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COMPARATIVE ANALYSIS OF BINARY AND MULTICLASS POTATO LEAF DISEASE CLASSIFICATION USING VGG19 MODEL

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ABSTRACT
Agriculture in Nigeria, has been the source of livelihood yielding sustainable development across the country. However, potato farming in Nigeria faces numerous challenges such as unknown diseases and challenges in potato leaf disease classification. This study discovered a problem in potato leaf disease classification using VGG19 model in which binary class of potato leaf (potato early blight and potato late blight diseases) was not enough for dataset generalization. Therefore, this study aimed to conduct a comparative analysis of binary and multiclass potato leaf disease classification using VGG19 model. The research used comparative analysis tools to compare the result of the binary class (early blight and late blight leaves) and multiclass (early blight, late blight, virus disease and healthy potato leaves) in which VGG19 model with binary class obtained at epoch 40, training accuracy of 93.25%, validation accuracy of 90.00% and testing accuracy of 91.67% while VGG19 model with multiclass obtained at epoch 40, training accuracy of 91.28%, validation accuracy of 87.50% and testing accuracy of 91.67%. The result showed that the higher the number of data classes in VGG19 model, the lower the training accuracy in VGG19 model. Finally, this work has achieved its aim and objective; and it can be evaluated for future study.

Keywords: Binary Class, Multiclass, Potato leaf disease, VGG19 model

INTRODUCTION
Nigeria's agro-ecological zones possess rich agricultural potential, offering fertile ground for transformative advancements in farming. One key area is plant disease classification, which enhances agricultural practices and promotes food security (Sibhatu & Qaim, 2024). The potato (Solanum tuberosum) is a vital global staple, rich in nutrients like vitamin C, protein, and fiber (Ghosh et al., 2023). However, it is vulnerable to various leaf diseases notably early blight, late blight, and mosaic virus which significantly reduce yield and quality.
Traditionally, disease identification relies on expert visual inspection, which is time-consuming and error-prone. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), enable automated disease classification with high accuracy, often rivaling human experts (Singh & Yogi, 2023). CNNs can detect subtle patterns in leaf images to identify specific diseases.
Ghosh et al. (2023) compared three CNN models: VGG19, DenseNet121, and ResNet50 for binary classification of potato leaf diseases (early and late blight). VGG19 achieved the highest accuracy (92.71%). However, this study identified a limitation which shows binary classification was insufficient for broader dataset generalization.
This study aims to address that gap by conducting a comparative analysis between binary and multiclass classification using the VGG19 model. The multiclass dataset includes early blight, late blight, viral infection, and healthy potato leaves. The study leverages advancements in image recognition and data augmentation to improve classification accuracy and real-world applicability.
Potato leaves are distinct in structure, featuring broad, smooth, unified leaflets with a flat texture and slight ridges. Unlike regular leaves, they play a crucial role in identifying plant health. Potatoes are rich in carbohydrates, potassium, vitamin C, fiber, vitamin B6, and folate, while being low in fat, calories, and sodium (Britannica, 2024). Due to their visible features, potato leaf diseases are often diagnosed through leaf inspection. Common diseases include late blight (Phytophthora infestans), early blight (Alternaria solani), bacterial wilt (Ralstonia solanacearum), and powdery mildew (Erysiphe cichoracearum). For this study, focus is placed on healthy potato leaves and three prevalent diseases observed during data collection in Northern Nigeria: early blight, late blight, and potato virus. Although healthy leaves are green, they are inedible and toxic, being part of the Solanaceae family like tomatoes and eggplants (Britannica, 2024) and is shown in figure 1.


Figure 1: Healthy Potato Leaf

Potato early blight leaf disease is caused by the fungus, Alternaria solani, which can cause disease in potato, tomato, other members of the potato family, and some mustards (Plant-village, 2024). This disease, also known as target spot, rarely affects young, vigorously growing plants. Potato early blight leaf is shown in figure 2.

Figure 2: Potato Early Bacterial Blight Leaf

Potato late blight leaf disease caused by the fungus phytophthora infestans is the most important disease of potato that can result into crop failures in a short period if appropriate control measures are not adopted (Plant-village, 2024). Losses in potato yield can go as high as 80% in epidemic years. It is shown in figure 3.

Figure 3: Potato Late Bacterial Blight Leaf

Potato virus leaf disease is caused by pathogen, a viral infection transmitted by aphids. It can remain latent in tubers, spreading to the next crop through infected seed potatoes.
Symptoms of potato virus leaf disease includes mosaic or mottled yellowing of leaves, yellowing of veins and areas between veins (chlorosis), leaves may curl or wrinkle stunted growth and reduced yield (Plant-village, 2024). Potato virus leaf disease is shown in figure 4.

Figure 4: Potato Virus Leaf

Ghosh et al. (2023) emphasized the critical role of potatoes in global food security and highlighted their vulnerability to various leaf diseases that threaten yield and quality. Their study evaluated three advanced CNN models: VGG19, DenseNet121, and ResNet50 for classifying potato leaf diseases using potato late blight and early blight leaf images. With the help of data augmentation, they measured model performance across metrics such as accuracy, precision, recall, and F1-score. VGG19 outperformed the others, achieving 92.71% accuracy. However, their approach focused only on binary classification (early and late blight), which proved insufficient for broader generalization.
To address early detection challenges, Rashid et al. (2021) proposed a two-stage deep learning model combining YOLOv5 for leaf segmentation and a CNN for disease classification, achieving 99.75% accuracy. Their work overcame regional image biases using robust validation.
Madhumitaa et al. (2024) improved soybean genotype classification under stress conditions using morphological traits and machine learning models. Among the tested

algorithms, SVM yielded 96.79% accuracy, demonstrating the value of integrating physical traits for agricultural classification.

Kumar and Patel (2023) introduced a Hierarchical Deep Learning CNN (HDLCNN) that combined image de-noising and fuzzy pattern extraction, outperforming traditional CNNs in detecting leaf diseases and supporting smart farming.

Ajoh et al. (2024) enhanced CNN performance for yam disease detection by using a hybrid ReLU–ELU activation function, which improved learning and robustness.

Lee et al. (2021) developed an optimized CNN architecture tailored for potato disease detection, achieving 99.53% accuracy while reducing parameter size by over 99%, making it ideal for real-time use.

Emuoyibofarhe et al. (2019) trained 46 models to detect cassava diseases (CMD and CBBD), with Cubic SVM achieving 83.9% accuracy in healthy/unhealthy classification.

Owomugisha et al. (2021) applied spectral data and matrix learning techniques for early detection of cassava diseases before symptoms appeared, identifying optimal wavelengths for diagnosis.

Metlek (2023) used segmented leaf images and deep feature extraction (ResNet50, MobileNetV2), followed by SVM and kNN classification. ResNet50 with SVM achieved 84.4% accuracy and was deployed via a web interface for farmers.

Jagadish et al. (2023) created an automated cassava disease detection system using labeled datasets to assist farmers in real-time crop monitoring, replacing manual inspection.

VGG19 model was proposed by Simonyan and Zisserman (2014) from the University of Oxford in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" which was submitted to ILSVRC-2014, it gained popularity for improving upon AlexNet by replacing large kernel filters with multiple 3×3 filters in sequence. The model was trained on the ImageNet dataset, which contains over 14 million images across nearly 1,000 classes.

Collectively, these studies show that while deep learning models perform well, limitations remain, especially in model generalization across diverse datasets. Building on Ghosh et al. (2023), this research identifies a gap in relying solely on binary classification. Therefore, it aims to conduct comparative analysis of binary and multiclass potato leaf disease classification using VGG19 model to solve this research gap.

MATERIALS AND METHODS

This research adopted "Experimental Research Design Methodology" to investigate the effect of class granularity on the performance of the VGG19 deep learning model in classifying potato leaf diseases. The study compares two classification scenarios: binary classification (two classes) and multiclass classification (four classes). In both cases, the same model architecture, training parameters, and dataset structure are used to ensure consistency and reliability of results. This comparative experimental approach allows for objective evaluation of model performance across both classification tasks using quantitative metrics. The methodology consists of seven key phases, which includes: Dataset Collection; Dataset Preprocessing and Augmentation; Architecture of VGG19 Model; Feature Extraction, Training, Validation and Testing of Dataset; Model Performance Evaluation Metrics; Comparative Analysis of Results; and Visualization and Statistical Interpretation.

Dataset Collection

This study identified four classes of potato leaf from local farms in Kaduna and was confirmed by a local farmer that the potato leaves were healthy potato leaf, potato virus leaf, potato early blight leaf and potato late blight leaf. Then, after the confirmation of the potato leaf classes, the potato leaf image was captured using Sony W610 Camera at a distance of 0.3m and these potato leaf images was gathered to form a single dataset. More so, these locally gathered potato leaf images will serves as dataset bank for future study.

Dataset Preprocessing and Augmentation

These images collected were preprocessed and resized to 224x224 pixels to make the suitable input dimension for the VGG 19 model. The dataset was split into 80% for training, 10% for testing and 10% for validating respectively. The dataset contains 1,200 images which includes four potato leaf classes, these include one control class for healthy potato leaf (300 images) and three classes of potato leaf diseases which are potato early blight Leaf (300 images), potato late blight leaf (300 images) and potato virus leaf (300 images). The reason for equal amount of data class size was to avoid data imbalance.

Architecture of VGG19 Model

The VGG model, or VGGNet, that supports 19 layers is also referred to as VGG19, which is a convolutional neural network model proposed by Simonyan and Zisserman (2014), from the University of Oxford. The VGG16 model was trained using Nvidia Titan Black GPUs for multiple weeks. As mentioned above, the VGGNet-19 supports 19 layers and can classify images into 1000 object categories, including keyboard, animals, plants, pencil, mouse, etc. Additionally, the model has an image input size of 224-by-224. Final, VGG-19 consists of 16 convolutional layers and three fully connected layers. Figure 5 shows VGG19 network structures.

Figure 5: VGG19 Network Structure (Wang et al., 2020)

Feature Extraction, Training, Validation and Testing of Dataset

The feature extraction was done by convolutional and pooling layers (feature extraction layers) of VGG19 model. After the last convolutional layers extract spatial feature maps from the input image, it passed to the fully connected layers (FCL). The first FC layer aggregates spatial and channel-wise features into a high-dimensional feature vector, learning global patterns across the image and passed it to second FC layer. The second FC layer refines the feature representation by learning higher-level combinations of features from the first FC layer while the third FC layer maps the high-dimensional feature vector (4,096 dimensions) to the number of output classes and passes it to a softmax layer to select the highest probability as the final predicted label for image classification. At each epoch, the model performance is evaluate on unseen data after train epoch to check its ability to generalize. Validation dataset are passed through the model at the end of each epoch and metrics like accuracy and loss are computed to monitor model's performance but the model's parameters are not changed or updated. Likewise, testing dataset are passed through the model after training and metrics like accuracy precision, recall, F1score, or confusion matric are used to calculated the model performance.

Model Performance Evaluation Metrics

The VGG 19 model performance evaluation for the potato leaf disease classification was done using these performance evaluation metrics: Accuracy, Precision, Recall, F1-Score, Macro F1 Score, Confusion Matrix and ROC Curve. Their equation and computations for performance metrics are below (Evwiekpaefe & Amrevuawho, 2023).

Accuracy

This is the sum of all TP divided by the number of instances in test dataset as expressed in equation (1).

$$\text{Accuracy}=\frac{\Sigma TP}{\text{Number of test data}} \quad (1)$$

Precision

Precision is the ratio of true positives and total positives predicted. It is expressed mathematically in equation (2)

$$\text{Precision TP} = \frac{TP}{\text{TP+EP}} \quad (2)$$

Recall

The recall (sensitivity) is the measure of your true positive over the count of actual positive outcomes which is expressed mathematically in equation (3).

$$\text{Recall}=\frac{TP}{\text{TP+FN}} \quad (3)$$

F1-Score

F1 score is the harmonic mean between precision and recall which is expressed mathematically in equation (4).

$$\text{F1 – Score} = \frac{2 \times \text{Precision x Recall}}{\text{Precision + Recall}} \quad (4)$$

Macro F1 – Score

This is the average over all F1-Score for a multiclass task and it is expressed mathematically in equation (5) where n is the number of classes in the target class.

$$\text{Macro F1 – Score} = \frac{\Sigma_i^n = F1 - Score}{n} \quad (5)$$

Confusion Matrix

The ground-truth labels and model predictions are shown in a table as a confusion matrix. In the confusion matrix, each row represents an instance in a predicted class, and each column represents an instance in an actual class (Evwiekpaefe & Lawi, 2024).

Table 1: Confusion Matrix Values

		Actual Values	
		Positive (1)	**Negative (0)**
Predicted Values	**Positive (1)**	TP	FP
	Negative (0)	FN	TN

Where TP, FP. FN and TN are interpreted as:

True Positive (TP): Predicted as True and it is True in reality.

True Negative (TN): Predicted as False and it is False in reality.

False Positive (FP): Predicted as True and it is False in reality.

False Negative (FN): Predicted as False and it is True in reality.

ROC Curve

The ROC Curve (Receiver Operating Characteristic curve) is a graphical representation used to evaluate the performance of a binary classification model. It illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold levels. The curve helps assess how well a model distinguishes between two classes. It is expressed mathematically in equation (6) and equation (7).

True Positive Rate (TPR) = True Positive (TP) (6)
True Positive (TP) + False Negative (FN)

False Positive Rate (FPR) = False Positive (FP) (7)
False Positive (FP) + True Negative (TN)

Comparative Analysis of Results

Comparative analysis of model results was done using performance evaluation metrics. After training both models, their performance was compared in terms of their total epoch metrics (training, validation and testing accuracy and loss).

Visualization and Statistical Interpretation

Line plot was used for visualization and paired t-test was used statistical interpretation of the binary and multiclass potato leaf classification using VGG19 model results.

Tools and Environment

Python Programming Language was used for training and analysis of binary class and multiclass of potato leaf disease classification using VGG19 model in Jupyter Notebook Environment of Spyder Anaconda IDE.

RESULTS AND DISCUSSION

Results and Evaluation of Multiclass Potato Leaf Disease Classification using VGG19 Model

The following were the performance and evaluation report obtained from "Multiclass Potato Leaf Disease Classification using VGG19 Model". These includes: the VGG19 Model training, validation, testing result and evaluation report.

Training, Validation and Testing Result of Multiclass Potato Leaf Disease Classification using VGG19 Model

The training, validation and testing result of the trained Multiclass VGG 19 Model were shown in figure 6 and figure 7 respectively. From the result, at epoch 40, VGG 19 Model achieved training accuracy of 91.28% and loss of 0.3794, validation accuracy of 87.50% and loss of 0.3893 and testing accuracy of 91.67% and loss of 0.4956.

```
Epoch 40/40
30/30 ━━━━━━━━━━━━━━━━━━━━ 190s 6s/step - accuracy: 0.9128 - loss: 0.3794 - val_accuracy: 0.8750 - val_loss: 0.4248
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format
nd using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras
4/4 ━━━━━━━━━━━━━━━━━━━━ 22s 5s/step - accuracy: 0.8625 - loss: 0.3893
Validation Accuracy: 87.50%
4/4 ━━━━━━━━━━━━━━━━━━━━ 21s 5s/step - accuracy: 0.8677 - loss: 0.4956
Test Accuracy: 91.67%
```

Figure 6: Training, Validation and Testing Report of the trained Multiclass Potato Leaf Disease Classification using VGG19 Model

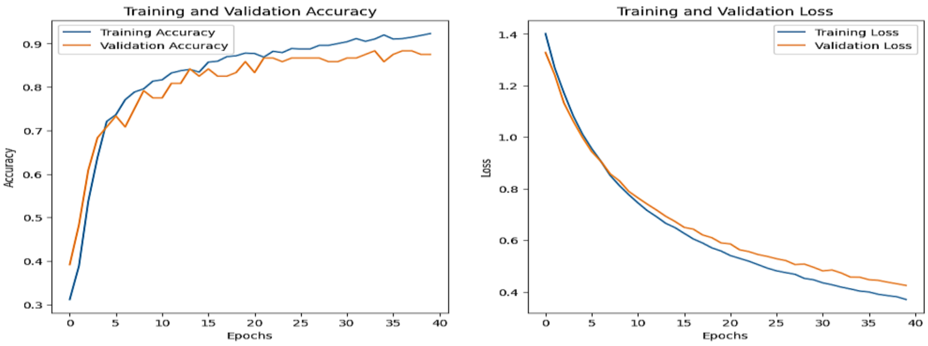

Figure 7: Training and Validation Accuracy and Training and Validation Loss of the trained Multiclass Potato Leaf Disease Classification using VGG19 Model

The figure 7 shows the graphical representation of training and validation accuracy as it increases across the epoch. Also, it shows the graphical representation of training and validation loss as it decreases across the epoch.

Evaluation Report of the trained Multiclass Potato Leaf Disease Classification using VGG19 Model

The evaluation report of trained Multiclass VGG 19 Model which includes the confusion matrix, ROC curve and classification report (precision, recall, f1-score and support) were shown in figure 8, figure 9 and figure 10 respectively.

Classification Report:

	precision	recall	f1-score	support
Potato leaf has Early Blight Disease	1.00	0.73	0.85	30
Potato leaf has Late Blight Disease	0.85	0.97	0.91	30
Potato leaf has Virus Disease	0.97	0.97	0.97	30
Potato leaf is Healthy	0.88	1.00	0.94	30
accuracy			0.92	120
macro avg	0.93	0.92	0.91	120
weighted avg	0.93	0.92	0.91	120

Figure 8: Classification Report of Multi Class

The figure 8 shows the values obtained from the different classes of potato leaf and its corresponding precision, recall, f1-score and support.

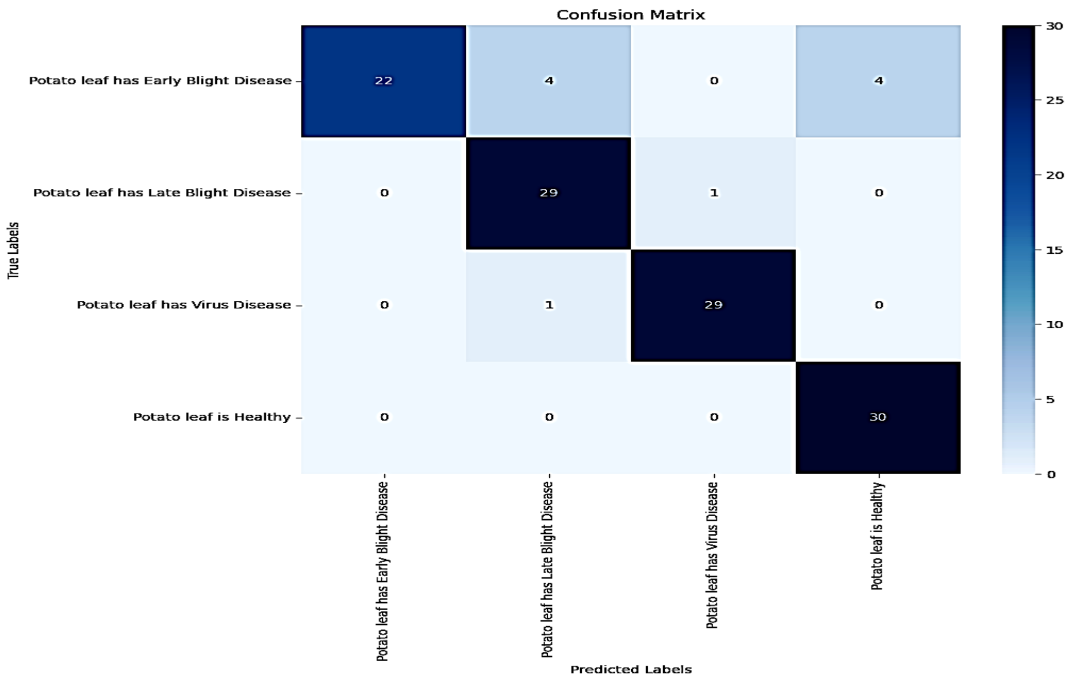

Figure 9: Confusion Matrix of Multiclass

The figure 9 shows the confusion matrix of the trained VGG 19 model for potato leaf disease classification. It also shows the actual values given in the test data and the predicted values by the VGG 19 model. However, the actual values were placed accordingly to the potato leaf classes respectively. More so, thirty healthy potato leaves, twenty-nine potato virus leaves, twenty-nine potato late blight leaves and twenty-two potato early blight leaves were correctly classified while one potato virus leaf was misclassified as potato late blight leaf, one potato late blight leaf was misclassified as potato virus leaf, four potato early blight leaves were misclassified as potato late blight leaves and four early blight leaves were misclassified as healthy potato leaves.

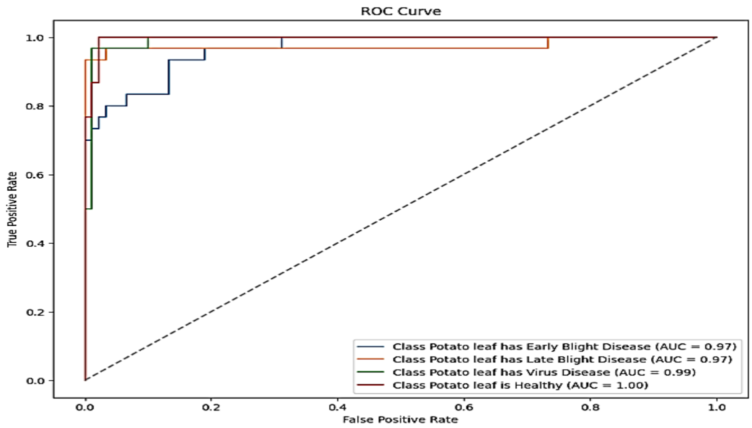

Figure 10: ROC Curve of Multiclass

Figure 10 illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold levels of the potato leaf classification.

Results and Evaluation of Binary Class Potato Leaf Disease Classification using VGG19 Model

The following were the performance and evaluation report obtained from “Binary Class Potato Leaf Disease Classification using VGG19 Model”. These includes: the VGG19 Model training, validation, testing result and evaluation report.

Training, Validation and Testing Result of Binary Class Potato Leaf Disease Classification using VGG19 Model

The same potato leaf dataset containing binary class (potato early blight and potato late blight) were trained using VGG 19 model as shown in figure 4.6. At epoch 40, VGG 19 model achieved training accuracy of 93.25% and loss of 0.2513, validation accuracy of 90.00% and loss of 0.2970 and testing accuracy of 91.67% and loss of 0.2735.

```
Epoch 40/40
15/15 ━━━━━━━━━━━━━━━━━━━━ 87s 6s/step - accuracy: 0.9325 - loss: 0.2513 - val_accuracy: 0.9000 - val_loss: 0.2702
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is
nd using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`
2/2 ━━━━━━━━━━━━━━━━━━━━ 10s 5s/step - accuracy: 0.8917 - loss: 0.2970
Validation Accuracy: 90.00%
2/2 ━━━━━━━━━━━━━━━━━━━━ 10s 5s/step - accuracy: 0.9028 - loss: 0.2735
Test Accuracy: 91.67%
```

Figure 11: Result of the Training, Validation and Testing Report of the trained Binary Class Potato Leaf Disease Classification using VGG19 Model

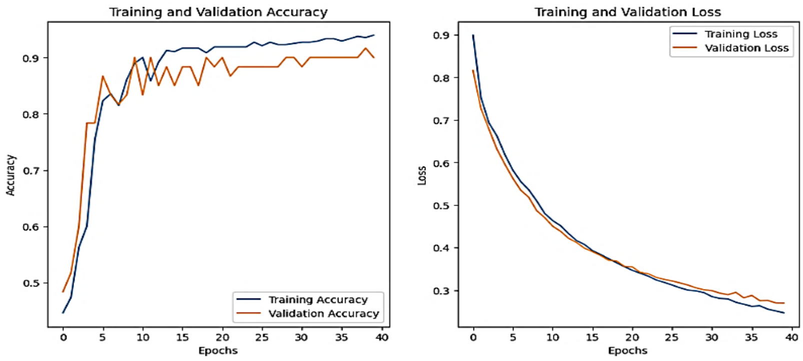

Figure 12: Training and Validation Accuracy and Training and Validation Loss of the trained Binary Class Potato Leaf Disease Classification using VGG19 Model

The figure 12 shows the graphical representation of training and validation accuracy as it increases across the epoch. Also, it shows the graphical representation of training and validation loss as it decreases across the epoch.

Evaluation Report of the trained the trained Binary Class Potato Leaf Disease Classification using VGG19 Model

The evaluation report of trained Binary Class VGG 19 Model which includes the confusion matrix, ROC curve and classification report (precision, recall, f1-score and support) were shown in figure 13, figure 14 and figure 15 respectively.

```
Classification Report:
                                      precision    recall  f1-score   support

Potato leaf has Early Blight Disease       0.96      0.87      0.91        30
 Potato leaf has Late Blight Disease       0.88      0.97      0.92        30

                            accuracy                           0.92        60
                           macro avg       0.92      0.92      0.92        60
                        weighted avg       0.92      0.92      0.92        60
```

Figure 13: Classification Report of Binary Class

The figure 13 shows the values obtained from the different classes of potato leaf and its corresponding precision, recall, f1-score and support

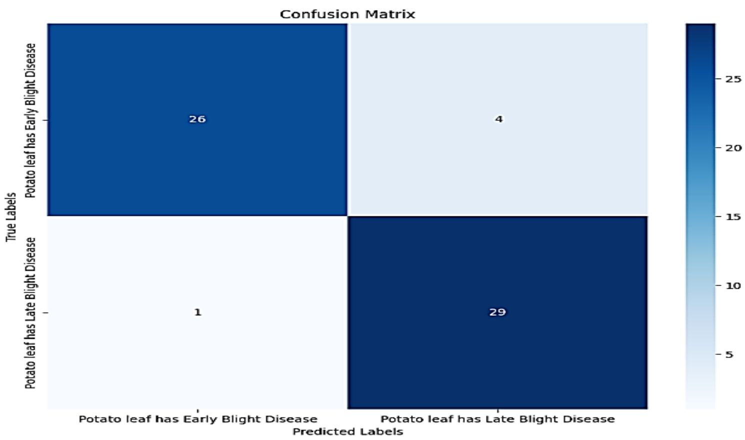

Figure 14: Confusion Matrix of Binary Class

The figure 14 shows the confusion matrix of the trained VGG 19 model for potato leaf disease classification. It also shows the actual values given in the test data and the predicted values by the VGG 19 model. However, the actual values were placed accordingly to the potato leaf classes respectively. More so, twenty-nine potato late blight leaves and twenty-six potato early blight leaves were correctly classified while one potato late blight leaf was misclassified as potato early blight leaf and four potato early blight leaf was misclassified as potato late blight leaves.

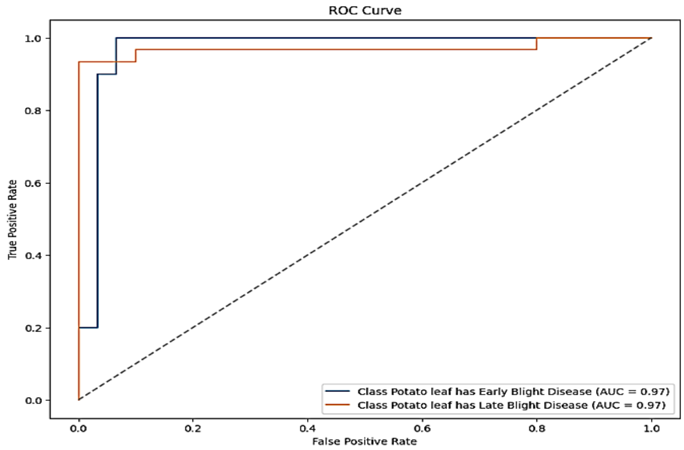

Figure 15: ROC Curve of Binary Class

The figure 15 illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold levels of the potato leaf classification.

Comparison between Binary and Multiclass Potato Leaf Disease Classification using VGG19 Model

From the result of this study, it shows that both data classes has same test accuracy but other results varies. However, Table 2 shows the constructive comparison between the Binary and Multiclass Potato Leaf Disease Classification using VGG19 Model.

Table 2: Comparison between Binary and Multiclass Potato Leaf Disease Classification using VGG19 Mode

S/N	Metrics	Binary Class (%)	Multiclass (%)
	Training Accuracy	93.25	91.28
	Training Loss	0.2513	0.3794
	Validation Accuracy	90.00	87.50
	Validation Loss	0.2970	0.3893
	Testing Accuracy	91.67	91.67
	Testing Loss	0.2735	0.4956

Visualization and Statistical Interpretation of Binary and Multiclass Potato Leaf Disease Classification using VGG19 Model

Paired t-test was used statistical interpretation of the binary and multiclass potato leaf classification using VGG19 model results across the 40 epochs which gave t-statistic of 7.4054 and p-value of 4.08e-05. Line plot was used for visualization of the binary and multiclass potato leaf classification using VGG19 model results across the 40 epochs which gave t-statistic of 8.1434 and p-value of 0.0.

```
print("Paired t-test result:")
print("t-statistic =", round(t_stat, 4))
print("p-value =", round(p_value, 6))

# Interpretation
if p_value < 0.05:
    print("🔍 The difference in accuracy is statistically significant.")
else:
    print("✅ No significant difference in accuracy between binary and multiclass.")
```

```
Paired t-test result:
t-statistic = 8.1434
p-value = 0.0
🔍 The difference in accuracy is statistically significant.
```

Figure 16: Paired t-test of the binary and multiclass potato leaf classification using VGG19 model

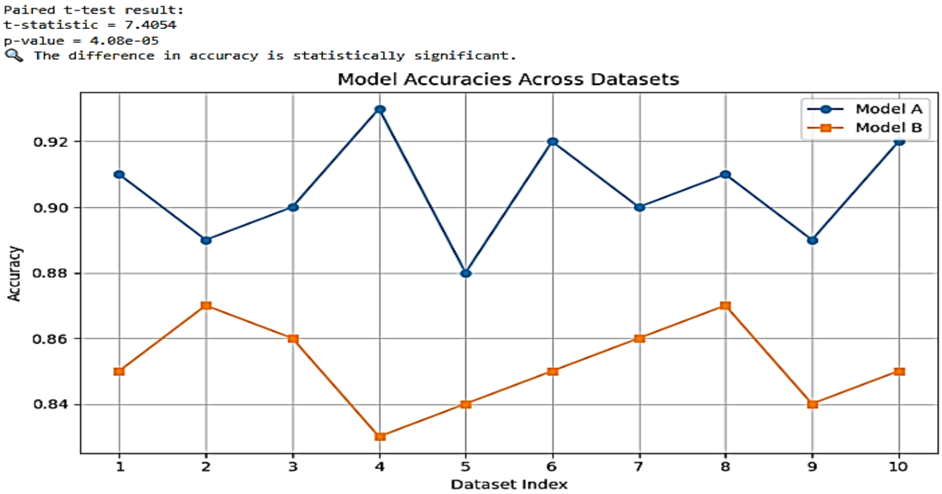

Figure 17: Line plot of the binary and multiclass potato leaf classification using VGG19 model

Discussion

The testing accuracy obtained from both binary class (two class) and multiclass (four class) potato leaf disease using VGG 19 model was 91.67% accuracy, the training accuracy of binary class and multiclass was 93.25% and 91.28% respectively while the validation accuracy of binary class and multiclass was 90.00% and 87.50% accuracy respectively. This indicates that VGG19 model trained on two disease classes showed slightly better performance in training and validation metrics, achieving higher accuracy and lower loss. However, both models reached the same testing accuracy of 91.67%. The higher testing loss in the multiclass (four-class) model may indicate greater difficulty in generalizing to more classes, suggesting that model complexity or dataset size may need to be adjusted for multiclass classification. Therefore, this indicates that the VGG 19 model's testing accuracy was good but the training and validation accuracy reduces as the dataset class increases, which means that there is likelihood of overfitting as dataset class increases. Finally, the higher the number of data class in VGG19 model, the lower the training and validation accuracy.

CONCLUSION

This research explored the comparative analysis of binary and multiclass potato leaf disease classification using VGG19 Model. This study used model evaluation metrics and comparative tools to comparatively analyze binary and multiclass potato leaf disease classification using VGG19 Model. Testing accuracy of both binary class (two class) and multiclass (four class) potato leaf disease using VGG 19 model was 91.67% accuracy, the training accuracy of binary class and multiclass was 93.25% and 91.28% respectively while the validation accuracy of binary class and multiclass was 90.00% and 87.50% accuracy respectively. This indicates that the VGG 19 model's testing accuracy was good but the training and validation accuracy reduces as the dataset class increases, which means that there is likelihood of overfitting as dataset class increases. Thus, the higher the number of data class in VGG19 model, the lower the training and validation accuracy.

While there are many works undertaken in the field of deep learning and plant classification, this study used model evaluation metrics and comparative tools to comparatively analyze binary and multiclass potato leaf disease classification using VGG19 Model. This study achievement and contribution to knowledge shows that the higher the number of data class in VGG19 model, the lower the training and validation accuracy.

This work has explored many research papers, identified gap, and tried to cover the identified gap by proffering solution classes of potato leaf disease classification using VGG 19 model. This work improved on the previous work by using model evaluation metrics and comparative tools to comparatively analyze binary and multiclass potato leaf disease classification using VGG19 Model which shows that shows that the higher the number of data class in VGG19 model, the lower the training and validation accuracy.

It is recommended that the "Comparative Analysis of Binary and Multiclass Potato Leaf Disease Classification Using VGG19 Model" be adopted and used for potato leaf disease classification thereby improving potato crop yield. More so, it is recommended that the future work should include improving VGG19 model. Moreover, work can further be extended to include the classification of other plant diseases.

REFERENCES

Ajoh, S. L, Ogala, E., Samuel, J. T., Akpa, J., & Daniel, A. M. (2024). A Combined Activation Function for Learning Performance Improvement of Convolution Neural Network for Yam Disease Classification. Journal of Software Engineering and Applications, 1 (3), 110 -127, April 2024.

Albelwi, S. & Mahmood, A. (2017). A Framework for Designing the Architectures of Deep Convolutional Neural Networks. Entropy 2017, 19(6), 1-20. https://doi.org/10.3390/e19060242

Alex, P. (2022). How to Train an Ensemble of Convolutional Neural Networks for Image Classification. Retrieved on 12th July, 2024 from https://medium.com/@alexppppp/how-to-train-an-ensemble-of-convolutional-neural-networks-for-image-classification-8fc69b087d3

Anbarjafari, G. (2022). Digital Image Processing. Retrieved on 12th July, 2024 from https://sisu.ut.ee/imageprocessing/book

Beheshti, N. (2022). Guide to Confusion Matrices and Classification PerformanceMetrics. Retrieved on 21st June, 2024 from https://towardsdatascience.com/guide-to-confusion-matrices-classification-performance-metrics-a0ebfc08408e

Britannica (2024). Potato. Encyclopedia Britanncia Retrieved on 21st August, 2024 from https://www.britannica.com/science/starch

Chugh, G., Sharma, A., Choudhary, P., & Khanna, R. (2020). Potato Leaf Disease Detection Using Inception V3. International Research Journal of Engineering and Technology (IRJET), 07 (11), 1363-1366, e-ISSN: 2395-0056, p-ISSN:2395-0072, www.irjet.net

Emuoyibofarhe, O., Emuoyibofarhe, J.O., Adebayo, S., Ayandiji, A., Demeji, O., & James, O. (2019). Detection and Classification of Cassava Diseases Using Machine Learning. International Journal of Computer Science and Software Engineering (IJCSSE), 8:7, July 2019 Page: 166-176. ISSN (Online): 2409-4285 www.IJCSSE.org

Evwiekpaefe, A. E, & Amrevuawho, O. F. (2023). Classification of Dermatologic Manifestations of Cardiovascular Disease Using Efficient NetV2 CNN Model. International Journal of Intelligent Computing and Information Sciences, IJICIS, 23 (1), 115-127. https://doi.org/10.21608/ijicis.2023.184311.1242

Evwiekpaefe, A. E., & Lawi, V. P. (2024). An Artificial Neural Network Model for Predicting Children at Risk of Defaulting from Routine Immunization in Nigeria. Journal of Information Systems and Informatics, 6 (2), 810-829. https://doi.org/10.51519/journalisi.v6i2.689

Ghosh, H., Rahat I. S., Shaik, K., Khasim, S., & Yesubabu, M. (2023). Potato Leaf Disease Recognition and Prediction using Convolutional Neural Networks. Journal of EAI Endorsed Transactions on Scalable Information Systems 2023, 10 (6), 1-8. https://publications.eai.eu/index.php/sis/issue/view/409

IBM (2020a). Deep learning. International Business Machine. Retrieved on 21st June, 2024 from https://www.ibm.com/topics/machine-learning

IBM (2020b) Machine learning. International Business Machine. Retrieved on 21st June, 2024 from https://www.ibm.com/topics/machine-learning

Jadon, S. & Jasim, M. (2019). Video Summarization using Keyframe Extraction and Video Skimming. Retrieved on 12th July, 2024 from https://www.researchgate.net/publication/336510662

Jagadish, K., Jagadhiswar, Sai, P. K., Vishnu, V. B., Jahnavi, P., Janaki, M., & Rao, R.K. (2023) Detection and Classification of Cassava Diseases using Machine Learning. International Journal for Research in Applied Science & Engineering Technology (IJRASET) 11 (12), 803-807. http:www.ijraset.com

Kumar, A. & Patel, V. K. (2023). Classification and identification of disease in potato leaf using hierarchical based deep learning convolutional neural network. Multimed Tools Appl 82, 31101–31127. https://doi.org/10.1007/s11042-02314663-z

Lee, T. Y., Lin, A., & Yu, J. Y., (2021). High Efficiency Disease Detection for Potato Leaf with Convolutional Neural Network. SN COMPUT. SCI. 2 (297), 691-699.

Madhumitaa, P. S., Ragav, I. C., Kiranmayi C., Prabhavathy, V. M & Prabhavathy P. (2024). Drought and Salinity Stress Classification in Soya bean Crops: Comparative Analysis of Machine Learning Models. 2024 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication (IConSCEPT), Karaikal, India, 2024, 1-5. https://doi.org/10.1109/IConSCEPT61884.2024.10627854.

Malinowski, E., Zimányi, E., Joseph, S. K., Warehouse, D., Inmon, B., Analytical, O., Olap, P., Gatziu, S., Vavouras, A., Nilsson, A. A., & Merkle, D. (2019). Data Vault 2.0, 1 (1), 1–15; https://doi.org/10.1007/978-3-322-94873-1

Metlek, S. (2021). Disease Detection from Cassava Leaf Images With Deep Learning Methods in Web Environment. Int. Journal of 3D Printing Tech. Dig. Ind., 5(3): 625-644.

Owomugisha, G., Melchert, F., Mwebaze, E., Quinn, J.A., & Biehl, M. (2021) Matrix Relevance Learning From Spectral Data for Diagnosing Cassava Diseases. IEEE Access Journal. 9, (83355-83363) doi:10.1109/ACCESS.2021.3087231

Plant-village (2024). Potato. Plant Village. Retrieved on 21st August, 2024 from https://plantvillage.psu.edu/topics/potato/infos

Rashid, J., Khan, I., Ali, G., Almotiri, S.H., AlGhamdi, M. A., & Masood K., (2021). Multi-Level Deep Learning Model for Potato Leaf Disease Recognition. Electronics 2021, 10(17), 2064; https://doi.org/10.3390/electronics10172064

Sibhatu, K.T., & Qaim, M. (2024). Rural food security, subsistence agriculture, and seasonality. Retrieved on 21st August, 2024 from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0186406

Simske, S. (2019). Meta-analytics: consensus approaches and system patterns for data analysis. Morgan Kaufmann.

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. https://arxiv.org/abs/1409.1556

Wang, W., Tian, J., Zhang, C., Luo, Y., Wang, X., & Li, J. (2020). An improved deep learning approach and its applications on colonic polyp images detection. BMC Medical Imaging 20 (83), 1-14. https://doi.org/10.1186/s12880-020-00482-3

Zhang, C., & Zhang, Z. (2024). Improving multiview face detection with multi-task deep convolutional neural networks. Retrieved on 21st August, 2024 from 2014 IEEE Winter Conference on Applications of Computer Vision, WACV 2014, Colorado, USA. 1036–1041. https://doi.org/10.1109/WACV.2014. 6835990