assisting farmers in effective crop management. The proposed work presents the results of data and verifies the accuracy of this method by presenting cases of various crops. This approach has the potential to significantly contribute not only to the early detection of crop diseases but also to the overall improvement of annual crop yields.

The novelty and key contribution of our study are as follows:

- Introduction of a hybrid AI-based model combining deep learning architectures with a machine learning classifier (SVM) for crop disease detection.
- Implementation of multiple deep learning models like AlexNet, VGG-16, ResNet50, and MobileNet, for analyzing leaf images of rice, potato, and corn.
- Integration of SVM with pre-trained deep learning models to improve classification performance. Demonstration of high accuracy (95.68%) using the MobileNet + SVM combination.
- Development of a solution that is technically feasible and practical for real-world agricultural applications in Pakistan.
- Contribution towards sustainable agriculture and economic development by leveraging AI.

Materials and Methods:

The complete block diagram of the experimental setup as proposed in this work is provided below in Figure 1. The diagram shows the process starting from dataset collection, followed by data preprocessing, and splitting into training and validation data. The figure clearly illustrates the necessity of first gaining a solid understanding of the different learning models before delving deeper into the proposed hybrid model. The proposed model is a hybrid model that consists of a pre-trained Deep Learning model and a Support Vector Machine. The purpose of the Deep Learning model is to extract the features from images by using transfer learning and SVC is employed to classify the images. The classification layer of Deep Learning is replaced to extract features and then input these features into SVC depicted in Figure 6. This study utilizes four deep learning models: AlexNet, VGG-16, ResNet50, and MobileNet. A brief discussion of each learning model with the SVM classifier used in this work is presented in the paragraph below.

AlexNet [21] consists of 5 convolutional layers succeeded by max-pooling layers and 3 fully connected layers followed by Softmax with "dropout" regularization to reduce overfitting. Moreover, Vgg-16 implies the Visual Geometry Group from Oxford with 16 layers. It was presented by [22] that the architecture of this network is very simple having 5 blocks of convolution and each block follows a max pooling layer and then 3 flatten layers. It uses the ReLU activation function for hidden layers and the softmax activation function is used in the output layer. Later, ResNet50 was introduced by [23] to handle the problem of performance because when going deeper into CNN, the performance of the network becomes worse. To account for this issue, authors have proposed residual blocks which provide shortcut connections to the activation some layers which can skip one or more layers. Another learning model MobileNets has two layers: (i) Depth-wise convolution, a separate filter operates independently on each input channel. (ii) Pointwise convolution employs 1×1 kernels to linearly combine the outputs from the depth-wise layer. Both layers incorporate batch normalization and ReLU activation.

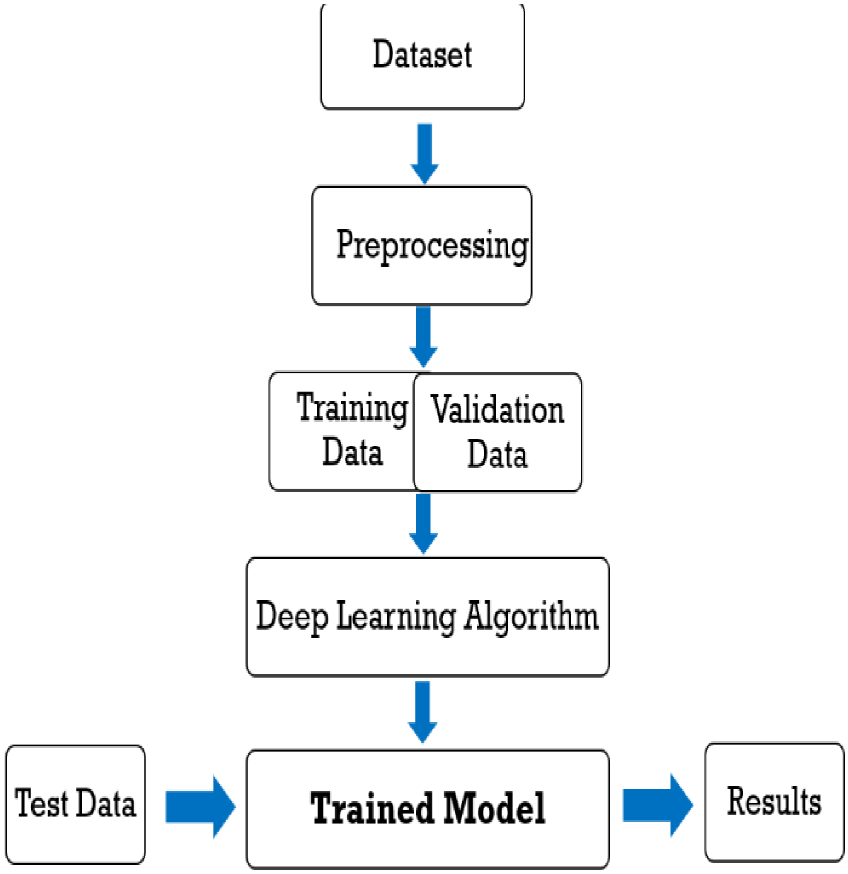


Figure 1. The overall block diagram of the proposed experimental setup for disease detection in crops

SVM is a training algorithm where the margins between the pattern and decision boundary are maximized. SVM is used to deal with highly non-linear data and it uses the trick of kernel function to minimize the effect of non-linearity. It can be presented as:

$$||\beta||_2^2 + C\sum_{i=1}^{n}((1 - y_i) * \mathrm{f}(x_i)) \qquad (1)$$

$||\beta||_2^2$ – Regularization term that adds L2 penalty to avoid overfitting

C – is a tuning parameter that is used to optimize the loss function.

$(1 - y_i)f(x_i)$ – is the Hing loss equation

$$f(x_i) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \ldots \ldots \ldots \ldots \ldots + \beta_p x_p$$

where $\beta_1, \beta_2, \ldots \ldots \ldots, \beta_p$ are parameters.

In equation (1), the left term represents the L2 regularization penalty, and the right term is used to calculate the loss. This study aims to minimize the loss in such a way that it can add penalties for minimization. According to equation **Error! Reference source not found.**), it is an optimization problem where the target is optimizing the loss function.

Support Vector Classifiers (SVC) are the boundaries that separate the two classes by a line known as a hyperplane in machine learning. Support Vectors are the samples on the plane nearest to the SVC that are responsible for deciding the SVC hyperplane. When using SVM, the goal is to select the support vectors in such a way, that the distance between support vectors and the SVC should be maximized. In this study, the publicly available PlantVillage dataset was utilized to train and evaluate the proposed hybrid deep learning and SVM-based model for crop disease detection. The dataset consists of images of healthy and diseased plant leaves across various crops and disease types. The complete PlantVillage dataset contains 61,486 images spanning 39 categories and 14 crop species, including corn, potato, and rice. These images cover a range of disease types, such as fungal, bacterial, viral, and mite-induced infections. For our study, a subset of 11,000 images was selected, representing 11 different classes (1,000 images per class) of healthy and diseased crops. Before training, the dataset underwent a series of preprocessing steps to enhance model performance. All images were resized to a uniform dimension of 224×224 pixels to meet the input requirements of the deep learning models, resulting in a final dataset shape of (11,000, 224, 224, 3), which was saved in Hierarchical Data Format (HDF).

Data augmentation techniques, including horizontal flipping and noise injection, were applied to increase data diversity and reduce overfitting. Additionally, the images were normalized to standardize pixel intensity values, facilitating improved convergence during model training. The samples of the dataset are provided below in Figure 2-4. Figure 2, displays corn leaves in four categories. Each row represents multiple images with specific characteristics: the 1st row shows Healthy leaves, the 2nd row shows Common Rust (rust-colored pustules), the 3rd row shows Leaf Spots (distinct lesions), and the 4th row shows Northern Leaf Blight (elongated grayish-brown lesions). Figure 3, shows dataset images of potato leaves in three categories: Healthy (top row), Early Blight (middle row, yellowing with dark spots), and Late Blight (bottom row, extensive necrosis). Each row shows typical visual indicators for distinguishing disease stages in potato leaves. Figure 4, shows dataset images of rice leaves categorized by health and disease type. The first row shows Healthy leaves with no visible damage. The second row displays Brown Spot disease, identified by small brown lesions. The third row depicts Hispa infection, characterized by visible feeding scars and discoloration. The fourth row shows Leaf Blast, with symptoms including grayish lesions with a dark border.

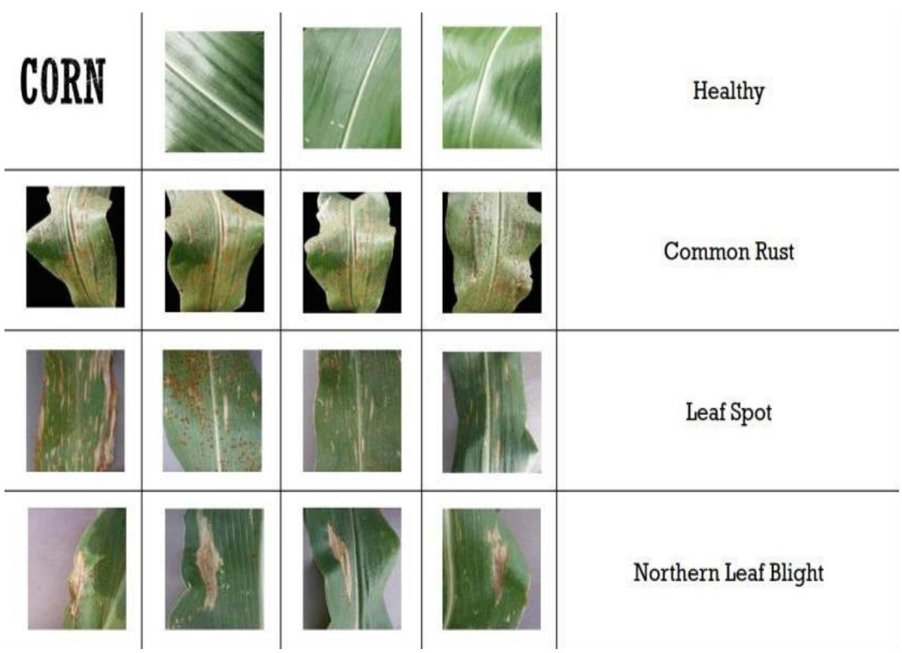


Figure 2. Sample images from the dataset showing healthy corn leaves and those affected by diseases such as common rust, leaf spot, and northern leaf blight

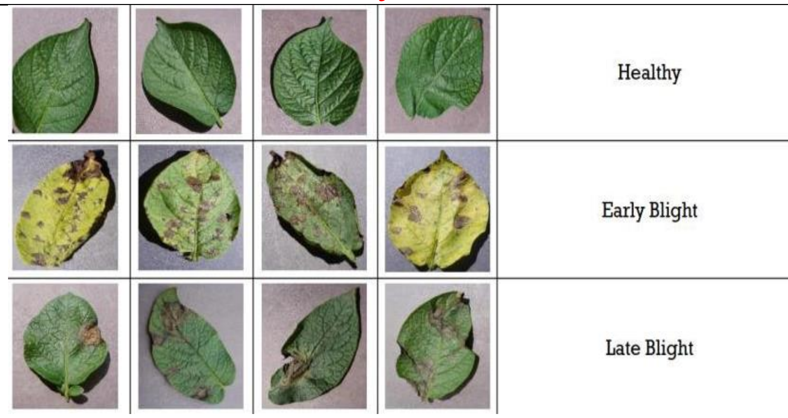


Figure 3. Dataset images of healthy potato leaves and those affected by early blight and late blight

Figure 4. Dataset images of rice leaves categorized as healthy or diseased, including cases of brown spot, hip, and leaf blast

The data was split into three parts: Training, Validation, and Testing. The model was trained on the training set while being periodically evaluated using the validation set. The performance of the model was evaluated by unseen Test data. The 11 different classes of crops were labeled as shown in Table 1. Moreover, the Dataset was split and has been visualized in Figure 5.

Table 1. Labeling of the dataset, showing 11 different crop classes with their class label, class name, and the number of images in each class.

Class Label	Class Name	No of Images
0	Corn Common Rust	1000
1	Corn Healthy	1000
2	Corn Leaf Spot	1000
3	Corn Northern Leaf Blight	1000
4	Potato Early blight	1000
5	Potato Healthy	1000
6	Potato Late Blight	1000
7	Rice brown Spot	1000
8	Rice Healthy	1000
9	Rice Hispa	1000
10	Rice Leaf Blast	1000

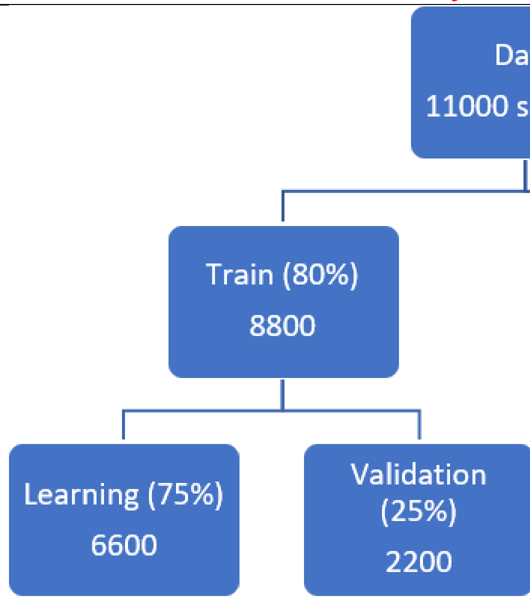


Figure 5. The figure shows the division of the dataset: 80% for training and 20% for testing

Results:

In this research, we split data into two experiments, in experiment 1 all four models i.e., AlexNet, Vgg-16, ResNet50, and MobileNet were trained on the training dataset and validated on the validation dataset. These train models were then tested using the Test data which is unseen to the trained model. In Experiment 2, using the same dataset, we trained four deep-learning models along with an SVC and then presented the results. The performance was evaluated using the performance metrics (Accuracy, Precision, Recall).

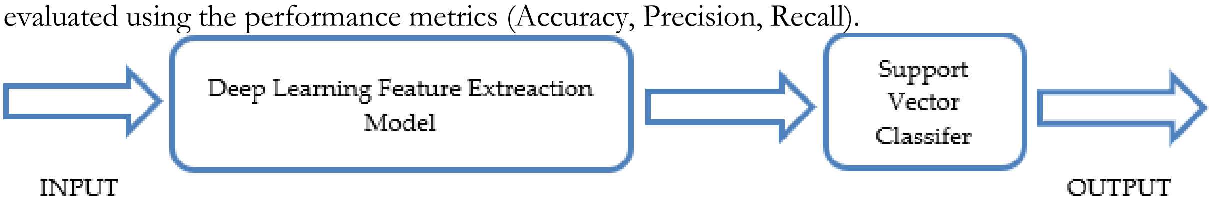
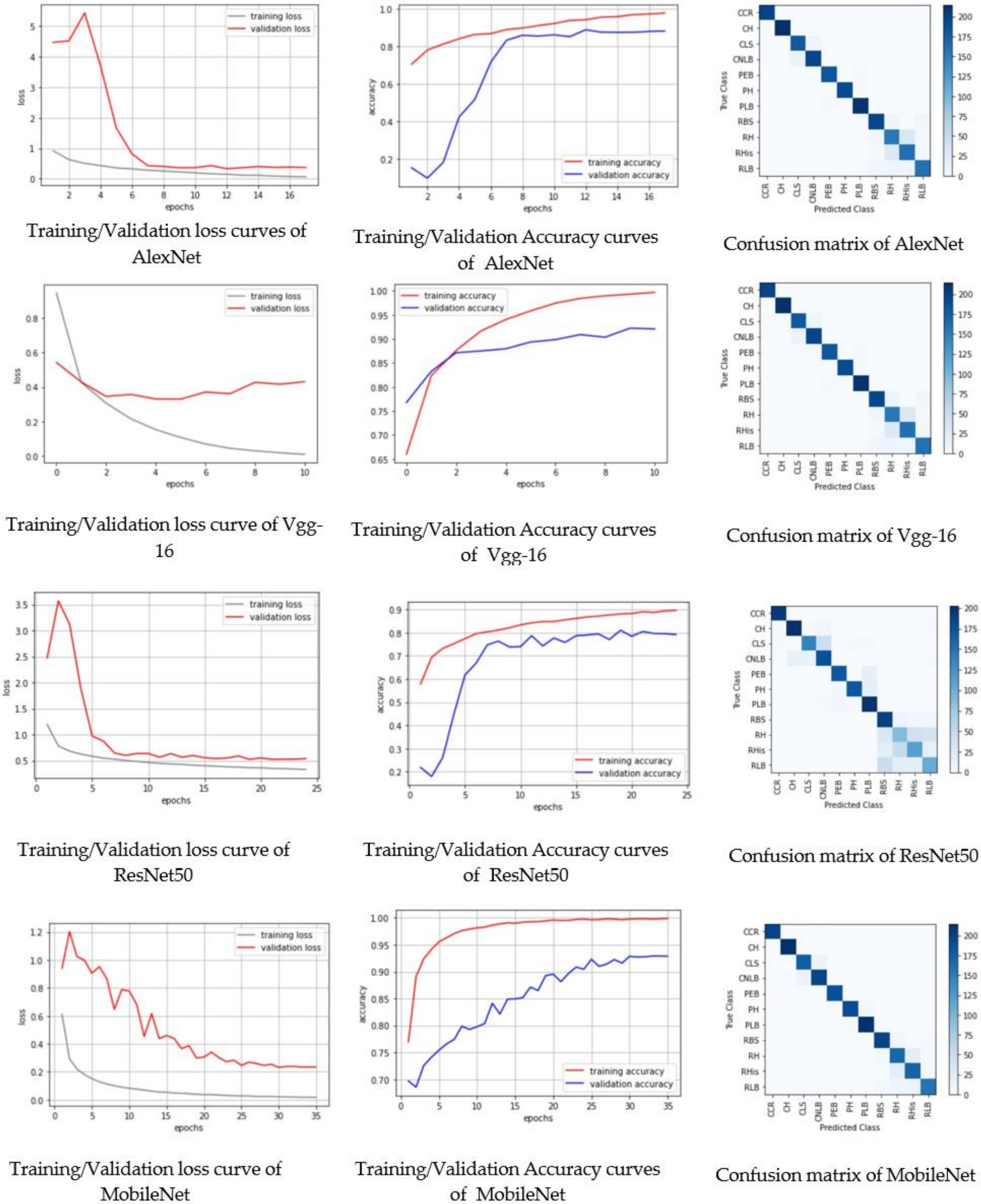


Figure 6. The proposed hybrid model combining Deep Learning for feature extraction and a Support Vector Classifier (SVC) for final classification

In Experiment 1, four pre-trained deep learning models were trained and validated on our dataset as discussed and the obtained results are summarized in Figure 7 and Table 2. In Figure 7, each model's loss and accuracy curves over epochs are shown, with training metrics in red and validation metrics in gray (loss) or blue (accuracy). Corresponding confusion matrices illustrate classification performance, with true class labels on the y-axis and predicted classes on the x-axis, highlighting each model's accuracy in distinguishing among classes. The results show that MobileNet provides the highest accuracy and recall rates in these four models. The results further elaborate that the highest accuracy is normally achieved at the largest number of epochs. The more rigorous the training is, the more accurate the result will be. On the other hand, all the models were predicting the results within the specified range.

Table 2. Evaluation measures (Accuracy, Precision, Recall, and F1 Score) for standalone deep learning models (AlexNet, VGG-16, ResNet50, and MobileNet) in Experiment 1.

Model	AlexNet	Vgg-16	ResNet50	MobileNet
Accuracy	93.05 %	93.05 %	79.50 %	94.27 %
Precision	93.10%	93.11%	79.52%	94.38%
Recall	93.04%	93.05%	79.5%	94.27%
F1 Score	93.06%	93.07%	79.16%	94.29%



Training/Validation loss curves of AlexNet

Training/Validation Accuracy curves of AlexNet

Confusion matrix of AlexNet

Training/Validation loss curve of Vgg-16

Training/Validation Accuracy curves of Vgg-16

Confusion matrix of Vgg-16

Training/Validation loss curve of ResNet50

Training/Validation Accuracy curves of ResNet50

Confusion matrix of ResNet50

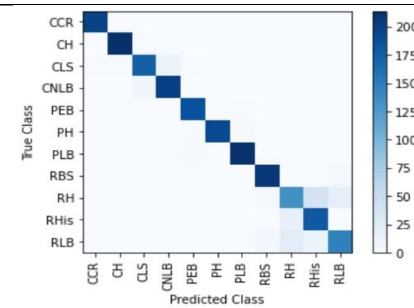
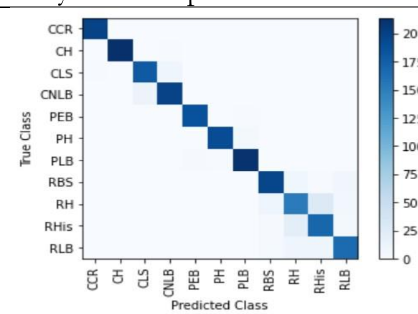
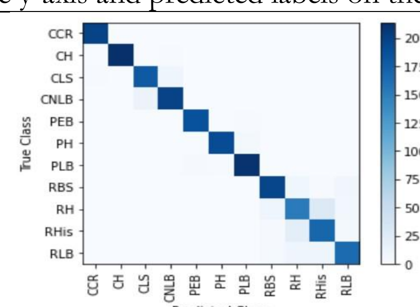
Training/Validation loss curve of MobileNet

Training/Validation Accuracy curves of MobileNet

Confusion matrix of MobileNet

Figure 7. From left to right, the figure displays training/validation loss, training/validation accuracy, and the confusion matrix for each model (AlexNet, VGG-16, ResNet50, and MobileNet) in Experiment 1

In Experiment 2, the results of the proposed model are presented in Table 3 and Figure 8. In this phase, pre-trained deep learning models were integrated with an SVC to evaluate their combined performance as shown in Figure 6. ResNet50 and MobileNet with SVM have enhanced the model performance and the results for AlexNet and VGG16 with SVM have enhanced their performance to 1% as compared to pre-trained deep learning models alone. This study has employed the grid search method to optimize SVC for our dataset. AlexNet along with SVC has found the gamma 0.0005179474679231213 and C equal to 10, VGG16 has gamma 0.00019306977288832496 and C equal to 10, ResNet50 has gamma 1e-05 and C 26826.957952797275, and MobileNet has gamma 0.0005179474679231213 and C 10. In Figure 8, each matrix represents the mapping between true class labels (y-axis) and predicted class labels (x-axis), with darker shades indicating higher classification accuracy. The left side of the figure specifies the SVM hyperparameters: C and Gamma, used for the corresponding model, showcasing the impact of these parameters on classification accuracy. A comparison table of predesigned models with our proposed work has been provided in Table 4 which summarizes the proposed approach and pre-designed models. It can be observed that this hybrid technique (SVM + pre-designed model) outperforms and exhibits more accurate retrieval results.

C: 10 Gamma: 0.0005179474679231213	
SVM parameters for AlexNet + SVM	Confusion matrix for AlexNet + SVM with true labels on the y-axis and predicted labels on the x-axis
C: 10 Gamma: .00019306977288832496	
SVM parameters for Vgg16 + SVM	Confusion matrix for Vgg16 + SVM with true labels on the y-axis and predicted labels on the x-axis
C: 26826.957952797275 Gamma: 1e-05	
SVM parameters for ResNet50+ SVM	Confusion matrix for ResNet50 + SVM with true labels on the y-axis and predicted labels on the x-axis

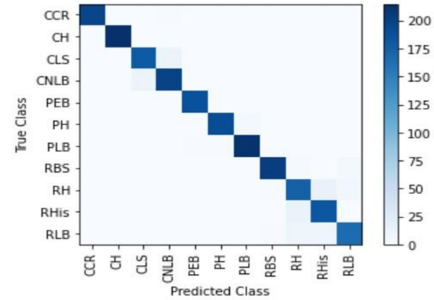
C: 10 Gamma: 0.0005179474679231213	
SVM parameters for MobileNet+ SVM	Confusion matrix for Mobilenet + SVM with true labels on the y-axis and predicted labels on the x-axis

Figure 8. The figure shows the C and gamma values for the models, along with the confusion matrices for Experiment 2, illustrating the classification performance across multiple classes.

Table 3. Evaluation measures (Accuracy, Precision, Recall, and F1 Score) for different hybrid models combining deep learning architectures with SVM in Experiment 2.

Model	AlexNet+SVM	Vgg-16+SVM	ResNet50+SVM	MobileNet+SVM
Accuracy	92.95 %	93.55 %	86.05 %	95.68 %
Precision	92.96%	93.56%	85.90%	95.74%
Recall	92.95%	93.54%	86.04%	95.68%
F1 Score	92.86%	93.54%	85.89%	95.69%

Table 4. Comparison of classification accuracy between pre-designed models and the proposed hybrid approach integrating SVM.

Pre-Designed Models		Proposed Work	
Model	**Accuracy**	**Model**	**Accuracy**
AlexNet	93.05%	AlexNet + SVM	93.95%
Vgg-16	93.05%	Vgg-16 +SVM	93.55%
ResNet50	79.5%	ResNet50 + SVM	86.05%
MobileNet	94.27%	MobileNet + SVM	95.68%

Discussion:

The hybrid model proposed in this research, integrating deep learning models with SVM for crop disease detection, demonstrates promising results as evidenced by the experiments conducted. The study unfolds into two main phases: Experiment 1, focuses on training and validating four distinct deep learning models (AlexNet, Vgg-16, ResNet50, and MobileNet) individually, and in Experiment 2, these pre-trained models are combined with SVM for further analysis.

In Experiment 1, the evaluation of individual deep learning models on the dataset sheds light on their performance metrics, namely accuracy, precision, recall, and F1 score. Notably, MobileNet emerges as the top performer among the four models, exhibiting the highest accuracy and recall rates. The trend of training epochs versus accuracy is perceptible, with more intense training typically resulting in better accuracy but it is important to balance computational expense against benefit. In Experiment 2, we attempt to integrate SVM with pre-trained deep learning models to boost performance. The experimental findings show a significant improvement in model performance when SVM is applied with deep learning models, especially in the ResNet50 and MobileNet cases. These improvements are supported by the optimization of SVM parameters using the grid search method, specific to the dataset. The optimized parameters for every model-SVM pair further highlight the efficacy of this method in achieving maximum classification accuracy. The comparative analysis given in Table 4 highlights the advantage of the proposed hybrid method over individual deep learning models. Across the board, the combination of SVM with pre-trained models results in improved accuracy and performance, with notable improvements witnessed in the instances of ResNet50 and MobileNet. This underscores the complementary nature of deep learning and SVM, where the deep learning models excel in feature extraction while the SVM specializes in classification, thereby leveraging the strengths of both methodologies to achieve superior results.

In comparison to existing state-of-the-art methods for leaf disease detection, our proposed MobileNet + SVM model demonstrates superior classification performance. Prior studies have reported notable accuracy levels using various deep learning and hybrid approaches. For instance, a YOLOv5-based approach achieved a mean average precision (mAP) of 76%, with a precision of 90% and recall of 67%, on a custom rice dataset [24]. Another method incorporating an attention-based deep separable neural network optimized via Bayesian techniques reported an accuracy of 94.65% [25]. Similarly, a model leveraging pre-trained deep neural networks for feature extraction, combined with traditional machine learning classifiers, achieved up to 94% accuracy [26]. Despite the promising performance of these approaches, our model outperformed them by achieving an accuracy of 95.68%, thus demonstrating its effectiveness in capturing relevant features while maintaining computational efficiency.

Conclusion and Future Work:

Overall, the focus of this research is the development and evaluation of a hybrid model for the detection of various diseases in crop leaves using deep learning and SVM. The study covered two experiments: In the first experiment, four deep learning models i.e., AlexNet, Vgg-16, ResNet50, and MobileNet were trained and validated on the dataset. As a result, MobileNet was the best performer among all presenting the highest accuracy and recall rates. In the second experiment, a hybrid approach was implemented using deep learning models with the SVM classifier. This hybridization showed impressive results. ResNet50 and MobileNet coupled with SVM demonstrated significant improvements in accuracy in comparison to their standalone counterparts. In particular, the combination of MobileNet with SVM achieved an impressive accuracy of 95.68%; the highest among all.

In summary, this research has successfully developed a hybrid model and demonstrated its effectiveness for crop disease detection thus leveraging the feature extraction potential of deep learning and the classification capability of SVM. The amalgamation of hyperspectral images holds significant importance in advancing the capabilities of disease detection systems. Hyperspectral images can provide a more detailed view of crop health. They capture spectral information beyond what is visible to the human eye. Furthermore, this hybrid model can be utilized beyond disease detection. It can serve as a basic tool for precision farming, a fast-growing field that utilizes real-time data and analysis for the optimization of agriculture practices. Verily, this research holds promising and far-reaching prospects. The continued refinement of the hybrid model along with the integration of hyperspectral imaging would be a revolutionizing step towards crop management and disease control. As technology keeps on advancing, the fusion of deep learning, SVM, and hyperspectral data would be a game changer for farmers since it offers the tools required to maximize yield and food security at the expense of reduced environmental impact.

Conflict of Interest: We hereby declare that we have no conflicts of interest about the research/project/article titled " A Hybrid Model for Crop Disease Detection based on Deep Learning and Support Vector Machine". We affirm that we have no financial or personal relationships with individuals or organizations that could inappropriately influence our work or decision-making process about this research/project/article.

Author Contribution: Mr. Abdul Rehman, Mr. Abdul Basit, and Mr. Arslan Hafeez conceptualized the idea and performed the experimentation. Dr. Muhammad Akram and Dr.

Aashir Waleed supervised the research and reviewed the results/conclusions. Mr. Muhammad Zubair contributed to data collection and preprocessing.

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