An Enhanced Deep Learning approach for crop health monitoring and disease prediction

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Research Article

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An Enhanced Deep Learning approach for crophealth monitoring and disease prediction

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Abstract:

Global warming and lack of immunity in crops have recently resulted in a significant increase in the spread of agricultural diseases. This leads to large-scale crop destruction, less cultivation, and ultimately financial loss for farmers. Identification and treatment of illnesses have become a big issue because of the fast development in disease diversity and lack of farmer knowledge. This paper investigates the application of deep learning for crop disease prediction using a newly acquired dataset of leaf images from Ghana. The dataset focuses on four major crops: cashew, tomato, cassava, and maize. The paper introduces hybrid deep learning models in terms of various evaluation metrics in identifying healthy and diseased plants based on leaf images. This paper also developed a novel hybrid model for this new dataset. The hybrid model ResNet50+VGG16 resulted in higher precision and accuracy in its predictions, evidencing strong performance and reliability. This work contributes to the development of accurate and accessible tools for crop disease diagnosis, potentially leading to improved agricultural practices and increased crop yields. Through the integration of newer and advanced deep learning techniques, this research will provide a significant step in the field of agriculture for monitoring crop health disease and prediction.

Keywords: ResNet50, VGG16, Crop disease Prediction, deep learning, hybrid model, increased crop yields.

Introduction:

The agricultural sector plays a pivotal role in contemporary society. Its significance cannot be overstated, as it serves as the backbone for ensuring food security and driving economic development. In 2050, The projected global population will be almost ten billion people. Consequently, the world's food production systems would face a lot of pressure. Food security depends on agriculture; however, many factors continuously put crop yields in danger. Among these threats, crop pests and diseases greatly contribute to low yields resulting in losses estimated at 20-40% annually from global agricultural output. These losses not only ruin farmers but also threaten the global food supply. Agricultural production faces significant challenges due to crop damage caused by pests and diseases. Delays in the detection of plant pests and diseases lead to food insecurity in general. Early detection helps prevent and control plant pests and diseases and is also important for managing and determining agricultural practices. Traditional methods for pest and crop condition monitoring often rely on manual scouting, which can be time-consuming, labor-intensive, and prone to human error.

Plant pests and diseases can harm agriculture. Plants affected by pests or diseases show signs or lesions on leaves, stems, flowers or fruits. There are usually patterns that can be used to diagnose different conditions for each pest and disease. One of the main sources of plant pests and diseases is the plant leaves, where the symptoms of the pest/disease start to appear. Recently, the detection of crop pests and diseases has been an important task, which has attracted the attention of researchers. This is partly because farmers rely on extension agents to use their training and experience to control pests and diseases. This human intervention is not only objective but also error-prone, slow, laborious and ineffective. Inexperienced extension workers may provide incorrect diagnoses and provide incorrect mitigation measures that may cause damage to the environment.Fortunately, advancements in artificial intelligence (AI), particularly deep learning, offer a promising solution to these challenges. Deep learning algorithms excel at pattern recognition and classification tasks, particularly when dealing with complex visual data like images. This has opened exciting possibilities for the application of deep learning in agriculture, specifically for automated pest and cropcondition monitoring.

Crop pests and diseases are a major danger to global food security, resulting in large output losses every year. Traditional pest detection approaches, such as manual scouting, are labor-intensive, subject to human error, and frequently result in delayed identification. This emphasizes the critical need for more effective and precise methods of cop and pest identification in agricultural contexts.

Deep learning has emerged as an effective approach to image recognition and classification. Using deep learning techniques, we can create automated systems that evaluate agricultural photos and accurately detect healthy crops, pest species, and probable crop illnesses. This research investigates the use of a deep learning-based architecture for crop and pest identification. Our suggested approach has the potential to transform agricultural practices, allowing farmers to make more educated pest control decisions, and ultimately contributing to higher crop yields and a more secure food supply.

This paper aims to propose a new hybrid deep learning architecture framework that can be used to classify and identify diseases using the image of the infected plant. This paper explores the potential of deep learning techniques for revolutionizing crop and pest detection in agricultural settings. We propose a hybrid deep learning-based framework that leverages the power of convolutional neural networks (CNNs) to analyze agricultural images and accurately identify healthy crops, various pest species, and potential crop diseases. By implementing such a system, farmers can gain early insights into pest infestations and crop health, enabling them to make informed decisions regarding pest control measures, optimize crop management practices, and ultimately contribute to a more secure and sustainable food production system.

Dataset Description:

This dataset is collected from farms located around Ghana, West Africa. This dataset contains disease as well as healthy images of 4 plants: Cashew, Cassava, Maize and Tomato. This constitutes around 24,881 raw images as shown in Fig.1.and 102,976 augmented colour images as shown in Fig.2. This paper makes use of both resources for better predictions and accurate results and classification. This dataset has a split of 6,549 raw and 25,811 augmented images for Cashew, 7,508 raw and 26330 augmented images for Cassava, 5389 raw and 23657 augmented images for Maize and lastly 5435 raw and 27178 augmented images for Tomato respectively.

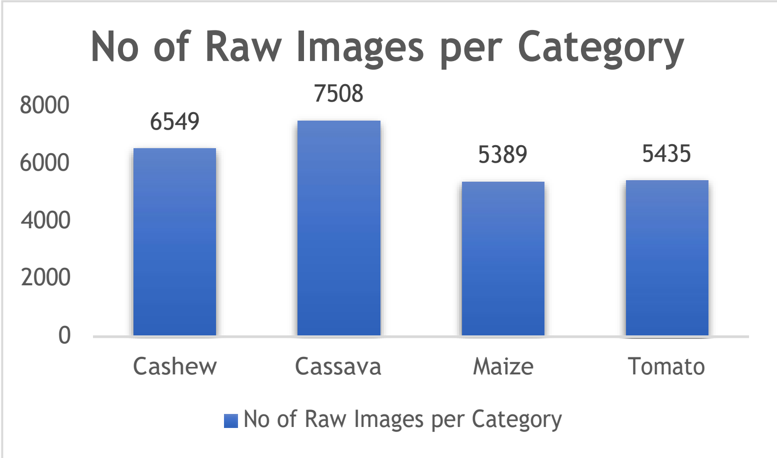

Fig 1: Distribution of Raw Images

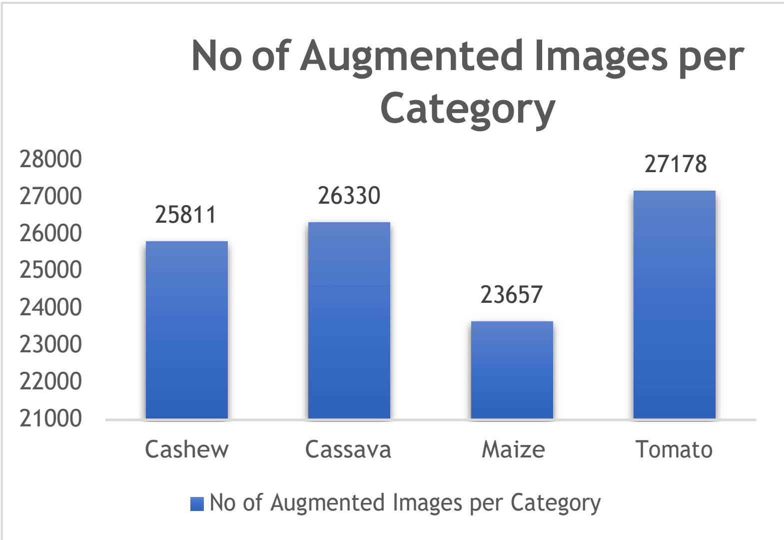

Fig.2: Distribution of Augmented Images

Each category contains sub-categories of diseases, below Fig.3. is for Cashew subcategories such as Anthracnose, Gummosis, Leaf Miner, Red rust, Healthy.Fig.4. depicts the cassava disease having subcategories such as Bacterial blight, Brown spot, green mite, Mosaic, Healthy.Fig.5. depicts the maize crop disease and its subcategories such as Fall armyworm, Grasshopper, Healthy, Leaf beetle, Leaf blight, Leaf spot, Streak virus. Fig 6 depicts the disease caused in tomato and its subcategories such as Healthy, Leaf blight, Leaf curl, Septoria leaf spot, Verticillium wilt.

Fig.3: Image Category-Cashew

Fig.4: Image Category-Cassava

Fig.5: Image Category-Maize

Fig.6: Image Category-Tomato

Related works:

Patrick Kwabena Mensah et al. [1] provide the core dataset for this paper. This dataset is being used in this paper for prediction and classification purposes. This could help improve crop yields and reduce food insecurity. The dataset was shot using a Canon camera, and then they were de-identified and validated by expert plant virologists. Jun Liu et al. [2] support this paper by using deep learning as a prediction technique for image classification of disease plants. It highlights our paper's motivation for the early detection of plant diseases using advancements in technologies and newer methods such as AI and deep learning. Shengyi et al. [3] researched crop pest recognition and used convolutional neural networks along with a parallel attention mechanism which is also deployable which makes it suitable for real-world problems. However, this research was only able to classify limited types of crop pests. Muammer türkoğlu et al. [4] have evaluated the performance results of different deep learning models along with feature extraction models like KNN etc even though they did not deploy any hybrid deep learning models to achieve the desired output and correct classification. S Divya Meena et al. [5] Created by fine-tuning the model parameters of various pre-trained architecture models, including DenseNet201, Hyperparameter Search 2D layer. However, this paper did not incorporate many diseases or plant species into the framework and might have also used many other models for their implementation such as AlexNet etc. Selvaraj et al. [6] have employed a transfer learning approach to train a model that can identify pests on banana plants. Although the generalizability of the model to real-world settings was not evaluated, they incorporated various images from several sources. Syeda Airas Burhan et al. [7] discuss upon plant disease detection and classification techniques. They emphasize the point that traditional methods are time-consuming and prone to errors so they use CNN and deep learning to achieve the result. Here ironically, they were only able to conduct this research on a limited amount of data. The actual results might vary if we use a larger dataset in place. Lawrence C. Ngugi et al. [8] used many deep learning algorithms such as CNN, SVM and many other machine learning algorithms in their paper. They compared the outputs of nearly 10 CNN models out of which DenseNet performed the highest. The limitations are inaccuracies caused by reliance on small datasets. Small datasets can lead to overfitting, where the system performs well on the data it is trained on, but poorly on new data. This paper also mentions that it could not distinguish between diseases with similar symptoms. Anuradha Badage [9] used Canny's edge detection algorithm to extract features out of the input images and use machine learning to perform analytics over the data. Still, this paper has achieved a minimum accuracy and had images being classified wrong too. Bo Wang et al. [10] studied using the

AlexNet architecture to identify the insect pest in the plant images. Even though other deep learning models achieve more accuracy when we input the same on a large dataset the results might vary. Similar to paper [8] M.Chithambarathanu et al. [11] has also compared several popularly known machine learning models such as Random forest and deep learning models such as Deep belief Network etc. in his paper. This paper used the images of citrus and cotton. Even Arun et al. [12] used several significant object detection frameworks achieving a mAP of 74.77% for the COCO dataset. Hiroaki kuzuhara et al. [13] has presented with a two-stage detection and identification by proposing a YOLOv3 for region proposal network along with Xception model as a re-identification method. Saim Khalid et al. [14] compared different version of YOLO from v3 to v8 and found that v8 has achieved the highest mAP of 84.7% and also developed an android application for real time pest detection. To get a more accurate understanding of the motivation of the project, the paper Ana Claudia T et al. [15] has been taken to understand and get deeper analytics on the 92 studies that were conducted during the period of 2016-2022. The main aim of this paper is to analyze the methodologies and limitations of all the analyzed papers. Wei Li at al. [16] employed three different deep learning models such as Faster CNN, Mask RCNN, YOLOv5. This paper has achieved a good accuracy inn their predictions. MingYuan Xin et al. [17] proposed a newer architecture in his paper by integrating a deep learning model-Deep CNN such as YOLO v4 in this case and Google data analytics into picture. This paper also introduces newer terms of analytics into picture such as 3D panoramic image synthesis algorithm etc. Thenmozhi k et al. [18] has used several pretrained models in the research such as AlexNet and ResNet. The limitations lie in the pace where the project did not also include a healthy dataset alongside for the comparison of the model performance. Iftikhar A. et al. [19] used several versions of real time detection deep learning model-YOLO, and compared its result alongside. Sangeetha T et al. [20] research also gives you a review of the proceeding of the different ways that are available for pest identification and classification that uses Machine learning and deep learning models.

Methodology:

This paper uses several deep-learning models such as VGG16, Convolution Neural Network (CNN), Inception, ResNet, DenseNet and MobileNet and we also implemented several hybrid models involving combinations of all the above-listed models with two of the most suitable optimisers Adam and SGD with momentum.

<u>Convolution:</u> $$Z[l]=W[l]*A[l-1]+b[l] \quad (1)$$

<u>Fully connected:</u> $$Z[l]=W[l]\cdot A[l-1]+b[l] \quad (2)$$

<u>Activation Function:</u> $$A[l]=\mathrm{ReLU}(Z[l]) \quad (3)$$

Visual Geometry Group (VGG16):

VGG16, a convolutional neural network noted for its clarity and image categorization abilities, uses 16 layered convolutional layers to achieve high accuracy. While training from the start is computationally expensive, its pre-trained weights facilitate transfer learning in a variety of computer vision applications.

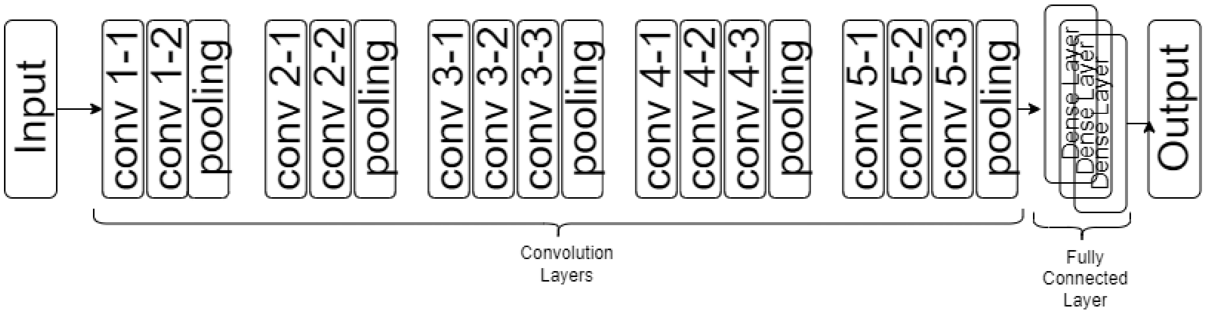

Fig.7: VGG16 Implementation [11]

Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) excel at analyzing visual data like images. They use special "convolutional" layers to identify patterns and features, making them ideal for tasks like object detection and image classification. CNNs have revolutionized computer vision and are a cornerstone of deep learning.

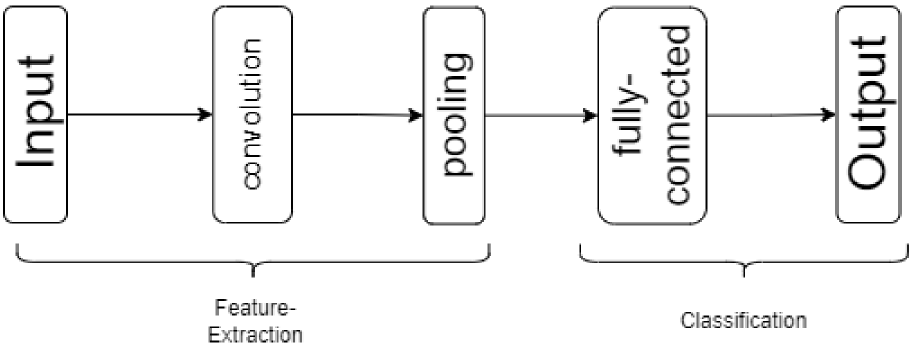

Fig.8: Basic CNN [12]

Inception:

Inception models, a deep learning architecture, use efficient "inception modules" that stack convolutional layers in parallel paths. This extracts diverse features at different resolutions, boosting accuracy in image recognition tasks like object detection and classification. While powerful, Inception models can be computationally demanding.

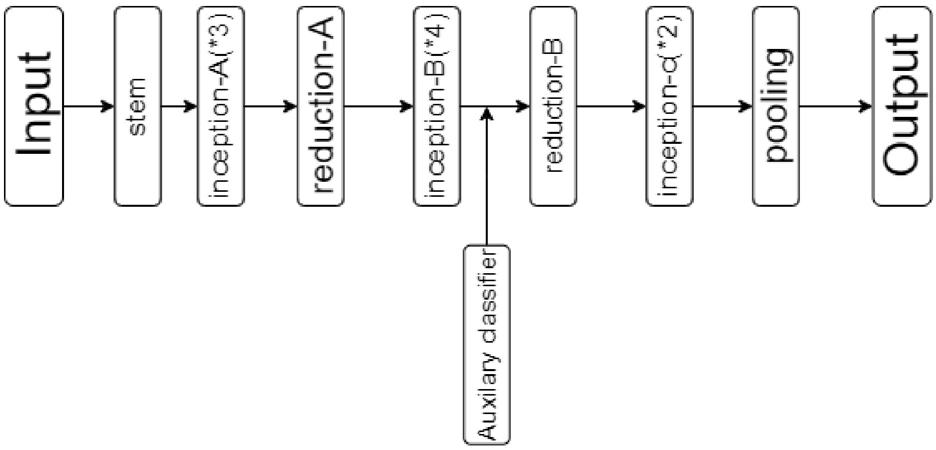

Fig.9: Inception Model Architecture [13]

Dense Net:

DenseNets, or Densely Connected Convolutional Networks, boast a unique architecture. Each layer connects directly to all subsequent layers, promoting strong feature propagation and encouraging feature reuse. This dense connectivity allows DenseNet to achieve high accuracy with fewer parameters compared to traditional CNNs.

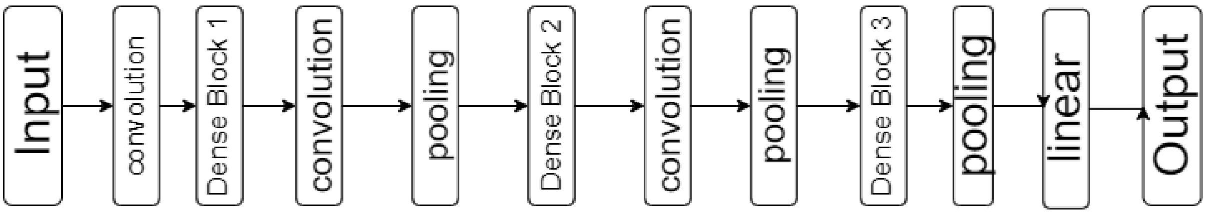

Fig.10: DenseNet Architecture [14]

MobileNet:

MobileNet is a lightweight convolutional neural network architecture designed for mobile and embedded devices. It prioritizes efficiency by using depthwise separable convolutions, reducing computational cost while maintaining good accuracy for image classification tasks. This makes it ideal for applications where processing power and battery life are limited.

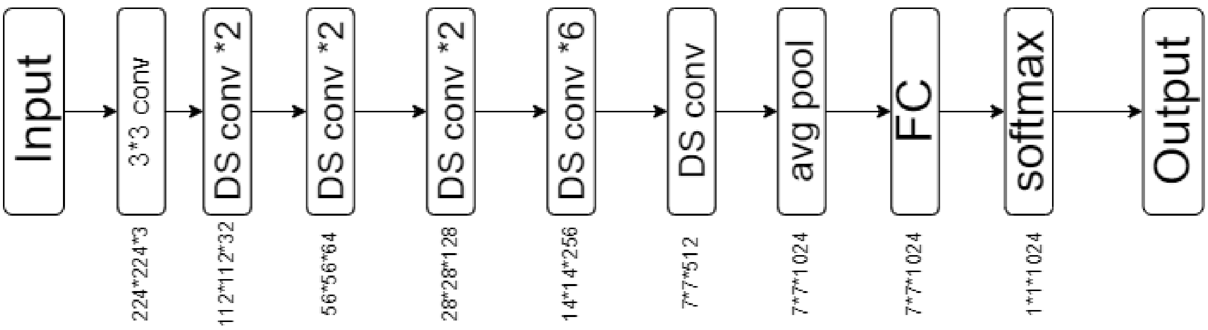

Fig.11: Mobile Net Architecture [15]

ResNet:

ResNet, or Residual Network, is a deep neural network architecture developed by Microsoft Research in 2015. ResNet uses skip connections to address the vanishing gradient problem, allowing for the training of extremely deep neural networks with hundreds of layers. ResNet, which uses residual blocks to learn residual functions, makes deep network optimization easier and has proven to be highly effective in a variety of computer vision tasks.

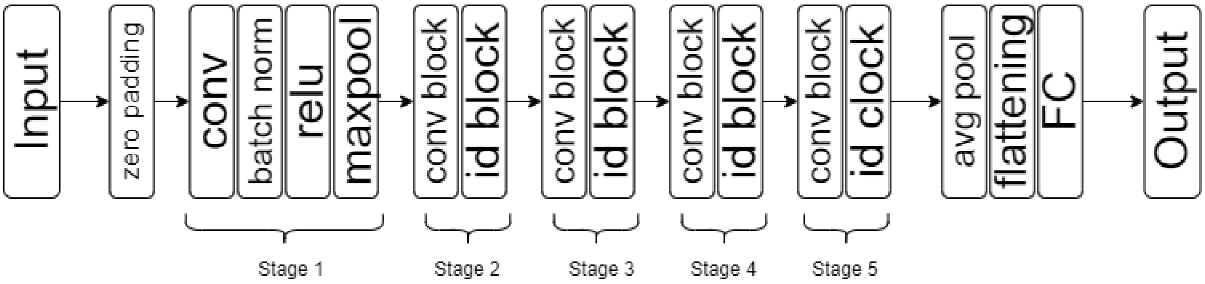

Fig.12.: ResNet Architecture [16]

Hybrid Model:

A hybrid model often combines several machine learning approaches or architectures to maximize their capabilities. A hybrid model, commonly used in transfer learning, combines pre-trained models with custom architectures to improve performance. Hybrid models can effectively tackle complicated tasks by mixing varied models, on different CNNs, under a single framework, providing greater flexibility and adaptation to changing data features.

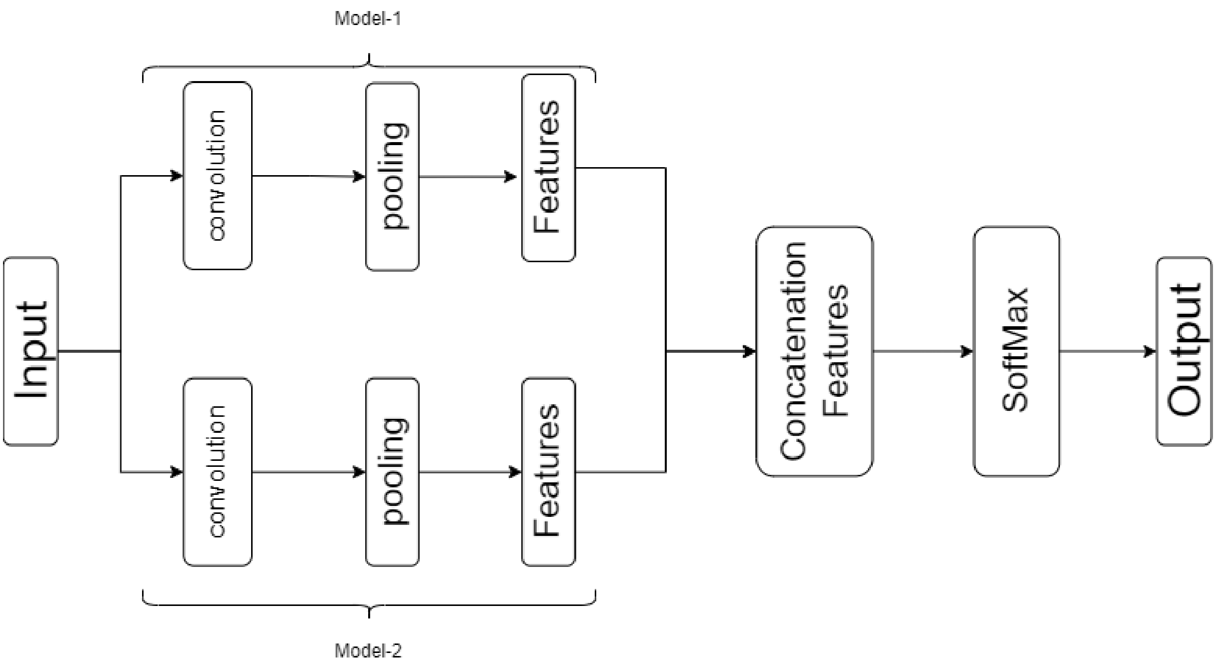

Fig.13: Multi-Class Hybrid Model [17]

Multi-branch CNN Model:

A multi-branch CNN Model uses different CNN architectures to capture different aspects of the given data and fuze it together to extract all the local and global aspects of the input data.

Adam Optimizer:

In machine learning, the Adam optimizer is a well-known technique for training neural networks. It is based on the strengths of two existing optimizers: stochastic gradient descent with momentum and RMSprop. This combination enables Adam to effectively overcome the obstacles of training complex models, making it a popular choice among machine learning practitioners.

SGD with Momentum:

Stochastic Gradient Descent (SGD) with momentum overcomes a limitation of SGD by accumulating previous gradients. It employs a momentum term to nudge updates in the same direction as earlier changes, smoothing out oscillations and hastening convergence to the loss function's minimum. This makes it an effective tool for training neural networks.

Proposed Work Architecture:

This paper focuses on building a multi-branch CNN architecture-hybrid model that consists of VGG16 and ResNet50 CNN models. This model is then compared with many other popular pre-trained CNN models such as Inception, MobileNet and other hybrid combinations. So, when coming to the idea of using multi-branch CNN architecture, each branch processes the input image differently or focuses on different aspects of the image. In the case of this current paper ResNet50 and VGG16 are used. This allows the model to extract diverse and complementary features from the input data. Transfer learning is used along with the weights from 'imagenet', which resulted in the reduction of training computation time.

The fully connected layers are not used for feature extraction. Flattening is used for ResNet50, while VGG16 uses Global Average Pooling. Now after extracting all the aspects of feature extraction from different models, we do a feature fusion where the extracted features from each branch are fused to create a unified representation that captures both local and global information about the input image.

To make sure that the model does not suffer from over-fitting, the model is given a drop-out layer where some neurons are nullified whilst, maintaining important and key features from the image. The model then is fed into two more dense layers where one layer has a ReLu activation function and the final layer with SoftMax activation function along with the number of classes to be predicted.

Lastly, the models are being tested with a dataset that is not seen during the training period and the values such as Accuracy, Precision, Recall are being analyzed and compared.

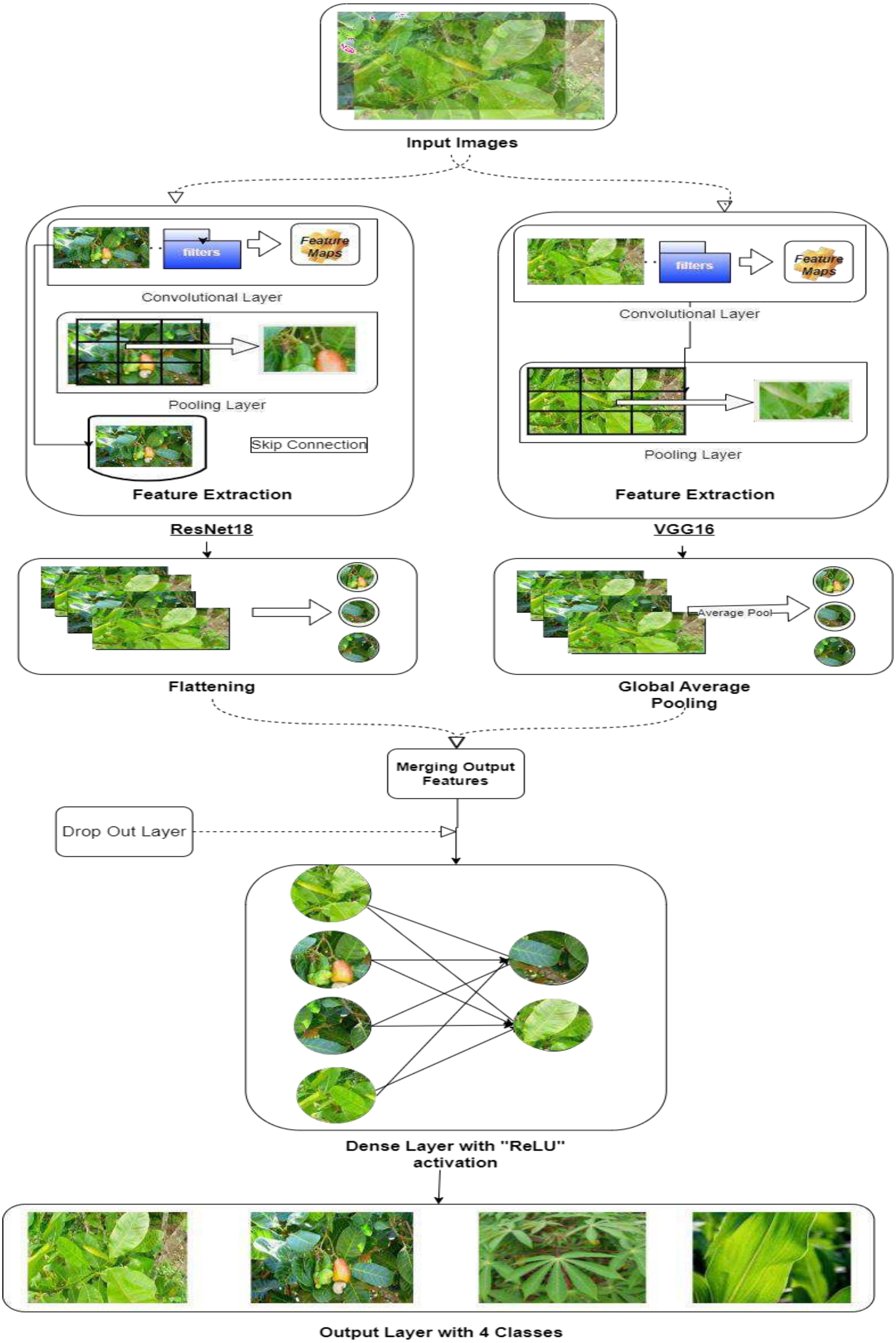

Fig.14. Proposed Architecture

Evaluation Metrics:

Accuracy:

Accuracy is a statistic for assessing the correctness of a model's predictions. It is calculated as the proportion of correct forecasts to the total number of predictions. The Equation 4 is as follows.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Precision:

Precision is a statistic used to evaluate the accuracy of a model's positive Predictions, reflecting the proportion of the correctly predicted cases out of all projected positive cases. It states the model's ability to avoid incorrect positive predictions. The Equation 5 is as follows

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

Recall:

Recall, known as sensitivity, is a metric that assesses a model's ability to correctly distinguish all positive instances from true positive situations. It shows the fraction of true positive forecasts among all the positive cases.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

Evaluation Results:

The model that we proposed has 2 divisions:

1. Classification Stage:
   In the classification stage, the model is given the whole dataset and the model is trained to classify the category of the plant leaf that is being given as input.

2. Identification Stage:
   After classification, the model then runs the snippet that corresponds to the predicted class of the image. For example: If I give a healthy cassava leaf image, the model first classifies the leaf as cassava and then runs another algorithm that identifies whether the plant is healthy or not. It also gives you the disease that the plant is affected with, provided the input image comes under one of the classes the model is being trained for.

Classification Stage:

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing Loss	Testing Accuracy
0.001	64	10	Adam	Hybrid	DenseNet+ResNet50	0.2010	0.9486	0.3189	0.9245	0.3689	93.08
					VGG16+Inception	0.0265	0.9907	0.1405	0.9627	0.1404	96.26
					VGG16+MobileNetV2	0.0537	0.9802	0.1729	0.9451	0.1729	94.51
					Inception+ResNet50	0.0316	0.9913	0.1643	0.9654	0.1643	96.54
					Inception+MobileNetV2	0.3746	0.8585	0.5595	0.7875	0.5594	78.75
					ResNet50+MobileNetV2	0.0095	0.9968	0.1408	0.9730	0.1408	97.30
					DenseNet+VGG16	0.0598	0.9854	0.0922	0.9568	0.0604	96.75
					VGG16+ResNet50	0.0200	0.9946	0.1198	0.9760	0.1197	97.59
0.001	64	10	SGD with Momentum	Hybrid	DenseNet+ResNet50	0.0035	0.9996	0.0792	0.9766	0.0791	97.65
					VGG16+Inception	0.1999	0.9484	0.3268	0.9275	0.3267	92.75
					VGG16+MobileNetV2	0.0649	0.9782	0.0955	0.9652	0.0955	96.52
					Inception+ResNet50	0.9383	0.5036	1.1339	0.2395	1.1338	23.94
					Inception+MobileNetV2	1.2374	0.3869	1.1263	0.2104	1.2162	21.03
					ResNet50+MobileNetV2	0.0019	0.9998	0.0981	0.9725	0.0980	97.24
					DenseNet+VGG16	0.0125	0.9963	0.1718	0.9596	0.1718	95.95
			Proposed	Model:	VGG16+ResNet50	0.0025	0.9997	0.0700	0.9791	0.0700	97.91

Table 1: Comparison of Accuracy and Loss values

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Precision	Recall
0.001	64	10	Adam	Hybrid	DenseNet+ResNet50	0.9623	0.9578
					VGG16+Inception	0.9634	0.9627
					VGG16+MobileNetV2	0.9489	0.9451
					Inception+ResNet50	0.9664	0.9654
					Inception+MobileNetV2	0.8342	0.7875
					ResNet50+MobileNetV2	0.9733	0.9730
					DenseNet+VGG16	0.9548	0.9354
					VGG16+ResNet50	0.9761	0.9760
0.001	64	10	SGD with Momentum	Hybrid	DenseNet+ResNet50	0.9771	0.9766
					VGG16+Inception	0.9345	0.9275
					VGG16+MobileNetV2	0.9662	0.9652
					Inception+ResNet50	0.4489	0.2395
					Inception+MobileNetV2	0.4370	0.2104
					ResNet50+MobileNetV2	0.9733	0.9725
					DenseNet+VGG16	0.9617	0.9596
			Proposed	Model:	VGG16+ResNet50	0.9793	0.9791

Table 2: Comparison of Precision and Recall values

From the above results of **Table 1** and **Table 2** we could easily arrive to the conclusion that during the initial stage of the processthat is classification the model performed well in both the training and in the testing phase with the combination of ResNet50 and VGG16 resulting in a very high accuracy rate of 97.91. We could also seethat the model also has a similar precision and recall score indicating that the model is performing goodin the identification of healthy and diseased crops.

Identification Stage:

A. Cashew

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing Loss	Testing Accuracy
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.1126	0.9619	0.1611	0.9571	0.1611	95.70
					VGG16+MobileNetV2	0.1268	0.9515	0.3566	0.8572	0.3565	85.72
					Inception+ResNet50	0.1468	0.9726	3.1711	0.7481	3.1711	74.80
					Inception+MobileNetV2	0.9462	0.7932	1.7124	0.7056	1.1712	70.55
					ResNet50+MobileNetV2	0.0393	0.9907	0.3894	0.9731	0.3894	97.30
					VGG16+ResNet50	0.0326	0.9929	0.3499	0.9562	0.3498	95.62
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	1.2095	0.4268	1.2118	0.4457	1.2117	44.56
					VGG16+MobileNetV2	0.2463	0.9036	0.2346	0.9149	0.2345	91.49
					Inception+ResNet50	1.3158	0.3918	1.2421	0.4329	1.2421	43.29
					Inception+MobileNetV2	1.3971	0.3545	1.3941	0.3552	1.3941	35.52
					ResNet50+MobileNetV2	0.0254	0.9945	0.0884	0.9770	0.0884	97.69
			Proposed	Model:	VGG16+ResNet50	0.0306	0.9921	0.0823	0.9788	0.0822	97.88

Table 3: Comparison of Accuracy values for cashew

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Precision	Recall
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.9579	0.9571
					VGG16+MobileNetV2	0.8933	0.8572
					Inception+ResNet50	0.8463	0.7481
					Inception+MobileNetV2	0.7944	0.7056
					ResNet50+MobileNetV2	0.9731	0.9731
					VGG16+ResNet50	0.9584	0.9562
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	0.4356	0.4457
					VGG16+MobileNetV2	0.9180	0.9149
					Inception+ResNet50	0.3744	0.4329
					Inception+MobileNetV2	0.1262	0.3552
					ResNet50+MobileNetV2	0.9770	0.9770
			Proposed	Model:	VGG16+ResNet50	0.9789	0.9788

Table 4: Comparison of Precision and Recall values for cashew

From the above results of **Table 3** and **Table 4** we could easily arrive to the conclusion that for the cashew crop classification the model performed well in both the training and in the testing phase with the combination of ResNet50 and VGG16 resulting in a very high accuracy rate of 97.88. We could also see that the modelalso has a similar precision and recall score indicating that the model is performing good in the identification of healthy and diseased crops.

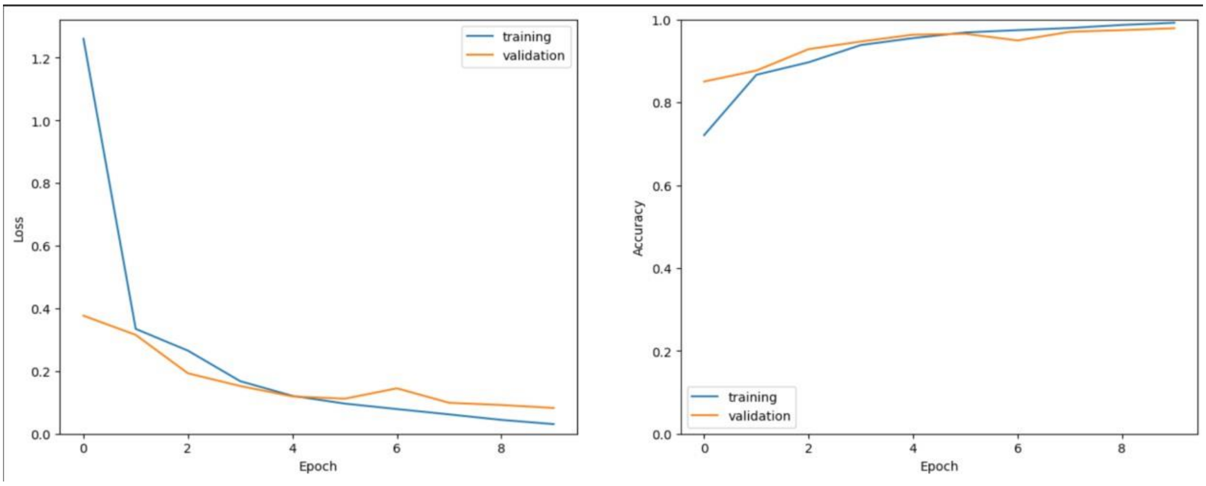

Fig.15: Accuracy and Loss Plot of VGG+ResNet in Cashew with SGD Optimizer and momentum

B. Cassava

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing Loss	Testing Accuracy
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.1721	0.9382	0.2240	0.9403	0.2239	94.03
					VGG16+MobileNetV2	0.1181	0.9604	0.2072	0.9387	0.2072	93.87
					Inception+ResNet50	0.1507	0.9499	0.2733	0.9375	0.2733	93.75
					Inception+MobileNetV2	0.7825	0.7045	0.7032	0.7428	0.7032	74.28
					ResNet50+MobileNetV2	0.0146	0.9977	0.1209	0.9699	0.1208	96.98
					VGG16+ResNet50	0.0113	0.9993	0.1063	0.9714	0.1062	97.13
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	1.5441	0.3500	1.5449	0.3482	1.5449	34.81
					VGG16+MobileNetV2	0.3170	0.8824	0.2610	0.9068	0.2609	90.67
					Inception+ResNet50	1.5443	0.3500	1.5451	0.3482	1.5450	34.81
					Inception+MobileNetV2	1.5441	0.6500	1.5450	0.3482	1.5449	34.81
					ResNet50+MobileNetV2	0.0229	0.9947	0.0993	0.9698	0.0992	96.97
			Proposed	Model:	VGG16+ResNet50	0.0284	0.9931	0.1002	0.9723	0.1001	97.22

Table 5: Comparison of Accuracy values for cassava

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Precision	Recall
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.9423	0.9403
					VGG16+MobileNetV2	0.9410	0.9387
					Inception+ResNet50	0.9437	0.9375
					Inception+MobileNetV2	0.7594	0.7428
					ResNet50+MobileNetV2	0.9700	0.9699
					VGG16+ResNet50	0.9714	0.9714
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	0.1212	0.3482
					VGG16+MobileNetV2	0.9105	0.9068
					Inception+ResNet50	0.1212	0.3482
					Inception+MobileNetV2	0.1212	0.3482
					ResNet50+MobileNetV2	0.9698	0.9698
			Proposed	Model:	VGG16+ResNet50	0.9727	0.9723

Table 6: Comparison of Precision and Recall values for cassava

From the above results of **Table 5** and **Table 6** we could easily arrive to the conclusion that for the cassava crop classification the model performed well in both the training and in the testing phase with the combination of ResNet50 and VGG16 resulting in a very high accuracy rate of 97.22. We could also see that the modelalso has a similar precision and recall score indicating that the model is performing good in the identification of healthy and diseased crops.

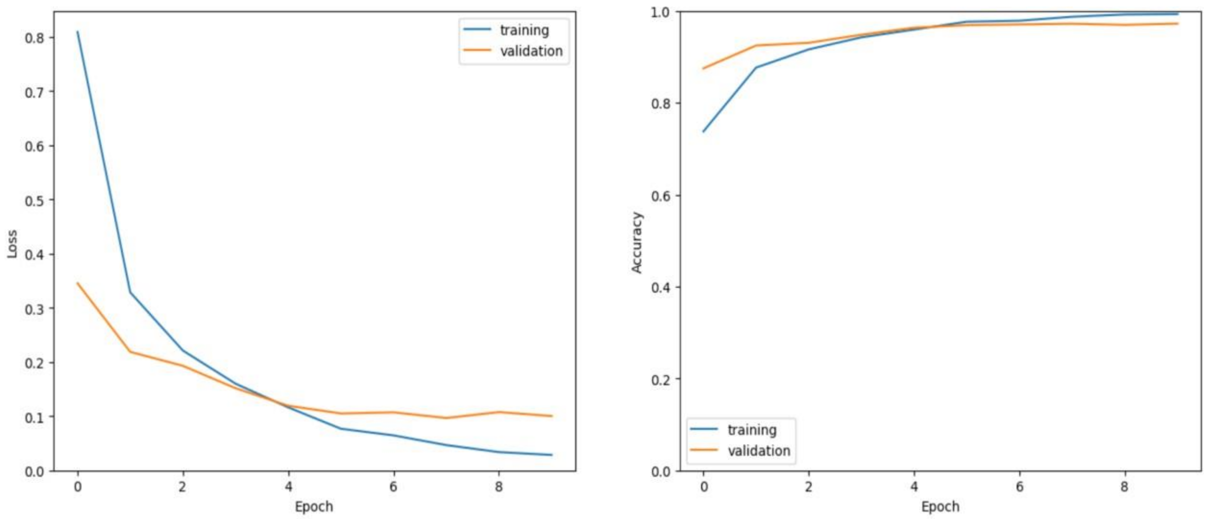

Fig.16: Accuracy and Loss Plot of VGG+ResNet for cassava with SGD Optimizer and momentum

C. Maize

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing Loss	Testing Accuracy
0.001	64	10	Adam	Hybrid	VGG16+Inception	1.2423	0.9139	2.0216	0.8857	2.0216	88.57
					VGG16+MobileNetV2	0.1362	0.9448	0.2418	0.9121	0.2418	91.20
					Inception+ResNet50	0.7629	0.9198	1.0358	0.9142	1.0358	91.41
					Inception+MobileNetV2	0.8787	0.6548	0.8858	0.6533	0.8858	65.32
					ResNet50+MobileNetV2	0.1003	0.9599	0.2652	0.9251	0.2652	92.50
					VGG16+ResNet50	0.1065	0.9593	0.2612	0.9278	0.2611	92.78
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	1.0881	0.6305	1.0885	0.6271	1.0885	62.71
					VGG16+MobileNetV2	0.2909	0.8809	0.2762	0.8899	0.2762	88.98
					Inception+ResNet50	1.7693	0.2844	1.7582	0.2892	1.7582	28.91
					Inception+MobileNetV2	1.7709	0.2825	1.7617	0.2866	1.7616	28.66
					ResNet50+MobileNetV2	0.0946	0.9596	0.2034	0.9274	0.2033	92.73
			Proposed	Model:	VGG16+ResNet50	0.1024	0.9618	0.1968	0.9283	0.1968	92.82

Table 7: Comparison of Accuracy values for Maize

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Precision	Recall
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.8958	0.8857
					VGG16+MobileNetV2	0.9032	0.8867
					Inception+ResNet50	0.9173	0.9142
					Inception+MobileNetV2	0.6166	0.6533
					ResNet50+MobileNetV2	0.9257	0.9251
					VGG16+ResNet50	0.9279	0.9278
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	0.5525	0.6271
					VGG16+MobileNetV2	0.8922	0.8899
					Inception+ResNet50	0.2800	0.2892
					Inception+MobileNetV2	0.0821	0.2866
					ResNet50+MobileNetV2	0.9275	0.9274
			Proposed	Model:	VGG16+ResNet50	0.9287	0.9283

Table 8: Comparison of Precision and Recall values for Maize

From the above results of **Table 7** and **Table 8** we could easily arrive to the conclusion that for the maize crop classification themodel performed well in both the training and in the testing phase with the combination of ResNet50 and VGG16 resulting in a very high accuracy rate of 92.82. We could also see that the model also has asimilar precision and recall score indicating that the model is performing good in the identification of healthy and diseased crops.

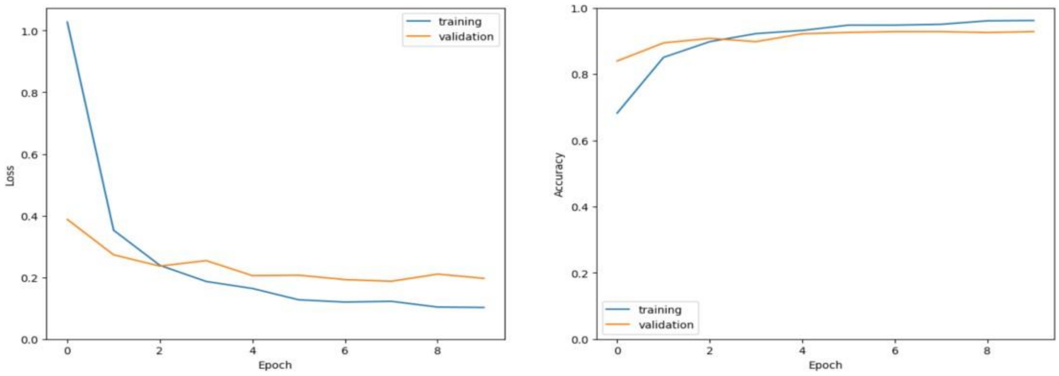

Fig.17: Accuracy and Loss Plot of VGG+ResNet for maize with SGD Optimizer and Momentum

D. Tomato

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Testing Loss	Testing Accuracy
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.8519	0.6647	0.8785	0.6505	0.8785	65.04
					VGG16+MobileNetV2	0.3561	0.8708	0.6187	0.7913	0.6187	79.13
					Inception+ResNet50	0.3707	0.9077	0.8762	0.8799	0.8761	87.99
					Inception+MobileNetV2	1.5017	0.6352	1.0845	0.6972	1.0845	69.71
					ResNet50+MobileNetV2	0.3376	0.8740	0.3811	0.8808	0.3811	88.07
					VGG16+ResNet50	0.0457	0.9940	0.3169	0.9192	0.3169	91.91
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	1.3924	0.4721	1.3875	0.4746	1.3875	47.46
					VGG16+MobileNetV2	0.8000	0.6818	0.8158	0.6870	0.8157	68.69
					Inception+ResNet50	1.3935	0.4721	1.3884	0.4746	1.3884	47.46
					Inception+MobileNetV2	1.3935	0.4721	1.3884	0.4746	1.3884	47.46
					ResNet50+MobileNetV2	0.3215	0.8766	0.3601	0.8953	0.3601	89.53
			Proposed	Model:	VGG16+ResNet50	0.0495	0.9940	0.3237	0.9209	0.3236	92.09

Table 9: Comparison of Accuracy values for Tomato

Learning Rate	Batch Size	Epochs	Optimizer	Model Type	Model Combination	Precision	Recall
0.001	64	10	Adam	Hybrid	VGG16+Inception	0.7413	0.6505
					VGG16+MobileNetV2	0.8321	0.7913
					Inception+ResNet50	0.8871	0.8799
					Inception+MobileNetV2	0.7289	0.6972
					ResNet50+MobileNetV2	0.8821	0.8808
					VGG16+ResNet50	0.9190	0.9192
0.001	64	10	SGD with Momentum	Hybrid	VGG16+Inception	0.2253	0.4746
					VGG16+MobileNetV2	0.7164	0.6870
					Inception+ResNet50	0.2253	0.4746
					Inception+MobileNetV2	0.2253	0.4746
					ResNet50+MobileNetV2	0.8955	0.8953
			Proposed	Model:	VGG16+ResNet50	0.9215	0.9209

Table 10: Comparison of Precision and Recall values for Tomato

From the above results of **Table 9** and **Table 10** we could easily arrive to the conclusion that for the tomato crop classification the model performed well in both the training and in the testing phase with the combination of ResNet50 and VGG16 resulting in a very high accuracy rate of 92.09. We could also see that the modelalso has a similar precision and recall score indicating that the model is performing good in the identification of healthy and diseased crops.

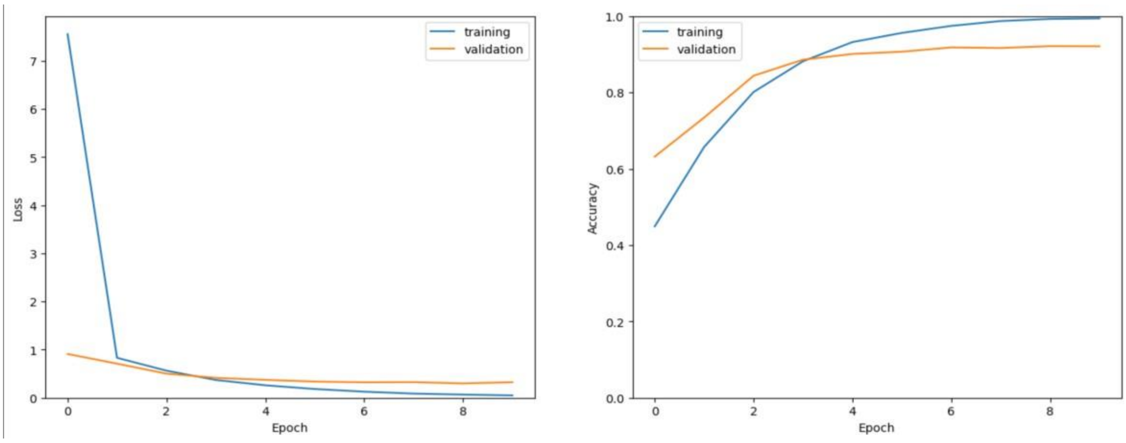

Fig.18: Accuracy and Loss Plot of VGG+ResNet for tomato with SGD Optimizer and momentum

Here from the identification stage, we also conclude with the same result of using ResNet50+VGG16 as a hybrid model for this identification stage too. When we look in the accuracy, precision and recall values of the proposed model we could see tat our model clearly stands out by achieving te highest values all across the tables. Thus, considering the above scores of various evaluation metrics such as Training, Testing and Validation Accuracies and Losses, Precision and Recall, we come to see that for both classification of plants and identification of diseases, the proposed model VGG16 + ResNet18 along with SGD and momentum=0.9 comes as the best model in both the classification and identification stages. Concluding, that this tuning of the deep learning model combination and parameters allows for better performance and optimal results.

Conclusion:

In conclusion, the development of a hybrid deep learning model integrating two deep learning convolutional neural networks for disease classification and identification in crops using image datasets is a groundbreaking advancement in precision agriculture. By leveraging the strengths of multiple deep learning architectures like ResNet, MobileNet, DenseNet, and VGG16 this model can accurately analyze and classify diseases in crops based on visual information from images. The hybrid nature of the model combining ResNet50 + VGG16 enables it to capture a wide range of features and patterns present in crop images, enhancing its ability to detect and diagnose diseases with high accuracy. This paper identifies VGG16 + ResNet50 as the best model for both classification and disease identification tasks.The impact of this project extends to newer crop disease management leading to improved crop yield, reduced losses and sustainable agricultural practices. Accurate and early detection of diseases allows farmers to take timely preventive measures such as targeted treatments or crop management strategies thereby optimizer health and productivity. In addition, the development of this hybrid deep learning model for crop disease classification and identification signifies a significant step forward in modern agriculture, with far-reaching implications for global food security, environmental sustainability, and economic prosperity in the agricultural sector. The future work of this project is to introduce newer model combinations into picture and develop the current for a real-time object detection model using the necessary tools.

Declarations:

Ethical Approval – Not applicable

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Conflict of Interest – There is no conflict of interest among authors

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