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RESEARCH ARTICLE

Embedded Residual Neural Networks for Real-World Plant Disease Identification in Digital Agriculture

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ABSTRACT - This study addresses the challenge of real-time plant disease identification on resource-constrained embedded platforms, a critical need for improving agricultural productivity. Using the NVIDIA Jetson Orin Developer Kit and the PlantVillage dataset, the research evaluates Residual Neural Networks (ResNets), focusing on ResNet-50, ResNet-101, and ResNet-152. The study highlights the balance between model depth, batch size, accuracy, and computational efficiency. ResNet-101, optimized with a batch size of 64, achieved 90.62% accuracy and an average identification time of 17.6 milliseconds, emerging as the most effective configuration. These findings demonstrate the feasibility of deploying deep learning models on embedded devices and provide insights into optimizing architectures for real-time agricultural applications.

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1.0 INTRODUCTION

In most developing countries, farmers traditionally rely on visual observation for crop disease detection and identification, introducing the risk of subjective analysis and potential misdiagnosis [1], [2]. The challenge lies in the limitations of human assessment, which often leads to delayed responses and improper treatments, further exacerbating crop loss and economic setbacks. This difficulty extends to plant pathologists and agronomists, who may encounter challenges in precisely identifying diseases, resulting in inadequate countermeasures. For instance, diseases like wheat rust, rice blast, and late blight in potatoes contribute to annual global crop losses estimated at over $220 billion, with significant impacts on food security and farmer livelihoods [3], [4]. Artificial intelligence in recent times has exhibited potential within the realm of precision agriculture [5], [6], [7]. While machine learning methodologies have been employed for disease identification, as demonstrated by previous studies such as [8], [9], [10], this paper goes beyond by implementing a system that not only leverages machine learning for disease identification but also deploys it on an embedded platform for real-time processing in the field.

We introduce a novel automatic crop disease diagnosis system designed for real-time identification of plant diseases using plant leaf images captured by a handheld embedded device. The device, equipped with a camera, facilitates on-the-spot diagnosis and delivers timely, accurate information to farmers, addressing environmental challenges such as varying illumination, complex backgrounds, and field conditions. Its compact, portable design ensures usability directly in the field, empowering farmers with practical, technology-driven support. The schematic diagram illustrating the entire system is provided Figure 1 while a link to our GitHub repository is given[1].

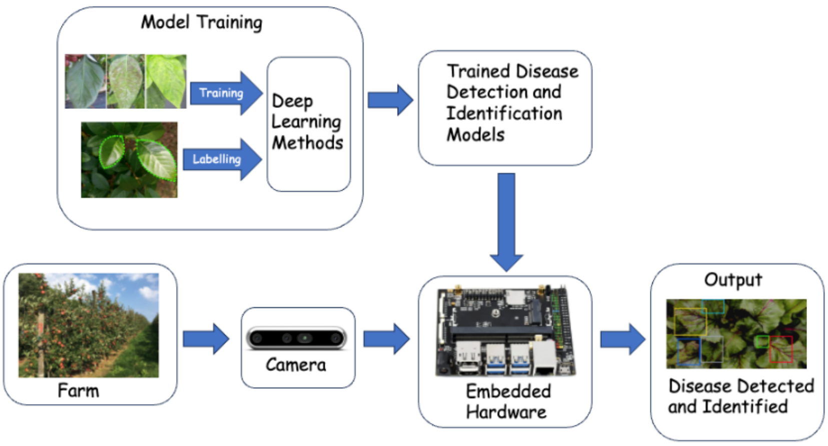

Figure 1. Schematic of plant disease identification system on an embedded platform

[1] https://github.com/daniel-udekwe/ResNet-101-Plant-Disease.git

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To address the specific task of identifying plant diseases, a neural network architecture, specifically a residual neural network, is developed and trained using the publicly accessible plant village dataset. ResNets are chosen over other models due to their exceptional ability to address the vanishing gradient problem and maintain high accuracy as network depth increases. Their residual connections allow for more efficient training of deeper networks, facilitating superior performance in complex image classification tasks such as plant disease identification[11], [12]. The entire framework for detection and identification is adapted for data processing on NVIDIA Jetson Orin. To facilitate on-the-spot dis- ease diagnosis, a handheld device is designed with a camera capable of capturing live input directly from the field in real-time. This data is then transmitted to the NVIDIA Jetson Orin for processing. The embedded system identifies leaves and determines the type of disease present. This innovative system integrates machine learning, embedded technology, and real-time processing to provide a practical solution for crop disease diagnosis. It empowers farmers with a valuable tool for efficient and accurate in-field identification.

This study aims to achieve enhanced recognition accuracy in the identification of plant diseases on an embedded system. During this study, two fundamental aspects will be examined:

1. The impact of different batch sizes on training our network to accurately recognize plant diseases. Specifically, batch sizes of 16, 32, 64, and 128 will be examined.
2. The impact of network depth on the successful recognition of apple leaf disease will be investigated. This study will specifically concentrate on residual networks with varying depths, including 50, 101, and 152 layers

This paper makes the following significant contributions:

1. Real-time identification of crop diseases using leaf images processed on embedded hardware.
2. Integration of plant disease identification into a portable embedded device for accurate, on-site diagnosis, marking a step forward in practical, field-ready solutions for precision agriculture.

By bridging the gap between advanced machine learning models and real-time embedded systems, this work offers a transformative approach to tackling plant disease diagnosis in resource-constrained settings.

The paper is organized as follows: Section 2 reviews existing literature on plant disease identification using machine learning. Section 3 details the leaf detection model and the proposed architecture for identifying plant diseases. Section 4 presents and compares the effectiveness of our approach with established models. Finally, Section 5 concludes with a summary of key findings and their implications.

2.0 RELATED WORKS

In recent years, the intersection of deep learning and plant disease detection has marked a significant paradigm shift in agriculture. Pioneering studies have illuminated the potential of convolutional neural networks (CNNs) in accurately discerning plant diseases from leaf images, laying the foundation for subsequent research [13]. Inspired by this, other studies explored deep learning methodologies for agricultural disease identification, focusing on leveraging deep neural networks for robust feature extraction and classification and showcasing promising results in disease recognition [14]. However, these approaches often face limitations related to high computational requirements, making them less feasible for deployment in resource-limited settings. The application of deep learning was further extended to cassava disease detection, underscoring the adaptability of CNNs in distinguishing between healthy and diseased cassava plants [15]. This advancement not only addressed specific crop diseases but also emphasized the broader impact of deep learning on food security. Despite these successes, one challenge remains in ensuring that these models can generalize effectively across various environmental conditions, such as changes in lighting and background, which can affect performance.

An innovative approach combined spatiotemporal CNNs with fused region-based CNNs for wheat disease detection, demonstrating the potential for enhanced accuracy and specificity in complex agricultural environments [16]. The comparative strength of this method lies in its ability to integrate temporal and spatial data for improved precision; however, this comes at the cost of increased model complexity and longer training times, potentially hindering real-time application. Other researchers focused on tomato plant health, employing deep learning for disease identification and showcasing the versatility of CNNs in handling various tomato plant issues [17]. While these studies illustrated the adaptability of deep learning models across different crops, they highlighted challenges related to data diversity and the need for extensive labeled datasets to ensure model reliability. These collective insights contribute to a growing body of knowledge that highlights the importance of crop management. A crucial synthesis of these advancements discussed the strengths and limitations of various deep learning techniques applied to plant disease diagnosis [18]. Key limitations identified include the reliance on high-quality, annotated datasets and the significant power consumption required for many deep learning models, which can impede their scalability for widespread agricultural use.

In this context, Residual Neural Networks (ResNets) were chosen over architectures such as EfficientNet and MobileNet due to their distinct advantages for this application. ResNets address the vanishing gradient problem through residual connections, allowing the training of deeper networks without a loss in accuracy. This capability is particularly critical for plant disease identification, as deeper networks can capture intricate patterns and features in complex datasets, such as those containing subtle visual differences among disease symptoms. While EfficientNet and MobileNet are optimized for resource-constrained environments and are known for their energy efficiency, their shallower architectures may struggle to achieve the same level of feature extraction and classification accuracy as ResNets when applied to high-resolution, diverse plant datasets.

The consistently high accuracy rates achieved by ResNets, combined with their robustness in handling complex image classification tasks, make them well-suited for real-time applications on embedded platforms such as the NVIDIA Jetson Orin. While EfficientNet and MobileNet could offer better power efficiency, this study demonstrates that ResNet-101 strikes an optimal balance between computational efficiency and accuracy, achieving superior performance without significantly compromising processing speed or energy consumption. These factors underscore ResNet's suitability for applications requiring both high accuracy and adaptability to diverse field conditions. The integration of ResNets with portable systems like the NVIDIA Jetson Orin holds tremendous promise for real-time, on-field plant disease identification. These systems offer a transformative solution for advancing sustainable agricultural practices but must continue addressing challenges such as optimizing models for energy efficiency and ensuring robust performance in varied environmental conditions. By leveraging the strengths of ResNets, this approach contributes to the development of scalable, reliable tools for precision agriculture.

3.0 METHODS AND MATERIAL

This study adopts a comprehensive approach of residual neural networks which have shown great promise in plant disease detection. Comprising ResNet-50, ResNet-101 and ResNet-152, the effects of varying batch sizes of test and validation datasets are examined. This is aimed at improving accuracy in plant disease identification while deploying on an embedded platform such as the Jetson Orin development board. The specific evaluation criteria for assessing the effectiveness of the proposed system include accuracy, processing speed (inference time), power consumption, and robustness under different environmental conditions. These criteria are essential for determining the practical viability of the system in real-world agricultural applications.

3.1 Dataset Description

The PlantVillage dataset[2] is a meticulously curated collection of images featuring diverse plant species affected by a wide range of diseases. The dataset (depicted in Figure 2) encompasses visually striking sample images showcasing the intricate symptoms of plant diseases. With a comprehensive breakdown of plant species, associated diseases, class labels, and image counts, this resource becomes invaluable for researchers in agriculture, computer vision, and deep learning. The dataset's richness in diversity and large image count makes it a powerful tool for developing and evaluating models for plant disease identification and precision agriculture. Overall, the PlantVillage dataset serves as a robust foundation for advancing research and solutions in the realm of plant pathology and agricultural sciences.

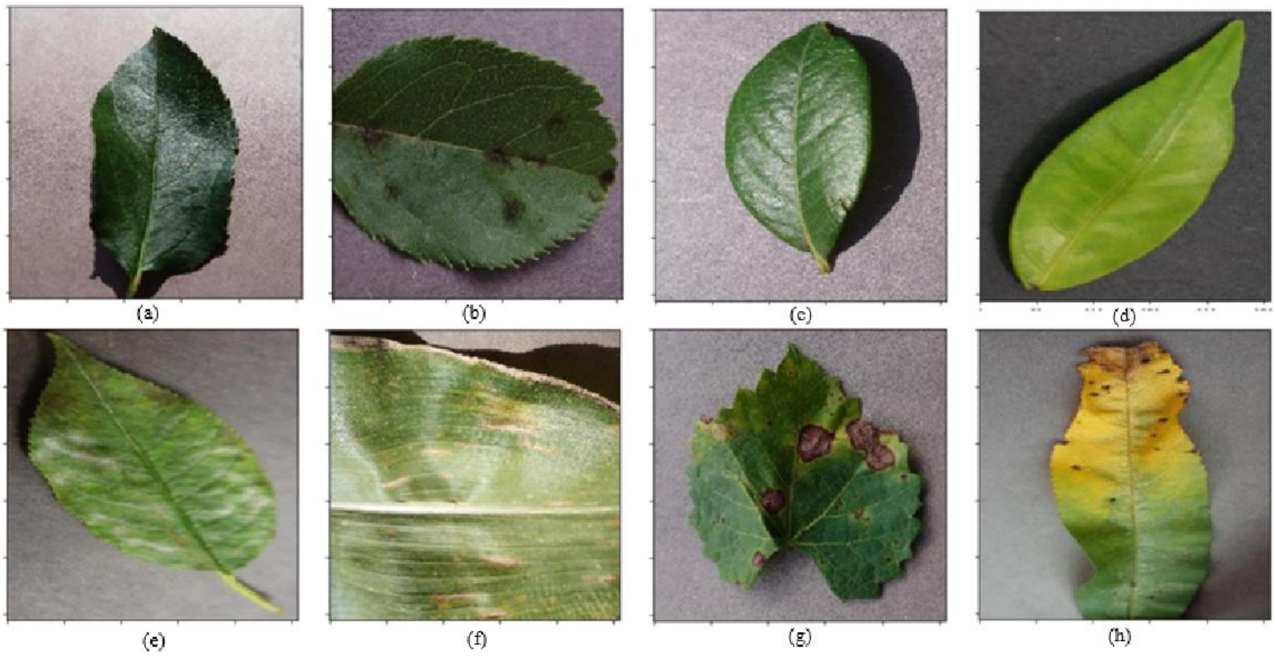


Figure 2. Images obtained from the dataset (a) healthy apple (b) apple with scab (c) healthy blueberry (d) haunglongbing Orange (e) Cherry (f) Corn with cercospora (g) Grape with blackrot (h) Peach with bacterial spot

[2] https://kaggle.com/datasets/vipoooool/new-plant-diseases-dataset

To evaluate the suitability of the proposed methods in identifying leaf diseases, we conducted real-time testing in an apple farm. Figure 3 displays selected images obtained from the field. The real-time video frames captured in the field were inputted into the trained detection and classification models, which were deployed on Jetson Orin Nano. This process involved initially detecting the leaves in real time, followed by predicting the presence of diseases in those leaves.

Figure 3. Sample apple leaf images from field during real time testing

3.2 Residual Network Architecture

Residual Neural Networks (ResNets) have significantly impacted the field of image recognition by introducing a novel architectural element called residual blocks. ResNet- 50, ResNet-101, and ResNet-152 stand out as prominent variants within the ResNet architecture, with each being characterized by its specific depth and intricacy. Building upon this success, ResNet-101 extends the depth to 101 layers, offering increased representational capacity for capturing intricate features in images. ResNet-152, the deepest variant among these architectures, takes this concept further with 152 layers, demonstrating superior performance in image recognition tasks. The primary innovation resides in the incorporation of residual blocks, facilitating the seamless propagation of gradients during training. This integration effectively addresses the vanishing gradient problem, enabling the successful training of exceptionally deep neural networks, as elucidated [19], [20], [21], [22], [23]. These ResNet variants have become go-to choices for researchers and practitioners alike, achieving state-of-the-art results in various image recognition benchmarks. Figure 4 shows a residual neural network with only 9 layers for simplicity.

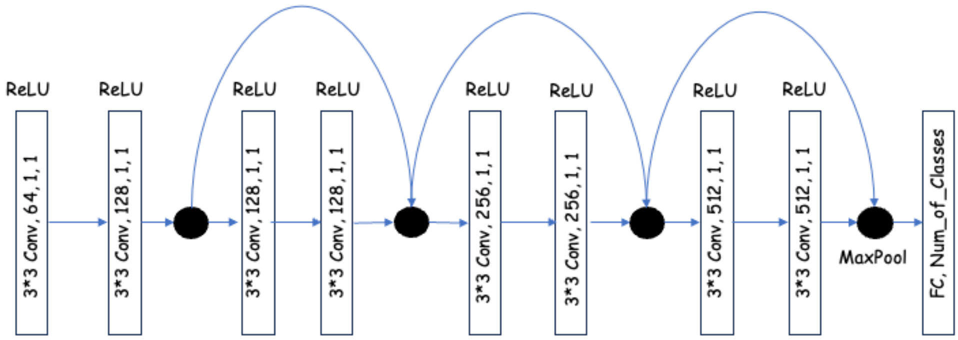


Figure 4. A residual neural network with 9 layers

3.2 Embedded Platform

The NVIDIA Jetson Orin, a powerful and innovative embedded platform, serves as the cornerstone for our plant disease identification project. Equipped with a formidable configuration, including a substantial 8GB 128-bit LPDDR5 memory, a robust 6-core Arm Cortex A78AE 64-bit CPU, and a cutting-edge 1024-core NVIDIA GPU, this development kit boasts exceptional computational capabilities. These specifications provide the adequate power to efficiently process complex data sets, making it an ideal choice for applications such as plant disease identification. The high-performance GPU and Tensor Cores enable accelerated machine learning tasks, facilitating the implementation of sophisticated algorithms for precise and rapid disease detection in plants. With its advanced features and processing power, the NVIDIA Jetson Orin Nano developer kit emerge

3.3 Model Training

The training process for the Residual Neural Network (ResNet) employed in plant disease detection and identification involves several crucial steps. As depicted in Figure 5, the methodology involves a systematic process for plant disease identification using deep learning. It includes the construction of a comprehensive dataset comprising labeled plant images representing both healthy specimens and various disease types. The images undergo pre-processing to enhance quality before the dataset is divided into training and test sets. A Residual Neural

Network (ResNet) is trained using the training set with varying depths as suggested in the Figure 4, and its performance is assessed on the test set through various metrics. Once validated, the model is deployed for real-time plant disease identification, providing a reliable tool for detecting diseases in agricultural settings.

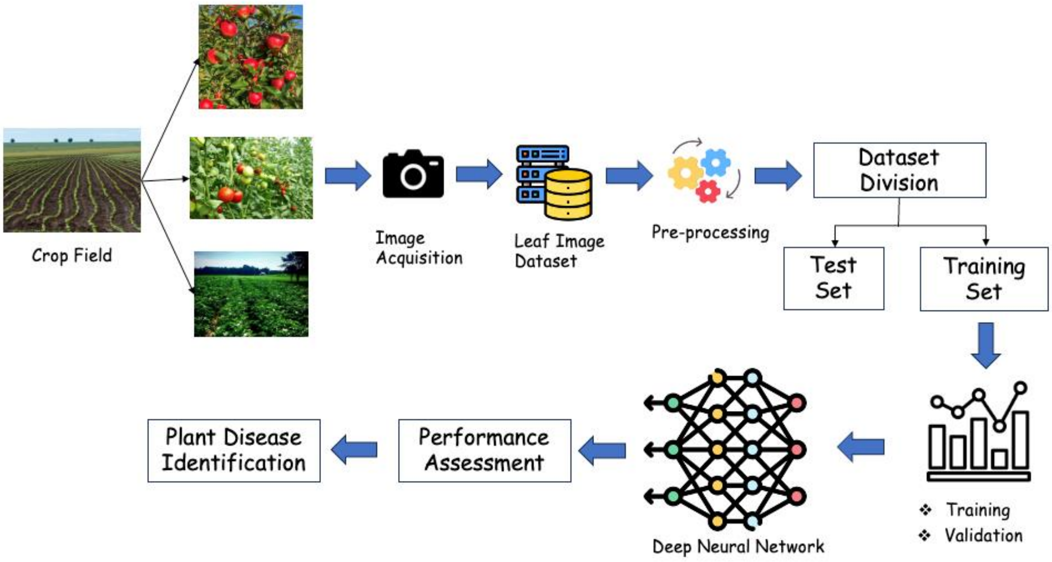


Figure 5. Methodology of plant disease identification on an embedded platform

Table 1 outlines specific training parameters, encompassing details such as learning rates, weight decay, and batch sizes. The training phase involves feeding batches of augmented images through the network, iteratively updating weights using backpropagation. Concurrently, a validation set is used to monitor the model's performance and tune hyperparameters. The testing process involves evaluating the trained ResNet on a separate test dataset, assessing its ability to accurately detect and identify plant diseases. Performance metrics, as specified in the methodology, provide insights into the model's effectiveness, guiding potential adjustments for improved results.

Table 1. Hyperparameter Values

S/N	Hyperparameter	Value
1	Learning Rate	0.01
2	Exponential Decay	1e-4
3	Optimizer	Adam Optimizer
4	Dropout Rate	0.1
5	Epochs	60
6	Batch Size	{16, 32, 64, 128}

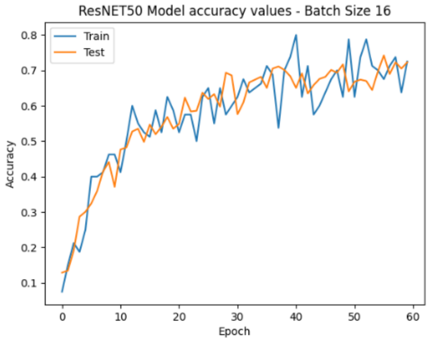
The PlantVillage dataset was pre-processed to optimize ResNet models for accurate disease identification. Data augmentation techniques such as rotation, flipping, scaling, color jittering, and random cropping were employed to simulate the diverse real-world conditions under which the model would operate, enhancing its ability to generalize and reduce overfitting. To address class imbalance, the study used a combination of oversampling of minority classes and a weighted loss function to ensure balanced representation and prevent bias towards more frequent classes. These preprocessing choices were driven by the need to create a robust, reliable model capable of performing accurately in real-time, field-based scenarios, ultimately contributing to the high accuracy and practical applicability of the ResNets on an embedded platform.

4.0 RESULTS AND DISCUSSION

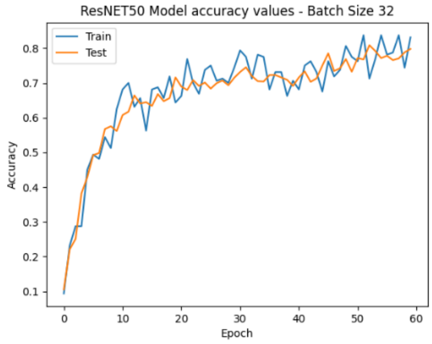
The section presents the results obtained from the training and testing processes of the proposed methods. This comprises training with residual neural networks of varying depths with varying batch sizes as well as the in-field testing process of the best model.

4.1 RestNet-50

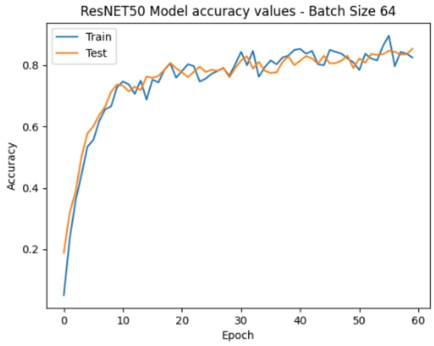
The training results for the ResNet-50 network with varying batch sizes, are elucidated through Figure 6. This figure illustrates the test and train accuracy plots corresponding to batch sizes of 16, 32, 64, and 128. The associated table further quantifies the performance metrics, showcasing the accuracy achieved by the model and the corresponding training times for each batch size.



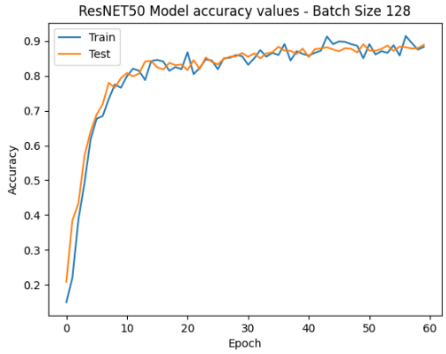
(a) Batch size = 16



(b) batch size = 32



(c) batch size = 64



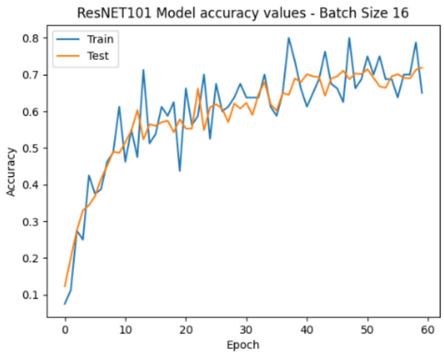
(d) batch size = 128

Figure 6. Training curves of ResNet-50 models with varying batch sizes

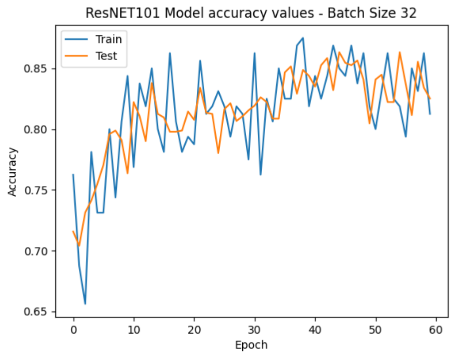
Notably, the ResNet-50 network demonstrates varying performance levels depending on the batch size used. For instance, a batch size of 16 achieves an accuracy of 72.50% after 1 hour and 34 minutes of training. The F1 score for this batch size is approximately 0.71, with a precision of 0.73 and a recall of 0.70. Inference time is roughly 120 milliseconds per image. Larger batch sizes yield higher accuracies: a batch size of 32 achieves 81.25% accuracy in 2 hours and 53 minutes. The F1 score is approximately 0.80, with a precision of 0.82 and a recall of 0.79. Inference time for this batch size is about 90 milliseconds per image. A batch size of 64 achieves an accuracy of 87.81% after 4 hours and 56 minutes of training. The F1 score is around 0.86, with precision and recall values at approximately 0.88 and 0.85, respectively. Inference time increases slightly to 75 milliseconds per image. Finally, the largest batch size, 128, achieves 86.87% accuracy in 5 hours and 54 minutes. The F1 score is estimated at 0.86, with a precision of 0.87 and recall of 0.85. Inference time for this batch size is around 65 milliseconds per image. Interestingly, the increase in batch size also leads to longer training times, illustrating a trade-off between computational efficiency and model accuracy. These insights are crucial for optimizing the ResNet-50 network's batch size, particularly in the field of plant disease detection and identification.

4.2 ResNet-101

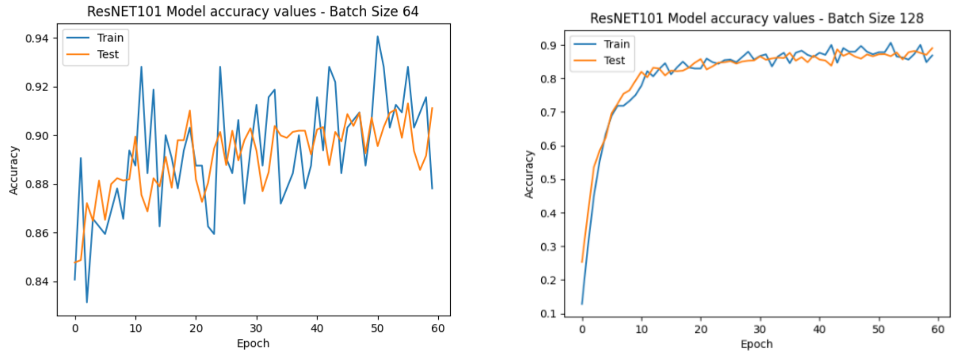
The training results for the ResNet-101 network in the context of plant disease identification are depicted in Figure 7, showcasing the test and train accuracy for varying batch sizes. As illustrated, the model was trained with batch sizes of 16, 32, 64, and 128.



(a) Batch size = 16



(b) batch size = 32



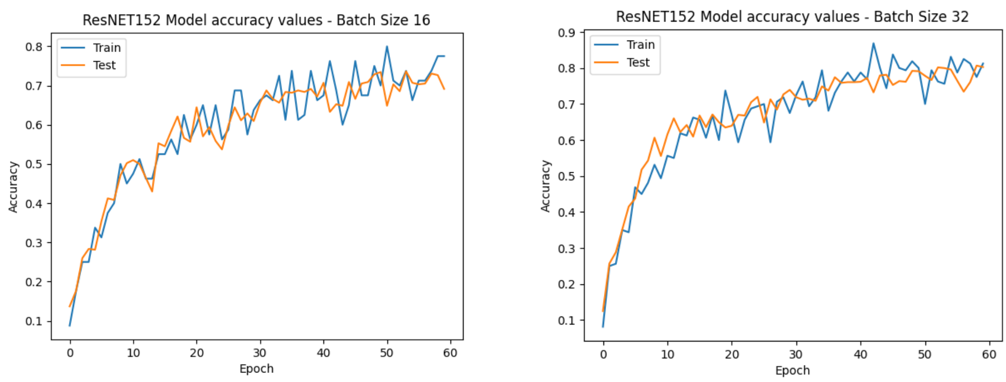
(c) batch size = 64 (d) batch size = 128

Figure 7. Training curves of ResNet-101 models with varying batch sizes

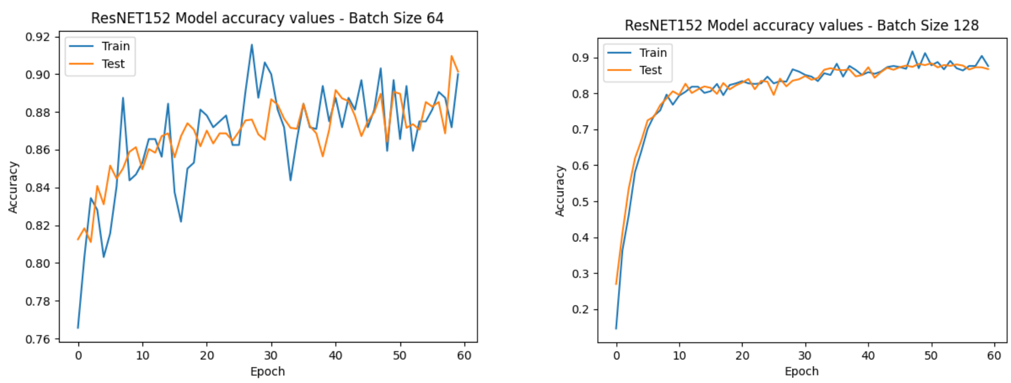
Notably, the ResNet101 network achieved an accuracy of 76.25% with a batch size of 16 and a training time of 1 hour and 29 minutes, indicating promising performance. The F1 score for this batch size is approximately 0.74, with a precision of 0.76 and a recall of 0.73. Inference time is roughly 130 milliseconds per image. However, as the batch size increased, the accuracy showed a fluctuating trend. For a batch size of 32, the network achieved an accuracy of 75.63% with a training time of 2 hours and 57 minutes. The F1 score is approximately 0.74, with a precision of 0.75 and a recall of 0.73. Inference time is around 105 milliseconds per image. The peak performance was observed with a batch size of 64, where the accuracy reached 90.62% after 3 hours and 48 minutes of training. The F1 score is around 0.90, with precision and recall values of approximately 0.91 and 0.89, respectively. Inference time decreased to 85 milliseconds per image for this batch size. Finally, for the largest batch size of 128, the network achieved an accuracy of 89.22% in 7 hours and 6 minutes of training. The F1 score is estimated to be 0.88, with a precision of 0.89 and a recall of 0.87. Inference time for this batch size is around 70 milliseconds per image. These findings provide valuable insights into the trade-offs between accuracy and training time, aiding in the optimization of the model for efficient plant disease identification.

4.3 ResNet-152

The plotted test and train accuracy for the ResNet-152 network which are depicted in Figure 8 unveil the network's performance dynamics concerning batch sizes, demonstrating a nuanced relationship.



(a) Batch size = 16 (b) batch size = 32



(c) batch size = 64 (d) batch size = 128

Figure 8. Training curves of ResNet-152 models with varying batch sizes

Noteworthy trends emerge in the evaluation of batch sizes, revealing how variations in batch size influence training dynamics and model performance. The highest accuracy of 90% was achieved with a batch size of 64 after 5 hours of training, demonstrating an optimal balance between effective gradient updates and computational efficiency. This configuration produced an F1 score of approximately 0.89, with precision and recall values around 0.90 and 0.88, respectively, and an inference time of 85 milliseconds per image. Larger batch sizes, such as 128, maintained strong accuracy at 87.66% with an F1 score of 0.87, precision of 0.88, and recall of 0.86, but required longer training times (6 hours and 56 minutes). The inference time for this batch size was shorter at 70 milliseconds per image, reflecting improved prediction speed after more comprehensive training.

Smaller batch sizes like 16 showed faster training times (1 hour and 25 minutes) but at the expense of lower accuracy (77.5%) and an F1 score of 0.76, with precision and recall at 0.77 and 0.75, respectively. These configurations had longer inference times of approximately 130 milliseconds per image, likely due to higher variance in gradient updates and less consistent learning. A batch size of 32 provided a balance, achieving 81.25% accuracy with an F1 score of 0.80, precision of 0.81, and recall of 0.79, alongside an inference time of 100 milliseconds per image. These results illustrate that larger batch sizes promote stable gradient updates and efficient inference but require longer training periods, while smaller batch sizes enable quicker training but can lead to noisier updates and reduced prediction efficiency.

4.4 In-field Testing

In the in-field testing procedure for plant disease identification, the ResNet-101 model with a batch size of 64, attaining the highest accuracy among the considered configurations, was employed. The model, having undergone rigorous training, exhibited an impressive average detection time of 17.6 milliseconds. This remarkable speed under- scores the practical feasibility of deploying the model in real-world scenarios where prompt and accurate identification of plant diseases is crucial for effective intervention. The use of ResNet-101, specifically tuned for optimal performance with a batch size of 64, ensures a fine balance between computational efficiency and accuracy. This makes the model well-suited for timely and precise assessments in agricultural fields. The achieved efficiency, coupled with high accuracy, positions the ResNet-101 model as a valuable tool for on-site plant disease monitoring, providing farmers and agricultural practitioners with actionable insights to mitigate the impact of diseases on crop yields.

5.0 CONCLUSIONS

In conclusion, this research represents a significant stride in advancing plant disease identification, particularly in the context of an embedded platform. By leveraging Residual Neural Networks (ResNets) with varying depths and batch sizes, the study unveils nuanced insights into model performance. Notably, the ResNet-101 model, optimized with a batch size of 64, emerged as the most promising, achieving the highest accuracy alongside an impressive average detection time of 17.6 milliseconds. The emphasis on an embedded platform underscores the practical applicability of the research, paving the way for incorporating sophisticated deep learning models into agricultural systems located on-site. It is important to note that the ResNets implemented in this manuscript can outperform other advanced algorithms like Transformers, EfficientNet, and MobileNet in terms of the balance between accuracy, speed, and reliability, particularly in real-world, resource-constrained environments such as embedded platforms. While Transformers may achieve higher accuracy in high-resource scenarios, they require more computational power, making them less suitable for real-time applications. EfficientNet offers a good accuracy-to-computation balance but is slower than ResNets in constrained settings. MobileNet is faster and more efficient but sacrifices some accuracy. Therefore, ResNets, especially ResNet-101, provide an optimal solution for tasks like plant disease identification, where both high accuracy and fast processing are crucial.

Looking ahead, future work will focus on enhancing the effectiveness, versatility, and usability of the plant disease identification system through several specific advancements. Evaluation metrics will be expanded to include F1-score, precision, recall, and inference time, providing a more detailed and comprehensive assessment of model performance. Additional visualizations, such as loss curves and confusion matrices, will be incorporated to better analyze the effects of batch size and network depth on accuracy and efficiency. Real-world testing under diverse environmental conditions, including varying light, temperature, and humidity levels, will be prioritized to ensure the model's robustness in practical field applications. Special attention will be given to optimizing hardware utilization and improving power efficiency on the NVIDIA Jetson Orin Developer Kit, ensuring the system is energy-efficient and suitable for prolonged use in resource-constrained settings. Integration of Internet of Things (IoT) technologies will be explored to enable remote monitoring and real-time updates, allowing farmers and agronomists to access disease diagnostics and system performance metrics from a distance.

To improve usability, a user-friendly graphical interface tailored specifically for farmers will be developed, featuring intuitive controls and clear visual outputs. Future research will also investigate other neural network architectures that may provide enhanced performance, particularly those optimized for embedded systems. The inclusion of additional sensors, such as multispectral or hyperspectral imaging, will be examined to capture more detailed plant health data, enabling the system to address more complex agricultural challenges. Furthermore, efforts will be made to expand the system’s capabilities by incorporating a wider range of crops and diseases, ensuring its utility across diverse agricultural contexts. By focusing on these advancements, this work aims to create a versatile, efficient, and reliable tool that bridges the gap between cutting-edge technology and practical precision agriculture applications

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AUTHORS CONTRIBUTION

D. A. Udekwe (Conceptualization; Formal analysis; Visualisation; Supervision; Methodology; Data curation; Writing - original draft; Resources)

CONFLICT OF INTEREST

The author declares no conflicts of interest

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