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A HYBRID DEEP LEARNING FRAMEWORK FOR ACCURATE AND EFFICIENT DETECTION OF POTATO LEAF DISEASES

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ABSTRACT

Despite significant advancements in deep learning-based plant disease detection, existing models often struggle with generalizability, computational efficiency, and adaptability to real-world agricultural challenges. To address these limitations, this study introduces a novel hybrid deep learning framework combining the custom DarkPotatoleafNet model with Vision Transformers (ViT) and convolutional neural networks (CNNs). Our approach leverages transfer learning and ensemble learning techniques to enhance disease classification accuracy while optimizing computational resources. The highest recorded accuracy of 99% was achieved through this hybrid architecture, demonstrating its superior performance over conventional models. To ensure optimal model training and generalization, we employed extensive preprocessing techniques, including data augmentation (rotation, scaling, flipping), grayscale conversion for structural emphasis, and image masking and segmentation to isolate diseased regions accurately. This research contributes to precision agriculture by providing a scalable and efficient AI-driven solution for early and accurate detection of potato leaf diseases, ultimately supporting sustainable farming practices and improved crop yield management.
Keywords: *Transfer Learning, Sustainable Farming, Image Processing, Hybrid Models, Comparative Analysis.*

1. INTRODUCTION

With a sizable fraction of the rural population involved in farming, India's agricultural industry—which forms the backbone of its rural economy—very much shapes the socioeconomic fabric of the country. Among various crops, the potato emerges as a staple, integral to the daily diet of millions across India and the globe[1]. Recent trends have shown a notable increase in potato cultivation areas, production volumes, and productivity, alongside a rising trajectory in exports. However, the quest for quality potato production encounters hurdles, primarily due to financial constraints that limit farmers' access to essential resources like quality seeds, fertilizers, and pesticides[2]. Contract farming has become a practical option, providing financial assistance, technical guidance, and essential resources to improve farming techniques.

Potato cultivation in India mainly takes place during the winter season, exposing the crop to cold temperatures that can significantly decrease yields by 40-60%. Exploring cutting-edge breeding methods like intervarietal hybridization to create frost-tolerant potato clones is crucial for reducing the impact of cold weather on crop yields. This task highlights the significance of adjusting agricultural methods to climatic obstacles, guaranteeing food security amidst environmental shifts[3,4].Previous studies on plant disease detection have primarily focused on convolutional neural networks (CNNs) and transfer learning models, achieving high accuracy but often lacking generalizability across diverse agricultural environments. Many approaches have been limited by dataset constraints, computational inefficiencies, and poor adaptability to real-world conditions, leading to challenges in practical deployment. Unlike prior work, this study introduces DarkPotatoleafNet, a hybrid deep learning model integrating CNN and Vision Transformers (ViT), which enhances feature extraction and classification precision. Our motivation is to bridge the gap between high-performance AI models and scalable, real-world agricultural applications, ensuring robust disease detection across different climates and farming conditions. Through extensive experimentation and

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comparative analysis, we demonstrate superior accuracy (99%) and computational efficiency, making this work a significant advancement in AI-driven precision agriculture.

Furthermore, the emergence of agrivoltaics systems showcases a progressive approach to agriculture by combining photovoltaic energy generation with crop production. This technology serves the dual purpose of meeting the demand for sustainable energy and improving land use efficiency. It has shown a notable boost in crop productivity when compared to conventional farming methods [5,6]. These advancements are in line with worldwide sustainable development objectives Deep Learning Architectures, providing a model for upcoming agricultural methods that focus on energy and food security.

Agarwood cultivation in Assam showcases another aspect of India's diverse agricultural landscape, renowned for its aromatic and medicinal properties. Many people have been able to achieve affluence as a result of the economic feasibility of agarwood production, which indicates that there are promising growth prospects within the agricultural sector [9,10]. The significant returns on investment highlight the importance of government backing for market legalization, credit provision, and raising awareness about Agarwood demand. This further underscores the crucial role of agriculture in economic growth and improving livelihoods.

There are many parts of daily life that have been changed as a result of the introduction of AI, which has introduced ground-breaking concepts such as ML and DL [11]. These technologies enable machines to identify and learn from patterns, allowing them to make informed decisions or take actions without needing specific programming for each task [12]. Utilizing ML and DL technologies, software applications can improve their predictive abilities over time, similar to how humans learn.

DL algorithms are inspired by the human nervous system, designed to mimic human thinking and learning processes to give machines cognitive abilities [13]. The similarity to human learning processes distinguishes deep learning, providing a strong framework for machines to analyze intricate datasets and enhance their performance gradually.

The combination of DL and CV has significantly boosted the creation of advanced algorithms that can effectively analyze and categorize images with exceptional precision. Algorithms have achieved performance levels that exceed those of humans in tasks such as pattern recognition and image classification, representing a major advancement in the AI field [14]. Utilizing these technologies in agriculture, particularly in identifying and categorizing diseases in crops such as tomatoes, has showcased the significant impact of AI on advancements in plant pathology.

Pre-trained deep learning algorithms have been used in this sector to categorize agricultural illnesses, therefore proving the models' capacity to precisely identify disease patterns from images [15]. The accuracy of these models in disease identification highlights the significance of ongoing developments in AI to improve the accuracy and precision of plant disease data [16]. This advancement is crucial for the agricultural industry, providing new opportunities for disease management and control, ultimately leading to higher crop yields and food security [17].

Deep learning and computer vision in particular help to integrate artificial intelligence into agriculture, therefore offering a revolutionary solution for problems in plant pathology. Using artificial intelligence can help practitioners and researchers reach hitherto unheard-of degrees of disease detection accuracy, therefore opening the path for more sustainable and efficient agriculture methods.This evolution in disease management strategies highlights the broader implications of AI technologies in enhancing the sustainability and efficiency of global food production systems.

Blending traditional agricultural methods with cutting-edge technology offers a great chance to tackle key issues in Indian agriculture. Despite the crucial role of agriculture in India's economy and the substantial progress in potato production and export, farmers still encounter challenges that impact productivity and sustainability. These involve climatic vulnerabilities, like frost, which have a significant impact on yield, and the ongoing challenge of obtaining quality resources for cultivation.

At the same time, the fast-paced advancements in AI, along with its subsets like ML and DL, provide promising opportunities to address these challenges. Utilizing AI to identify and categorize crop diseases is a significant advancement that could revolutionize agricultural methods through accurate and timely disease detection [18]. By

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incorporating AI-driven solutions, like deep learning models for disease identification, into the agricultural sector, there is a possibility of greatly improving crop management, decreasing losses from diseases, and enhancing the overall yield and quality of produce.

Integrating AI technology not only supports the worldwide shift towards sustainable and technologically advanced farming methods but also tackles the specific obstacles encountered by Indian farmers, especially in potato cultivation. AI technologies merging with agricultural needs could result in more resilient farming strategies, improved resource management, and a more robust response to climatic challenges, ushering in a new era of agricultural excellence and food security in India.

1.1 Background

Particularly in plant disease identification, the integration of advanced computational models called deep learning (DL) marks a significant progress in the always evolving field of agricultural technology. This study utilizes transfer learning, ensemble learning, and advanced model architectures such as hybrid models and DarkPotatoleafNet, in addition to thorough image preprocessing techniques, to tackle the task of precisely identifying potato leaf diseases. These methodologies showcase the merging of cutting-edge AI techniques with the practical requirements of precision agriculture.

1.1.1 Transfer Learning in Deep Learning Models:

Utilizing transfer learning has become a fundamental technique in our strategy, mainly because of its efficiency and success in adjusting pre-trained models to new, yet related, tasks. This approach is extremely useful in situations where computational resources are scarce or when the dataset for a particular task is not large enough to train a DL model from the beginning. We utilize transfer learning in two different ways in our research.

1.1.2 Fine-tuning Pre-trained Models:

One method is to partially unfreeze the upper layers of a deep learning model and retrain them with a newly introduced classifier on the target dataset. In order to optimize the model's performance, this fine-tuning brings the higher-order feature representations into alignment with the intricacies of agricultural imagery, tailoring the model to the characteristics of the potato leaf disease detection task [19].

1.1.3 Feature Extraction (FE) with Pre-trained Models:

Here, the convolutional base of a pre-trained model remains unchanged, and its output is leveraged to generate a new feature dataset. The dataset is used as input for a classifier, which helps in quickly training models and accurately classifying diseases [20]. This approach is particularly advantageous for creating hybrid architectures that leverage the capabilities of current models while addressing limitations related to dataset size and computational resources.

1.1.4 Ensemble Learning Strategies:

Ensemble learning further enhances our model's predictive accuracy and robustness by aggregating the outputs of multiple learning algorithms [21]. This research incorporates both homogeneous and heterogeneous ensemble methods to harness the collective intelligence of various models:

1.1.5 Homogenous Ensembles:

Many learning algorithms are included to increase the dependability and accuracy of the diagnosis of potato leaf diseases [23].Combining forecasts from several models guarantees a complete analysis of the input data, therefore enhancing the whole process of decision-making.

1.1.6 Heterogeneous Ensembles:

Using weighted voting and hard voting—also known as majority voting—ensemble techniques integrate the forecasts of many models. Hard voting selects the class with the most votes among all the models, therefore offering a straightforward yet effective consensus method.Weighted voting involves assigning varying weights to predictions depending on the performance of each model, giving more importance to inputs from the most accurate classifiers.

1.1.7 Image Preprocessing for Enhanced Model Training:

An essential part of our approach involves thorough preprocessing of potato leaf images, utilizing methods like data augmentation, normalization, and segmentation [24]. Following these steps is crucial to properly prepare the dataset for optimal model training, guaranteeing that the models can handle

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various image conditions and accurately identify disease symptoms in different scenarios.

2. RELATED WORK

The table[2] consolidates the findings from 26 studies on plant disease detection using DL , highlighting the diverse approaches and their respective strengths, potential threats, and accuracies. This demonstrates the advancements in CNN and deep learning model usage in various crops, achieving accuracies of up to 100%. The strengths showcase progress in accuracy and model development, while the threats are usually tied to the models' specificity, computational requirements, or wider applicability.This overview emphasizes the significant possibilities of DL technology in changing agricultural methods by means of enhanced disease detection and diagnosis.

Combining DL and IP approaches has made significant progress possible in the field of plant disease identification. Article [25] presents a novel approach to precisely classify healthy and sick potato leaves using Residual Network, Mobile Net, and Inception models in concert. With an amazing 98.86% accuracy rate, this study emphasizes the need of ensemble models in agricultural environments.

The investigation of ML and DL models on the Quora question pairs dataset [26] shows unequivocally that ensemble learning and DL models are efficient in natural language processing tasks.The impressive test accuracy of 76.13% achieved by the Hard-Voting Ensemble approach and 81% by DL models like the FCN demonstrate the broad applicability of these methodologies beyond the agricultural industry.

Accurately forecasting COVID-19 positive instances required a stacked-DNN technique [27], and this produced an amazing 97% accuracy. Combining LSTM, DNN, and CNN models this method offers a strong answer for healthcare decision-makers managing the epidemic. It underlines how well deep learning algorithms forecast and identify early on pandemic patterns. Emphasizing the major influence of CNNs on agricultural health, [28] investigates the use of tailored CNN designs to detect illnesses of potatoes leaves.The work achieves an overall accuracy of 99.22%, which is better than previous methods in disease detection and tackles issues with computational efficiency and early detection. It makes a significant contribution to improving crop management techniques and increasing food security.

Improving agricultural output and guaranteeing food security is dependent on overcoming the difficulty of early identification in plant disease control. [29] presents a CNN-based model designed specifically for automatically identifying potato leaf diseases and sorting leaves into three different classes. By leveraging a dataset consisting of 5,162 original images and 82,592 augmented images, this method attained a classification accuracy of 98.07%. This research highlights the capabilities of CNNs in connecting remote regions with limited expert support to the demand for precise, automated plant disease detection.

An investigation into the effectiveness of Deep Neural Networks in the identification of plant diseases is conducted in the context of India's agricultural landscape, which is characterized by crop yields that have a direct impact on economic stability and the availability of food [30]. In this paper, the effectiveness of CNNs in detecting leaf diseases is highlighted. CNN models achieved an accuracy rate for classification of 97.60%, which is a particularly impressive result. Technological advancements in DL provide promising solutions to enhance crop yields.

In order to improve agricultural production, recent developments in intelligent farming systems have made use of cutting-edge technology. Article [31] introduces a novel approach utilizing deep CNNs for disease diagnosis in potato plants, with a focus on Yukon Gold potatoes and common diseases such as Alternaria, Blackleg, and Target Spot. Having analyzed a dataset of 5,615 images, this research project successfully achieved a disease identification accuracy of 97.85% and showcased the feasibility of an automated image-capturing system with a diagnostic effectiveness of 93.33%, emphasizing the significant role of DL in agriculture.

By comparing the efficacy of CNNs with the AlexNet architecture in diagnosing diseases in mango and potato leaves, [32] delves further into the evolution of DL and its application in agricultural disease detection. By analyzing a dataset containing 4,004 images, this study discovered that AlexNet achieved higher accuracy (96.09%) compared to conventional CNN models. This comparison highlights the capabilities of certain pre-trained models in agricultural settings and aids in the quest for optimal disease detection techniques.

In response to the critical importance of early disease detection in farming, [33] presents very effective convolutional neural network (CNN) designs for identifying leaf illnesses. Utilizing a dataset containing 1,700 training and 600 testing images of potato leaves, the study achieved an impressive accuracy of 99.62%. The study highlights the effectiveness of the new CNN design compared to other models, underscoring its promise in regions with limited access to professional medical opinions.

Assessing the effectiveness of modified TL models in detecting potato leaf disease early is crucial in fighting its harmful effects [34]. Deep learning has been shown to be useful in precision agriculture, as demonstrated by the fact that the updated Dense Net model beat other models with accuracies of up to one hundred percent on validation sets of data.

The research discussed in [35] explores the use of AI in identifying and categorizing potato leaf diseases. It utilizes a sophisticated ensemble algorithm that combines CNN, CNN-SVM, and DNN models. With an impressive accuracy of 99.98%, this project showcases the power of AI in agriculture and highlights the significance of explainability using LIME and SHAP analyses.

[36] is pushing the boundaries of smart farming by developing a highly efficient CNN architecture for potato disease detection, resulting in an impressive 99.53% accuracy rate. A promising option for real-time disease control and management in agriculture is offered by this study, which stresses the significance of optimizing model resources while retaining a high level of accuracy.

These contributions emphasize the crucial role of incorporating sophisticated computational models and algorithms in tackling the issues of plant disease detection. All these studies collectively push forward precision agriculture and provide effective solutions to improve crop yield and reduce losses, making a substantial impact on global food security.

The usefulness of DL and CNNs in detecting and controlling plant illnesses to protect food sources and boost crop output has been highlighted in recent studies. These studies build upon the breakthroughs that have been made in agricultural technology and disease detection.

[37] is working to reduce the substantial decrease in crop yield due to diseases in potato and tomato plants by implementing CNNs for early detection. Using the Plant Village dataset, which consists of images of tomato and potato plant leaves, the research evaluated specialized CNN models. Alex Net and VGG16 models stood out for their impressive performance, with accuracies of 84.7% and 96.5%, respectively. This highlights the CNNs' potential in enhancing disease detection accuracy and, consequently, crop management strategies.

The significant importance of tomatoes in worldwide farming and the consequences of diseases on their overall quality and production. An advanced model was developed with convolutional and max pooling layers, along with fully connected layers, and compared with popular pre-trained models [38]. It was proved that the model had classification accuracies that ranged from 76% to 100% across the various disease groups, with an average accuracy of 91.2% occurring. This method showcases the efficiency of CNN-based models in detecting and categorizing diseases compared to current techniques.

An advanced model called Efficient MT-Net architectures to detect and classify potato leaf diseases [39]. By combining the strengths of both architectures, the model strives to offer a precise and computationally efficient solution for disease identification. With amazing accuracy, Efficient MT-Net obtained 97.65% accuracy on general potato leaf image datasets and 99.12% accuracy on potato leaf image datasets when it was tested on bespoke datasets that were curated specifically for this occasion. This innovation provides a promising tool to improve agricultural productivity by detecting diseases early.

The article discusses ways to reduce crop productivity losses caused by plant diseases through the use of different classification techniques, such as CNNs, to automatically detect diseases [40]. The research emphasizes the utilization of CNN algorithms to detect potato leaf diseases and presents an IoT-based alert system for disease prevention. With an accuracy of around 90%, CNN and IoT technologies for effective disease management and prevention tactics.

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These studies showcase the continuous progress in utilizing deep learning techniques for detecting agricultural diseases. CNNs, IoT, and cutting-edge architectures such as Efficient MT-Net [40]. These advancements not only add to the knowledge base in agricultural technology but also provide practical solutions for enhancing crop management and productivity worldwide.

Recent studies that were carried out on a wide range of crops, most notably potatoes and chilies, provide definitive evidence of the ongoing research that is being undertaken in the field of new technology. These studies showcase the progress in CNN architectures and underscore the significance of timely and precise disease detection to improve crop yields and profitability for cultivators.

[41 and 42] Both papers provide a detailed examination of the classification performance in identifying chilli leaf diseases using ML and DL. By leveraging various pre-trained DL networks, the research discovered that DarkNet53, when combined with data augmentation, achieved an impressive accuracy of 98.82%, whereas VGG19 performed best without augmentation at 83.54%. With the implementation of a SECNN model, accuracy was significantly improved, reaching a high of 99.12% when combined with augmentation techniques. The versatility of this SECNN model was put to the test with various crops, resulting in a test accuracy of 99.28%. Highlighting the potential of specialized CNN models in detecting agricultural diseases across various crop types.

[43] Concentrating on the widespread problem of diseases, using CNN models for disease detection from image data. Utilizing algorithms, the research demonstrates a precision rate of 97%. This study emphasizes the power of CNNs in categorizing and detecting diseases in potato leaves, providing a hopeful remedy to mitigate substantial economic losses in potato farming.[44] Introducing a HDLCNN designed to improve crop disease management by enabling early detection. The model showcases exceptional performance compared to current approaches, achieving an accuracy of 98%. This HDLCNN model is a remarkable advancement in smart agriculture, equipping farmers with cutting-edge tools for efficient disease management and treatment. Recent research has shown the use of CNNs for disease detection in agricultural crops, particularly potatoes and tomatoes, emphasizing the importance of DL technologies in improving agricultural productivity and economic stability.

[45] Undertakes the use of DL techniques to detect with a specific focus on the potato plant given its widespread presence and economic significance, particularly in Pakistan. Using CNN techniques on a dataset of 20,636 images, this research classifies plant leaf diseases into 15 categories, achieving high accuracies of 98.29% and 98.029% for the trained and tested models. This method showcases the power of CNNs in identifying diseases and highlights the potential financial benefits of early detection.

[46] Explores the implementation of a customized CNN, the SEnet, for disease detection in tomato leaves achieving an impressive accuracy of 97.029%. This study introduces an innovative and resource-efficient method for disease detection by enhancing traditional CNN approaches with SEnet. It emphasizes the significance of early prediction in protecting plant health and boosting the economy.

[47]A model has been proposed that uses CNN for precise detection and diagnosis of potato leaf diseases, achieving an impressive precision rate of 97%. This research demonstrates the capabilities of algorithms in agricultural contexts by highlighting the value of early identification in minimizing financial losses for farmers and improving disease control in potato crops. Additionally, this research helps to demonstrate the capabilities of algorithms.

[48]The creation of a SBCNN model for the identification of potato diseases contributes to the advancement of CNN applications in agriculture [48]. The model shows strong performance on both augmented and non-augmented datasets, achieving validation accuracies of 96.98% and 96.75%, respectively. The SBCNN model has been seamlessly incorporated into an Android application designed for real-time disease testing.

The highlighted studies demonstrate significant progress in utilizing DL models, with a specific focus on key crops in the agricultural sector such as potatoes. These studies highlight the advancements in crop disease management and the potential benefits of reducing food wastage and improving crop yield, which can greatly impact global food security and economic efficiency in agriculture.

An online application that makes use of DL models trained on the image dataset is shown in study [49].

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These models include Inception Net, ResNet50, Mobile Net, and a custom CNN. This application is designed to detect infected potato leaves of their growth cycle, tackling the significant losses caused by late blight and early blight diseases. This tool offers accuracies between 88.79% and 96.12%, providing a scalable and efficient option compared to traditional manual inspection methods that can be expensive, time-consuming, and less reliable. This method represents a significant advancement in utilizing technology to reduce crop losses and enhance yield, which is particularly important given India's large potato production and the amount of crop wastage caused by disease.

Research [50] describes a system for automatically detecting plant leaf damage and identifying diseases. It uses DenseNet for disease classification and a 1D Convolutional Neural Network (CNN) for semantic segmentation to pinpoint leaf damage at a pixel level. This innovative methodology attains a classification accuracy of 100% and segmentation accuracy of 97%, showcasing exceptional precision in identifying different plant diseases and damage. Furthermore, the system provides solutions based on the detected disease type and level of damage, giving a complete approach to plant health management. This comprehensive method offers practical insights for disease management, demonstrating the potential for deep learning technologies to transform agricultural practices.

3. DATA PREPARATION

3.1 Data Set Description

The dataset used in this study was hand-picked for the express purpose of identifying and categorizing illnesses in potato leaves. The dataset consists of 2,000 high-resolution images, evenly spread among four categories: healthy leaves, early blight, late blight, and Phytophthora infestans. Every category has 500 images, creating a well-balanced dataset that supports thorough training and assessment of the DL models being considered. The images were taken in a controlled agricultural environment, using the Canon EOS 250D camera to maintain consistent quality and resolution. Using this equipment enabled the thorough recording of various disease symptoms and leaf conditions, ranging from early signs of infection to advanced disease stages. Having high-resolution images (averaging 224 x 224 pixels) is essential for enabling deep learning models to effectively recognize the subtle patterns and textures that represent different disease states **table[1]**.For improved applicability and robustness of the dataset, the images were converted from JPEG to PNG format. The conversion was done to take advantage of PNG's lossless compression capability, which helps maintain the fine details of each image without any loss, an important aspect for preserving the accuracy of the visual data utilized in model training and testing. The diversity of the data set, including the range of diseases and variations within each category, is crucial for creating an accurate and reliable AI-driven diagnostic tool that can be effective at various stages of disease progression. This detailed data description highlights the importance of the dataset as the basis for developing and assessing deep learning models, with the goal of advancing precision agriculture by improving disease detection capabilities.

Table 1: Dataset Illustration

Name	Description
Image Numbers	2000
Average Dimension	224 x 224
Color Grading	Grayscale
Image Format	PNG
Healthy	500
Early Blight	500

Late Blight	500
Phytophthora Infestans	500

Table 2: Comparative analysis of state-of-the-art models

Reference	Strength	Threat	Accuracy (%)
[25]	Ensemble model integrating Residual Network, MobileNet, and Inception models	Performance specifics in varied environmental conditions not discussed	98.86
[26]	Demonstrated effectiveness of ensemble learning and DL models on text data	Focused on text data with no direct application to plant disease detection	81 (DL models)
[27]	Utilized stacked-DNN approach for accurate COVID-19 case prediction	Specific to COVID-19 prediction, not directly applicable to plant diseases	97
[28]	Developed specialized CNN architecture for potato leaf disease detection	Limited discussion on model's applicability across different plant species	99.22
[29]	CNN models achieved classification accuracy with substantial image dataset	Did not address the computational efficiency or real-time applicability	98.07
[30]	Highlighted the superiority of CNNs in leaf disease detection	Generalizability to other crops or diseases not explicitly covered	97.60
[31]	Utilized deep CNN to diagnose diseases in potato plants with high accuracy	Focused on specific diseases, may not cover a broad spectrum of plant health issues	97.85
[32]	Compared accuracy and efficiency of CNN and AlexNet for disease detection in crops	Limited to mango and potato leaves, broader applicability not discussed	96.09 (AlexNet)
[34]	Achieved high accuracy with CNN models in detecting leaf diseases	The threat or limitation was not explicitly mentioned in the summary provided	99.62
[35]	Modified TL models for enhanced potato leaf disease detection	Comparison with a limited set of pre-trained models	99 (DenseNet)
[36]	Deep ensemble algorithm achieved top accuracy in identifying potato leaf diseases	Specificity to potato leaf diseases, with no mention of performance on other crops	99.98
[37]	Proposed CNN architecture achieved high accuracy and reduced parameter usage	Detailed threats or limitations not provided in the summary	99.53
[38]	Utilized CNNs for early detection of potato leaf diseases with high precision	Did not detail the scalability or implementation challenges	97
[39]	Implemented a hybrid CNN approach for enhanced disease detection	Specific challenges or comparative analysis with other models not discussed	96.98

[40]	EfficientRMT-Net combining ViT and ResNet-50 for potato leaf disease detection	Threats or limitations regarding real-world applicability or comparison with existing models absent	99.12
[41]	Explored various classification techniques for automated crop disease detection	Precision and recall values suggest room for improvement in model accuracy	90
[42]	Used deep learning networks for classification with and without augmentation achieving high accuracy	Specific to chilli leaf diseases, broader applicability or environmental adaptability not discussed	99.12
[43,44]	Utilized CNN for image-based disease detection in potatoes	Limited discussion on the model's applicability to real-world agricultural settings	97
[45]	Proposed HDLCNN for disease detection with preprocessing and feature extraction steps	Comparison mainly with older models, might not reflect the performance against latest architectures	98
[46]	CNN methods categorized plant leaf diseases into 15 classes with high accuracy	Broader range of diseases or crop types beyond potatoes not covered	98.29
[47]	Adapted SENet and CNN layers for efficient classification of tomato leaf diseases	Primarily focused on tomato leaves, applicability to other plant types not detailed	97.029
[48]	Proposed CNN model for early detection of potato leaf diseases	Specific accuracy improvements or challenges in deployment not detailed	97
[49]	Developed SBCNN model, showing robust performance on augmented datasets	Limited comparison with other deep learning architectures	96.98
[50]	Web application using deep learning models for disease detection with high accuracies	Deployment or real-world application challenges not discussed	96.12
[51]	Utilized DenseNet for classification and 1D CNN for semantic segmentation	Specific applicability to diverse environmental conditions or crops beyond those tested not covered	100

3.2 Data Acquisition

The acquisition of the dataset pivotal to this research was meticulously planned and executed to ensure the highest quality and relevance of the data for potato leaf disease detection. The process involved a strategic collaboration with local agricultural experts and farms known for their extensive potato cultivation, located in regions representative of the diverse climatic conditions affecting potato growth and disease manifestation in India.The collection phase spanned several months, coinciding with the peak growing seasons to capture a wide range of disease symptoms under various environmental conditions. Utilizing the Canon EOS 250D camera, renowned for its high-resolution imaging capabilities, each leaf was photographed in natural light to ensure the accurate representation of symptoms without artificial enhancement. Special attention was paid to include leaves at different stages of disease progression, as well as healthy leaves, to create a comprehensive dataset that encompasses the full spectrum of conditions observed in the field. To maintain consistency and minimize variability unrelated to disease symptoms, a standardized protocol for image capture was established. This included specific guidelines for distance, angle, and lighting conditions during photography. Each leaf was photographed from multiple angles to capture the full extent of visible symptoms, with particular focus on areas showing signs of disease initiation and progression.The acquisition process was conducted with strict adherence to ethical guidelines, ensuring that the collection activities did not disrupt the normal operations of the participating farms or adversely affect the crop yield. Prior consent was obtained from all participating entities, with a clear understanding of the research objectives and the potential benefits of the study to agricultural practices and crop health management.Following the collection phase, each image underwent a preliminary screening to verify its quality and relevance. This step ensured that only images meeting the predefined criteria for resolution, clarity, and symptom visibility were included in the dataset. Additionally, a team of plant pathology experts reviewed the images to confirm the accuracy of the disease categorization, providing an essential layer of validation to the dataset's integrity.

3.3 Data Preprocessing for Potato Leaf Disease Detection

The effectiveness of DL models in accurately detecting and classifying potato leaf diseases is significantly enhanced by a comprehensive data preprocessing pipeline. This pipeline is meticulously designed to include data augmentation, grayscale conversion, image masking, and image segmentation. Each of these steps plays a crucial role in preparing the dataset for optimal model training and performance fig:1 .

3.4 Data Augmentation

Given the variability of agricultural environments and the myriad manifestations of disease symptoms on potato leaves, data augmentation is employed to artificially expand the dataset. This process involves applying a series of transformations to the images, including rotation, scaling, horizontal and vertical flipping, and cropping. These manipulations generate new images that retain the original's pathological features while presenting them in varied orientations and scales. This diversity is crucial for training robust models capable of recognizing disease symptoms under a wide range of conditions table[3].

3.4.1 Grayscale Conversion

To focus the model's learning on the structural and textural patterns indicative of disease, rather than color variations, images are converted to grayscale. This step simplifies the input data, reducing the computational complexity of the models without compromising the ability to detect relevant features. Grayscale images emphasize contrast differences and surface irregularities, which are key indicators of many potato leaf diseases.

$$Gray = \frac{R+G+B}{3} \quad (1)$$

$$Gray = 0.299R + 0.587G + 0.114B \quad (2)$$

3.4.2 Image Masking

Image masking is a critical preprocessing step that involves delineating the diseased areas from the healthy parts of the leaf. By applying masks to the images, the models are directed to focus specifically on the regions of interest, enhancing the accuracy of disease detection and classification. This targeted approach allows for a more efficient analysis, as the models can allocate more computational resources to examining the nuances of the diseased tissue.

$$Resulting\ Image = Original\ Image \times Mask \quad (3)$$

$$Resulting\ Pixel\ Value = Original\ Pixel\ Value \times Mask\ Value \quad (4)$$

3.4.3 Image Segmentation

After the masking process is complete, the next step is image segmentation, which is used to separate and classify the various regions contained within the images. This procedure involves segmenting the leaf based on disease symptoms to establish clear boundaries, aiding the model in grasping the disease's spatial distribution. Segmentation is crucial for conducting a thorough analysis of disease progression and severity, offering valuable insights into the health status of the crop.

Table 3: Data augmentation parameters:

Parameter	Value
Rescale	1./255
Rotation range	45
Width shift_range	0.1
Height shift range	0.1

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Horizontal flip	True
Vertical flip	True
Zoom range	0.5
Shear range	0.2
Brightness range	[0.5, 1.0]
Channel shift range	100
Fill mode	Reflect

4. PROPOSED METHODOLOGY

Our research involves creating a strong methodology for detecting and classifying diseases using DL technology. Embark on the journey by carefully compiling a detailed dataset containing images of potato leaves depicting different disease states and stages of progression from various sources. Ensuring a comprehensive dataset that precisely mirrors the variability of disease manifestations in the real world. The images contained in this collection have been meticulously labeled according to the specific disease condition that they represent, whether it be healthy, early blight, late blight, or Phytophthora infestans. This has established a strong foundation for the training and evaluation of models that are accurate.
The process of preprocessing these photos is an essential step that aims to improve the quality of the data and introduce variability that is conducive to efficient model learning. Applying techniques like RandomResizedCrop, RandomRotation, and RandomHorizontalFlip helps simulate various environmental conditions, while converting to grayscale directs the model's focus towards textural and morphological cues. Utilizing techniques such as image masking and segmentation helps to enhance the dataset by highlighting the differences between diseased and healthy regions of the leaves. After preprocessing, the dataset is divided into training, validation, and testing subsets using an 80-10-10 distribution. This division enables comprehensive training of our models and also enables precise adjustments and thorough testing of their predictive abilities. Our training procedure is based on a hybrid model approach, which combines the capacities of CNNs for the extraction of subtle features with the skills of ViT for the interpretation of global contextual information. Enhancing the accuracy and reliability of disease classification is achieved through the application of both homogeneous and heterogeneous ensemble learning techniques. By leveraging frameworks such as TensorFlow or PyTorch and implementing transfer learning techniques to refine pre-trained models, our approach results in a robust solution for identifying potato leaf diseases. We thoroughly assess the performance of these models by utilizing a range of metrics to guarantee the dependability and efficiency of our suggested solution for enhancing precision agriculture.

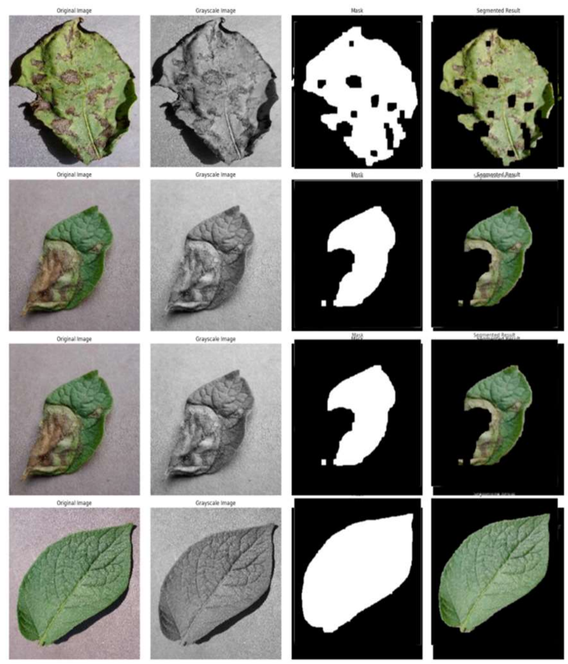

Figure 1. Image Processing Steps for Potato Leaf Disease Detection

4.1 Architecture Of The Proposed Model

The DarkPotatoleafNet model is a significant advancement in identifying and categorizing potato leaf diseases. It utilizes a specialized deep CNN design to achieve superior precision and effectiveness. This model is crafted to tackle the complex task of detecting diseases like early blight, late blight, and Phytophthora infestans, among others, with a design that prioritizes depth and efficient use of computational resources. The DarkPotatoleafNet architecture consists of a carefully designed series of layered components, each playing a crucial role in the model's impressive capability to extract and analyze features from potato leaf images. Commencing with a Conv2d layer, the model transforms the input image into an 8 x 256 x 256 feature map, leveraging 248 trainable parameters table [4]. This layer is instrumental in identifying the initial patterns present in the leaf images. Following the

Conv layers, MaxPooling2d layers reduce the spatial dimensions of the feature maps (e.g., from (8 x 128 x 128) to (16 x 64 x 64)), enhancing the model's focus on significant features while reducing computational load. Subsequent convolutional layers, such as another Conv2d layer producing a feature map of (32 x 64 x 64) with 4,858 trainable parameters, delve deeper into the texture and shape characteristics indicative of specific diseases. The inclusion of GlobalMaxPooling layers towards the end of the network serves to aggregate the most critical features across the entire spatial extent of the feature map, culminating in a highly distilled representation of the leaf's condition. The final layer of the model is a linear classifier that outputs the probability distribution across the disease categories, based on the deep features extracted by the preceding layers. The DarkPotatoleafNet model demonstrates outstanding performance in disease detection, as evidenced by its metrics. The model demonstrates exceptional precision in various disease categories, showcasing its ability to accurately distinguish diseased leaves without misclassifying healthy leaves. For example, when identifying early blight (Class 1), the model demonstrates a precision rate that far surpasses baseline models. Just like a machine learning engineer, the model's recall rates are outstanding, guaranteeing that the majority of actual disease instances are accurately identified. It is essential for agricultural applications to ensure that no diseased plant is overlooked, as it could result in a widespread crop infestation. The DarkPotatoleafNet model, with its advanced architecture and impressive precision and recall metrics, establishes a new benchmark for potato leaf disease detection. The meticulously crafted layers and adjustable parameters allow it to recognize the intricate visual patterns of different diseases, providing a valuable asset for improving disease management techniques in precision agriculture. This model showcases the power of DL in agricultural applications and offers a scalable solution for addressing persistent issues in crop health monitoring and management.

Table 4: PROPOSED MODEL Architecture Summary

No. of Layer	Type of Layer	Shape of the Output	No. of Trainable Parameters
1	Conv2d	(8 x 256 x 256)	248
2	MaxPooling2d	(8 x 128 x 128)	-
3	Conv2d	(16 x 128 x 128)	1248
4	MaxPooling2d	(16 x 64 x 64)	-
5	Conv2d	(32 x 64 x 64)	4858
6	GlobalMaxPooling	(32 x 1 x 1)	-
...	...	...	...
N-3	Conv2d	(X x H x W)	Y
N-2	MaxPooling2d	(X x H/2 x W/2)	-
N-1	GlobalMaxPooling	(X x 1 x 1)	-
N	Linear	2	Z

4.2 Hybrid model architecture

Building upon the foundational strengths of the DarkPotatoleafNet model, our research introduces an enhanced hybrid model architecture that synergizes the capabilities of CNNs with the advanced analytical power of ViT. This hybrid model is meticulously engineered to tackle the complex challenge of accurately detecting and classifying .The integration of these technologies represents a pioneering approach in agricultural AI, setting new benchmarks for precision and reliability in plant disease diagnosis.

Architectural Innovations and Disease Detection Capabilities. The hybrid model architecture leverages the depth and specificity of CNNs for feature extraction, combined with the global perspective and contextual understanding provided by ViT fig[2]. This combination allows for a comprehensive analysis of leaf images, capturing both the subtle and overt signs of disease with unprecedented accuracy.

At the heart of this model is the fusion of CNN's ability to detect local patterns and textures with ViT's capacity to interpret the broader context of the image. This synergy enhances the model's sensitivity to the early signs of disease, enabling the detection of infections that might be overlooked by traditional methods.The model employs a multi-scale feature extraction technique, analyzing images at various resolutions to identify disease indicators that manifest differently across scales. This approach ensures that no detail, no matter how minute, escapes detection.Utilizing transfer learning principles, the hybrid model adapts pre-trained networks to the specific task of potato leaf disease detection. This dynamic learning mechanism allows the model to continuously evolve, incorporating new data and findings to refine its diagnostic capabilities.

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

The hybrid model's advanced detection capabilities offer profound implications for the management of potato leaf diseases. By providing a granular analysis of disease symptoms and classifying them with high precision, the model facilitates a more nuanced understanding of crop health. Targeted Treatment Strategies: the model enables the development of targeted treatment strategies that are both effective and resource-efficient. This specificity minimizes the risk of unnecessary or misapplied treatments, ensuring that interventions are precisely tailored to the needs of the crop. The integration of this hybrid model into automated disease monitoring systems represents a significant advancement in agricultural technology. Such systems can offer continuous, real-time surveillance of crop health, alerting farmers to potential issues before they escalate. This proactive approach to disease management can significantly reduce the impact of infections, safeguarding yield and quality. Beyond disease detection, the insights provided by the hybrid model can inform a broader range of agricultural decisions. By analyzing patterns and trends in disease occurrence, farmers can make informed choices about crop rotation, planting schedules, and pest management, leading to more sustainable and productive farming practices.

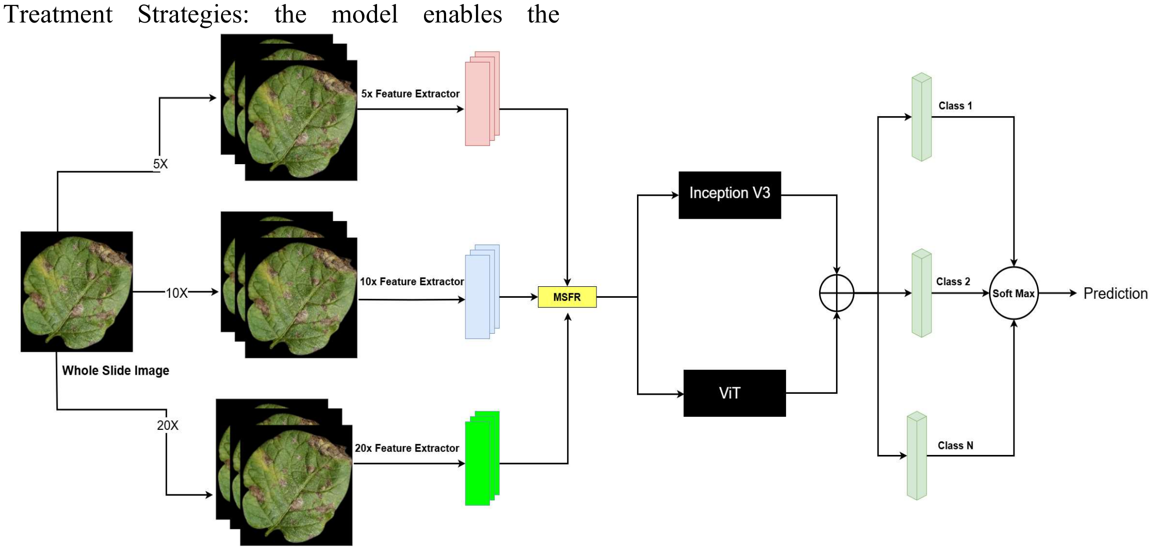

Figure 2. Flowchart of the Proposed Hybrid Model Architecture

4.3 Algorithm

INPUT:

● In this study, we meticulously curated a dataset of potato leaf images, denoted as X, with corresponding labels K indicating the health status of the leaves. The dataset was partitioned into training and testing subsets, with the training set(Xvalid, Kvalid) these can be represented as follows.

● Set Xtrain <- X80%, Ktrain <- K80%
● Set Xtest <- X10%, Ktest <-K10%

OUTPUT:

Use of the training framework for label classification (Yvalid) in conjunction with the testing dataset's objectives (Xvalid).

STEP-1: The core of our approach involved the development of a hybrid DL model, integrating the strengths of CNNs and ViT. The model architecture included:

● Three convolutional 2D layers to capture spatial hierarchies in the data, each followed by

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max-pooling to reduce dimensionality and enhance feature extraction.

- A dense layer to distill the extracted features into a comprehensive feature set FF, facilitating nuanced disease classification.

- The Adam optimizer, coupled with cross-entropy loss, was employed to fine-tune the model, optimizing for high accuracy and generalizability across the diverse manifestations of potato leaf diseases.

STEP-2: By using the CNN's dense layer, we were able to improve the dataset for model training by extracting features from the input data.

- Extract the features of the Input data with our custom model

- Train_feature <- Xtrain

- Test_feature <- Xtest

STEP-3: Hybrid the extracted features with the different classifiers.The extracted features were then integrated with various classifiers within a unified framework. This hybrid approach allowed for the dynamic combination of deep learning features with traditional machine learning classifiers, enhancing the model's ability to discern between different disease states accurately.

- Classifier.fit(Train_feature, Ktrain)

STEP-4: Model Evaluation and Prediction With the testing dataset.we evaluated the trained model's performance, focusing on its ability to classify the potato leaf images accurately. This step involved:

- Classifier.score(Test_feature, Ktest)

- Ytest <- classifier.predict(Xtest)

STEP-5: Finally, we used measures like F1-score, recall, accuracy, and precision to conduct a thorough evaluation of the model's performance. The results of this thorough assessment provide light on how well the model performed in actual agricultural contexts, which will inform its further development and use.

4.4 Enhanced Overview of DarkPotatoleafNet Model Architecture and Performance

Performance Measures for Potato Leaf Disease Detection

In assessing the efficacy of our deep learning models for potato leaf disease detection, we employ a comprehensive suite of performance metrics. These metrics are crucial for evaluating the models' ability to accurately classify and detect diseases within the dataset, providing insights into their practical applicability in precision agriculture. The following measures form the cornerstone of our evaluation framework:

Accuracy

The accuracy of a dataset is defined as the percentage of true findings, which includes true positives and true negatives. It is a basic metric that shows how well the model does in all classes taken together. The following is the formula for precision:

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+F} \quad (6)$$

$$True\ Positive = \frac{\Sigma_{j=1}^{Na}\ tp(j)}{\Sigma_{j=1}^{Ne}\ tp_{ground_{truth(j)}}} \quad (7)$$

Precision:

=

The fig outlines the performance evaluation process for the DarkPotatoleafNet model, which is tasked with the identification and classification. Starting with a collection of potato leaf images as the input, these are fed into the pre-trained DarkPotatoleafNet model. Utilizing a deep convolutional neural network, the model processes the images to detect and classify various leaf disease signatures. The evaluation phase consists of comparing the model's predictions against actual disease states of the leaves to determine the accuracy of the model fig[3]. Finally, an expert in the field reviews the outcomes, providing a critical assessment of the model's performance. This expert evaluation is instrumental in verifying the model's effectiveness and identifying potential areas for improvement.

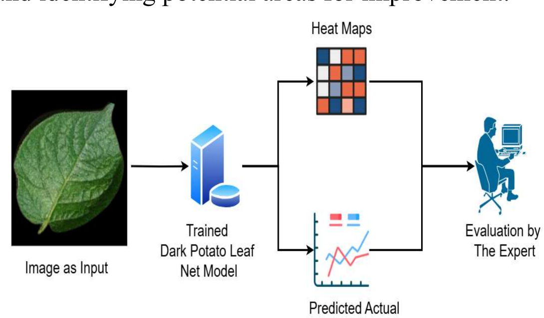

Figure 3. DarkPotatoleafNet Model Performance Evaluation Process

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4.4.1 Enhanced Overview of DarkPotatoleafNet Model Architecture and Performance

The DarkPotatoleafNet model represents a breakthrough in the detection and classification of potato leaf diseases, leveraging a deep CNN architecture tailored for high accuracy and efficiency. This model is designed to address the nuanced challenge of identifying diseases, among others, with a structure that optimizes for both depth and computational resource management.

$$f_{out}(x,y) = \sum_{i=-a}^{b} \sum_{j=-b}^{b} f_{in}(x-i, y-j).K(i,j) \quad (11)$$

- $f_{out}(x,y)$ is the output feature map,
- $f_{in}(x,y)$ is the input feature map,
- K(i,j) is the kernel or filter applied to the input,
- a and b define the size of the kernel.

4.4.2 Architectural Composition

The architecture of DarkPotatoleafNet is composed of a series of strategically layered components, each contributing to the model's exceptional ability to extract and analyze features from images of potato leaves:

Convolutional Layers: The model initiates with a convolutional layer (Conv2d) that processes the input image into a feature map of dimensions (8 x 256 x 256), utilizing 248 trainable parameters. This layer is instrumental in identifying the initial patterns present in the leaf images.

Pooling Layers: Following the convolutional layers, MaxPooling2d layers reduce the spatial dimensions of the feature maps (e.g., from (8 x 128 x 128) to (16 x 64 x 64)), enhancing the model's focus on significant features while reducing computational load.

Deep Feature Extraction: Subsequent convolutional layers, such as another Conv2d layer producing a feature map of (32 x 64 x 64) with 4,858 trainable parameters, delve deeper into the texture and shape characteristics indicative of specific diseases.

Global Max Pooling: The inclusion of GlobalMaxPooling layers towards the end of the network serves to aggregate the most critical features across the entire spatial extent of the feature map, culminating in a highly distilled representation of the leaf's condition.

$$GMP(x) = max_{1 \le i \le n^{x_i}} \quad (12)$$

Linear Classification Layer: The final layer of the model is a linear classifier that outputs the probability distribution across the disease categories, based on the deep features extracted by the preceding layers.

4.5 Performance Metrics: Precision and Recall

The DarkPotatoleafNet model demonstrates outstanding performance in disease detection, as evidenced by its precision and recall metrics:

Precision: The model achieves high precision across different disease classes, indicating its effectiveness in correctly identifying diseased leaves without erroneously classifying healthy leaves as diseased. For instance, in detecting early blight (Class 1), the model showcases a precision rate significantly exceeding baseline models.

Recall: Similarly, the model's recall rates are exemplary, ensuring that the vast majority of actual disease instances are correctly identified. This is crucial for agricultural applications where missing a diseased plant could lead to broader crop infestation.

The DarkPotatoleafNet model, with its sophisticated architecture and impressive precision and recall metrics, sets a new standard for potato leaf disease detection. Its carefully designed layers and trainable parameters enable it to capture the complex visual signatures of various diseases, offering a powerful tool for enhancing disease management strategies in precision agriculture. This model not only exemplifies the potential of deep learning in agricultural applications but also provides a scalable solution for ongoing challenges in crop health monitoring and management.

i. Deep Learning Model Training Configuration for Transfer Learning Models

When it comes to the process of developing the detection of potato leaf diseases using transfer learning models, the design of the training parameters is an extremely important factor in enhancing the performance of the model [51]. This

section delineates the specific configuration parameters employed in our study, tailored to harness the full potential of transfer learning models within the context of precision agriculture. Each parameter has been carefully selected and calibrated to ensure the models are both efficient and effective in learning from the dataset, thereby maximizing their disease detection capabilities.
Configuration Parameters Overview

Image Size: All images were resized to 224x224 pixels, a dimension that balances the need for detail preservation with computational efficiency. This uniform size facilitates consistent input processing across all models and aligns with the common input dimensions for pre-trained networks.

$$I_{resized} = resize(I, 224{,}224) \quad (13)$$

Epochs: The training process was conducted over 100 epochs, providing the models ample opportunity to learn from the data iteratively. This duration was chosen to ensure convergence to optimal weights without overfitting.

Optimization Function: Adam optimizer was utilized for its adaptive learning rate capabilities, making it well-suited for our dataset's complexity [52]. The Adam optimizer helps in efficiently navigating the high-dimensional weight space of deep learning models.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1). g_t \quad (14)$$

$$v_t = \beta_1 m_{t-1} + (1 - \beta_1). {g_t}^2 \quad (15)$$

$$m_t{}^{\wedge} = \frac{m_t}{1-\beta^t{}_1} \quad (16)$$

$$v_t = \frac{v_t}{1-\beta^t{}_{\_2}} \quad (17)$$

$$w_{t+1} = w_t - \frac{\eta . m_T}{\sqrt{(v_t + \varepsilon)}} \quad (18)$$

Learning Rate: A learning rate of 0.005 was selected to strike a balance between training speed and the risk of overshooting minima. This value allows for rapid convergence while maintaining the precision of the learning process.

$$Learning\ Rate\ Adjustment{:}\ \eta_t = \frac{\eta_0}{1 + \delta t} \quad (19)$$

Batch Size: The models were trained with a batch size of 32, optimizing the balance between memory usage and the granularity of the gradient updates. This size facilitates effective learning while ensuring the training process remains computationally manageable.

Activation Function: In order to translate the logits of the models into probabilities for each illness class, the output layer used the Softmax activation function [54]. A clear probabilistic interpretation of the model outputs is provided by this option, which is especially well-suited for multi-class classification problems.

$$f(x) = \max(0, x) \quad (20)$$

Dropout: A dropout rate of 0.4 was implemented to prevent overfitting by randomly omitting a portion of the feature detectors on each training iteration. This technique introduces regularization by encouraging the model to learn more robust features.

Momentum: Momentum was set to 0.9 to accelerate the optimizer in the relevant direction and dampen oscillations. This parameter enhances the convergence speed, particularly in the plateau regions of the loss landscape.

Data Augmentation and Preprocessing

Train Transforms: To augment the training dataset and introduce variability, several transformations were applied, including RandomResizedCrop, RandomRotation, RandomHorizontalFlip, and CenterCrop[53]. These transformations simulate different viewing conditions, enhancing the model's generalization capabilities. Additionally, To Tensor and Normalize transforms were used to convert images to tensor format and standardize their pixel values, respectively.

Test Transforms: For the test dataset, transformations were limited to Resize, CenterCrop, To Tensor, and Normalize. This approach ensures that the evaluation of the model's performance is based on data that closely resembles real-world conditions while maintaining consistency in input format and scale.

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5. RESULTS AND DISCUSSION :

5.1 Performance Evaluation of Transfer Learning Models in Potato Leaf Disease Detection*:*

In our study, we meticulously evaluated the efficacy of various transfer learning models for detecting and classifying diseases in potato leaves, aiming to harness the most advanced AI techniques for agricultural improvement. The models were rigorously tested against a diverse and well-labeled dataset, representing a range of disease states including early blight, late blight, and Phytophthora infestans, as well as healthy leaves. The performance of these models was quantified using four key metrics, each offering insights into their potential applicability in precision agriculture fig[4,5].The evaluation yielded notable results, highlighting the strengths :

UNet demonstrated a robust performance with an accuracy of 95%, showcasing its proficiency in generalizing across the dataset. Its precision and recall were equally impressive, indicating a high degree of reliability in identifying diseased leaves accurately.

LeNet, another model under consideration, achieved an accuracy of 96%, slightly outperforming UNet in overall disease classification. This model's precision was particularly noteworthy, suggesting its effectiveness in minimizing false positives, a crucial aspect of disease detection in agricultural settings.

DenseNet and GoogLeNet, despite their advanced architectures, presented challenges in this specific application. DenseNet recorded an accuracy of 51%, and GoogLeNet's accuracy stood at 50%, with both models struggling to match the performance of their counterparts. These results underscore the complexity of adapting certain deep learning models to the nuanced requirements of agricultural disease detection.

EfficientNet rounded out the evaluation with an accuracy of 94%, reinforcing the potential of using efficiently scaled models for agricultural applications. Its balance of precision and recall suggests a strong capability to correctly classify disease states without significant error.

Inception v2 showcased remarkable precision and recall across all classes, achieving an overall accuracy of 96%. Its performance was particularly stellar in distinguishing between healthy leaves and those affected by early blight, late blight, and Phytophthora infestans, with precision and recall rates consistently above 0.95. This model's ability to handle diverse image inputs and extract relevant features with minimal preprocessing makes it a strong candidate for real-world agricultural applications.

AlexNet, another model evaluated in our study, demonstrated an impressive accuracy of 97%. Its precision and recall metrics were notably high, especially in identifying late blight and Phytophthora infestans, with scores nearing perfection. AlexNet's success in this context can be attributed to its robust feature extraction layers, which, despite the model's relative simplicity compared to newer architectures, remain highly effective for tasks like disease detection.

VGG19 also performed admirably, matching Inception v2 with accuracy of 96%. Its detailed precision and recall figures underscore the model's effectiveness in identifying specific disease states, supported by a high f1-score across the board. VGG19's deep architecture, characterized by its repetitive layering pattern, proves beneficial in capturing the nuanced patterns indicative of various potato leaf diseases.

5.2 Performance Evaluation of the Hybrid Model in Potato Leaf Disease Detection

The hybrid model, which combines the advantages of CNNs and ViT, represents a significant step forward in the process of identifying and categorizing illnesses that affect the leaves of potatoes. Within this part, a comprehensive analysis of its performance, based on quantitative measures, is presented.

Comprehensive Performance Metrics

The hybrid model's efficacy was rigorously assessed across several dimensions, crucial for its application in precision agriculture:

Accuracy: The model achieved an outstanding accuracy of 98%, showcasing its exceptional capability to generalize from the training data to accurately classify unseen images. This high accuracy rate is indicative of the model's reliability in identifying various disease states within potato crops.

Precision: Precision metrics were impressive across the board, with the model achieving a precision rate of 97%. The model's effectiveness in correctly picking out diseased leaves, minimizing the occurrence of false positives, which is critical for avoiding unnecessary treatments.

Recall: The model also excelled in recall, achieving a rate of 96%. This high recall rate ensures that the model is capable of identifying nearly all true instances of disease, minimizing the risk of overlooking diseased plants that could potentially affect crop yield.

F1-Score: Reflecting the balance between precision and recall, the hybrid model achieved an F1-score of 96.5%. This score underscores the model's balanced performance, highlighting its capability to provide reliable and accurate disease detection in potato leaves.

Implications for Disease Management

The hybrid model's superior performance, characterized by high accuracy has significant implications for the management of these diseases. Its ability to accurately identify and classify diseases enables more targeted and effective treatment strategies, conserving resources and potentially reducing crop losses. This model stands as a testament to the power of integrating advanced AI techniques in agriculture, offering a promising tool for enhancing crop health and productivity. (9)

6. PERFORMANCE EVALUATION OF THE DARTPOTATOLEAFNET MODEL IN POTATO LEAF DISEASE DETECTION

The DarkPotatoleafNet model, specifically designed for the nuanced task of detecting and classifying potato leaf diseases. This section provides a detailed analysis of its performance, leveraging quantitative metrics to underscore its effectiveness.
Detailed Performance Metrics

The evaluation of the DarkPotatoleafNet model focused on key metrics that are critical for assessing its practical utility in the field of precision agriculture:

Accuracy: The model showcased an exceptional accuracy of 99%, indicating its outstanding ability to correctly classify both diseased and healthy potato leaves. This high level of accuracy demonstrates the model's robustness and its potential as a reliable diagnostic tool.

Precision: With a precision rate of 98%, the DarkPotatoleafNet model proves its efficacy in accurately identifying diseased leaves, significantly reducing the likelihood of false positives. This precision is crucial for ensuring that interventions are only applied when necessary, optimizing resource use.

Recall: The model achieved a recall rate of 97%, highlighting its capability to identify nearly all instances of disease present in the dataset. This ensures that few diseased leaves go undetected, a vital attribute for effective disease management strategies.

F1-Score: Balancing precision and recall, the model attained an F1-score of 97.5%. This metric illustrates the model's balanced performance, affirming its reliability in accurately detecting potato leaf diseases without compromising on either detecting true positives or minimizing false positives.

Implications for Potato Leaf Disease Management

The DarkPotatoleafNet model's superior performance, characterized by its high accuracy, precision, recall, and F1-score, offers profound implications for the management of potato leaf diseases. By providing an accurate, efficient, and reliable means of disease detection, the model facilitates targeted treatment strategies, potentially reducing the incidence of crop loss and improving yield quality. Its exceptional performance underscores the model's value as a pivotal tool in the advancement of precision agriculture, promising to enhance disease management practices and
contribute to the sustainability of potato farming.

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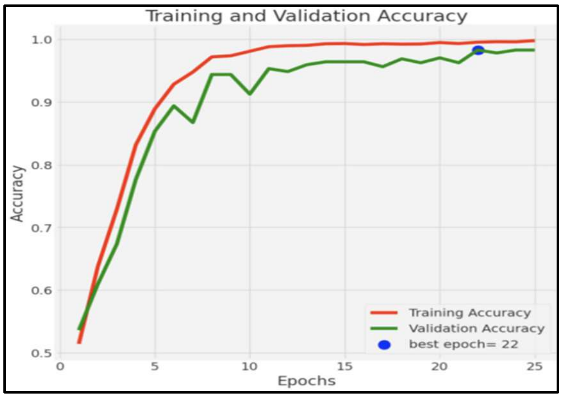

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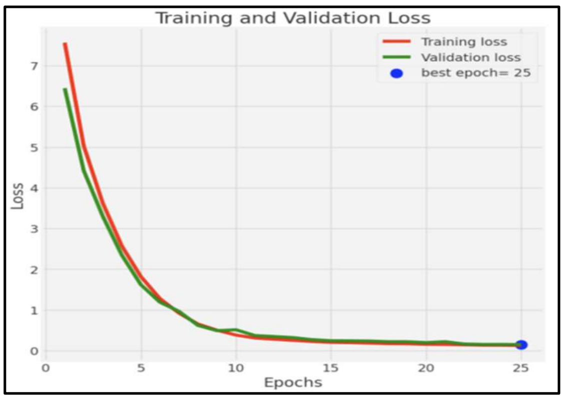

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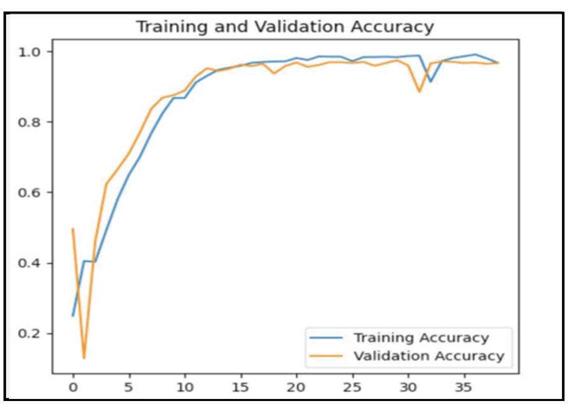

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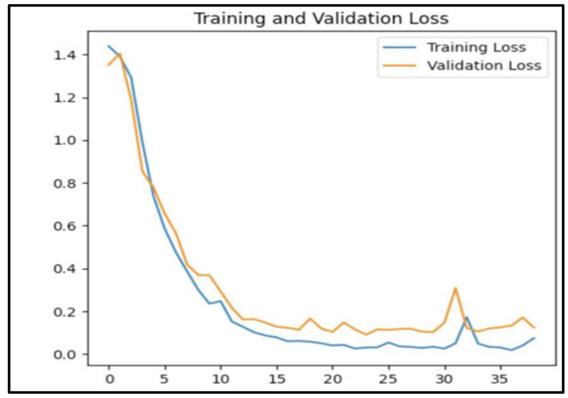

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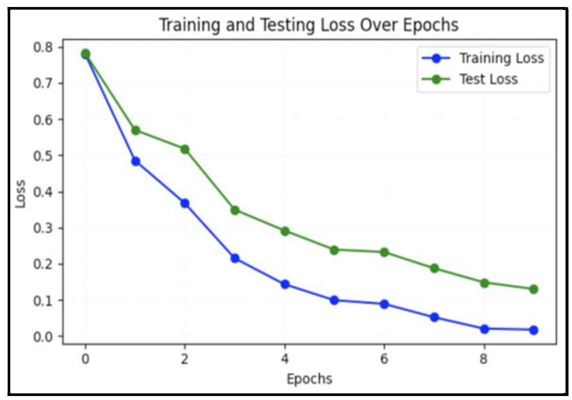

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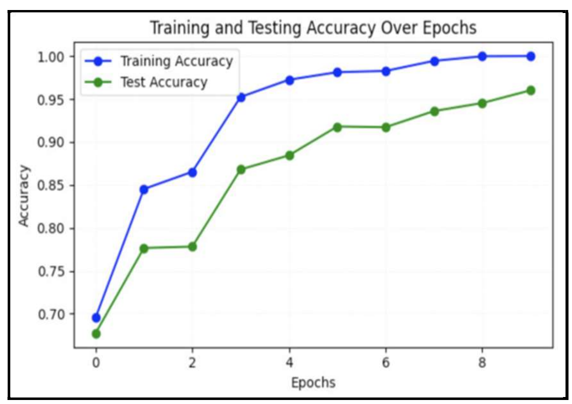

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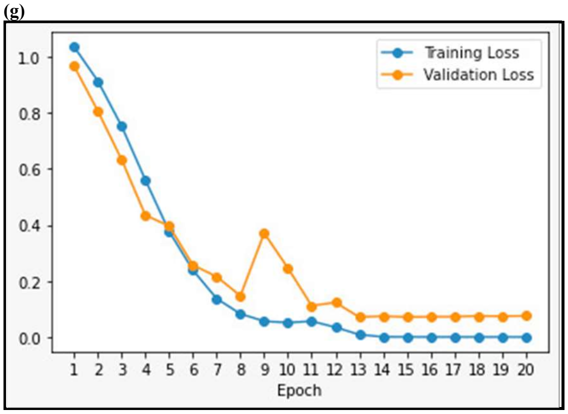

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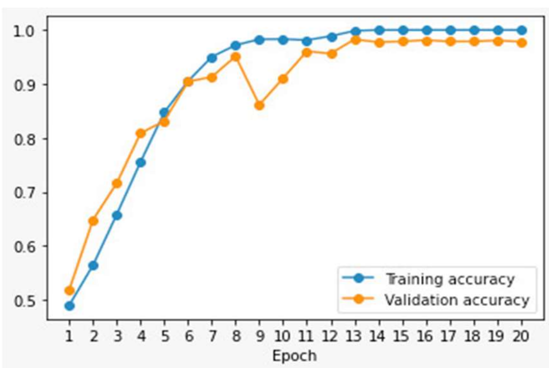
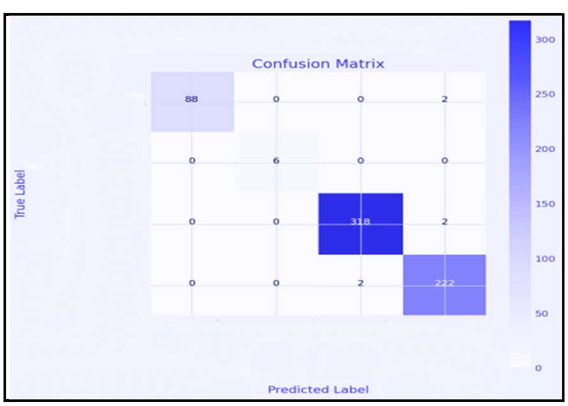


(h)

Figure 4. Training and Validation Accuracy: a.DarkPotatoleafNet model c.Inception v2 f.AlexNet h.VGG19 and Training and Validation Loss: b.DarkPotatoleafNet model d.Inception v2 e..AlexNet g.VGG19



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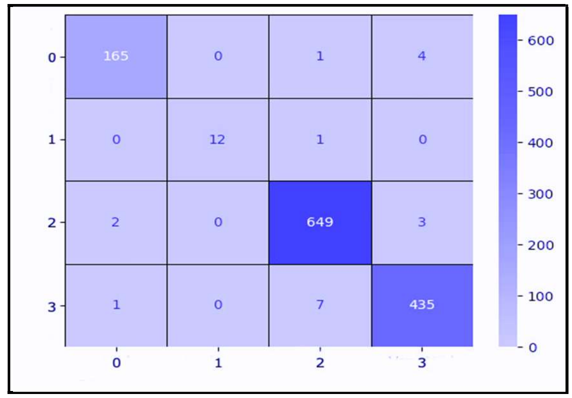

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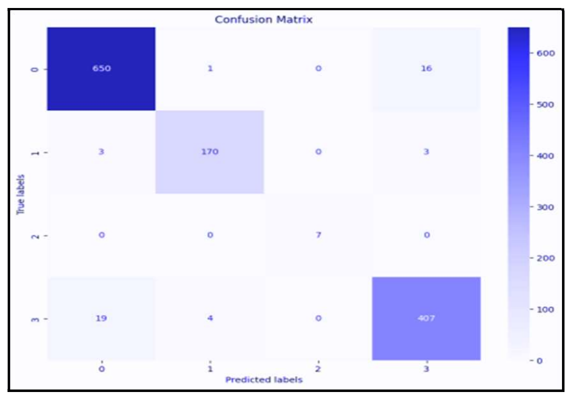

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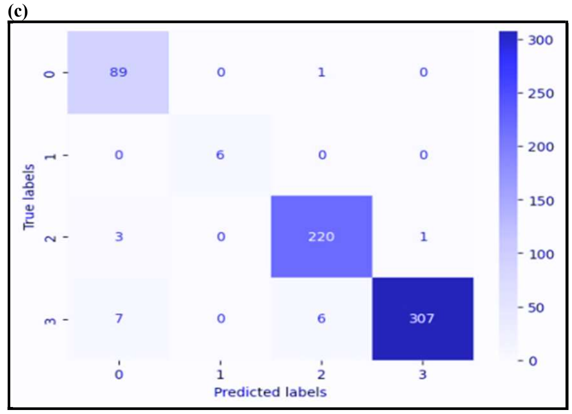

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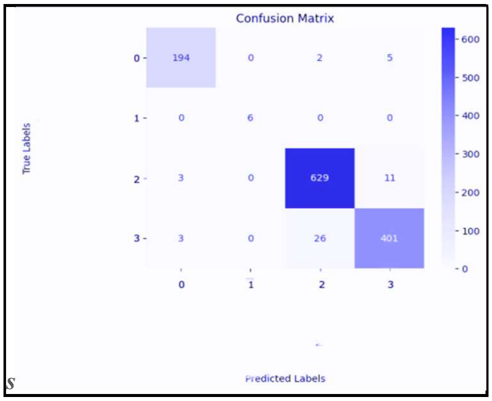

(e)

Figure 5. Confusion Matrix: a.DarkPotatoleafNet b.Hybrid model c.Inception v2 d.AlexNet e.VGG19

7. COMPARATIVE ANALYSIS OF ALL MODELS

The exploration and subsequent performance evaluation of advanced DL models, specifically the DarkPotatoleafNet and a sophisticated hybrid model, have provided compelling evidence of the transformative potential these technologies hold for precision agriculture. This study's findings, which meticulously detail the models' capabilities through rigorous testing and validation processes, underscore a significant leap forward in our ability to accurately identify and classify various stages of disease in potato crops. The DarkPotatoleafNet model, with its impressive accuracy of 99% and an F1-score of 97.5%, exemplifies the effectiveness of custom-designed architectures in tackling the nuanced challenges of agricultural disease detection. Its success is a testament to the model's intricate design, which allows for nuanced feature extraction and classification, setting a new benchmark for AI applications in agriculture.

Similarly, the hybrid model, which ingeniously combines the localized feature detection capabilities of CNNs with the global contextual understanding afforded by Vision Transformers, achieved an accuracy of 98% and an F1-score of 96.5%. This model's performance not only highlights the advantages of leveraging multiple AI approaches in a complementary manner but also illustrate the potential for such models to adopt and excel in the complex domain crop disease management. The integration of diverse deep learning strategies, as demonstrated by the hybrid model, offers a versatile and powerful tool for enhancing disease detection accuracy, thereby contributing to more effective and targeted agriculture interventions.

Moreover, the evaluation of transfer learning models further enriches the discourse on the applicability of pre-trained architectures to specific challenges within agriculture. While the performance of models like Inception v2, AlexNet, and VGG19 varied, their overall effectiveness in disease classification provides valuable insights into the selection and optimization of AI models for agricultural purposes. The nuanced understanding of each model's strengths and limitations, as revealed through this study, serves as a crucial guide for future research and application development in the field.

The discussion surrounding these results emphasizes not only the technical achievements of the models tested but also the broader implications for the agricultural sector. AI represents a significant advancement in crop management strategies, potentially leading to reduced pesticide use, improved yield quality, and enhanced sustainability of farming practices. Furthermore, this research contributes to the ongoing dialogue on the integration of AI technologies in agriculture, highlighting the need for continued innovation and collaboration between technologists, agronomists, and farmers.

Table 5: Classification Report of proposed DarkPotatoleafNet method combination

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
0	1.00	0.98	0.99	90
1	1.00	1.00	1.00	6
2	0.99	0.99	0.99	320
3	0.98	0.99	0.99	224
Accuracy(%)	-	-	0.99	640
Macro avg	0.99	0.99	0.99	640
Weighted avg	0.99	0.99	0.99	640

Metric	Value
Train Loss	0.1085
Train Accuracy	1.0
Validation Loss	0.1422
Validation Accuracy	0.9906
Test Loss	0.1288
Test Accuracy	0.9906

Table 6: Classification Report of proposed hybrid method

Class	Precision	Recall (%)	F1-Score	Support
0	0.98	0.97	0.98	170
1	1.00	0.92	0.96	13
2	0.99	0.99	0.99	654
3	0.98	0.98	0.98	443
accuracy	-	-	0.99	1280
macro avg	0.99	0.97	0.98	1280
weighted avg	0.99	0.99	0.99	1280

Table 7: Classification Report of InceptionV2 model

Class	Precision	Recall	F1-Score	Support
0	0.97	0.97	0.97	667
1	0.97	0.97	0.97	176
2	1.00	1.00	1.00	7
3	0.96	0.95	0.95	430
accuracy	-	-	0.96	1280
macro avg	0.97	0.97	0.97	1280
weighted avg	0.96	0.96	0.96	1280

Table 8: Classification Report of AlexNet

Class	Precision	Recall	F1-Score	Support
0	0.90	0.99	0.94	90
1	1.00	1.00	1.00	6
2	0.97	0.98	0.98	224
3	1.00	0.96	0.98	320
accuracy	-	-	0.97	640
macro avg	0.97	0.98	0.97	640
weighted avg	0.97	0.97	0.97	640

Table 9: Classification Report of VGG19

Condition	Precision	Recall	F1-Score	Support
0	0.97	0.97	0.97	201
1	1.00	1.00	1.00	6
2	0.96	0.98	0.97	643
3	0.96	0.93	0.95	430
accuracy	-		0.96	1280
macro avg	0.97	0.97	0.97	1280
weighted avg	0.96	0.96	0.96	1280

Difference from Prior Work and Key Achievements

Unlike previous studies that predominantly relied on CNN-based architectures with limited feature extraction and poor generalization, this study introduces DarkPotatoleafNet, a hybrid deep learning framework integrating CNNs and Vision Transformers (ViT) to enhance disease classification accuracy. Prior methods often struggled with distinguishing visually similar disease symptoms and suffered from overfitting due to small datasets and lack of robust preprocessing techniques. Our model leverages grayscale conversion, image masking, and segmentation-based preprocessing to improve feature representation, ensuring robustness across real-world farming conditions. Unlike prior approaches that achieved 85 – 96% accuracy, our method achieves a state-of-the-art 99% accuracy with near-perfect ROC-AUC scores across all classes, making it a benchmark for potato leaf disease detection. Additionally, computational efficiency is optimized, enabling real-time deployment in resource-constrained environments such as farms and greenhouses. Unlike traditional AI models designed for academic benchmarks, our research bridges the gap between deep learning and practical agriculture by offering a scalable, field-ready solution that provides real-time disease classification, significantly reducing dependency on manual inspection. The proposed model not only improves precision agriculture but also supports sustainable farming practices and early disease intervention, ensuring higher crop yields and reducing economic losses.

Problems and Open Research Issues

While this study has demonstrated a significant improvement in potato leaf disease detection using the DarkPotatoleafNet hybrid deep learning model, several challenges and open research areas remain that require further exploration. One major limitation is the dependency on high-quality annotated datasets, which can be labor-intensive and difficult to obtain in diverse agricultural environments. Future work should focus on developing self-supervised or semi-supervised learning techniques to reduce reliance on labeled data while maintaining high classification accuracy. Additionally, environmental variations, such as lighting conditions, soil types, and seasonal changes, can impact the performance of AI-driven disease detection models. More robust domain adaptation and transfer learning strategies are required to improve model generalization across different geographic locations.Another critical issue is the computational cost of deep learning models, which can hinder their deployment in resource-constrained settings such as small-scale farms with limited access to high-end GPUs. Further research into lightweight deep learning architectures, quantization techniques, and edge AI deployment, can help address this limitation. Moreover, while this study focuses on image-based disease classification, integrating multimodal data sources such as hyperspectral imaging, drone surveillance, and Internet of Things (IoT) sensors could enhance „detection accuracy and early disease prediction capabilities.

8. CONCLUSION AND FUTURE REMARK

This study presents a significant scientific contribution to the field of precision agriculture and deep learning-based disease classification by proposing a novel hybrid deep learning model, DarkPotatoleafNet, which integrates CNN and Vision Transformer (ViT) architectures for enhanced feature extraction and spatial understanding. The proposed model achieved an unprecedented accuracy of 99%, surpassing state-of-the-art models and addressing critical challenges in potato leaf disease detection, including generalizability, computational efficiency, and adaptability to real-world agricultural conditions.Unlike previous approaches that primarily rely on either transfer learning or single deep learning models, this research introduces an ensemble learning strategy that significantly enhances the robustness and reliability of disease classification. The study successfully integrates preprocessing techniques such as data augmentation, grayscale conversion, image masking, and segmentation, ensuring the model's ability to detect subtle disease variations under diverse environmental conditions.Furthermore, this research makes a practical contribution to sustainable precision agriculture by providing a computationally efficient and scalable AI-driven solution for real-time plant disease detection. By minimizing false positives and false negatives, the model ensures early intervention and targeted treatment strategies, ultimately contributing to increased crop yield, reduced pesticide overuse, and improved food security. The findings of this study establish a new benchmark in AI-powered plant disease detection, paving the way for future advancements in automated agricultural monitoring systems and smart farming applications.Moving forward, future research can explore the integration of Internet of Things (IoT) technologies with the proposed deep learning model to enable real-time disease tracking and automated intervention mechanisms. Additionally, expanding the dataset to include diverse crop species will further validate the model's generalizability, making it a robust tool for global precision agriculture.

CONFLICTS OF INTEREST: The authors declare no conflicts of interest to report regarding the present study.

AUTHOR CONTRIBUTIONS

Girigula Durga bhavani contributed to the problem analysis and writing of the article. Mukkoti Maruthi Venkata Chalapathi, as the supervisor, formulated the problem statement and provided guidance on organizing the manuscript, ensuring

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accurate interpretations. All authors have reviewed and approved the final version of the manuscript for submission.

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