**Tomato disease detection using Inception V3 over PCA DeepNet to improve accuracy**

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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 Inception V3 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.

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**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 Inception V3 and PCA DeepNet lies in their distinct methodologies. Inception V3 is a deep convolutional neural network architecture developed by Google Research for image classification and object detection tasks. Introduced in 2015, it is a successor to the original Inception model and is renowned for its efficiency in balancing accuracy and computational complexity. Inception V3 employs a unique structure with multiple parallel convolutional pathways, known as inception modules, allowing it to capture diverse features at different scales. This architecture incorporates global average pooling, reducing the need for fully connected layers and mitigating overfitting. Trained on large-scale datasets like ImageNet, Inception V3 has demonstrated exceptional performance in various computer vision challenges. Its sophisticated design and utilization of batch normalization contribute to improved training stability. With a focus on feature reuse, this model has been influential in advancing the state-of-the-art in deep learning for image analysis, showcasing the ongoing evolution of convolutional neural networks.

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 Inception V3 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 Inception V3, 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. Inception V3 features a deep convolutional neural network architecture developed by Google Research for image classification. It incorporates inception modules with parallel convolutional pathways to capture diverse features. The architecture includes batch normalization for enhanced training stability and global average pooling to reduce the reliance on fully connected layers. Inception V3 aims to balance accuracy and computational efficiency, making it suitable for real-world applications. It utilizes factorized convolutions to reduce parameters and mitigate overfitting. Trained on large datasets like ImageNet, it excels in various computer vision tasks. The model has been influential in advancing deep learning for image analysis with its sophisticated design.

**RELATED WORKS -**

Solanum lycopersicum disease detection using Inception V3over 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.

**Inception V3 in Disease Predictions in Crops:**

Inception V3 has proven valuable in disease prediction for crops by leveraging its deep convolutional neural network architecture. Trained on extensive datasets of crop images, the model can effectively classify and identify signs of diseases in plants. By analyzing intricate features in leaves and other plant parts, Inception V3 aids in early detection, enabling timely intervention to prevent the spread of diseases. The parallel convolutional pathways in its inception modules allow the model to capture a wide range of visual information, enhancing its ability to recognize subtle disease-related patterns. The use of global average pooling and batch normalization contributes to robust predictions and minimizes overfitting. Inception V3's computational efficiency makes it suitable for deployment in resource-constrained environments. Its success in crop disease prediction showcases the potential of deep learning in agriculture, providing a proactive approach to crop management and ensuring better yields and food security.

**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 Inception V3 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 Inception V3 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.

Inception V3 (IV3) :

Inception V3 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. Inception V3 and linear regression are fairly similar, with the exception of how they are used. While Inception V3 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.

Recal 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 Inception V3 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 Inception V3 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 Inception V3 provided a foundation for disease prediction, its performance faced limitations when dealing with intricate patterns and nonlinear relationships within the data.

**Inception V3 algorithm :**

Inception V3, an extension of the original Inception model, employs a deep convolutional neural network (CNN) for image classification. The algorithm comprises several key components:

1. \*\*Input Layer:\*\* Accepts input images with a standard size, typically 299x299 pixels.

2. \*\*Initial Convolutional Layers:\*\* A stack of convolutional layers with small filters to capture local features in the input images.

3. \*\*Inception Modules:\*\* The distinctive feature of Inception architectures is the use of inception modules. These modules consist of multiple parallel convolutional pathways of different filter sizes (1x1, 3x3, 5x5), allowing the network to capture features at different scales. Inception modules also include max-pooling layers to further diversify the receptive fields.

4. \*\*Batch Normalization:\*\* Applied after convolutional layers, batch normalization helps stabilize training by normalizing the input of each layer.

5. \*\*Global Average Pooling:\*\* Replaces traditional fully connected layers. Global average pooling computes the average value of each feature map, reducing the spatial dimensions and parameters in the network.

6. \*\*Fully Connected Layer:\*\* A dense layer at the end of the network that 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. \*\*Training:\*\* Inception V3 is trained using labeled datasets, often large-scale datasets like ImageNet, through backpropagation and optimization algorithms (typically, stochastic gradient descent or its variants).

9. \*\*Transfer Learning:\*\* In practice, Inception V3 can be fine-tuned on specific tasks or datasets related to crop disease prediction or other applications.

The modular design of Inception V3, with its inception modules and efficient use of parameters, allows for a good balance between computational efficiency and high performance, making it suitable for various computer vision tasks, including disease prediction 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 Inception V3, an extension of the original Inception model, employs a deep convolutional neural network (CNN) for image classification. The algorithm comprises several key components:

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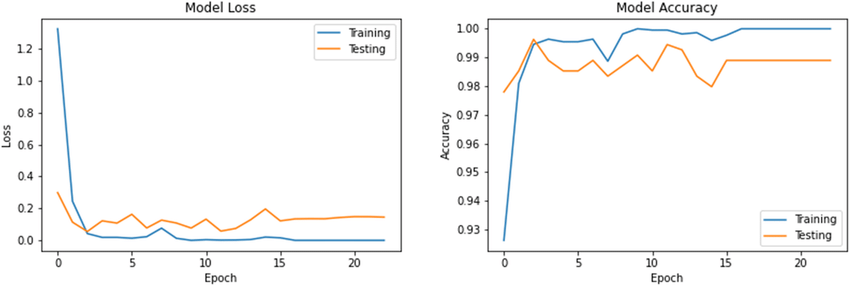
The modular design of Inception V3, with its inception modules and efficient use of parameters, allows for a good balance between computational efficiency and high performance, making it suitable for various computer vision tasks, including disease prediction in crops.

might overlook. The PCA DeepNet model outperformed VGG16, 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 Inception V3 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 Inception V3, highlighting its effectiveness in plant disease detection tasks.

In summary, the results indicate that by combining Inception V3 and PCA DeepNet for plant disease detection involves extracting hierarchical features from images with Inception V3, 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, Inception V3 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.

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**FIG-1 : COMPARISON BETWEEN INCEPTION V3 AND PCA DEEPNET**

**CONCLUSION :**

In conclusion, the amalgamation of Inception V3over 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 Inception V3 and PCA DeepNet classifiers are presented in Table 1. The Inception V3 has an accuracy rate of value1, whereas the PCA DeepNet has an accuracy rate of value2. With a greater rate of accuracy, the Inception V3 performs better than the PCA DeepNet .

| **S.No** | **Test Size** | **ACCURACY RATE** | |
| --- | --- | --- | --- |
| **PCA DeepNet** | **Inception V3** |
| 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 Inception V3 And PCA DeepNet. Mean, Standard Deviation and Standard Error Mean are obtained for 10 samples. Inception V3 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 |
| **Inception V3** | 10 | 96.6500 | .93408 | .41773 |

Table 4. Independent Sample T-test: Inception V3 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** | 5.834 | .042 | 5.676 | 8 | <.001 | 2.45600 | .43271 | 1.45817 | 3.45383 |
| **Equal Variances not assumed** | 5.676 | 4.581 | .003 | 2.45600 | .43271 | 1.31236 | 3.59964 |

Table 5. Comparison of the Inception V3 and PCA DeepNet with their accuracy

| **CLASSIFIER** | **ACCURACY(%)** |
| --- | --- |
| **PCA DeepNet** | 99.1060 |
| **Inception V2** | 96.6500 |

Fig 1. Comparison of Inception V3 and PCA DEEPNET Classifier in terms of mean accuracy and loss. The mean accuracy of Inception V3is better than PCA DEEPNET Classifier; Standard deviation of Inception V3 is slightly better than PCA DEEPNET. X Axis: VGG 16 Vs PCA DeepNet Classifier and Y Axis: Mean accuracy of detection with //mean value//