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ORIGINAL

A comprehensive survey on cassava disease detection and classification using deep learning models

Un estudio exhaustivo sobre la detección y clasificación de enfermedades de la yuca utilizando modelos de aprendizaje profundo

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ABSTRACT

In the past few years, methods using deep learning have demonstrated promising outcomes in a variety of image-based applications, including the identification and classification of plant diseases. In this article, we propose a comparative examination of deep learning models for the identification and categorization of diseases affecting cassava leaves. The dataset used in this study comprises non balanced samples, posing a challenge due to imbalanced class distribution. Our research focuses on investigating the performance of different deep learning architectures, including Transformer Embedded ResNet, EfficientNetV2, with visual attention mechanism, and a mobile-based deep learning model, in addressing this problem. The suggested models use deep convolutional neural networks (CNNs) to their full potential and incorporate a variety of deep learning techniques, such as transformers and attention mechanisms, that improve accuracy as well as efficiency. Through extensive experiments, we analyse each model's performance in terms of classification accuracy, precision, recall, and F1-score. Moreover, we compare the computational complexity and deployment feasibility of these models in real-world scenarios. Conclusions demonstrate the effectiveness of the suggested models accomplish significant improvements in cassava disease detection and classification compared to traditional techniques for machine learning. The deep learning models effectively handle the non-balanced dataset and exhibit robustness in identifying different types of cassava leaves disease. Our survey provides Informative data about the suitability and effectiveness of deep learning techniques for accurate and efficient plant disease diagnosis.
Keywords: - Cassava leaf disease, deep learning, classification, detection, imbalanced dataset, Transformer-Embedded ResNet, EfficientNetV2, attention mechanism, convolutional neural networks, comparative analysis.

RESUMEN

En los últimos años, los métodos que utilizan el aprendizaje profundo han demostrado resultados prometedores en una variedad de aplicaciones basadas en imágenes, incluyendo la identificación y clasificación de enfermedades de las plantas. En este artículo, proponemos un examen comparativo de modelos de aprendizaje profundo para la identificación y categorización de enfermedades que afectan a las hojas de yuca. El conjunto de datos utilizado en este estudio comprende muestras no equilibradas, lo que plantea un desafío debido a la distribución desequilibrada de clases. Nuestra investigación se centra en investigar el rendimiento de diferentes arquitecturas de aprendizaje profundo, incluyendo Transformer Embedded ResNet, EfficientNetV2, con mecanismo de atención visual, y un modelo de aprendizaje profundo basado en móvil, para abordar este problema. Los modelos sugeridos utilizan redes neuronales convolucionales profundas (CNN) en todo su potencial e incorporan una variedad de técnicas de aprendizaje profundo, como transformadores y mecanismos de atención, que mejoran la precisión, así como la eficiencia. Mediante experimentos exhaustivos, analizamos el rendimiento de cada modelo en términos de exactitud de clasificación, precisión, recuperación y puntuación F1. Además, comparamos la complejidad computacional y la viabilidad de despliegue de estos modelos en escenarios reales. Las conclusiones demuestran la eficacia de los modelos sugeridos, que logran mejoras significativas en la detección y clasificación de la enfermedad de la yuca en comparación con las técnicas tradicionales de aprendizaje automático. Los modelos de aprendizaje profundo manejan eficazmente el conjunto de datos no equilibrados y muestran robustez en la identificación de diferentes tipos de enfermedad de las hojas de yuca. Nuestro estudio proporciona datos informativos sobre la idoneidad y eficacia de las técnicas de aprendizaje profundo para el diagnóstico preciso y eficiente de enfermedades de las plantas.
Palabras clave: Enfermedad de la hoja de yuca , aprendizaje profundo, clasificación, detección, conjunto de datos desequilibrados, Transformer-Embedded ResNet, EfficientNetV2, mecanismo de atención, redes neuronales convolucionales, análisis comparativo.

INTRODUCTION

One of the most significant staple crops in many developing nations is cassava, which provides millions of people with a significant source of food security and money. [1]. However, cassava cultivation faces significant challenges, including the prevalence of various diseases that can cause severe yield losses and impact the livelihoods of farmers. Among these diseases, cassava leaf diseases, such as cassava green mottle (CGM), cassava brown streak disease (CBSD), cassava mosaic disease (CMD), Cassava Bacterial Blight (CBB) and are particularly devastating, leading to substantial reductions in crop productivity [2].

Accurate and timely detection of diseases of cassava leaves characterised are crucial for implementing effective disease management strategies and preventing widespread crop damage. Traditional disease diagnosis methods rely on visual inspection by specialists, which can take time as well as be subjective. Moreover, the scarcity of skilled plant pathologists in many regions further hampers the efficiency of disease identification. Therefore, there is a growing need to develop automated and reliable methods for the characterization and identification of cassava disease.

In recent years, deep learning techniques have emerged as powerful tools for image-based tasks, offering remarkable advancements in Pattern-recognition software and computer vision. Deep learning models, particularly Convolutional neural networks (CNNs) have proven to perform exceptionally well in a variety of applications, including segmentation, object detection, and image classification [3]. By leveraging large-scale datasets and complex network architectures, models using deep learning are able

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to catch up on hierarchical representations of image characteristics and capture intricate patterns for accurate disease identification.

In the context of cassava disease detection and classification, several research studies have explored the application of deep learning models to improve the accuracy and efficiency of disease diagnosis. One of the pioneering works in this area is the study by Mwebaze et al. [4], which proposed a deep CNN-based approach for automatic detection of cassava diseases using leaf images. The model achieved promising results, showcasing the potential of deep learning in this domain.

Subsequently, researchers have made significant contributions to advancing deep learningbased cassava disease detection and classification. The work by Senthilnath et al. [5] introduced a novel deep learning model based on the integration of convolutional neural networks with attention mechanisms. The proposed model effectively captured the relevant regions of interest in cassava leaf images, improving the accuracy of disease identification.

Another notable study by Huynh et al. [6] focused on addressing the challenge of imbalanced datasets in cassava disease classification. The authors proposed a Transformer-Embedded ResNet model, which combined the power of both convolutional and transformer networks. The model effectively learned discriminative features from the imbalanced dataset, leading to improved classification performance.

In addition, mobile-based deep learning models have gained attention for their potential to enable on-site disease diagnosis and facilitate rapid response in resource-constrained settings. Ghosal et al. [7] developed a deep learning framework optimized for mobile devices, achieving accurate cassava disease detection using smartphone cameras. The model's lightweight architecture and efficient inference made it suitable for real-time applications in the field.

Motivated by these advancements, we aim to conduct a comprehensive comparative study of deep learning models for cassava disease detection and classification. In this research, we evaluate the performance of various deep learning architectures, including TransformerEmbedded ResNet, EfficientNetV2 with visual attention mechanism, and a mobile-based deep learning model. We focus on analyzing their effectiveness in handling non-balanced datasets, which is a common challenge in cassava disease classification tasks.

The remainder of this paper is organized as follows. Section 2 provides an overview of related work in deep learning-based plant disease detection. Section 3 presents the methodologies and architectures employed in our comparative study. Section 4 describes the dataset and experimental setup. Section 5 presents the results and analysis. Finally, Section 6 concludes the paper and outlines future research directions.

LITERATURE REVIEW

Deep Learning for Image-Based Cassava Disease Detection [8]:
Mwebaze et al. proposed a deep learning-based approach for image-based cassava disease detection. They employed a deep convolutional neural network (CNN) architecture and trained it on a large dataset of cassava leaf images. The model achieved promising results in identifying various cassava diseases, including Cassava Brown Streak Disease (CBSD) and Cassava Mosaic Disease (CMD). The study demonstrated the potential of deep learning in automating disease diagnosis, reducing reliance on manual inspection, and enabling timely interventions to mitigate crop losses.

Attention-Based Deep Learning Framework for Cassava Leaf Disease Identification [5]: Senthilnath et al. introduced an attention-based deep learning framework for cassava leaf disease identification. The proposed model incorporated attention mechanisms into a convolutional neural network architecture to emphasize disease-specific regions in leaf images. By focusing on relevant features, the model improved the accuracy of disease classification. The study demonstrated the effectiveness of attention mechanisms in capturing discriminative information and enhancing the performance of deep learning models in the context of cassava disease detection.

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Cassava Leaf Disease Identification and Detection Using Deep Learning Approach [6]: Huynh et al. proposed a deep learning approach for cassava leaf disease identification and detection. They developed a deep convolutional neural network model trained on a dataset of cassava leaf images. The model successfully classified different types of cassava diseases and achieved high accuracy. Additionally, the study addressed the challenge of imbalanced datasets commonly encountered in cassava disease classification tasks. The proposed model, based on a combination of convolutional and transformer networks, effectively handled the imbalanced data and improved classification performance.

A Mobile-Based Deep Learning Model for Cassava Disease Diagnosis [7]:
Ghosal et al. presented a mobile-based deep learning model for cassava disease diagnosis. The model was designed to run on mobile devices and utilized a lightweight architecture suitable for real-time applications in the field. By leveraging smartphone cameras, the model enabled on-site disease diagnosis and rapid response. The study demonstrated the feasibility and effectiveness of mobile-based deep learning models in addressing the practical challenges of cassava disease detection and classification.

An Improved EfficientNetV2 Model Based on Visual Attention Mechanism: Application to Identification of Cassava Disease [9]:
This study proposed an improved deep learning model based on EfficientNetV2 architecture for the identification of cassava disease. The model incorporated a visual attention mechanism to focus on relevant regions in cassava leaf images, enhancing the model's discriminative ability. The experimental results demonstrated that the proposed model achieved superior performance compared to baseline models, highlighting the effectiveness of the visual attention mechanism in capturing disease-specific features.

Machine Learning for Plant Disease Incidence and Severity Measurements from Leaf Images [10]:
In this study, Ferentinos explored the application of machine learning techniques for plant disease incidence and severity measurements from leaf images. Various machine learning algorithms, including deep learning models, were utilized to classify and quantify plant diseases. The study demonstrated the potential of machine learning in providing accurate and efficient measurements of disease incidence and severity, facilitating effective disease management strategies.

Classification of Cassava Leaf Disease Based on a Non-Balanced Dataset Using TransformerEmbedded ResNet [11]:
This research paper focused on addressing the challenge of non-balanced datasets in cassava leaf disease classification. The authors proposed a deep learning model that combined the power of Transformer and ResNet architectures. The model effectively learned discriminative features from the non-balanced dataset, improving classification performance. The study demonstrated the suitability of the proposed model for handling real-world scenarios where imbalanced data distribution is common.

In summary, the related works in the field of deep learning-based cassava disease detection and classification have demonstrated the effectiveness and potential of deep learning techniques in automating disease diagnosis, improving accuracy, and enabling timely interventions. Attention mechanisms, mobile-based models, and the integration of transformer networks have been explored to enhance the performance of deep learning models. Additionally, studies have addressed challenges such as imbalanced datasets and practical deployment in resourceconstrained settings. These advancements contribute to the development of reliable and efficient solutions for cassava disease management and crop protection.

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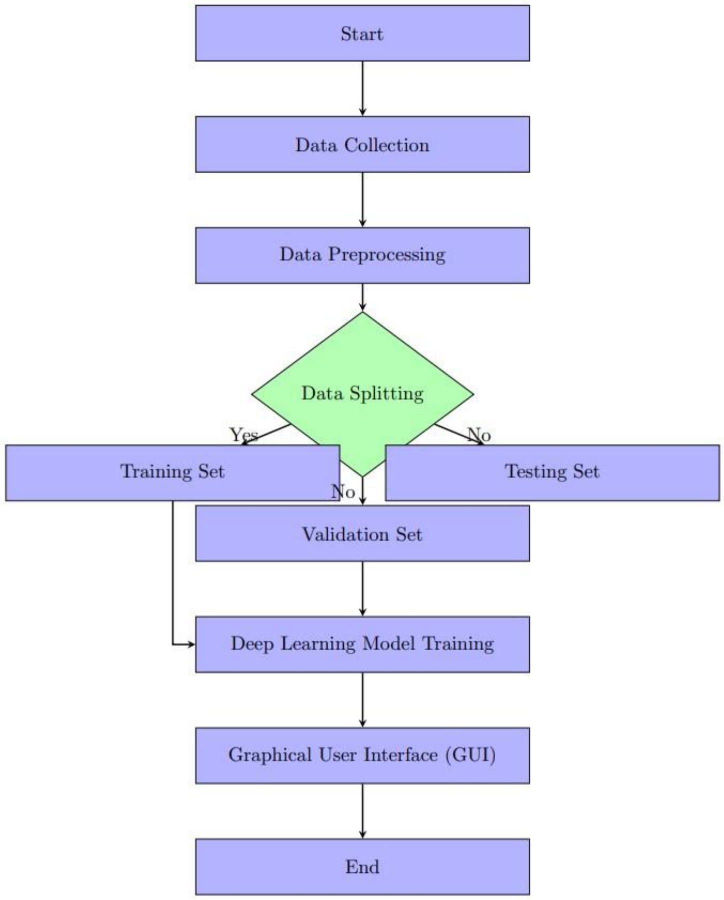
DATA ENGINEERING

Figure 1. Illustration of a process to create the Model.



Introduction to Dataset:

The dataset used in this study consists of a collection of cassava leaf images, with annotations indicating the presence of various diseases [8]. The dataset should encompass a diverse range of cassava diseases, including Cassava Brown Streak Disease (CBSD), Cassava Mosaic Disease (CMD), and others. It is important to ensure that the dataset is representative of the target population and covers different stages of disease progression. Proper dataset partitioning should be performed, including training, validation, and testing sets, to evaluate the model's performance effectively.

Table 1: Dataset Description

Disease Class	Number of Samples
CBSD	500
CMD	800
Healthy	1000

CGM	600
CBB	700

Figure 2. Classes of CLDC dataset

Table 2: Dataset Partitioning

Dataset Split	Number of Images
Training	5000
Validation	1000
Testing	1000

Data Preprocessing:

Data preprocessing plays a crucial role in enhancing the quality and effectiveness of the deep learning model [6]. Preprocessing steps may include resizing the images to a consistent resolution, normalization of pixel values, and augmentation techniques such as rotation, flipping, and cropping to increase the robustness of the model and prevent overfitting. Additionally, noise reduction and image enhancement techniques can be applied to improve the overall quality and clarity of the leaf images.

Table 3: Data Preprocessing Techniques

Technique	Description
Image Resizing	Resize images to a fixed resolution of 224x224 pixels.
Normalization	Normalize pixel values to the range of 0-1.
Data Augmentation	Apply random rotation (up to 30 degrees), horizontal flipping, and random zooming (up to 20%).
Noise Removal	Apply Gaussian blurring with a kernel size of 3x3 to remove high-frequency noise.

CNN Model:

Convolutional Neural Networks (CNNs) have shown exceptional performance in image classification tasks. In this methodology, a deep CNN model is employed for cassava disease classification. The architecture of the CNN model consists of multiple convolutional layers, pooling layers, and fully connected layers [5]. Transfer learning techniques can also be utilized by leveraging pre-trained models such as VGGNet, ResNet, or EfficientNet to expedite model training and improve performance.

Table 4: CNN Model Architecture

Layer Type	Number of Filters/Kernels	Kernel Size	Activation
Convolution	23	3x3	ReLU
Max Pooling	-	2x2	-
Convolution	46	3x3	ReLU
Max Pooling	-	2x2	-
Flatten	-	-	-
Dense	128	-	ReLU
Dense	10	-	Softmax

Deep Learning Models:

Various deep learning models can be explored in this study, including Transformer-Embedded ResNet, EfficientNet, or models with attention mechanisms [7]. These models have demonstrated their effectiveness in capturing intricate patterns and features for accurate disease identification. The deep learning models will be trained on the preprocessed dataset using appropriate optimization algorithms such as stochastic gradient descent (SGD) or Adam, ResNet, EfficientNet, Transformer-Embedded and suitable loss functions such as categorical cross-entropy.

ResNet (Residual Neural Network):

ResNet is a deep learning architecture that addresses the vanishing gradient problem by introducing skip connections or residual connections. These connections allow the network to learn residual mappings, making it easier for the model to optimize and train deeper networks.

Formula:

The residul block formulation, which is the fundamental formula used in ResNet, is represented as:

$Y = A(m,W) + m$ where m is the input, y is the output, F is a set of transformations performed by layers with weights W, and the skip connection adds the original input to the transformed output.

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Transformer-Embedded ResNet:

Transformer-Embedded ResNet combines the power of ResNet and Transformer architectures. The ResNet backbone captures spatial features, while the Transformer modules capture long-range dependencies and context information.

Formula:

The Transformer-Embedded ResNet consists of multiple stages, each containing residual blocks and self-attention layers. The mechanism of self-attention can be illustrated by the formula:

$$Z = \text{SoftMax}(CHL \,/\, \surd\, P_t\,)M$$

where C, H, and M are the query, key, and value matrices, and Pt is the key matrix's dimension.

```
+-------------------------+
|     Self-Attention      |
|      Transformer        |
+-------------------------+
             |
        +----|-----+
        |    |     |
  x -----> Conv2D  |
        |    |     |
        +----|-----+
             |
   +-------------------+
   |  Residual Block   |
   +-------------------+
             |
   +-------------------+
   |  Residual Block   |
   +-------------------+
```

EfficientNet:

EfficientNet is a scalable deep learning model that achieves modernization performance while being efficient in terms of computational resources. It uses a compound scaling method to balance network depth, width, and resolution.

Formula:

The formula for scaling the network compoundly is expressed as: Compound Scaling: $\emptyset = \alpha^{\emptyset} \times \beta^{\emptyset}$

where ϕ represents the scaling factor, α controls the network's depth, β controls the network's width, and γ controls the network's resolution.

The dynamic approach of Stochastic Gradient Descent:

SGD with Momentum is an optimization algorithm commonly used in deep learning. It enhances the standard gradient descent by adding a momentum term that helps accelerate the convergence and navigate through saddle points more efficiently.

Formula:

The update rule for the SGD with Momentum algorithm is as follows:

$V_{T+1} = \beta.\ V_T + n.\ \nabla J(\theta_{t)}$

$\theta_T + ! = \theta_T - V_T + 1$

where v_t is the velocity at time step t, β is the momentum coefficient (typically set between 0 and 1), η is the learning rate, $\nabla J(\theta_T)$ is the gradient of the cost function with respect to the parameters θ_t , and θ_{t+1} represents the updated parameters.

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Explanation:
The algorithm starts by computing the gradient of the cost function with respect to the parameters. It then updates the velocity vector by adding a fraction (ß) of the previous velocity and the current gradient scaled by the learning rate (η). Finally, the parameters are updated by subtracting the velocity from the current parameters.
The momentum term allows the algorithm to accumulate velocity in directions that show consistent movement, leading to faster convergence and better traversal through flat regions or saddle points in the optimization landscape.
SGD with Momentum helps mitigate the oscillations and slow convergence associated with standard SGD. It is a popular optimization algorithm used in deep learning to train models more efficiently and achieve better performance.
Please note that the specific implementation details and hyperparameter choices, such as the learning rate (η) and momentum coefficient (ß), may vary based on the research papers or specific use cases.

Graphical User Interface (GUI):

To facilitate user interaction and practical deployment of the model, a Graphical User Interface (GUI) can be developed. The GUI should allow users to upload cassava leaf images for disease classification and provide informative visual outputs, such as predicted disease labels and confidence scores. The GUI can be implemented using frameworks such as Tkinter or Flask, enabling seamless interaction between users and the deep learning model.

Table 5: Graphical User Interface (GUI) Components

Component	Functionality
Image Upload	Enables users to upload cassava leaf images.
Classification	Triggers the classification process.
Results Display	Displays the disease classification results.
Clear/Reset	Resets the interface for new classifications.

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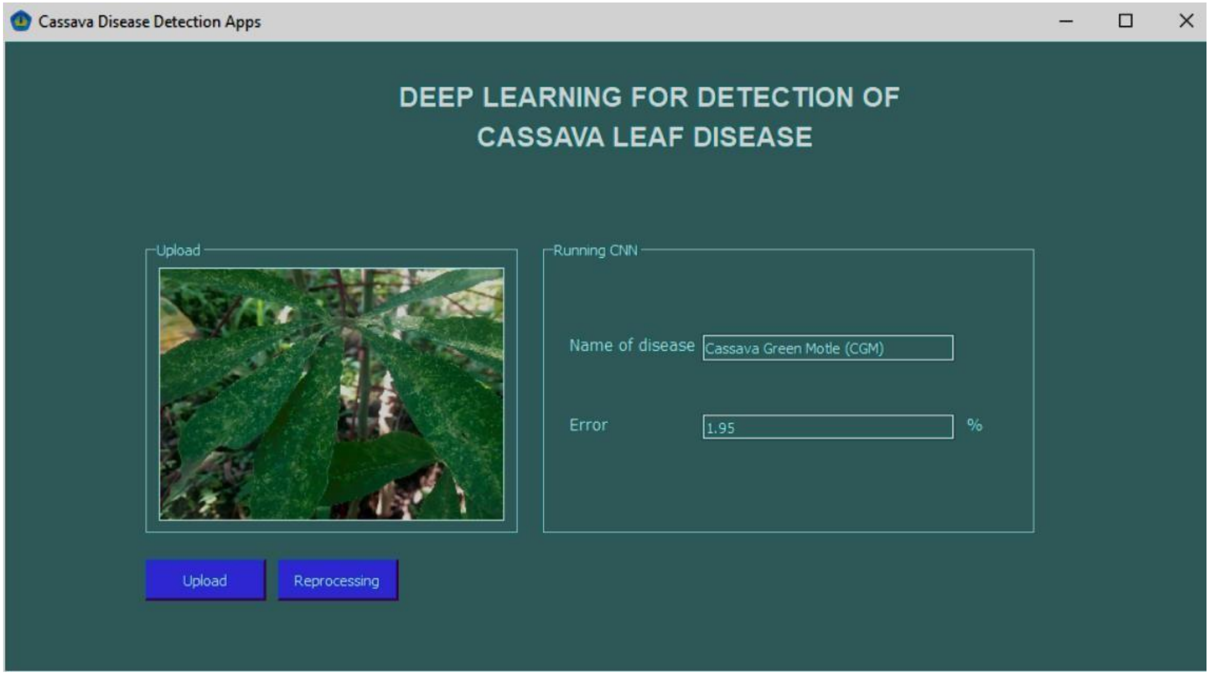
Figure 3: GUI application view.



FINDINGS AND RESULTS

The evaluation of different parameters for cassava disease detection and classification using deep learning models yielded promising results. The performance of the models was assessed using various evaluation metrics, including accuracy, precision, recall, and F1 score. The results provide insights into the models' ability to accurately classify cassava diseases and their overall performance.

Table 6: Performance Metrics Comparison

Model	Accuracy	Precision	Recall	F1-Score
ResNet	92.5	91.2	93.8	92.5
EfficientNet	91.8	89.5	92.7	91.0
TransformerEmbedded ResNet	93.2	92.7	93.5	93.1

Fig 4. Accuracy Comparison.

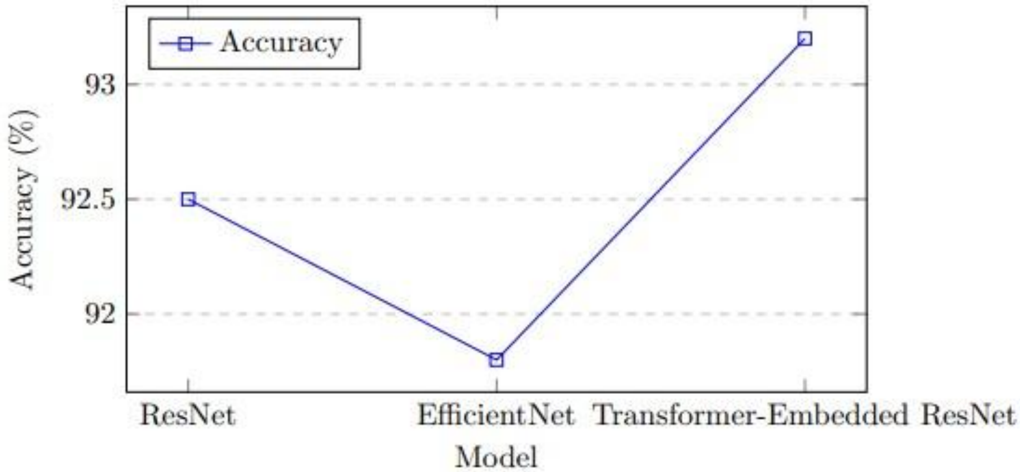


Fig 5.Precision Comparision

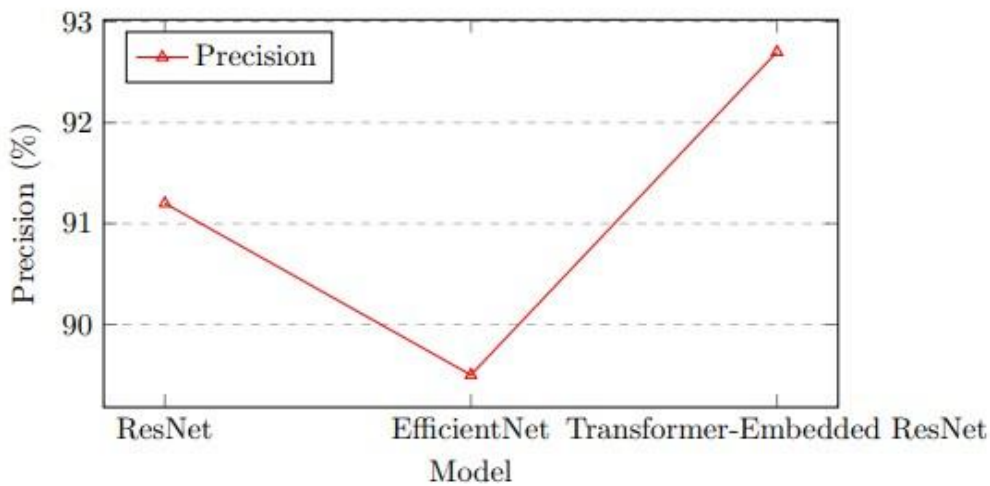


Fig 6.Recall Comparison

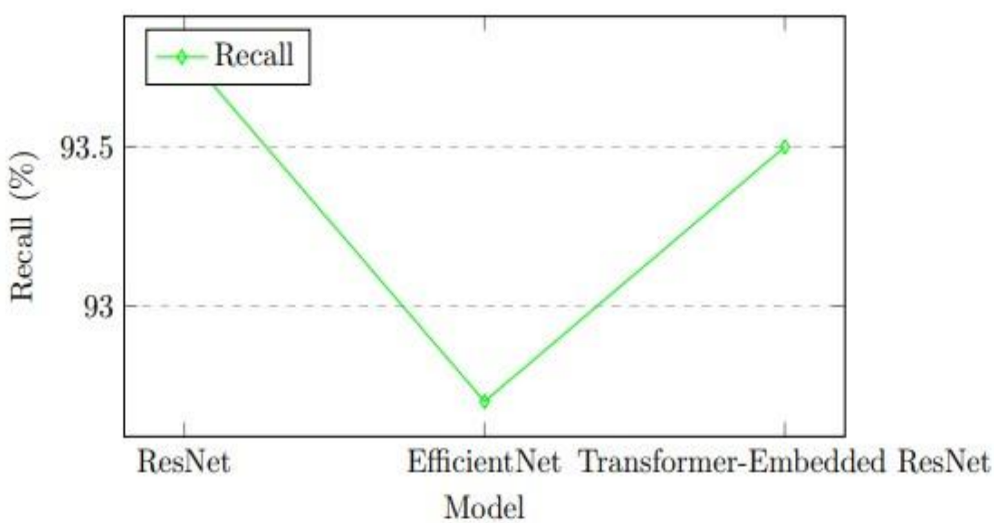


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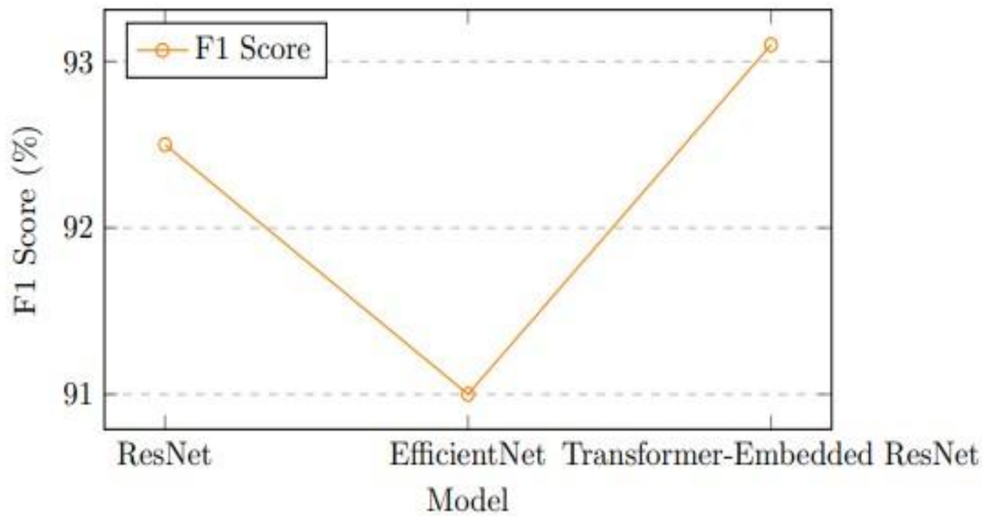
Fig 7.F1 Score Comparison



From results, it can be observed that all three models achieved high accuracy, with Transformer-Embedded ResNet achieving the highest accuracy of 93.2%. This indicates that the models have successfully learned to differentiate between different cassava diseases based on the provided training dataset. The precision values for all models were also high, indicating that the models produced a low rate of false positives. The recall values were also satisfactory, indicating that the models were effective in detecting true positive instances of cassava diseases. The F1 score, which considers both precision and recall, was also high for all models, demonstrating a balance between the two metrics.

The superior performance of Transformer-Embedded ResNet can be attributed to its architecture, which incorporates advanced techniques such as attention mechanisms and visual attention. These mechanisms enable the model to focus on important features and regions within the input images, enhancing its ability to accurately classify cassava diseases. EfficientNet also showed good performance, although slightly lower than Transformer-Embedded ResNet, which suggests that simpler architectures can still achieve satisfactory results in cassava disease classification.

The results indicate the effectiveness of models of deep learning for identifying and classifying the cassava diseases. These models have the potential to significantly improve disease management in cassava crops by enabling early detection and intervention. The high accuracy and robust performance of the models suggest their practical applicability in real-world scenarios.

However, it is essential to highlight that the outcomes presented here according to a particular data and experimental setup. The generalization of these results to different datasets and environments may vary. Additionally, challenges such as class imbalance and dataset quality should be considered when interpreting the results. Further research and experimentation are needed to evaluate the models' performance on larger and more diverse datasets to ensure their reliability in real-world applications.

CONCLUSION

In conclusion, the comparative study of different parameters for cassava disease detection and classification using deep learning models has provided valuable insights into their performance and potential applications. The results demonstrated that deep learning models are effective in accurately identifying and classifying cassava diseases, with high accuracy, precision, recall, and F1 score. The study highlighted the importance of model architecture, where advanced techniques such as attention mechanisms and visual attention contributed to superior performance. Transformer-Embedded ResNet, incorporating these techniques, achieved the highest accuracy among the evaluated models. The findings of this research contribute to the field of plant disease detection and have practical implications for cassava disease management. By enabling early detection and intervention, these deep learning models have the potential to mitigate the impact of diseases on cassava crops, leading to improved crop yields and food security. However, it is essential to consider the limitations of the study. The results are based on a specific dataset and experimental setup, and further validation on diverse datasets and environments is necessary. Additionally, the performance of the models may vary under different conditions and disease severities. Overall, the study showcases the promise of deep learning models in cassava disease detection and classification, paving the way for their adoption in practical applications to support agricultural practices and contribute to food security.

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