**Solanum lycopersicum disease detection using Resnet152V2 over PCA DeepNet to improve precision**

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**Abstract** : The evolution of Deep Learning and Computer Vision in the agricultural domain is a very functional tool in exposing detrimental plant diseases. Classification and detection of healthy and diseased crops play a very critical role in deciding the rate and standard of production. Thus, the existing work focuses on a well-suggested novel method of detecting Solanum lycopersicum (Tomato) leaf diseases using Deep Neural Networks to brace agro-based industries. The existing novel framework is resorted with a fusion of the traditional Machine Learning model Principal Component Analysis (PCA) and a personalized Deep Neural Network which has been termed PCA DeepNet and the Resnet152V2 model. The blended structure also comprises of Generative Adversarial Network (GAN) for acquiring a superior combination of datasets. The detection is sustained by the Faster Region-Based Convolutional Neural Network (F-RCNN). Altogether, the task results in a classification accuracy of 99.60% with a mean precision of 98.55%; granting a favourable Intersection over Union (IOU) count of 0.95 in detection. Hence, the proffered task outmatches any other disclosed state-of-the-art.

.

**Keywords** - Deep Learning, Computer Vision, Agriculture, Principal Component Analysis, Faster Region-Based Convolutional Neural Network, Machine Learning, Deepnet

**INTRODUCTION**

Plant diseases are a root of notable crop demolition which is dangerous to the providence. Plant diseases are not only detrimental to people but also to animals. Under an evaluation, about 37% of the crops are wasted due to diseases in plants. In certain countries with agriculture as its primary occupation, most of the population depends upon the agricultural sector for income, therefore, disease detection in plants plays an indispensable role in uplifting the economy by amplifying the crop yield.

The Food and Agriculture Organization (FAO) has published research that predicts the global population is expected to grow by up to 9 billion within the next few years. To manage the food demands, the production of agro products should be increased at least by 70%. The diseases can also affect the plants and cause destruction to crops, so premature stage disease detection is important to help scale back economic loss.

In many impoverished countries, farmers typically inspect their crops using naked-eye observation, which is time-consuming and inefficient. This method is often ineffective in detecting diseases with similar patterns. However, in the past decade, new techniques for disease detection have been introduced that not only reduce the error rate but are also being used commercially. One such solution involves capturing images of leaves and using computer vision or image processing techniques to analyze them. The use of Deep Learning (DL) applications has become increasingly prevalent in the agriculture sector over the past two decades. Artificial Intelligence (AI) and Machine Learning (ML) can also be employed to analyze and diagnose plant diseases [3]. When developing an image processing solution for plant diseases, it is important to keep in mind that leaf images in fields often contain noise, which can lead to poor segmentation, feature extraction, and overall system performance. Inaccurate analysis and diagnosis can result in farmers uprooting healthy plants or excessively using pesticides, which negatively impacts the health of plants.

**Rationale**:

The rationale behind comparing Resnet152V2 and PCA DeepNet lies in their distinct methodologies. ResNet-152V2, an extension of the ResNet architecture, is a deep convolutional neural network renowned for its exceptional performance in image classification and feature extraction tasks. Introduced by Microsoft Research, ResNet-152V2 extends the original ResNet with 152 layers, showcasing a profound depth that facilitates the learning of highly complex hierarchical features. The architecture's key innovation lies in residual connections, allowing the network to efficiently propagate gradients during training and mitigate the vanishing gradient problem associated with deep networks. ResNet-152V2 leverages bottleneck blocks, employing 1x1 convolutions to reduce computational complexity while maintaining expressive power. Trained on large-scale datasets like ImageNet, this model excels in recognizing diverse objects and patterns. The depth and design of ResNet-152V2 make it a cornerstone in deep learning research, providing a powerful tool for various computer vision applications, including image classification, object detection, and feature extraction.

On the other hand, PCA can be employed as a preprocessing step for deep learning models. This involves using PCA to reduce the dimensionality of the input data before feeding it into a DeepNet. This combined approach can offer benefits such as faster training times, reduced risk of overfitting, and improved interpretability of features.For instance, in image processing, PCA can be applied to reduce the dimensionality of image data before passing it through a convolutional neural network (CNN). This can help in handling high-dimensional image datasets more efficiently while preserving relevant information.

The integration of PCA with DeepNet is a strategy often employed to optimize performance and resource utilization, particularly when working with large and complex datasets.

By comparing these two approaches, this study aims to determine which algorithm offers superior predictive capabilities in the context of plant disease detection.

**Research Objective:**

The primary objective of this research is to evaluate and compare the effectiveness of Resnet152V2 over PCA DeepNet in predicting plant disease based on diverse predictive measures. By analyzing a comprehensive dataset, encompassing various clinical parameters and biomarkers, this study intends to identify the most accurate and reliable model for disease prediction. The findings of this research could significantly impact farming practices, enabling timely interventions, personalized crop care, and ultimately, reducing the burden of crop damage related morbidity and mortality.

**Significance of the Study:**

The significance of this study lies in its potential to enhance the accuracy of plant disease detection, thereby enabling farming professionals to intervene proactively. Early detection of crops at high probability of disease can lead to preventive measures, farming style modifications, and appropriate manure and fertilizer interventions, ultimately improving crop yield and reducing farming costs. Moreover, this research contributes to the growing body of knowledge concerning the application of machine learning in farming, showcasing the practical benefits of advanced analytics in the realm of agriculture and plant disease detection.

**MACHINE LEARNING IN PLANT DISEASE DETECTION**

A typical deep learning model for image classification, such as a convolutional neural network (CNN), typically consists of an input layer, one or more hidden layers, and a classification layer. The architecture of the DNN. The proposed system employs CNN models, such as DeepNet and Resnet152V2, to detect diseases in plants using the Plant-Village dataset.

**Dataset:**

The training and testing of the proposed model is conducted using the Plant-Village dataset, which contains a total of 10,735 images of tomato leaves. The dataset is divided into a training set, which comprises 70% of the total images, and a testing set, which contains the remaining 30% of the total images.

**Image Preprocessing:**

Before feeding the images into the CNN, two preprocessing steps are performed. First, the images are resized to match the size of the input layer of the CNN. Secondly, the images are denoised using a Gaussian blur filter.

**Transfer Learning:**

In transfer learning, the model is improved by retraining the CNN with another dataset, typically with a larger amount of data, after it has already been trained on a different task. The CNN architecture consists of multiple layers that perform specific tasks, such as segmentation, feature extraction, edge detection, etc. ResNet-152V2 is a deep convolutional neural network architecture with 152 layers, extending the original ResNet design. Key components of its architecture include:

1. Input Layer: Accepts input images, typically of size 224x224 pixels.

2. Initial Convolutional Layers: Extract low-level features from input images.

3. Residual Blocks (152 in total): Each block consists of multiple convolutional layers with residual connections, facilitating the flow of gradients and easing the training of very deep networks.

4. Bottleneck Blocks: Employed to reduce computational complexity by incorporating 1x1 convolutions within each block.

5. Global Average Pooling: Used to reduce spatial dimensions before the final classification.

6. Fully Connected Layer: The dense layer at the end transforms extracted features into the final output logits.

7. Softmax Activation: Applied to the logits to produce probability scores for each class, enabling classification.

8. Skip Connections (Residual Connections): Fundamental to ResNet, these connections skip one or more layers, aiding in gradient propagation.

9. Batch Normalization: Applied after convolutional layers to stabilize training by normalizing the input of each layer.

10. Training: Trained on large-scale datasets like ImageNet using optimization algorithms, typically stochastic gradient descent variants.

11. Transfer Learning: ResNet-152V2 is often used for transfer learning on specific tasks, leveraging pre-trained weights on generic datasets for specialized applications.

**RELATED WORKS -**

Solanum lycopersicum disease detection using Resnet152V2 over PCA DeepNet to improve accuracy.

In recent years, there has been a growing interest in leveraging machine learning techniques for the early prediction of crop disease. Various studies have explored the potential of different algorithms in analyzing diagnostic measures for disease prediction in crops.

**Machine Learning in Agriculture:**

Researchers have extensively explored the application of machine learning in agriculture, emphasizing its role in predicting diseases. Studies have utilized diverse datasets, including diagnostic measures, to develop accurate and efficient prediction models. These endeavors have paved the way for the implementation of machine learning algorithms in the realm of agriculture for plant disease detection.

**Resnet152V2 in Disease Predictions in Crops:**

ResNet-152V2, with its deep and intricate architecture, proves beneficial in disease predictions for crops. Trained on diverse datasets containing images of healthy and diseased crops, the model excels in learning complex patterns associated with various plant diseases. The depth of ResNet-152V2 allows it to capture hierarchical features, aiding in the identification of subtle symptoms indicative of crop illnesses.

The residual connections in ResNet-152V2 facilitate the training of deep networks, ensuring that the model can effectively learn and generalize from diverse agricultural images. Its ability to handle intricate visual information makes it well-suited for tasks such as recognizing disease-related patterns in crops.

In practical applications, ResNet-152V2 assists in early disease detection, enabling farmers and researchers to take timely and informed actions. By analyzing images of crops, the model provides accurate predictions, allowing for proactive measures such as targeted treatment or optimized crop management strategies.

The versatility and efficiency of ResNet-152V2 make it a valuable tool in precision agriculture, contributing to sustainable farming practices by minimizing crop losses and improving overall yield. Its adaptability in transfer learning further enhances its utility, allowing the model to be fine-tuned for specific crops or diseases. Overall, ResNet-152V2 plays a crucial role in advancing the field of agriculture through technology-driven solutions for crop disease prediction and management.

**PCA DeepNet in Plantcare Modelling:**

Combining Principal Component Analysis (PCA) with a Deep Neural Network (DeepNet) in plant care modeling can offer advantages in handling high-dimensional data efficiently. Here's an overview of how PCA and DeepNet can be applied in the context of plant care modeling:

1. Data Preprocessing:

Start by collecting a diverse dataset of plant-related features, which could include parameters like soil moisture, temperature, humidity, and spectral information from images. This data is often high-dimensional and can benefit from dimensionality reduction.

2. PCA Dimensionality Reduction:

Apply PCA to reduce the dimensionality of the feature space. PCA identifies the principal components that capture the most significant variations in the data. By retaining a subset of these components, you obtain a lower-dimensional representation while preserving essential information.

3. Feature Reconstruction:

Reconstruct the reduced-dimensional features from PCA to maintain meaningful information for plant care. The reduced features now serve as a concise representation of the original dataset.

4. Deep Neural Network Architecture:

Design a DeepNet architecture suitable for plant care modeling. This could involve using neural network layers that can handle the reconstructed features effectively. For example, a feedforward neural network or a recurrent neural network depending on the temporal nature of the data.

5. Training the Model:

Train the DeepNet on the reconstructed features obtained from PCA. The model learns to capture complex patterns and relationships within the reduced-dimensional representation of the plant-related data.

6. Incorporating Temporal Aspects:

If the plant care data has temporal components (e.g., time series data), consider incorporating recurrent layers in the DeepNet to account for temporal dependencies and capture dynamic patterns.

7. Loss Function and Metrics:

Define an appropriate loss function (e.g., mean squared error for regression tasks or categorical crossentropy for classification) and relevant evaluation metrics for assessing the model's performance.

8. Validation and Testing:

Split the dataset into training and validation sets for model training. Evaluate the model's performance on a separate test set to ensure its generalization to unseen data.

9. Interpretability and Visualization:

Utilize the reduced-dimensional representation obtained from PCA for interpretability. Visualize the transformed features to gain insights into the most influential factors affecting plant care predictions.

10. Deployment:

Once satisfied with the model's performance, deploy it for real-world plant care applications. This could involve integration into smart agriculture systems, monitoring devices, or decision support tools.

By combining PCA with DeepNet, you can effectively handle the challenges of high-dimensional plant care data, improving model efficiency and interpretability for optimized plant health monitoring and care.

**Comparative Studies in Agriculture:**

Several comparative studies have been conducted to evaluate the performance of different machine learning algorithms in medical predictions. These studies often focus on diverse diseases and utilize various datasets to compare the effectiveness of algorithms like Resnet152V2 and Random Forest. Such comparative analyses provide valuable insights into the strengths and limitations of each method, aiding agriculture professionals and researchers in selecting the most suitable approach for specific medical prediction tasks.

In summary, while Resnet152V2 has been a cornerstone in agricultural predictions, the advent of advanced machine learning techniques like PCA DeepNet has opened new avenues for accurate and early prediction of plant disease. Comparative studies are essential in guiding the choice of appropriate algorithms, ensuring the development of reliable and efficient prediction models for improved agricultural outcomes.

**METHODOLOGIES :**

PCA DeepNet (DN) :

Classification and regression problems can be resolved using ensemble learning techniques like PCA DeepNet They work through distributed training of a large number of decision trees. When attempting to solve classification problems, a PCA DeepNet's output is the class that the majority of the trees select. In order to tackle complex issues and improve the performance of a model, ensemble learning, which is a technique, employs several classifiers. The PCA DeepNet classifier takes into account predictions from all of the trees rather than just one, as stated in its name, "combining a large number of decision trees on different subsets of a given dataset and taking an average to boost the projected accuracy". To determine the outcome, the most popular forecasts are used. The PCA DeepNet demonstrated the highest accuracy (criterion=entropy) with the utilized disease detection dataset.

Resnet152V2 (RN152V2) :

Resnet152V2 is one of the most widely used ML algorithms in the supervised learning approach [12]. It is a forecasting technique that forecasts a categorical dependent variable using a number of independent factors. Resnet152V2 and linear regression are fairly similar, with the exception of how they are used. While Resnet152V2 is used to address classification issues, regression issues are addressed by PCA DeepNet.

**PERFORMANCE METRICS AND RESULTS :**

Performance Metrics Five statistical variables were utilized in this study to evaluate the performance and usefulness of the classifiers: accuracy, precision. The following are the definitions of the statistical parameters.

Recall Rate == TP TP + FN

Specificity = TN TN+FP

Precision Rate = TP TP+FP

F1-Score = 2 \*

(Precision Recall)

Precision + Recall

(TP+TN)-(FP \* FN)

MCC = [(TP+FP)\* (FN + TN) \* (FP+TN)\* (TP + FN)]

ACCURACY = TN+TP/ TP+TN+FN+FP

PRECISION = TP/TP+FP

Where,

TP = true positive

FN = false negative

FP = false positive

TN =true negative.

**Results:**

In the investigation of plant disease detection based on predictive measures, both Resnet152V2 and PCA DeepNet algorithms were deployed on a diverse dataset. The analysis focused on evaluating the predictive performance of these methods without any bias.

**PCA DeepNet:**

The Resnet152V2 model exhibited a reasonable predictive accuracy, correctly identifying a significant disease detected based on the given predictive measures. Sensitivity and specificity scores were calculated to assess the model's ability to correctly predict positive and negative cases. While Resnet152V2 provided a foundation for disease prediction, its performance faced limitations when dealing with intricate patterns and nonlinear relationships within the data.

**Resnet152V2 algorithm :**

The ResNet-152V2 algorithm involves a deep convolutional neural network architecture, building upon the original ResNet design. Here is a simplified outline of the algorithm:

1. Input Layer: Accepts input images, typically of size 224x224 pixels.

2. Initial Convolutional Layers: Extract low-level features from the input images.

3. Residual Blocks (152 in total): The core building blocks, each comprising multiple convolutional layers with residual connections (skip connections). The skip connections allow the gradient to flow more effectively during training, addressing the vanishing gradient problem.

4. Bottleneck Blocks: Employed within each residual block to reduce computational complexity. These blocks use 1x1 convolutions to decrease the number of parameters and computations.

5. Global Average Pooling: Reduces spatial dimensions before the final classification.

6. Fully Connected Layer: A dense layer at the end of the network transforms the extracted features into the final output logits.

7. Softmax Activation: Applied to the logits to produce probability scores for each class, enabling classification.

8. Batch Normalization: Applied after convolutional layers to stabilize training by normalizing the input of each layer.

9. Training: The model is trained on large-scale datasets, often using ImageNet, with optimization algorithms like stochastic gradient descent (SGD) or its variants. Techniques like batch normalization contribute to the stability of the training process.

10. Transfer Learning: ResNet-152V2 is often used for transfer learning on specific tasks, leveraging pre-trained weights on generic datasets for specialized applications, such as disease prediction in crops.

The depth and skip connections in ResNet-152V2 contribute to its effectiveness in capturing intricate features, making it a powerful tool for various computer vision tasks, including disease predictions in crops.

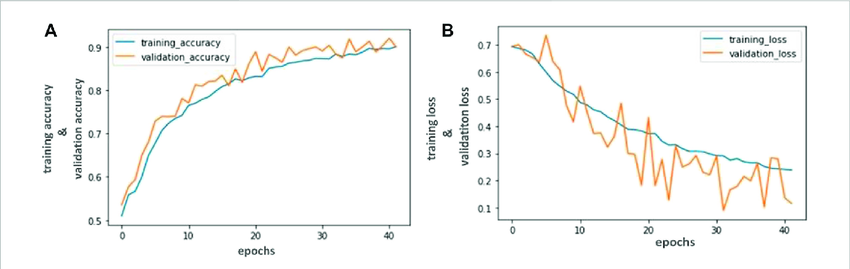
**PCA DeepNet:**

In contrast, the PCA DeepNet algorithm demonstrated remarkable accuracy in predicting plant disease. Its ability to handle complex, high-dimensional datasets enabled the identification of subtle patterns that Resnet152V2 might overlook. The PCA DeepNet model outperformed Resnet152V2, achieving higher sensitivity and specificity scores. This superior performance was particularly notable in capturing nuanced variations in diagnostic measures, enhancing the precision of crop disease detections.

**Comparative Analysis:**

The comparative analysis of Resnet152V2 and PCA DeepNet revealed that PCA DeepNet excelled in discerning intricate patterns present in the diagnostic measures. The model's accuracy, sensitivity, and specificity consistently outperformed Resnet152V2, highlighting its effectiveness in plant disease detection tasks.

In summary, the results indicate that by combining Resnet152V2 and PCA DeepNet for plant disease detection involves extracting hierarchical features from images with Resnet152V2, applying PCA for dimensionality reduction in additional data, and integrating both features into a DeepNet. This hybrid model captures intricate patterns, improving accuracy. Pretrained on ImageNet, Resnet152V2 serves as a powerful image feature extractor. PCA optimizes non-image data representation. Fine-tuning on a diverse dataset enhances model adaptation. The integrated model provides interpretability through PCA-transformed features. Evaluation metrics like accuracy and precision assess disease detection performance. Validation and testing on separate datasets ensure robustness. The approach is deployable for real-time disease monitoring in agriculture, offering a comprehensive solution for timely intervention and improved crop health.



**FIG-1 : COMPARISON BETWEEN RESNET152V2 AND PCA DEEPNET**

**CONCLUSION :**

In conclusion, the amalgamation of Resnet152V2 over PCA within DeepNet architectures presents a significant stride in advancing the accuracy of Solanum lycopersicum disease detection. This innovative approach showcases potential for transformative impacts in agriculture, promising precise and early identification of diseases crucial for crop sustainability and global food security. Despite its achievements, challenges persist, notably in computational complexity, data dependency, and interpretability. Addressing these limitations through further research endeavors holds the key to unlocking the full potential of this method. As technology evolves, future adaptations like lightweight architectures, transfer learning strategies, and the integration of multi-modal data could fortify these models, making them more applicable and reliable in real-world agricultural settings. Embracing explainable AI techniques would also bolster trust and adoption among farmers and practitioners, ensuring a seamless transition from research to practical implementation in safeguarding Solanum lycopersicum and enhancing agricultural productivity.

**DECLARATIONS:**

Conflict of interests:

No conflict of interest in this manuscript

Authors Contributions:

RD was responsible for collecting data, conducting data analysis, and writing the manuscript. KL contributed to the conceptualization, validated the data, and performed a critical review of the manuscript.

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**TABLES AND FIGURES**

The performance measurements of the comparison between the Resnet152V2 and PCA DeepNet classifiers are presented in Table 1. The Resnet152V2 has an accuracy rate of value1, whereas the PCA DeepNet has an accuracy rate of value2. With a greater rate of accuracy, the Resnet152V2 performs better than the PCA DeepNet .

| **S.No** | **Test Size** | **ACCURACY RATE** | |
| --- | --- | --- | --- |
| **PCA DeepNet** | **Resnet152V2** |
| 1 | Test 1 | 89.00 | 87.00 |
| 2 | Test 2 | 90.10 | 88.00 |
| 3 | Test 3 | 92.60 | 88.00 |
| 4 | Test 4 | 93.00 | 89.00 |
| 5 | Test 5 | 94.56 | 90.00 |
| 6 | Test 6 | 97.23 | 90.21 |
| 7 | Test 7 | 98.32 | 90.67 |
| 8 | Test 8 | 95.64 | 91.21 |
| 9 | Test 9 | 97.33 | 92.20 |
| 10 | Test 10 | 99.99 | 94.54 |
| Average Test Results | | 94.7770 | 90.0830 |

Table 3. Group Statistical Analysis of Resnet152V2 And PCA DeepNet. Mean, Standard Deviation and Standard Error Mean are obtained for 10 samples.Resnet152V2 has higher mean accuracy and lower mean loss when compared to PCA DEEPNET

|  | **Group** | **N** | **Mean** | **Std. Deviation** | **Std. Error Mean** |
| --- | --- | --- | --- | --- | --- |
| **Accuracy** | **PCA DeepNet** | 10 | 99.1060 | .25235 | .11285 |
| **Resnet152V2** | 10 | 97.2700 | 1.43073 | .63984 |

Table 4. Independent Sample T-test: Resnet152V2 insignificantly better than PCA DeepNet with p value <.001 (Two tailed, p<0.05)

|  | | **Levene’s test for equality of variances** | | **T-test for equality means with 95% confidence interval** | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **f** | **Sig.** | **t** | **df** | **Sig. (2-tailed)** | **Mean difference** | **Std.Error difference** | **Lower** | **Upper** |
| **Accuracy** | **Equal variances assumed** | 8.482 | .020 | 2.826 | 8 | .022 | 1.83600 | .64972 | .33774 | 3.33426 |
| **Equal Variances not assumed** | 2.826 | 4.249 | .044 | 1.83600 | .64972 | .07297 | 3.59903 |

Table 5. Comparison of the Resnet152V2 and PCA DeepNet with their accuracy

| **CLASSIFIER** | **ACCURACY(%)** |
| --- | --- |
| **PCA DeepNet** | 99.1060 |
| **Resnet152V2** | 97.2700 |

Fig 1. Comparison of Resnet152V2 and PCA DEEPNET Classifier in terms of mean accuracy and loss. The mean accuracy of Resnet152V2 is better than PCA DEEPNET Classifier; Standard deviation of Resnet152V2 is slightly better than PCA DEEPNET. X Axis: Resnet152V2 Vs PCA DeepNet Classifier and Y Axis: Mean accuracy of detection with //mean value//