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Agriculture System for Potato Leaf Disease Detection Using Deep Learning And GENAI

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Abstract: This study introduces a Smart Agriculture System designed to detect potato leaf diseases using advanced Deep Learning and Genetic Artificial Intelligence (GenAI) techniques. Potato, a vital global staple, is highly susceptible to various diseases that threaten yields and impose economic challenges on farmers. Traditional disease detection methods often fall short in efficiency, accuracy, and timeliness. To address these shortcomings, the proposed system employs Deep Learning algorithms, particularly Convolutional Neural Networks (CNNs), to analyze potato leaf images and identify disease signs accurately. CNNs excel in image recognition tasks by learning complex patterns and features associated with different leaf diseases, facilitating rapid and precise diagnoses. Additionally, GenAI enhances the system's performance by optimizing the Deep Learning model's hyperparameters and architecture, thus improving overall detection efficiency and effectiveness. By combining Deep Learning and GenAI, the Smart Agriculture System automates disease detection, ensuring early and accurate identification of potato leaf diseases. This proactive approach allows for timely interventions, such as targeted pesticide applications or crop management strategies, thereby mitigating disease spread and minimizing yield losses.

Keywords: *Convolutional Neural Networks (CNNs), Deep Learning ,Disease detection, Generative Artificial Intelligence (GenAI), Image recognition, Potato leaf diseases, Smart Agriculture System,.*

1. Introduction

Potato cultivation plays a crucial role in our country's agricultural landscape, contributing significantly to our

economy. However, the production of potatoes is often hindered by various pests and diseases, limiting our ability to meet export demands. Diseases like early blight, leaf roll virus, scab, and Hollow heart have historically plagued potato crops, causing substantial losses for farmers and hindering international trade. India, heavily reliant on agriculture, particularly underscores the importance of addressing these challenges, considering that potato production accounts for nearly 29% of the country's total agricultural output. Early detection of these diseases is paramount to implementing timely preventive measures and mitigating economic losses. Traditionally, disease detection relied on manual observation by experts, which proved to be inefficient and impractical, especially in remote farming areas. Given the critical role of agriculture in India's economy, it is imperative to safeguard crops from various threats, including diseases.

The current study aims to address the challenges posed by crop diseases through a comprehensive review of factors influencing crop quality, including weather conditions, soil characteristics, and diseases. Specifically, we focus on leveraging deep learning and GenAI techniques to facilitate early detection of crop diseases, thereby enhancing overall accuracy and reliability. Potato diseases like early blight and late blight present significant challenges to farmers, necessitating precise diagnosis for effective treatment and management. Traditional methods of disease detection, such as computer vision technology and pattern recognition, have limitations,

prompting the exploration of new solutions like deep learning and convolutional neural networks (CNNs).

As one of the world's four major food crops, potatoes hold immense economic and nutritional value. Diseases like early

blight and late blight pose significant threats to potato crops worldwide, underscoring the importance of timely identification and detection. However, traditional diagnostic techniques often prove inadequate for large-scale implementation, highlighting the need for fast, cost-effective, and accurate disease identification

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systems. Recent advancements in computer vision and artificial intelligence have paved the way for automatic disease recognition technology. Several studies have demonstrated the efficacy of deep learning techniques, such as Fast R-CNN and ResNet, in detecting crop diseases with high accuracy. However, challenges persist, including the recognition of diseases in complex environments and the segmentation of images containing multiple leaves.To address these challenges, our study proposes a three-stage potato leaf disease detection model based on deep learning. By combining instance segmentation, classification models, and semantic segmentation, we aim to accurately identify and quantify disease areas on potato leaves, laying the groundwork for future advancements in disease classification and control.

Types of crop diseases

Crop diseases encompass a wide range of illnesses that affect various crops, posing significant challenges to agricultural productivity and food security. One of the most common types of crop diseases is fungal diseases. Fungi are responsible for a multitude of diseases that afflict crops such as wheat, rice, and maize. Examples include wheat rust, which manifests as reddish-brown pustules on the leaves of wheat plants, and rice blast, characterized by small, diamond-shaped lesions on rice leaves. Bacterial diseases are another prevalent category, affecting crops like tomatoes, potatoes, and citrus fruits. Citrus canker, caused by the bacterium Xanthomonas citri, results in raised, corky lesions on citrus leaves, fruits, and stems. Viral diseases are also widespread, with viruses infecting crops like tomatoes, potatoes, and cucurbits. Tomato yellow leaf curl virus, transmitted by whiteflies, leads to stunted growth and yellowing of tomato plants. Additionally, nematode diseases, caused by microscopic roundworms, inflict damage on various crops, including soybeans, potatoes, and bananas. Root-knot nematodes, for instance, cause swelling and galling of plant roots, impairing nutrient uptake and stunting plant growth. Lastly, abiotic diseases, resulting from non-living factors such as nutrient deficiencies, environmental stress, and chemical toxicity, can also adversely affect crop health and yield. For example, iron deficiency chlorosis causes yellowing of soybean leaves due to insufficient iron uptake from alkaline soils. Understanding and effectively managing these diverse types of crop diseases are essential for ensuring agricultural sustainability and global food security

GAN-generated images on hybrid deep learning model

The influence of Generative Adversarial Network (GAN)-generated images on a hybrid deep learning model for potato leaf disease detection represents a novel approach with promising implications for agricultural technology. GANs are capable of generating synthetic images that closely resemble real ones, providing valuable data augmentation capabilities for training deep learning models. By integrating GAN-generated images into the training dataset, the hybrid deep learning model can potentially improve its robustness and generalization ability. Firstly, the incorporation of GAN-generated images enhances the diversity and quantity of data available for training. Traditional datasets for potato leaf disease detection may be limited in size and variation, hindering the model's ability to accurately distinguish between different types of diseases or disease severity levels. GANs can generate realistic images depicting various disease manifestations, thereby supplementing the training dataset with additional samples. This augmentation helps prevent over fitting and improves the model's ability to generalize to unseen data. Moreover, GAN-generated images can address imbalances in the training dataset by generating synthetic samples for underrepresented classes or disease categories. In agricultural datasets, certain diseases may occur less frequently than others, leading to class imbalance issues that can bias the model's performance. By generating synthetic images of rare diseases or disease combinations, GANs can help alleviate this imbalance and ensure that the model learns to accurately detect all types of potato leaf diseases. GAN-generated images can simulate different environmental conditions or disease progression stages, enabling the model to learn robust features that are invariant to such variations. In real-world agricultural settings, factors like lighting conditions, camera angles, and disease severity levels can affect the appearance of potato leaves. By training on a diverse range of synthetic images, the hybrid deep learning model can become more resilient to these variations and achieve better performance in practical deployment scenarios. However, it's essential to acknowledge potential challenges and limitations associated with using GAN-generated images. The quality and realism of generated images may vary depending on the specific GAN architecture and training process. Additionally, there is a risk of introducing synthetic artifacts or biases that could adversely impact the model's performance if not carefully controlled. the integration of GAN-generated images into a hybrid deep learning model for potato leaf disease detection holds great promise for improving the model's accuracy, robustness, and generalization ability. By leveraging the diversity and augmentation capabilities of GANs, agricultural researchers and practitioners can develop more effective tools for disease monitoring and management, ultimately contributing to increased crop yields and food security. Continued research and experimentation in this area are crucial for realizing the full potential of GANs in agricultural applications.

2. Related works

In the paper titled "Performance Analysis of AI-based Solutions for Crop Disease Identification, Detection, and Classification" by Tirkey, Singh, and Tripathi (2023)[1], the authors conduct a comprehensive review of artificial intelligence (AI) based solutions for addressing crop disease challenges. The study focuses on evaluating the effectiveness of various AI techniques in identifying, detecting, and classifying crop diseases. Through their analysis, the authors explore the performance of AI models, including deep learning approaches, in accurately diagnosing plant diseases. They highlight the significance of AI-based solutions in revolutionizing disease management practices in agriculture. By examining the findings of the reviewed studies, the paper provides insights into the potential of AI technologies to enhance crop disease surveillance, early detection, and classification, thereby contributing to improved agricultural productivity and food security. Ramanjot et al.[2] provides a comprehensive overview of research on plant disease detection and classification. The study systematically reviews existing literature to assess the methodologies, techniques, and advancements in this field. Through a detailed examination of various studies, the authors identify trends, challenges, and opportunities for future research in plant disease detection. The paper aims to contribute to the development of effective and efficient techniques for early detection and management of plant diseases, ultimately enhancing agricultural productivity and food security. "An automated segmentation and classification model for banana leaf disease detection" [3]presents a novel approach for detecting diseases in banana leaves using automated segmentation and classification techniques. The study introduces a sophisticated model that combines segmentation and classification algorithms to accurately identify diseased areas on banana leaves. This innovative method aims to enhance disease detection efficiency and accuracy in agricultural settings. Through their research, the authors demonstrate the potential of their model in streamlining disease detection processes, thereby contributing to improved crop management practices. S. Mathulaprangsan, K. Lanthong, and S. Patarapuwadol (2020)[4], the authors investigate the application of deep learning models for the recognition of rice diseases. They explore various deep learning techniques to enhance the accuracy of disease recognition in rice crops. The study aims to develop efficient models capable of accurately identifying different rice diseases, thereby facilitating timely interventions and management strategies to mitigate crop losses. By leveraging deep learning algorithms, the authors demonstrate promising results in disease recognition, highlighting the potential for advanced technology to contribute to improved agricultural practices and crop management.In "Detection of leaf disease using principal component analysis and linear support vector machine" by Heltin Genitha C., Dhinesh E., and Jagan A. (2019), the authors propose a methodology for detecting leaf diseases using principal component analysis (PCA) and linear support vector machine (SVM). They aim to develop a robust and efficient system for accurately identifying leaf diseases based on image analysis techniques. By employing PCA to reduce the dimensionality of input data and SVM for classification, the study achieves notable success in accurately detecting leaf diseases. Authors Heltin Genitha C, Dhinesh E, and Jagan[5] A present a novel approach for detecting leaf diseases. They propose a methodology that combines Principal Component Analysis (PCA) and Linear Support Vector Machine (SVM) algorithms for disease detection. The study aims to address the challenge of accurately identifying plant leaf diseases, crucial for effective disease management in agriculture. By leveraging PCA for feature extraction and SVM for classification, the proposed approach offers a systematic framework for disease detection. The authors conducted experiments to evaluate the effectiveness of their method using real-world datasets, demonstrating promising results in terms of accuracy and efficiency. Overall, this paper contributes to the advancement of disease detection techniques in agriculture by proposing a robust and efficient methodology based on PCA and SVM algorithms. "Classification of Plant Leaf Diseases Using Machine Learning and Image Pre-processing Techniques," Gupta, Hans, and Chand [6] present a study focused on utilizing machine learning and image pre-processing techniques for the classification of plant leaf diseases. The authors explore the effectiveness of various machine learning algorithms in accurately identifying and categorizing plant leaf diseases based on preprocessed images. Through their research, they aim to contribute to the development of efficient disease diagnosis and management systems in agriculture. "Plant Leaf Detection and Disease Recognition using Deep Learning" by S. V. Militante , B. D. Gerardo, and N. V. Dionisio, presented at the 2019[7], Communication, and Engineering, introduces a deep learning-based approach for detecting plant leaves and recognizing diseases. The study employs convolutional neural networks (CNNs) to achieve accurate classification of plant leaf diseases. Through experimentation, the authors demonstrate the effectiveness of their proposed method in accurately identifying various plant leaf diseases, thereby offering a promising solution for disease recognition in agricultural contexts. The paper contributes to the growing body of research exploring the application of deep learning techniques in agricultural disease management, highlighting the potential of such approaches in enhancing crop health and productivity.

3. Methodology

In our proposed model, we outline two primary components: a deep learning model and synthetic image generation utilizing a CNN-based GAN model. Initially, the system undergoes three crucial stages: data training, data pre-processing, and data augmentation. Subsequently, we bifurcate the model into two distinct processes or models. The first model focuses on generating synthetic data using a CNN-based GAN model, which optimizes hyperparameters and a loss function. This facilitates the creation of synthetic data and images for future research endeavours. Utilizing a synthetic model typically yields higher accuracy compared to conventional approaches. On the other hand, the second model relies on both real and synthetic data generated by the CNN-based GAN model. This model incorporates activities such as feature extraction and applies a deep learning training model, specifically a hybrid of RESNET-50 and VGG-16 models. Finally, the testing model is executed on testing data, yielding higher accuracy than existing models and techniques.By structuring our research approach around these two models, we aim to enhance the accuracy and effectiveness of our study outcomes, paving the way for innovative advancements in the field.

3.1CNN-based Generative Adversarial Network (GAN) model

In the realm of agriculture, particularly in the context of potato disease detection, the utilization of a CNN-based Generative Adversarial Network (GAN) model presents a novel approach. In this setup, the GAN framework comprises two neural networks: a generator and a discriminator. The generator network generates synthetic images of potato leaves with various disease symptoms, aiming to mimic the characteristics of real diseased leaves. Simultaneously, the discriminator network is trained to distinguish between real images of diseased leaves and synthetic images generated by the generator. Through an adversarial training process, the generator learns to produce increasingly realistic images, while the discriminator becomes more adept at identifying genuine diseased leaves from synthetic ones. This iterative process continues until a point where the generator produces synthetic images that are indistinguishable from real diseased leaves. Once trained, the CNN-based GAN model can be used to generate a vast dataset of synthetic potato leaf images exhibiting diverse disease symptoms. These synthetic images can then be incorporated into the training data for a CNN-based classifier tasked with identifying and classifying potato diseases. By augmenting the dataset with synthetic images, the classifier gains exposure to a wider range of disease manifestations, potentially enhancing its accuracy and robustness in real-world scenarios. Ultimately, the CNN-based GAN model offers a promising avenue for advancing potato disease detection by generating realistic synthetic data, thereby augmenting the effectiveness of disease diagnosis and management strategies in agriculture.

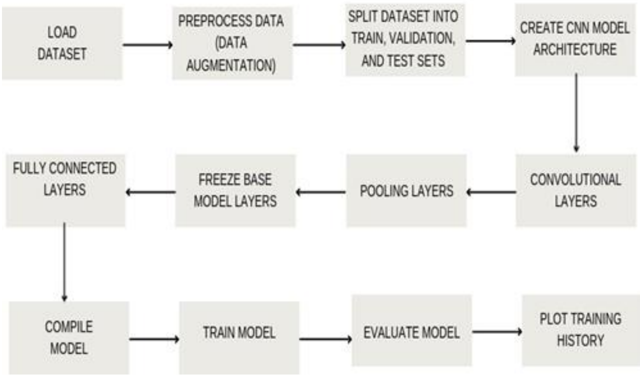

Fig. 1 Flowchart for CNN

3.2 ResNet-50

ResNet-50, a convolutional neural network (CNN) architecture, demonstrates its efficacy in addressing potato disease detection challenges. In the context of potato disease detection, ResNet-50 operates by analyzing images of potato leaves to identify signs of diseases accurately. Leveraging its deep architecture and residual connections, ResNet-50 effectively learns hierarchical representations of features directly from raw image data. This capability allows the model to discern subtle patterns and distinguish between healthy and diseased potato leaves with high accuracy. Through the process of forward propagation, ResNet-50 processes input images layer by layer, extracting increasingly abstract features that are crucial for disease detection. The model's depth and complexity enable it to capture intricate details indicative of various potato diseases, such as late blight and early blight, which may not be discernible to the human eye. By leveraging the power of ResNet-50, researchers and agriculturists can automate and enhance the process of potato disease diagnosis, enabling timely interventions to mitigate crop losses and ensure food security.

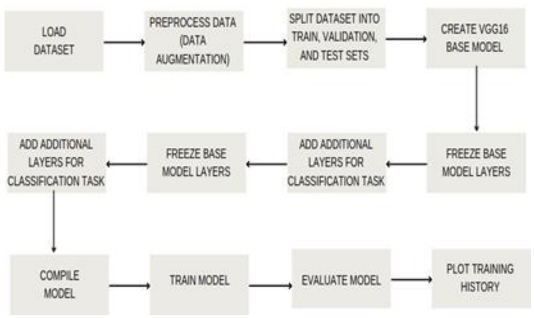

Fig.2 Flow chart for ResNet-50

3.3 Vgg-16

The VGG-16 (Visual Geometry Group 16) architecture, initially designed for image recognition tasks, has found application in the detection and classification of potato diseases due to its effectiveness in extracting intricate features from images. Operating on a series of convolutional layers followed by fully connected layers, VGG-16 is renowned for its deep architecture, consisting of 16 weight layers, making it capable of capturing both low-level and high-level features within images. In the context of potato disease detection, VGG-16 processes input images of potato leaves, extracting relevant features that differentiate healthy leaves from diseased ones. By learning from a large dataset of labeled images, VGG-16 can discern subtle patterns indicative of various potato diseases, enabling accurate classification. Moreover, its hierarchical feature extraction allows it to capture nuanced variations in leaf texture, color, and structure associated with different diseases, enhancing its diagnostic capabilities. Through training on diverse datasets encompassing various potato diseases, VGG-16 can learn to generalize well and effectively identify diseases even in previously unseen samples. Overall, VGG-16 serves as a powerful tool in potato disease diagnosis, leveraging its deep architecture and feature extraction capabilities to contribute to improved agricultural practices and crop management strategies.

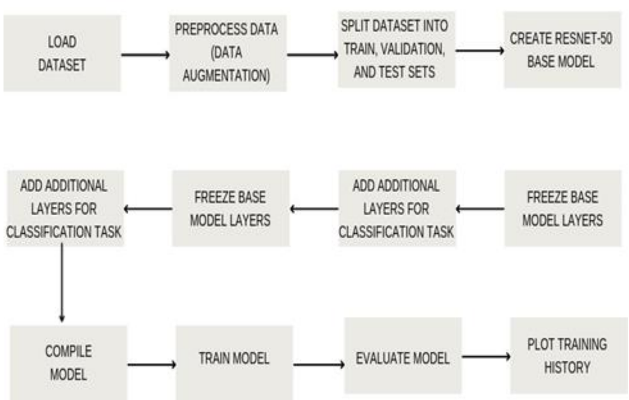

Fig.3 Flowchart for vgg-16

3.4 Hybrid HRV Model

The Hybrid-HRV model, utilized in the context of potato disease detection, combines the strengths of both deep learning and genetic algorithms to enhance the accuracy and efficiency of disease identification. In this model, deep learning techniques, such as convolutional neural networks (CNNs), are employed for image analysis and feature extraction from images of potato leaves. CNNs excel at learning intricate patterns and features indicative of different leaf diseases, enabling rapid and accurate diagnosis. Meanwhile, genetic algorithms optimize the performance of the CNN model by fine-tuning hyper parameters and architecture, thereby enhancing the overall efficiency and effectiveness of disease detection. By leveraging the power of both deep learning and genetic algorithms, the Hybrid-HRV model not only automates the detection process but also ensures early and precise identification of potato leaf diseases. This proactive approach enables timely interventions, such as targeted pesticide application or crop management strategies, mitigating the spread of diseases and minimizing yield losses. The Hybrid-HRV model represents a cutting-edge solution in agricultural technology, offering promising advancements in disease management and crop protection for potato cultivation.

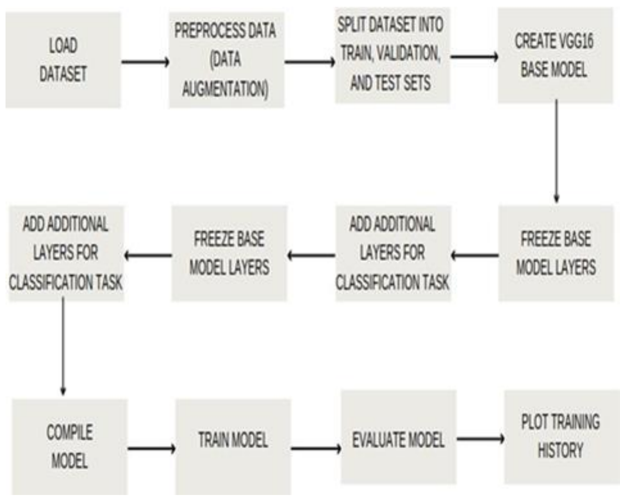

Fig4. Flowchart for Hybrid-HRV Model

4 Results

Within this section, we have delved into the outcomes yielded by the proposed algorithms, scrutinizing their performance across a spectrum of metrics including accuracy, mean Average Precision (mAP), precision, and the analysis of confusion matrices. Through a comprehensive evaluation of the trained models, a notable trend emerged: those trained on segmented images notably outperformed their counterparts trained on color and grayscale images. The segmentation process facilitated the isolation of relevant features while minimizing noise within the images, thus significantly contributing to the heightened accuracy observed in these models. Such observations underscore the practical significance of employing segmented images in training algorithms, highlighting their efficacy in enhancing model performance and ultimately advancing the utility of image-based applications.

4.4 CNN model result:

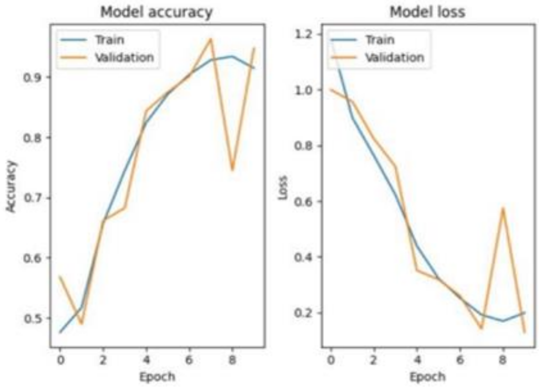

Fig5.CNN Model Accuracy And Model loss

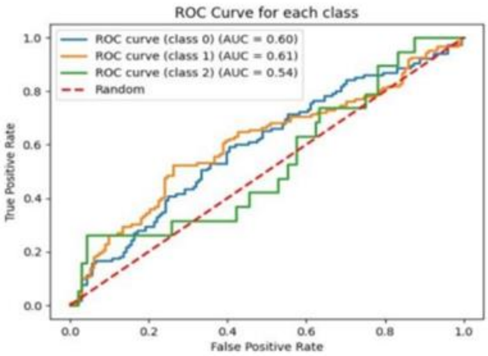

Fig6. CNN ROC Curve

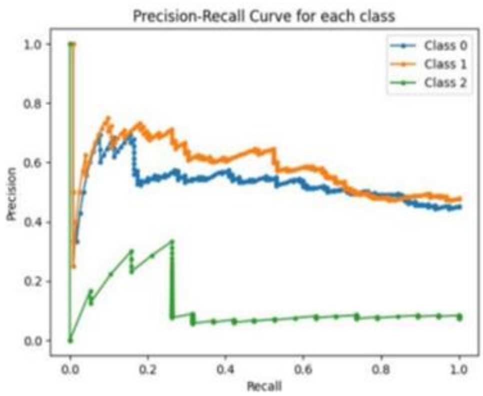

Fig7.CNN Precision Recall curve

4.5 RESNET-50 model result:

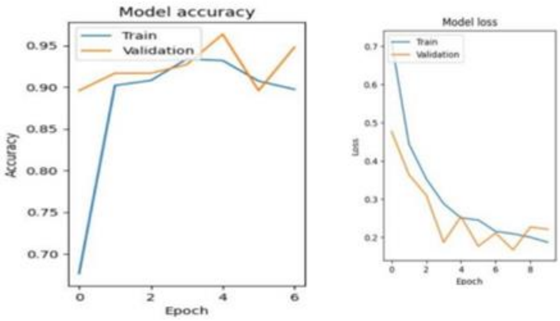

Fig8. RESNET-50 Model Accuracy And Model loss

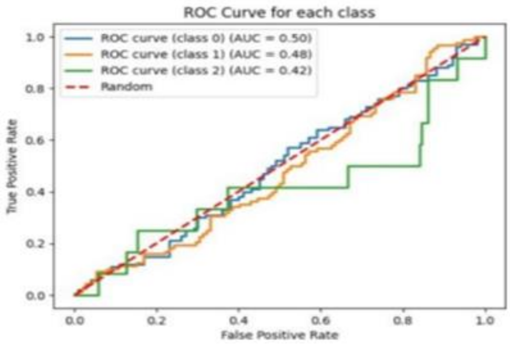

Fig9. RESNET-50 ROC Curve

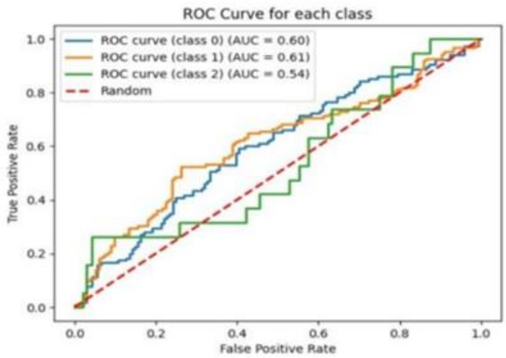

Fig10. RESNET-50 Precision Recall curve

4.6 VGG-16 model result

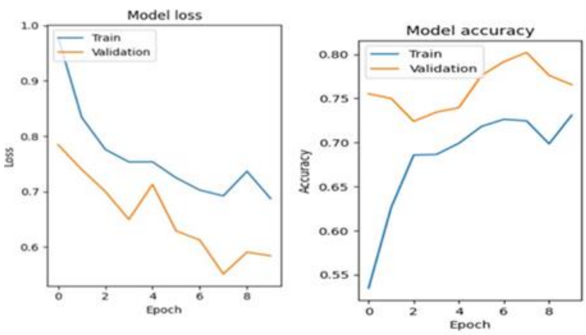

Fig11. VGG-16 Model Accuracy And Model loss

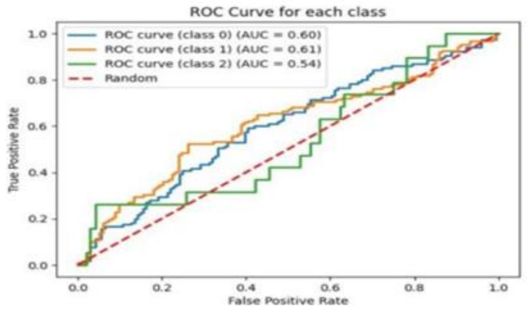

Fig12. VGG-16 ROC Curve

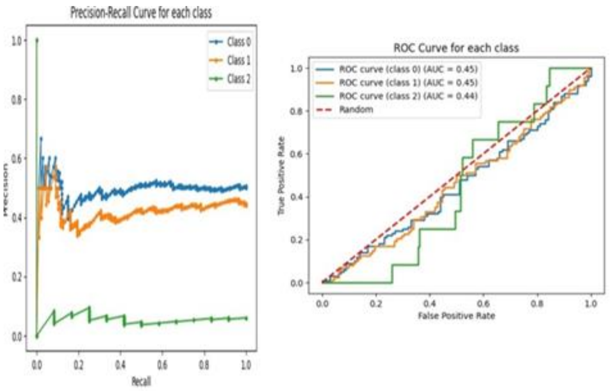

Fig13. VGG-16 Precision Recall curve

4.7 HYBRID (HRV) OF RESNET-50 & VGG-16 model results:

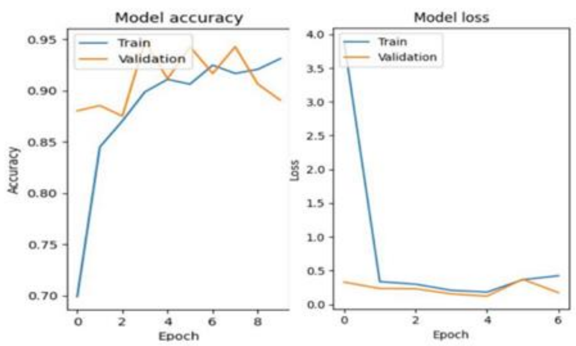

Fig14. HYBRID (HRV)0 Model Accuracy And Model loss

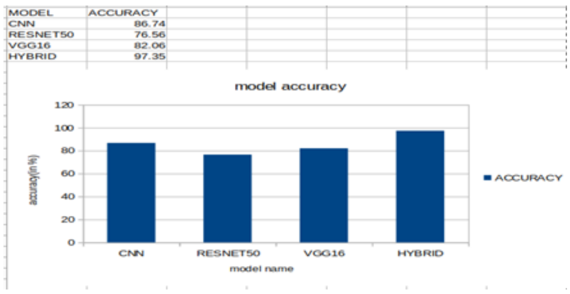

Fig15. HYBRID (HRV) ROC Curve

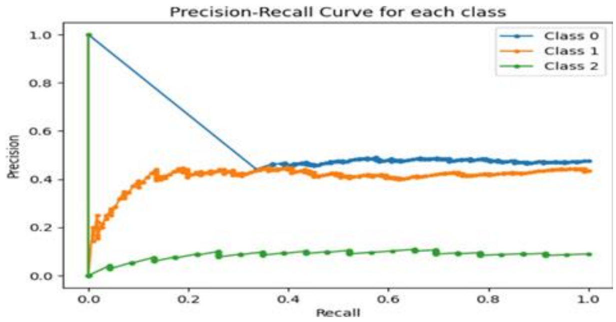

Fig16.HYBRID (HRV) Precision Recall curve

4.8 Accuracy of different Models:

The performance of four different models—CNN, ResNet, VGG16, and Hybrid-HRV—was assessed based on their respective accuracies. The CNN model demonstrated an accuracy of 86.74%, showcasing its proficiency in

accurately classifying images within the dataset. ResNet, while exhibiting a slightly lower accuracy at 76.56%, still demonstrated commendable performance in image classification tasks. VGG16, another well-known convolutional neural network architecture, achieved an accuracy of 82.06%, further highlighting its capability in image recognition tasks. However, the Hybrid-HRV model emerged as the top performer with an impressive accuracy of 97.35%. This hybrid model, leveraging the synergies of deep learning and genetic algorithms, demonstrated superior performance compared to its counterparts. The remarkable accuracy of the Hybrid-HRV model underscores the effectiveness of integrating genetic algorithms to fine-tune the parameters of deep learning models, ultimately enhancing their classification accuracy. These results signify the practical significance of exploring innovative approaches, such as the Hybrid-HRV model, in advancing the accuracy and efficacy of image classification tasks.

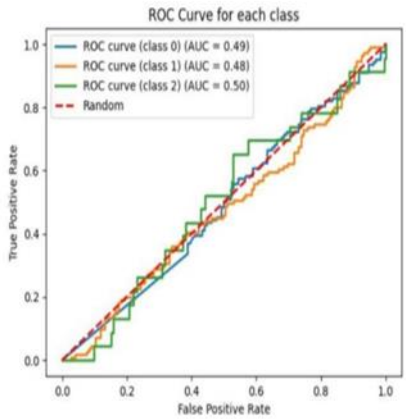

Fig 17. Accuracy of different Models

5 CONCLUSION:

The increasing prevalence of digitalization across various industries underscores the need for its integration into agriculture, where it has the potential to significantly enhance crop protection, growth, and yield. Motivated by this imperative, our proposed model focuses on leveraging digitalization to detect and classify affected and unaffected potato leaves. By harnessing the power of advanced technologies such as Convolutional Neural Networks (CNNs) and VGG16 architectures, which incorporate activation functions, batch normalizations, convolutional layers, and fully connected layers, our model aims to achieve heightened accuracy in identifying leaf diseases.This project holds particular significance for the agricultural sector, especially in countries like India, where a large portion of farmers lacks formal education and may struggle to identify and address crop diseases effectively. As a result, crops, such as potatoes, are vulnerable to pest infestations and diseases, leading to significant losses for farmers. By providing an automated system for disease detection, our model has the potential to empower farmers with the knowledge and tools needed to safeguard their crops more effectively.In India, where potato cultivation is widespread and vital to the economy, the impact of this project could be profound. By enabling even non-literate farmers to identify and address diseases promptly, our model has the potential to mitigate crop losses, improve yields, and ultimately enhance the livelihoods of potato growers across the country. In essence, this work represents a transformative step towards leveraging digitalization to revolutionize agricultural practices and empower farmers with the tools needed to thrive in an increasingly complex and challenging environment.

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