INVESTIGATING THE PERFORMANCE OF DEEP LEARNING MODELS, HYBRID MODELS, AND TRANSFER LEARNING MODELS FOR CROP DISEASE DETECTION ACROSS MULTIPLE CROPS

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Abstract—
Crop disease detection plays a crucial role in ensuring food security and improving agricultural practices. In this research, we investigate the performance of deep learning (DL) models, hybrid models combining DL and machine learning (ML), and transfer learning models for crop disease detection across multiple crops. To conduct this study, we employed various existing DL methods, DL + ML hybrid methods, and transfer learning methods. A comprehensive dataset was collected from Dantiwada Agriculture University, encompassing diverse crop diseases across multiple crops. Upon evaluating these models, our findings reveal that the transfer learning model exhibited superior performance compared to other algorithms. Specifically, on the potato crop, the transfer learning model achieved remarkable accuracy, precision, recall, and F1-Score, all reaching 99%. These results demonstrate the potential of transfer learning for crop disease detection, highlighting its ability to leverage knowledge from pre-trained models to enhance detection accuracy and overall performance. The implications of these findings extend to the agricultural sector, offering promising avenues for improving crop management and disease prevention strategies.

Index Terms— Plant Village, Crop disease, Deep Learning, Hybrid Algorithm, Transfer Learning

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I. INTRODUCTION

The occurrence of plant diseases has a detrimental impact on agricultural production, leading to increased food insecurity [1]. Early detection of plant diseases is essential for effective prevention and control, playing a vital role in agricultural management and decision-making [1]. In recent years, plant disease identification has become a critical issue.

Plant diseases often manifest as visible marks or lesions on various parts of the plant, with leaves being the primary source for identifying diseases [2]. Traditionally, disease identification has relied on subjective and time-consuming methods, such as on-site expert assessment or farmer experience, leading to inefficiencies and potential misjudgments [2]. To overcome these challenges, research on image processing techniques for plant disease recognition has gained significant attention.

While traditional image processing techniques have shown high accuracy in disease recognition, they suffer from several limitations, including cumbersome processes, subjectivity, reliance on spot segmentation, and artificial feature extraction [2]. Moreover, testing the performance of these models in complex environments remains challenging [2]. Therefore, there is a need to develop intelligent, rapid, and accurate plant leaf disease recognition methods.

Deep learning technology has significantly advanced in the identification of plant diseases recently [3]. Convolutional neural networks (CNNs), in particular, provide automatic feature extraction and classification, doing away with manual feature engineering [3]. CNNs have demonstrated excellent performance in image processing and classification tasks [4]. Several studies have successfully applied deep learning techniques for plant disease recognition, achieving high accuracy rates [6]-[8].

However, despite these promising results, the diversity of available datasets for training CNNs in plant leaf disease recognition remains limited [9]. Large and diverse datasets are essential for training robust CNN classifiers. To address this challenge, transfer learning, which involves retraining pre-trained CNNs with smaller datasets, has emerged as an effective approach [9]. By leveraging pre-trained CNNs, transfer learning enables the recognition of plant diseases with limited datasets. While previous research has addressed plant disease recognition using deep learning and traditional machine learning methods [4], [10], [11], there are gaps in recent developments regarding visualization techniques, early detection of diseases, and classification based on small samples [12], [13]. This paper aims to fill these gaps by presenting new visualization techniques and modified deep learning models for plant disease identification.

Agriculture is a crucial sector in various countries, and crop losses due to diseases have a significant impact on food production [14], [15]. The lack of expert availability, inadequate fertilizer management, and insufficient disease awareness contribute to lower production rates [16]. Plant diseases also result in environmental damage and financial losses [17], [18]. Rice, a major food crop, is susceptible to diseases such as sheath blight, leaf blast, and brown spot [19], [20]. In Asia, rice diseases cause significant production losses [21]. Currently, manual analysis and monitoring of plant diseases by experts are time-consuming and labor-intensive [22]. Automating disease detection through image processing provides an effective solution, enabling farmers to detect diseases promptly and prevent crop losses.

Several image processing and machine learning algorithms have been developed for plant disease diagnosis [23], [24], [25], [26], [27]. These methods involve capturing images of infected leaves, segmenting the infected regions, extracting features, and employing machine learning techniques for classification [28]. The use of artificial intelligence in agriculture, notably for the identification of plant diseases, is anticipated to increase as the world's population rises [29], [30]. With more research publications concentrating on plant disease identification, machine learning and deep learning techniques have become more prominent in this sector [29].

To overcome these difficulties, algorithms for image processing and machine learning have been created to detect plant illnesses in rice and other crops. Support vector machines (SVM), random forest (RF), and k-nearest neighbors (KNN) are examples of traditional machine learning techniques that have been used. These techniques rely on manually created characteristics including color, texture, and local descriptors [31]–[32]. Convolutional neural networks (CNNs), in particular, have emerged as a potential deep learning technique because they can automatically learn features from training data [33]. Various CNN architectures, including AlexNet, VGGNet, ResNet, and InceptionNet, have been employed for plant disease recognition in rice and other crops [34],[35]. These deep learning models have achieved remarkable performance in terms of accuracy and robustness.

The capacity of deep learning models to learn hierarchical representations from unprocessed input data is one of its main advantages. In the context of plant disease recognition, CNN models can learn discriminative features directly from leaf images, capturing both local and global patterns associated with different diseases. This eliminates the need for manual feature extraction and allows for end-to-end learning, leading to more accurate and efficient disease classification.

Transfer learning has proven to be highly effective in plant disease recognition, especially when limited labeled data is available. By utilizing pre-trained models trained on large-scale datasets like ImageNet, the learned features can be transferred to the task of plant disease recognition. This approach helps to overcome the challenge of data scarcity and improves the generalization capability of the model.

In addition to traditional CNN architectures, recent research has focused on developing modified deep learning models specifically tailored for plant disease recognition. These models incorporate techniques such as attention mechanisms, recurrent neural networks (RNNs),to enhance disease detection performance.

Attention mechanisms allow the model to focus on relevant regions of the image, giving more weight to informative regions and suppressing irrelevant background noise. This improves the model's ability to capture subtle disease symptoms and increases its interpretability. Attention-based models have shown promising results in plant disease recognition tasks [36],[37].

RNNs, specifically long short-term memory (LSTM) networks, have been utilized to model the sequential nature of plant diseases. By considering the temporal dependencies in disease progression, LSTM-based models can capture the dynamic changes in leaf symptoms over time. This enables early detection and prediction of diseases before they become visually apparent. LSTM-based models have demonstrated improved performance in early disease detection and monitoring [38],[39].

The work of this paper includes investigating the performance of deep learning models, hybrid models combining deep learning and machine learning, and transfer learning models for crop disease detection. The researchers collected a diverse dataset from Dantiwada Agriculture University, encompassing multiple crops and various crop diseases. The study demonstrates the potential of transfer learning in leveraging pre-trained models to enhance detection accuracy and improve overall performance. These results have significant implications for the agricultural sector, offering promising avenues for improving crop management and disease prevention strategies.

A. Novelty in research work

The contribution of this research lies in the exploration of advanced models and techniques for crop disease detection, with a particular focus on deep learning, hybrid models, and transfer learning. The following points highlight the key aspects and findings of this study:

- **Investigation of DL, DL + ML hybrid, and transfer learning models:** The research paper explores the performance of deep learning (DL) models, hybrid models combining DL and machine learning (ML), and transfer learning models for crop disease detection. This investigation provides insights into the effectiveness of these different approaches in addressing the challenges of crop disease detection.
- **Comprehensive dataset collection:** A diverse dataset encompassing various crop diseases across multiple crops was collected from Dantiwada Agriculture University. This dataset serves as a valuable resource for evaluating the performance of the different models and ensures the research's reliability and relevance to real-world scenarios.
- **Superior performance of transfer learning model:** The study reveals that the transfer learning model outperforms other algorithms in crop disease detection. Particularly on the potato crop, the transfer learning model achieved remarkable accuracy, precision, recall, and F1-Score, reaching an impressive 99%. This finding highlights the potential of transfer learning in enhancing detection accuracy and overall performance.
- **Leveraging pre-trained models for enhanced performance:** By employing transfer learning, the research demonstrates the ability to leverage knowledge from pre-trained models. This approach enhances the detection accuracy of crop diseases, showcasing the effectiveness of transferring learned features and patterns from existing models to improve the performance of the detection system.
- **Implications for agriculture and crop management:** The findings of this research have significant implications for the agricultural sector. The utilization of transfer learning techniques in crop disease detection offers promising avenues for improving crop management and disease prevention strategies. By enhancing detection accuracy, farmers and agricultural professionals can make informed decisions, implement timely interventions, and

effectively manage crop diseases, ultimately leading to improved agricultural practices and food security.

III. METHODOLOGY

This section presents the methodology adopted in this research, covering various aspects such as dataset summary, data pre-processing techniques, dataset splitting, architectural overview, and performance measurement metrics.

A. Dataset Summary

This research utilizes two datasets to train and evaluate the proposed model. The first dataset is the widely recognized benchmark dataset, Plant Village, which serves as a foundation for plant disease detection research. In addition to the Plant Village dataset, a newly collected dataset from Dantiwada Agriculture University, located in Gujarat, India, is utilized in this study.

➢ **Plant Village Dataset Description**

The dataset used in this study is the Plant Village dataset, which comprises a collection of 52,834 leaf images. The dataset is categorized into 37 distinct classes based on the species and disease condition of the leaves. These classes encompass both healthy leaf images and those affected by various diseases. The Plant Village dataset provides a comprehensive and diverse collection of leaf images, making it suitable for training and evaluating models in the domain of plant disease detection and classification. The summary of the used Plant Village dataset is mentioned in Table 1.

Table 1: Summary of Benchmark Plant Village Dataset

Plant Name	Plant Disease Names	Number of Images in Dataset
Apple	4 Classes: Healthy, Apple scab, Black rot, Cedar apple rust	Total Images-5943Healthy-1502, Apple scab-1504, Black rot-1497, Cedar apple rust-1440
Blueberry	Healthy	Total-1454
Cherry	2 Classes: Healthy, Powdery mildew	Total-1577 Healthy-156, Powdery mildew-1421
Corn	4 Classes: Healthy, Cercospora leaf Spot, Common rust, Northern Leaf Blight	Total- 5841 Healthy-1477, Cercospora leaf Spot-1410, Common rust-1477, Northern Leaf Blight-1477
Grape	4 Classes: Healthy, Black rot, Esca, Leaf blight (Isari-opsis), Anthracnose	Total Images- 5805 Healthy- 1423,Black rot- 1472, Esca (Black Measles)-1480, Leaf blight (Isari- opsis)-1430
Orange	1 Class Healthy	Total images- 1503 Healthy-1503
Peach	2 Classes Healthy, Bacterial spot	Total Images- 2891 Healthy-1432 Bacterial spot-1459
Pepper/bell	2 Classes: Healthy, Bacterial spot	Total Images- 2975 Healthy-1497 Bacterial spot-1478
Potato	3 Classes: Healthy, Early blight, Late blight	Total Images- 4426 Healthy-1456, Early blight-1485, Late blight-1485
Raspberry	1 Class: Healthy	Total Images-1490
Soybean	1 Class: Healthy	Total Images-1505
Squash	1 Class Powdery mildew	Total Images-1434
Strawberry	2 Classes: Healthy, Leaf scorch	Total Images-2900 Healthy-1456 Leaf scorch-1444
Tomato	9 classes: Healthy, Bacterial spot, Early blight, Late blight, Leaf Mold, Septoria leaf spot, Spider mites, Target Spot, Tomato mosaic virus	Total Images-13090 Healthy-1456, Bacterial spot-1444, Early blight-1425, Late blight-1480, Leaf Mold-1481, Septoria leaf spot-1436, Spider mites-1463, Target Spot-1457, Tomato mosaic Virus-1448

➢ **About Newly Gathered Dataset:**

The dataset from Dantiwada Agriculture University specifically focuses on three different diseases and consists of a total of 2,803 leaf images. This dataset complements the Plant Village dataset by providing additional samples of diseased leaves, thereby enriching the diversity of the training data. The inclusion of this newly collected dataset enables a comprehensive evaluation of the proposed model's performance on a range of diseases prevalent in the specific region and context of Dantiwada Agriculture University. The summary of the newly collected dataset is mentioned in Table 2.

Table 2: Summary of Dataset Collected from Dantiwada Agriculture University

Plant Name	Plant Disease Names	Number of Images in Dataset
Mustard	4 Classes: Alternaria blight, Powdery mildew, Sclerotinia stem rot, White rust	Total Images- 830 Alternaria blight -208 Powdery mildew-208 Sclerotinia stem rot-207 White rust-207
Grape	3 Classes: Anthracnose, Downey Mildew, Powdery mildew	Total Images-831 Anthracnose-234 Downey Mildew-338 Powdery mildew-259
Potato	5 Classes: Black heart, Black scurf, Early blight, Late blight, Wart	Total Images- 1142 Black heart-234 Black scurf-207 Early blight-286 Late blight-234 Wart-181

B. Data Preprocessing Techniques

In the data pre-processing phase, several techniques are applied to enhance the dataset's quality and diversity. The images are resized to a standardized resolution to ensure consistency, while image data augmentation techniques such as rotation, width and height shifts, zoom, horizontal splitting, and shear range are employed to introduce synthetic variations. These techniques improve the robustness of the training data and enable the model to learn more effectively by capturing a wider range of real-world scenarios. The combination of standardized image size and augmented variations prepares the dataset for training, enhancing the model's performance in accurately classifying and detecting crop diseases.

C. Splitting Dataset

The image data from Dantiwada Agriculture University was split in an 80:20 ratio, where 80% of the images were used for training the model, and the remaining 20% were set aside for validating the model's performance. This partitioning ensures that the model is trained on a substantial portion of the data while reserving a separate set for evaluating its generalization and effectiveness. The training set enables the model to learn patterns and features from the data, while the validation set provides an independent evaluation to assess its performance and identify any potential issues such as overfitting.

D. Architectural Overviews

The architectural overview section presents a comprehensive description of the methodologies employed in our research for crop disease detection using plant leaf images. We discuss the deep learning architectures utilized, including VGG16, VGG19, RESNET50, RESNET101, and InceptionB3, highlighting their key features and advantages. Furthermore, we outline the data preprocessing and augmentation techniques employed to enhance the robustness of our models. Additionally, we introduce the concept of transfer learning with VGG16 and the exploration of hybrid models combining deep learning with traditional machine learning algorithms. This section lays the foundation for the subsequent detailed discussions on experimental setup and performance evaluation.

- **VGG-16 Architecture:**

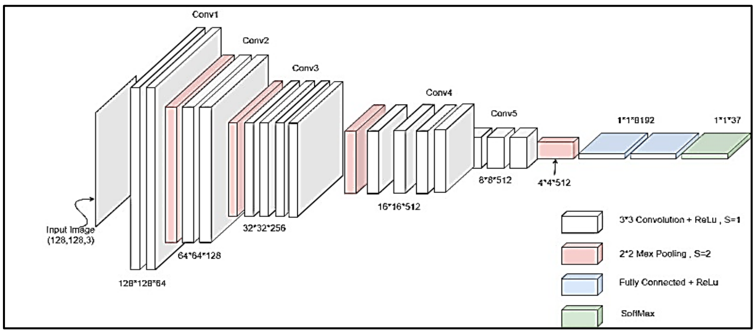

Figure 1: Architectural Diagram of VGG-16 Model

A CNN model of 16 layers, containing 13 convolutional layers and 3 fully linked layers, is the VGG-16 architecture. In VGG-16, each pooling layer uses 2x2 filters with a stride of 2, while each convolutional layer employs 3x3 filters with a stride of 1. The following mathematical description of the architecture is available:

1. Input: The input to the network is an image or a feature map of size 224x224x3 (width x height x channels).
2. Block 1:
   - Conv1_1 and Conv1_2: 64 filters of size 3x3x3 and 3x3x64 respectively, each with a stride of 1 and padding of 1.
   - MaxPooling: Max pooling with 2x2 filters and a stride of 2. This reduces the spatial dimensions by half.
3. Block 2:
   - Conv2_1 and Conv2_2: 128 filters of size 3x3x64 and 3x3x128 respectively, each with a stride of 1 and padding of 1.
   - MaxPooling: Max pooling with 2x2 filters and a stride of 2.
4. Block 3:
   - Conv3_1, Conv3_2, and Conv3_3: 256 filters of size 3x3x128, 3x3x256, and 3x3x256 respectively, each with a stride of 1 and padding of 1.
   - MaxPooling: Max pooling with 2x2 filters and a stride of 2.
5. Block 4:
   - Conv4_1, Conv4_2, and Conv4_3: 512 filters of size 3x3x256, 3x3x512, and 3x3x512 respectively, each with a stride of 1 and padding of 1.
   - MaxPooling: Max pooling with 2x2 filters and a stride of 2. 6. Block 5:
   - Conv5_1, Conv5_2, and Conv5_3: 512 filters of size 3x3x512 for each, with a stride of 1 and padding of 1.
   - MaxPooling: Max pooling with 2x2 filters and a stride of 2.
7. Fully Connected Layers:
   - Fully Connected – FC_1, FC_2: 4096 neurons with ReLU activation function.
   - Fully Connected – FC_3: 37 neurons with softmax activation function. This is the final layer, which outputs probabilities for 37 different classes.

- **VGG-19 architecture:**

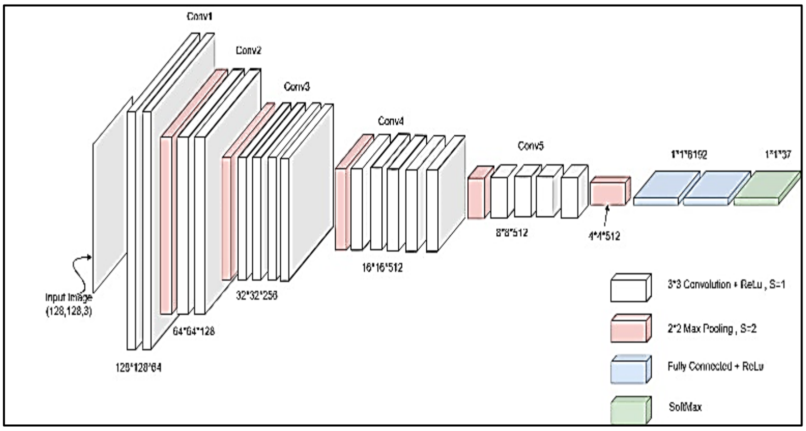

Figure 2: Architectural Diagram of VGG-19 Model

The VGG19 architecture has 19 layers total, 16 of which are convolutional and 3 of which are fully linked, and is made to handle input images with fixed sizes (typically 224x224 pixels). Mathematically, the VGG19 architecture can be represented as follows:

1. Convolutional Layers: The convolutional layers in VGG19 perform feature extraction by convolving the input image with a set of learnable filters. Each filter detects a specific pattern or feature in the image. Let's denote the input to the i^{th} convolutional layer as Xi, and the corresponding set of filters as Wi. Then, the output of the i^{th} convolutional layer, denoted as Hi, is obtained by applying the convolution operation followed by a non-linear activation function (usually ReLU):

Hi = ReLU(convolve(Xi, Wi) + bi)

Here, bi represents the bias term for the i^{th} layer.

2. Max Pooling Layers: The most important data is preserved while the spatial dimensions of the feature maps are reduced with VGG19's use of max pooling layers. Max pooling is typically applied with a fixed-size pool window (e.g., 2x2) and a stride of the same size.
3. Fully Connected Layers: After several convolutional and pooling layers, VGG19 applies three fully connected layers for classification. These fully connected layers

are first traversed before the feature maps are vectorized and flattened. To determine class probabilities, the outputs of the final fully connected layer are frequently passed through a softmax activation function.

- **ResNet50:**

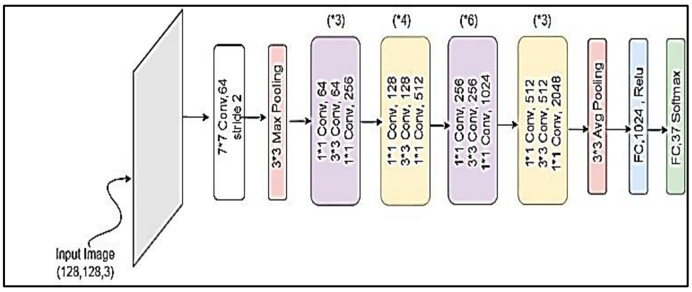

Figure 3: Architectural Diagram of ResNet50 Model

ResNet50 is a deep neural network composed of 50 layers, and it employs a residual learning framework to alleviate the vanishing gradient problem associated with training deep neural networks. ResNet50's main concept is the addition of residual blocks, which enable the network to learn residual functions rather than the underlying mapping directly.

- **ResNet101:**

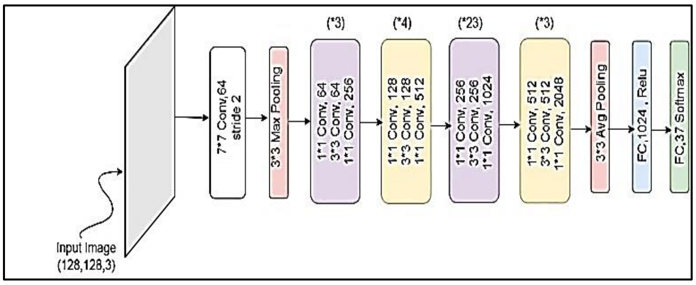

Figure 4: Architectural Diagram of ResNet101 Model

The ResNet-101 architecture extends the original ResNet architecture by adding more layers, resulting in a deeper and more powerful model. It is characterized by skip connections, mitigating the problem of vanishing gradients. Mathematically, ResNet-101 can be described as follows: It starts with a 7x7 convolutional layer, followed by batch normalization and ReLU activation. Max pooling with a 3x3 kernel and stride 2 is applied. Residual blocks, consisting of convolutional layers with skip connections, are stacked to learn residual mappings. Global average pooling is then performed, followed by fully connected layers and an activation function.

- **Inception V3:**

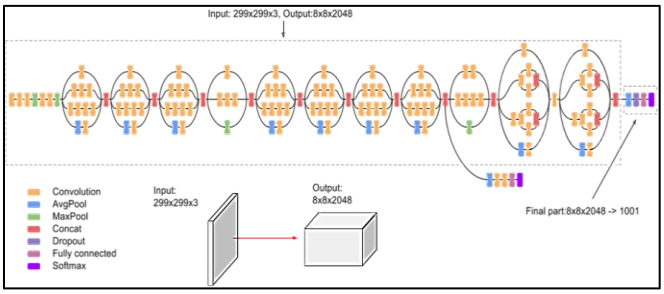

Figure 5: Architectural Diagram of Inception V3 Model

Inception v3 is a CNN architecture introduced as an improvement over Inception v2, designed for image recognition and classification tasks. Its mathematical description involves convolutional layers that apply learnable filters to the input image, pooling layers that reduce spatial dimensions, and the pivotal Inception module capturing multi-scale information. Inception v3 incorporates auxiliary classifiers in intermediate layers to address the vanishing gradient problem.

The architecture comprises stacked Inception modules, followed by fully connected layers and a softmax output layer. In summary, Inception v3 combines various layers to extract multi-scale features and achieve a balance between computational efficiency and accuracy in image recognition tasks.

➢ **VGG16+SVM:**

For image classification tasks, the VGG16+SVM architecture combines the VGG16 convolutional neural network (CNN) with a Support Vector Machine (SVM) classifier. Let's break down the mathematical description of each component:

1. VGG16:

The VGG16 is a deep CNN architecture consisting of 16 layers, primarily composed of convolutional layers and fully connected layers. The input to the VGG16 network is an image represented as a matrix of pixel values. The architecture applies a series of convolutional filters and non-linear activation functions to extract hierarchical features from the input image.

The input picture will be referred to as X with the dimensions (H, W, C), where H stands for the height, W for the width, and C for the number of channels (e.g., 3 for RGB images). The VGG16 network performs several convolutional operations using filters of various sizes (typically 3x3) and depths, followed by non-linear activation functions (usually ReLU) and max-pooling layers for down sampling.

The vector input to the fully connected layers is then created by flattening the output of the final convolutional layer. The retrieved features are then processed and mapped to the required output dimension by these completely connected layers. The VGG16 network's final output is a probability distribution across the various classes or labels that could be assigned to the input image.

2. SVM Classifier:

After the VGG16 network, the extracted features are fed into an SVM classifier. SVM is a classification technique for supervised machine learning. It works by identifying an ideal hyperplane in a high-dimensional feature space that separates several classes.

In the case of VGG16+SVM architecture, the features extracted by the VGG16 network are used as input to the SVM classifier. Let's denote the extracted features as F with dimension (D), where D represents the number of features.

The SVM classifier aims to find the hyperplane that maximally separates the feature representtations of different classes. Mathematically, the SVM algorithm finds the decision boundary by solving an optimization problem to maximize the margin between classes while minimizing classification errors. The decision boundary is represented as a hyperplane defined by the weight vector W and bias term b.

Given a feature vector F, the SVM classifier predicts the class label y by computing the decision function:

$f(F) = \text{sign}(W^T * F + b)$

Where W^T denotes the transpose of the weight vector W. The sign function assigns the predicted class label based on the positive or negative value of f (F).

Overall, the VGG16+SVM architecture combines the feature extraction capabilities of the VGG16 network with the robust classification properties of the SVM algorithm to perform image classification tasks.

➢ **VGG16+KNN:**

To combine VGG16 with the KNN classifier, we use the VGG16 model to extract high-level features from images. These features serve as inputs to the KNN classifier, which performs classification based on the similarity of the feature vectors. By utilizing the robust feature extraction capabilities of VGG16 and the flexibility of the KNN classifier, our hybrid approach aims to improve both the accuracy and efficiency of image classification.

➢ **VGG16+RF:**

The VGG16+RF architecture refers to a combination of the VGG16 convolutional neural network (CNN) model and the Random Forest (RF) algorithm. Here's a mathematical description of this architecture:

1. Random Forest (RF):

To generate predictions, an ensemble learning system called Random Forest combines different decision trees. Each decision tree is trained using a random subset of the input features and a random subset of the training data.

The RF algorithm can be mathematically described as follows:

For each decision tree t = 1 to T:

- Sample a random subset of training data D_t.
- Sample a random subset of input features F_t.
- Train a decision tree using D_t and F_t.

By combining all decision tree predictions, often via majority voting for classification tasks or averaging for regression tasks, the final prediction of the RF model is obtained.

In the VGG16+RF architecture, the output of the VGG16 model (F_fc) is used as input features for the RF algorithm. The RF model then performs further processing and prediction based on these features.

Please note that the mathematical description provided here is a simplified overview of the VGG16+RF architecture. The actual implement-tation may involve additional details, such as specific activation functions, regularization techniques, and hyperparameters tuning.

TRANSFER LEARNING USING VGG16:

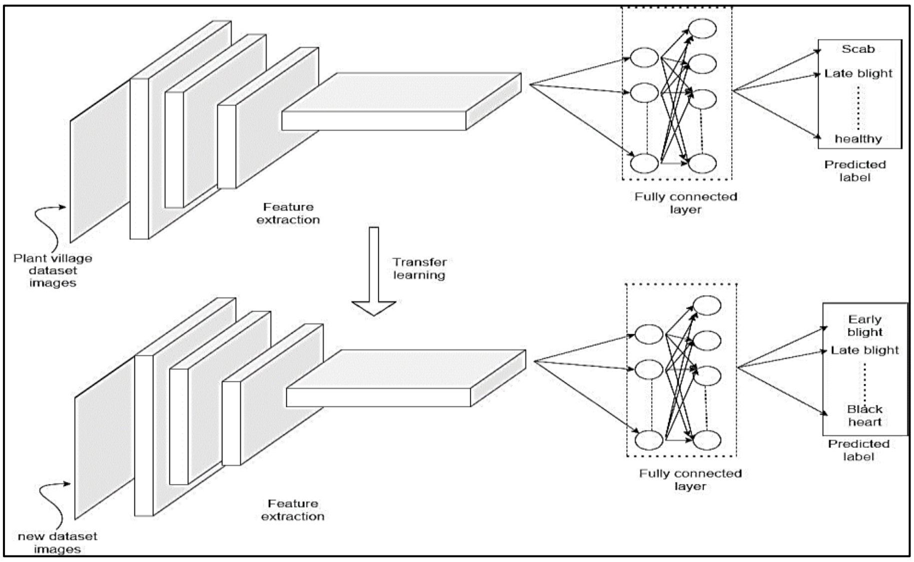

Figure 6: Architectural Diagram to Represent Transfer Learning

The VGG16 architecture was employed as a transfer learning approach for crop disease detection using the Plant Village Dataset, consisting of images depicting 37 different diseases. The pre-trained knowledge of the VGG16 model was leveraged to train and validate the model on a newly collected dataset obtained from Dantiwada Agriculture University. By utilizing transfer learning, the model benefited from the learned representations of the VGG16 architecture, enhancing its performance in identifying and classifying crop diseases in the newly acquired dataset.

E. Performance Measurement Metrics

In order to assess the performance of the proposed methods and algorithms for crop disease detection, several widely recognized metrics have been employed. These metrics provide a comprehensive evaluation of the detection system's effectiveness and its ability to accurately classify and detect crop diseases. In accordance with standard practices in the field of computer vision and pattern recogni-tion, the following performance measurement metrics have been utilized: accuracy, precision, recall, and F1-score.

Table 3: Performance Measurement Metrics

Performance Measurement Metric	Mathematical Notation
Accuracy	$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$
Precision	$Precision = \frac{TP}{TP + FP}$
Recall	$Recall = \frac{TP}{TP + FN}$
F1-Score	$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$

V. RESULTS ANALYSIS

In the results analysis section, a comprehensive evaluation of deep learning variants and hybrid algorithms was conducted using the Plant Village dataset. Initially, the models were individually applied to each crop, and their performance was assessed. Subsequently, the models were tested on combined datasets consisting of multiple crops to evaluate their ability to handle diverse agricultural scenarios. Furthermore, the performance of the models was examined when applied to the complete dataset containing all crops with their respective diseases. A similar analysis was carried out on the newly gathered dataset from Dantiwada Agriculture University. In this case, a transfer learning approach was employed, utilizing pre-trained models trained on the Plant Village dataset. The performance of the models with and without pre-training was compared to assess the efficacy of transfer learning. This section presents a detailed analysis of the obtained results, highlighting the strengths, limitations, and insights gained from the applied algorithms and transfer learning techniques.

A. Performance Analysis on Plant Village Dataset

Table-4 Comparative analysis of existing CNN architecture for the crop of Apple

Model	Accuracy	Precision	Recall	F1-Score
VGG16(Adam)	0.96	0.96	0.96	0.94
VGG16(RMSprop)	0.95	0.95	0.96	0.95
VGG19(Adam)	0.91	0.92	0.92	0.91
VGG19(RMSprop)	0.91	0.91	0.91	0.91
ResNet50(Adam)	0.95	0.94	0.94	0.94
ResNet50(RMSprop)	0.97	0.97	0.97	0.97
ResNet101(Adam)	0.95	0.96	0.96	0.96
ResNet101(RMSprop)	0.95	0.94	0.94	0.94
InceptionV3(Adam)	0.91	0.91	0.91	0.9
InceptionV3(RMSprop)	**0.88**	**0.88**	**0.88**	**0.87**

The performance of different deep learning models in classifying crop apple plants was evaluated using accuracy, precision, recall, and F1-score metrics. The results, presented in Table 4, showcase the effectiveness of various models. VGG16 with the Adam optimizer achieved the highest accuracy of 0.96, demonstrating its strong classification capabilities. VGG19, although slightly lower in accuracy at 0.91, consistently exhibited satisfactory precision, recall, and F1-score values. Among the ResNet models, ResNet50 with RMSprop stood out with an accuracy of 0.97, indicating its superior performance. The other ResNet models, along with InceptionV3, achieved accuracies ranging from 0.88 to 0.95. Overall, the findings suggest that VGG16 (Adam) and ResNet50 (RMSprop) perform exceptionally well in classifying crop apple plants, while opportunities for improvement exist for InceptionV3. These results provide valuable insights for developing accurate and efficient classification models in agricultural applications.

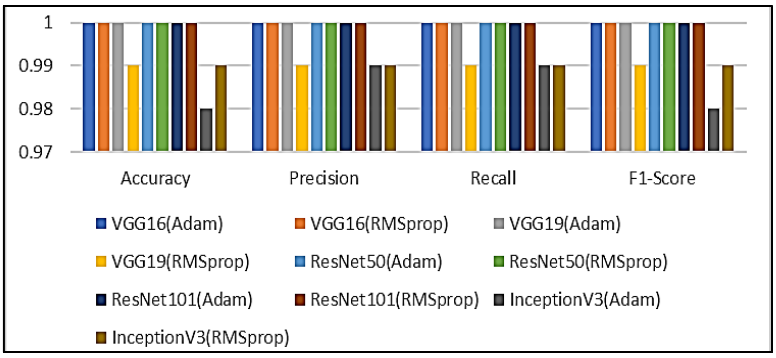

Figure 7: Comparative analysis of existing CNN architecture for the crop of Cherry

For the crop of Cherry, all models exhibited excellent performance, with most achieving perfect accuracy, precision, recall, and F1-score values of 1.00. The InceptionV3 model trained with Adam optimizer showed a slightly lower accuracy of 0.98 but maintained high precision, recall, and F1-score values of 0.99 and 0.98, respectively. These results demonstrate the effectiveness of the deep learning models in accurately classifying the crop Cherry plant, regardless of the chosen architecture and optimization algorithm. Further analysis and comparison with existing literature will be conducted to gain a deeper understanding of these results and identify any potential areas for improvement.

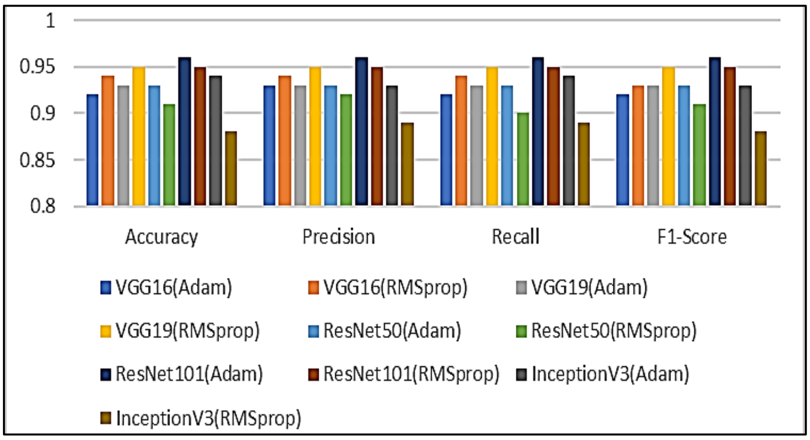

Figure 8: Comparative analysis of existing CNN architecture for the crop of Corn

Figure 8 presents the performance of various deep learning models on Corn plant classification. VGG16 achieved an Accuracy of 0.92 with both Adam and RMSprop optimizers, while VGG19 achieved an Accuracy of 0.93. ResNet50 achieved an Accuracy of 0.93 with Adam and 0.91 with RMSprop, whereas ResNet101 consistently achieved an Accuracy of 0.96. InceptionV3 achieved an Accuracy of 0.94 with Adam and 0.88 with RMSprop. The Precision, Recall, and F1-Score values were generally consistent with the Accuracy results. Overall, ResNet101 demonstrated the highest performance, consistently achieving the highest accuracy and balanced metrics. These findings provide valuable insights for the application of deep learning models in Corn plant classification tasks.

In a similar way, performance of DL variants on all the individual crops were carried out. Individually, it is possible to achieve an accuracy score up to 1.0. The performance starts degrading when more than one crop and followed by that all the crops were taken together to classify.

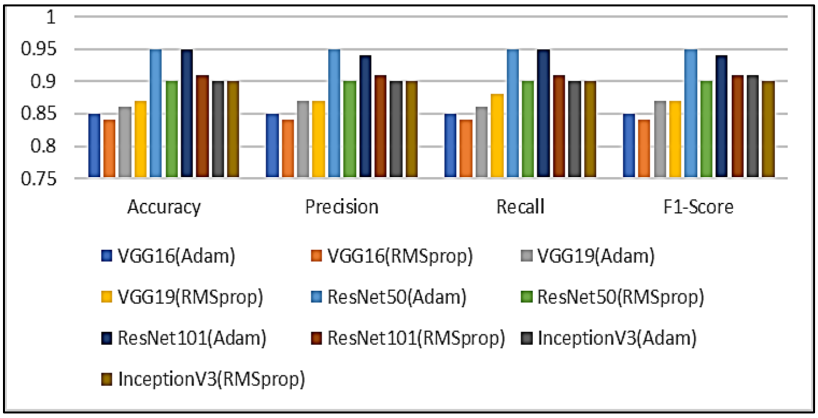

Figure 9: Comparative analysis of existing CNN architecture for the crop of Pepper, bell

Accuracy, precision, recall, and F1-score were some of the measures used to evaluate how well various models performed on the pepper crop, specifically the bell plant. The results showed variations in performance among the models and optimization algorithms. The ResNet50 model trained with the Adam optimizer achieved the highest accuracy of 0.95, indicating its strong overall correctness in predicting the bell plant. The VGG19 model trained with Adam optimizer achieved the highest precision and F1-score values of 0.87, while the ResNet50 model trained with the RMSprop optimizer obtained the highest recall of 0.95. The VGG16 and VGG19 models consistently performed well across the metrics, with accuracy scores ranging from 0.84 to 0.87. These findings highlight the effectiveness of different deep learning models for classifying the bell plant in crop Pepper. Future investigations can explore additional factors such as hyper parameter tuning and transfer learning to further enhance the models' performance.

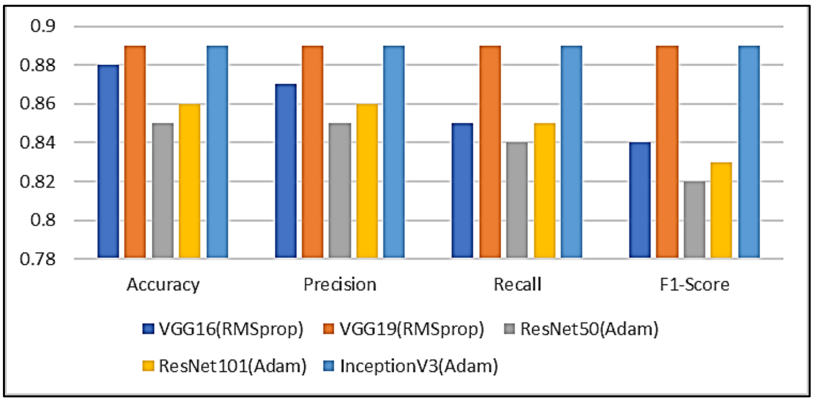

Figure 10: Comparative analysis of existing CNN architecture for the crop of all plants

Figure 10 highlights the accuracy, precision, recall, and F1-score values for different models, namely VGG16 (RMSprop), VGG19 (RMSprop), ResNet50 (Adam), ResNet101 (Adam), and InceptionV3 (Adam). Analysis of the results reveals that VGG16 and VGG19 achieve competitive accuracy rates of 0.88 and 0.89, respectively, with consistently high precision values, indicating their ability to minimize false positives. ResNet50, ResNet101, and InceptionV3 exhibit slightly lower accuracy scores ranging from 0.85 to 0.89 but demonstrate balanced precision, recall, and F1-score values. The choice of optimizer (RMSprop vs. Adam) appears to have minimal impact on the models' overall performance. These findings contribute insights for the development of robust computer vision models tailored for agricultural applications, emphasizing the potential of VGG16, VGG19, ResNet50, ResNet101, and InceptionV3 in crop plant classification tasks.

Table-5 Comparative analysis of Hybrid (DL + ML) architectures for the crop of All Plants

Algorithm	Accuracy	Precision	Recall	F1-Score
VGG16+RF	**0.76**	**0.77**	**0.76**	**0.76**
VGG16+SVM	0.91	0.92	0.91	0.91
VGG16+KNN	0.82	0.83	0.82	0.82

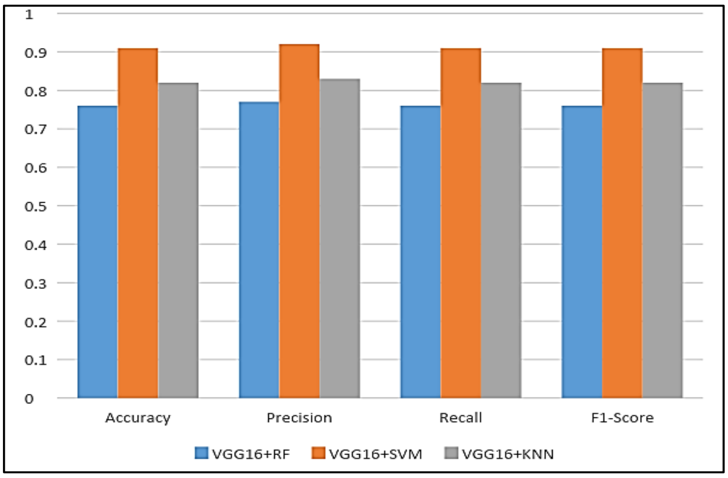

Figure 11: Comparative analysis of Hybrid (DL + ML) architectures for the crop of All Plants

Table 5 presents the performance evaluation of three algorithms, namely VGG16+RF, VGG16+ SVM, and VGG16+KNN, for crop classification in all plants. The results show that VGG16+SVM achieved the highest accuracy (0.91) along with superior precision, recall, and F1-score values (0.92, 0.91, and 0.91, respectively). Although VGG16+RF and VGG16+KNN achieved relatively lower accuracies (0.76 and 0.82, respectively), their performance remains notable. These findings emphasize the significance of selecting appropriate algorithms in crop classification tasks, with VGG16+SVM demonstrating its effectiveness in accurately classifying crops. However, further investigations on different datasets and algorithm variations are necessary to validate and generalize these findings.

B. Performance Analysis on Dataset Collected from Dantiwada Agriculture University

In the results analysis section, the focus shifted towards evaluating the performance of deep learning models on a newly collected dataset from Dantiwada Agriculture University. The dataset comprised images of three specific crops: Mustard, Grape, and Potato. The models were trained and tested both with and without utilizing a pre-trained model obtained from the benchmark dataset of Plant Village. This approach of transfer learning aimed to assess the impact of leveraging knowledge from the Plant Village dataset on the performance of the models when applied to the newly collected dataset. The analysis encompassed evaluations conducted on individual crops as well as on the dataset containing all the crops. By examining the outcomes of these experiments, valuable insights can be gained regarding the effectiveness of deep learning models, the benefits of transfer learning, and the specific performance characteristics of the models across different crops.

Table-6 Accuracy assessment of DL Variants with and without pre-trained model on newly collected dataset from Dantiwada Agriculture University

Plant	VGG16 Model	Pre-trained VGG16 model
Mustard	0.98	0.99
Potato	0.99	1
Grape	0.94	0.99
All	0.79	0.85

Here, we investigate the performance of a pre-trained VGG16 model using the Plant Village dataset in the context of computer vision and pattern recognition. Our aim is to evaluate the model's ability to accurately classify real-world images captured from Dantiwada Agricultural University in Gujarat. The results obtained from our experiments demonstrate the effectiveness of the pre-trained VGG16 model in accurately identifying different plant species. Specifically, the model achieved high classification accuracies for Mustard (0.98), Potato (0.99), and Grape (0.94). Moreover, the overall accuracy for classifying all plant species was found to be 0.79. However, by fine-tuning the pre-trained VGG16 model, we were able to improve the overall accuracy to 0.85. These findings highlight the potential of utilizing pre-trained models in real-world agricultural applications, paving the way for improved crop management and disease detection systems.

V. CONCLUSION

This research has made significant contributions to the field of crop disease detection by exploring advanced models and techniques, with a particular focus on deep learning, hybrid models, and transfer learning. The investigation involved evaluating the performance of various deep learning models, hybrid models combining deep learning and machine learning, and transfer learning models on a comprehensive dataset collected from Dantiwada Agriculture University. The results highlight the superiority of the transfer learning model, which outperformed other algorithms in terms of accuracy, precision, recall, and F1-score. Notably, the transfer learning model achieved exceptional performance on the potato crop, with all metrics reaching an impressive 99%. These findings underscore the potential of transfer learning in leveraging knowledge from pre-trained models to enhance detection accuracy and overall performance in crop disease detection.

The significance of this research extends beyond the realm of academia, with profound implications for the agricultural sector. By harnessing the power of transfer learning techniques in crop disease detection, farmers and agricultural professionals can make informed decisions, implement timely interventions, and effectively manage crop diseases. This research offers promising avenues for improving crop management and disease prevention strategies, ultimately contributing to enhanced agricultural practices and ensuring global food security. The utilization of transfer learning not only enhances the accuracy of disease detection but also demonstrates the capability to leverage existing knowledge from pre-trained models, enabling more efficient and effective detection systems. Overall, this study provides valuable insights into the potential of advanced models and transfer learning techniques in addressing the challenges of crop disease detection, paving the way for future advancements in the field.

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We extend our heartfelt gratitude to Dantiwada Agriculture University for their invaluable support in providing the plant leaves dataset encompassing diverse crops and their associated diseases. Their collaboration and contribution have been instrumental in the successful execution of this research, enabling us to evaluate the performance of our proposed crop disease detection models. We are sincerely thankful for their assistance and the opportunity to work with such a reputable institution, which has greatly enriched our understanding and furthered the advancement of knowledge in the field of agricultural research.

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