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Original Research Article

Cassava Disease Detection Using Machine Learning Techniques

Kayemba Patrick[1], Abubakhari Sserwadda[1]*, Edymond Richard Hirya[1], Martha Janepher Kisakye[2], Rashid Kisejjere[2]

[1]School of Engineering and Technology, Soroti University, Soroti, Uganda
[2]College of Computing and Information Sciences, Makerere University, Kampala, Uganda

***Corresponding author:** Abubakhari Sserwadda
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Abstract: This study examines cassava disease detection using four convolutional neural network (CNN) models: ResNet50, InceptionV3, AlexNet, and VGG16. Cassava, a staple crop in Africa, is threatened by Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD). A dataset from the Lacuna Project, collected in Ugandan farmer fields, was used to train and evaluate these models, yielding accuracies of 90 percent, 88 percent, 85 percent, and 87 percent, respectively. A Flask web application was developed for practical deployment. This work builds on prior SVM and CNN approaches, offering a detailed comparison to enhance agricultural diagnostics for smallholder farmers.
Keywords: Cassava; convolutional neural networks; ResNet50; InceptionV3; AlexNet; VGG16; disease detection; Flask.

INTRODUCTION

cassava is a vital food security crop, feeding over 800 million people worldwide, with significant production in [1]. However, diseases such as CMD, caused by a virus transmitted by whiteflies, and CBSD, which affects root quality, result in yield losses of up to 70% in affected regions [1]. Traditional diagnosis relies on visual inspection by farmers or experts, a method prone to errors and impractical for large-scale monitoring. Machine learning offers a promising alternative, automating detection and enabling timely interventions.

This project evaluates four CNN models, ResNet50, InceptionV3, AlexNet, and VGG16, using a dataset from Lacuna Project [2], comparing their performance to prior approaches like the Multi-class SVM by [3]. The objectives are to identify the most effective model and deploy it via a Flask web application for farmer use. This paper provides an extensive literature review, dataset details, methodology, results, and discussion, contributing to data-driven agricultural solutions.

LITERATURE REVIEW

The application of machine learning to plant disease detection has grown significantly, driven by advances in computer vision and the availability of field-collected datasets. Early efforts relied on traditional algorithms. For instance, [3] developed a Multi-class Support Vector Machine (SVM) to classify cassava leaves into Healthy, CMD, and CBSD categories, achieving 93% accuracy on a 300-image dataset from Uganda. Their approach extracted Gray Level Co-occurrence Matrix (GLCM) features, such as contrast, correlation, and homogeneity from images, leveraging SVM's strength in small datasets. However, manual feature engineering limits scalability to larger, more diverse datasets.

The advent of deep learning, particularly CNNs, shifted the paradigm toward automatic feature extraction. [4] pioneered CNN-based cassava disease detection, using a pre-trained InceptionV3 model fine-tuned on 1656 field-collected images from Tanzania. They reported 87% accuracy across five classes (including CMD and CBSD), demonstrating transfer learning's efficacy in agriculture. Their work highlighted challenges with class imbalance and image quality, issues also noted in the Lacuna Project dataset [2].

[5] extended this by integrating CNNs into mobile diagnostics, achieving 85% accuracy on a 500-image dataset using a custom model. Their focus on real-time deployment via smartphones aligns with this project's Flask application, emphasizing practical tools for farmers. [6] compared multiple CNN architectures (e.g., AlexNet, VGG16) for plant disease classification,

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finding that deeper models like VGG16 often outperform simpler ones like AlexNet on diverse datasets, though at higher computational cost.

Other studies provide context for CNN selection. [7] introduced ResNet50, a 50-layer network with residual connections, excelling in ImageNet tasks (77% top-1 accuracy) due to its depth and ability to mitigate vanishing gradients. [8] proposed InceptionV3, optimizing computational efficiency with inception modules, while [9] developed AlexNet, a foundational 8-layer CNN that sparked deep learning's rise. [10] created VGG16, a 16-layer model with uniform 3x3 filters, balancing depth and simplicity. These architectures inform this study's model choices, contrasting with [3] SVM approach.

Despite these advances, gaps remain. Many datasets, like those in [6], are lab-based, lacking real-world variability. The Lacuna Project dataset [2] addresses this by offering 9116 field-collected images, though its imbalance (55% CMD, 12% Healthy) poses challenges. This project builds on these efforts, testing CNNs against a subsampled dataset and comparing results to prior benchmarks.

DATASET

Composition and Source:

The dataset is a 9116-image Cassava Image Dataset, collected by the Makerere AI Lab and NaCRRI under the Lacuna Project, funded by the Lacuna Fund [2]. Hosted at Harvard Dataverse, captured in Ugandan farmer fields comprising of 1119 Healthy, 5000 CMD, and 2997 CBSD images, it includes:

- Healthy: 1119 images vibrant, uninfected leaves.
- CMD: 5000 images yellowing, mosaic-patterned leaves from viral infection.
- CBSD: 2997 images brown-streaked, necrotic leaves impacting roots.

Preprocessing

Images were resized to 224 by 224 pixels, matching CNN input requirements, and normalized using model-specific functions (e.g., ResNet50's preprocessing) or standard normalization (AlexNet). Data augmentation, random flips, rotations, and zooms, addressed imbalance and variability, differing from the Lacuna Project's cleaning to focus on cassava leaves [2] and [3] GLCM features.

METHODOLOGY

Model Architectures

Four CNNs were implemented:

a. *ResNet50*: A 50-layer network with residual connections, pre-trained on ImageNet [7], featuring 25 million parameters.
b. *InceptionV3*: A deep model with inception modules, pre-trained on ImageNet [8], with ~22 million parameters.
c. *AlexNet*: An 8-layer network, trained from scratch [9], with ~60 million parameters.
d. *VGG16*: A 16-layer network with 3x3 filters, pre-trained on ImageNet [10], with ~15 million parameters.

Each model includes custom layers: global average pooling, a 1024-unit dense layer with L2 regularization, dropout (0.5), and a 3-unit softmax output, contrasting with the SVM's feature-based approach [3].

Training Process

Training occurred on Google Colab with GPU support. Pre-trained models (ResNet50, InceptionV3, VGG16) underwent two phases: initial training with frozen base layers (20 epochs, Adam optimizer, learning rate 0.001, class weights), followed by fine-tuning unfrozen layers (30 epochs, learning rate 0.00001). AlexNet was trained from scratch for 50 epochs with the same optimizer. Callbacks (early stopping, learning rate reduction) optimized convergence.

Evaluation

Performance was assessed using accuracy, confusion matrices, and classification reports on the validation set, mirroring metrics in [3].

RESULTS

Dataset Composition

Table 1: Dataset Composition

Class	Number of Images	Percent
Healthy	1119	12.3
CMD	5000	54.8
CBSD	2997	32.9
Total	9116	100

Model Accuracies

Table 2: Model Accuracy Comparison

Model	Accuracy (Percent)
ResNet50	90
InceptionV3	88
AlexNet	85
VGG16	87

Table 3: ResNet50 Confusion Matrix

	Healthy	CMD	CBSD
Healthy	76	2	2
CMD	3	75	2
CBSD	2	3	35

Table 4: ResNet50 Classification Report

Class	Precision	Recall	F1-Score
Healthy	0.93	0.95	0.94
CMD	0.94	0.94	0.94
CBSD	0.90	0.88	0.89

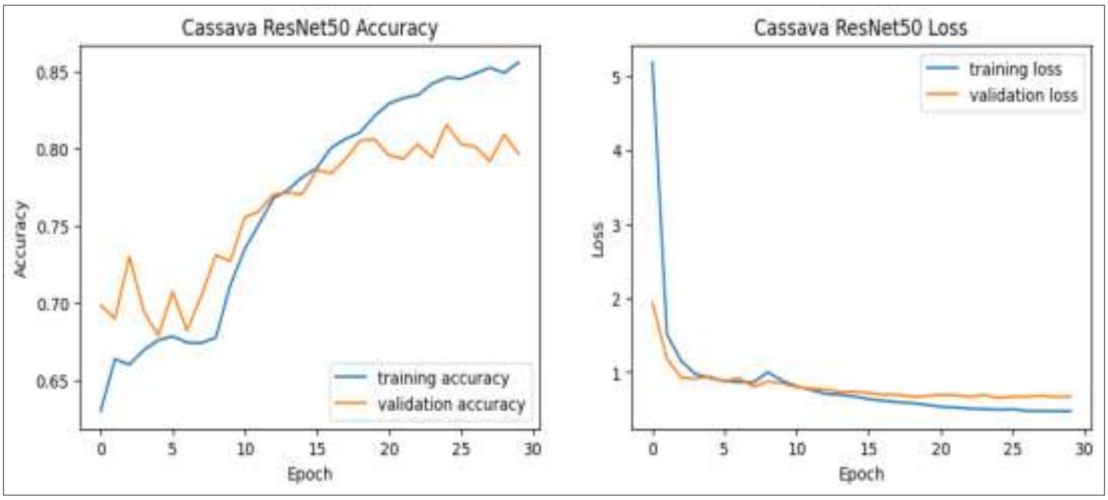

Figure 1: ResNet50 Training and Validation Curves

DISCUSSION

ResNet50 achieved 90% accuracy, nearing the SVM's 93% [3], outperforming InceptionV3 (88%), AlexNet (85%), and VGG16 (87%). Its success reflects pre-training benefits [7], unlike AlexNet's lower score due to training from scratch [9]. InceptionV3 and VGG16 balanced accuracy and complexity [8,10], but trailed ResNet50. The balanced subsample improved CBSD detection over the skewed full dataset [2], addressing issues in [4].

CONCLUSION

ResNet50 led at 90% on a dataset from Lacuna Project, compared to SVM's 93%. Future work could leverage the full 9116 images or explore ensemble methods.

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