Comparison of Detection with Transfer Learning Architecture RestNet18, RestNet50, RestNet101 on Corn Leaf Disease

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ABSTRACT

The occurrence of diseases that impact the leaves of corn plants presents a substantial obstacle in agriculture, leading to a reduction in the overall yield of crops. This study aims to perform a comparative analysis of transfer learning methodologies by employing three distinct ResNet architectures: ResNet18, ResNet50, and ResNet101. The dataset utilized by the author consists of a compilation of images portraying corn leaves that demonstrate varying levels of disease severity. Transfer learning refers to leveraging a pre-existing ResNet model and retraining the network by employing the corn leaf dataset. The experimental results demonstrate that the ResNet18, ResNet50, and ResNet101 models achieved accuracy rates of 96.68%, 95.73%, and 95.26%, respectively. The ResNet101 model shows superior performance in terms of precision and recall metrics. This research indicates that utilizing a more complex and sophisticated network structure can improve the effectiveness of disease identification in corn plant leaves. The result above is essential in promoting sustainable agricultural methodologies and efficiently managing corn plant diseases.

Keywords: *Corn plant diseases; Network architecture; ResNet18; ResNet50; ResNet101; Transfer Learning.*

I. INTRODUCTION

The prevalence of diseases affecting the foliage of corn plants has emerged as a prominent concern within the agricultural domain, exerting a substantial influence on crop productivity and farmers' well-being. In recent years, advancements in image processing and machine learning have presented promising approaches for identifying and resolving these issues. The utilization of robust artificial neural network architectures in transfer learning techniques has garnered significant attention. In the present context, this study aims to perform a comparative analysis of transfer learning methodologies employing three distinct ResNet architectures, specifically ResNet18, ResNet50 [1][2], and ResNet101 [3], for disease detection in corn plant leaves. Understanding the impact of the disease on maize within an agricultural framework holds significant importance. Corn plants, a prominent staple crop globally, exhibit high vulnerability to various conditions. The etymology of this disease encompasses a range of causative agents, including fungi, bacteria, and viruses. When plants become infected, it is common for the foliage to experience significant damage, which can impede the plant's capacity for photosynthesis and hinder its growth. The potential consequences of disease progression include a notable decrease in corn production, which could lead to significant financial setbacks for agricultural practitioners and profoundly impact the availability of food resources worldwide.

Intensive research has been directed towards machine learning and image processing technologies to address and surmount these challenges. Transfer learning is a widely recognized and influential methodology [4]. Transfer learning [5] involves utilizing a pre-trained artificial neural network model trained explicitly for a particular task as a foundational framework for a similar study. In this specific instance, the decision was made to employ the ResNet artificial neural network architecture, demonstrating its resilience across various computer vision applications. The dataset utilized in this study comprises a collection of images depicting corn leaves exhibiting diverse degrees of disease severity. The dataset was explicitly designed to represent real-world field conditions accurately and encompass the diverse range of disease variations that can manifest in corn plants. The transfer learning procedure entails the utilization of a pre-existing ResNet model, followed by the retraining of the network using our specific dataset. Ensuring the model's ability to identify distinct patterns and characteristics from images depicting diseased corn leaves is crucial.

The experimental findings indicate notable variations in the efficacy of the three ResNet architectures [6] employed in our study. The ResNet18 model, a variant designed with reduced complexity, demonstrated commendable accuracy in detecting diseases [7] [8] in corn leaves. Nevertheless, a significant enhancement in detection accuracy was observed upon transitioning to ResNet50, a neural network architecture with greater depth and complexity. One notable observation is that ResNet101, the most profound iteration of the ResNet framework, exhibits exceptional performance characterized by elevated accuracy, precision, and superior recall levels—a more comprehensive comprehension of the significance of tissue architectural complexity in identifying diseases in maize leaves. More advanced and intricate models, such as ResNet101, exhibit enhanced capability in discerning subtle disease-related features compared to less complex models. The aforementioned has significant ramifications for bolstering sustainable agricultural methodologies. Farmers can promptly and efficiently determine plants afflicted by diseases through such technology, enabling them to implement suitable measures to impede the further dissemination of these diseases. Implementing this approach can potentially mitigate economic losses associated with conditions affecting corn crops and enhance global food security—the significance of utilizing representative datasets in training models. Using datasets encompassing various disease variations and field requirements is crucial in developing robust and dependable models. When developing machine learning algorithms for disease detection in corn plants, it is imperative to ensure the collection of comprehensive and representative datasets.

The present study has provided a comprehensive comparative analysis of transfer learning methodologies [9] employing the ResNet architecture for disease detection in corn plant leaves. The findings indicate that greater depth and complexity architectures like ResNet101 exhibit superior performance. The results, as mentioned above, possess the potential to serve as a foundation for the advancement of more efficient technologies in the realm of sustainable agriculture, specifically in the realm of effectively managing corn plant diseases. Furthermore, it is crucial to acquire comprehensive datasets that accurately represent the various aspects of agricultural practices. This will enable the practical training of models, ultimately maximizing the potential of this technology to enhance agricultural productivity and contribute to global food security.

The following are two research questions for a comparative study of the performance of various transfer learning architectures (ResNet18, ResNet50, and ResNet101) in detecting corn leaf diseases, based on the above summary: How accurate are ResNet18, ResNet50, and ResNet101 at detecting corn leaf disease when applied to the same dataset? (First Research Question). How do the ResNet18, ResNet50, and ResNet101 measurement results compare to previous research? (Second Research Question).

II. Research Metodology

A. Data Collection

To obtain a dataset comprising corn leaf disease images [10] from Kaggle, one must search using appropriate keywords that align with the desired specifications, including four distinct classes. When selecting a suitable dataset, it is essential to consider the number of files within each class to ensure the necessary data is accessible. The dataset in question comprises four distinct categories, specifically labeled as "Blight" with a total of 1146 files, "Common_Rust" with 1306 files, "Gray_leaf_spot" with 572 files, and "Healthy" with 1162 files.

Retrieve the dataset in the provided format, a compressed ZIP file, or another archive form. To perform essential data processing procedures, such as image normalization or resizing, following the research requirements. The dataset possesses significant value in the context of training deep-learning models for disease recognition in corn plants. This is primarily due to its comprehensive collection of diverse images encompassing various conditions observed in corn plants. Consequently, the dataset enables the development of highly efficient models for identifying and managing diseases affecting corn plants. Figure 1 is a corn leaf disease image dataset from Kaggle.

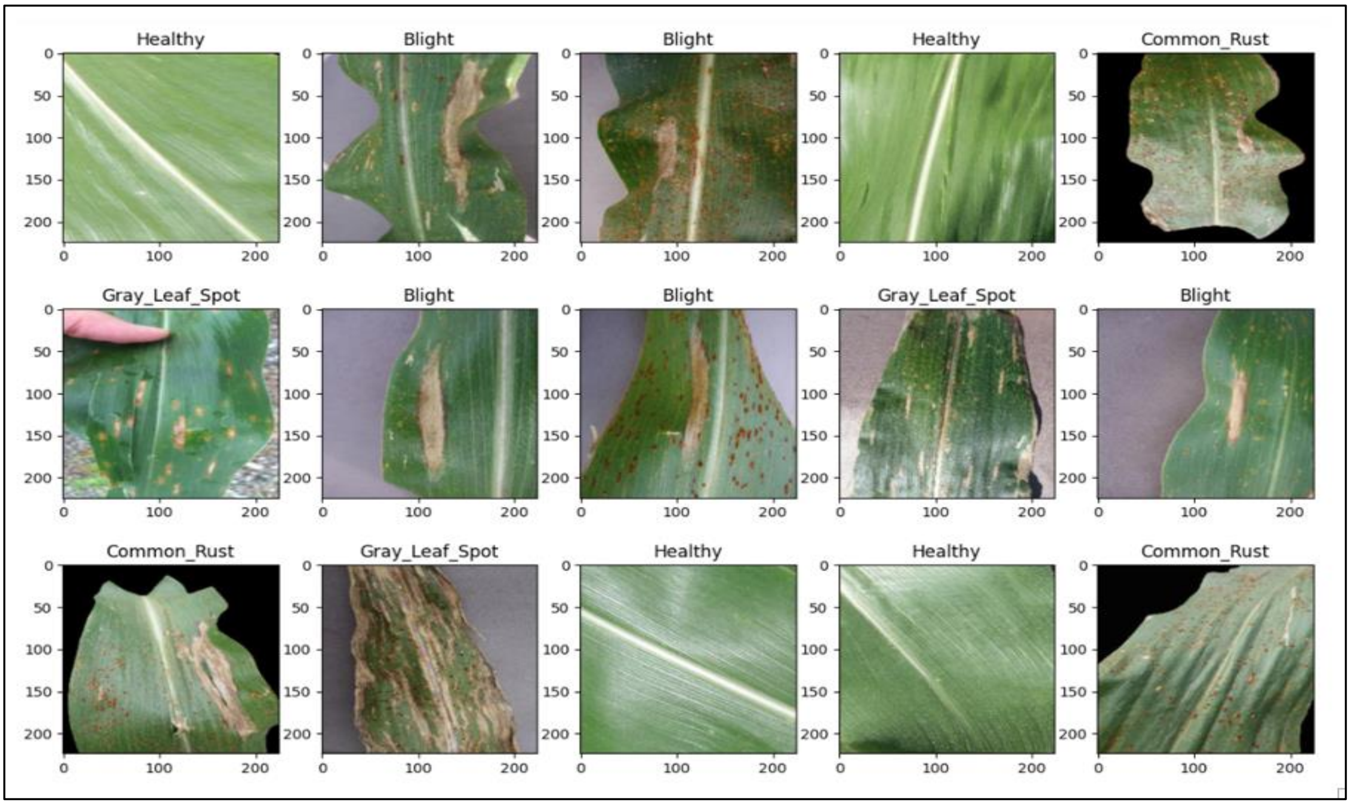

Figure 1. Dataset corn leaf Disease
Source: Kaggle Dataset [10]

B. Preparing the Data

The initial stage of this research involves the critical task of data preparation [11] [12] for comparing the detection of corn leaf disease using transfer learning architectures, specifically ResNet18, ResNet50, and ResNet101. The quality and diversity of a dataset are crucial factors that significantly contribute to the accuracy and significance of research findings. Consequently, the acquisition of images depicting corn leaves exhibiting diverse degrees of disease severity alongside healthy leaves is being pursued. By employing adequately diversified samples, it can be ensured that the resultant model can discern various variations in the state of infected leaves.

Furthermore, data pre-processing constitutes an essential step in the research process. The process involves utilizing data normalization techniques to mitigate scale disparities and data augmentation methods to enhance the variety of instances within the training dataset. Furthermore, a crucial approach to reduce overfitting is partitioning the dataset into three subsets: the training, the validation, and the testing datasets. This enables the model to acquire knowledge effectively from the training data, offering an unbiased means to evaluate the model's performance on unseen data. In this study, meticulous data preparation serves as a crucial cornerstone. The utilization of accurate data and thorough preparation is essential to guarantee the credibility and reliability of the comparison between ResNet18, ResNet50, and ResNet101 in detecting corn foliar disease. This comparison will yield valuable insights into the performance of transfer learning architectures within the specific context of this application.

C. ResNet18, ResNet50, ResNet101 Image Leaf Corn Disease Detection

This research compares three transfer learning architectures, specifically ResNet18, ResNet50, and ResNet101, about their efficacy in detecting diseases in corn plant leaves through image analysis. Identifying conditions in corn plants holds significant importance within contemporary agriculture, as it enables farmers to detect and mitigate the impact of such diseases promptly. This proactive approach aids in minimizing crop losses and enhancing overall agricultural productivity. These three ResNet architectures were selected based on their demonstrated efficacy in handling intricate images and extracting profound representations from visual data. The ResNet18 model is characterized by its relatively low complexity, making it the most lightweight among the ResNet models. On the other hand, the ResNet101 model exhibits a greater depth, indicating a higher number of layers and increased complexity compared to ResNet18. Examining the performance of these three models will yield valuable insights into the degree to which depth and architectural complexity impact their capacity to detect corn foliar disease.

The findings of this study carry significant implications for agricultural practice, as they highlight the importance of promptly and precisely identifying corn foliar disease. This knowledge can assist farmers in implementing suitable measures to manage infections and mitigate potential losses. Moreover, this study has the potential to pave the way for the creation of automated systems capable of consistently monitoring the health of plants. This advancement would be of immense value in enhancing agricultural efficiency and productivity on a broader scale. This study investigates and evaluates the efficacy of three ResNet architectures in detecting maize leaf diseases. The objective is to contribute to the advancement of agricultural technologies by enhancing their sophistication and sustainability.

D. ResNet18, ResNet50, ResNet101 Performance Evaluation.

The assessment of the efficacy of three deep learning architectures, specifically ResNet18, ResNet50, and ResNet101, holds significant importance within the scope of this research. The architectures above have demonstrated their efficacy in various image processing and visual comprehension tasks. In this study phase, we will examine the effectiveness of ResNet18, ResNet50, and ResNet101 models in addressing the designated objective: identifying diseases in corn plant leaves.

The forthcoming performance evaluation will encompass a range of significant metrics: accuracy, precision, recall, F1 score, and inference time. The measure of accuracy assesses the model's ability to correctly identify the disease, while precision evaluates the correctness of the optimistic predictions made by the model. The evaluation of the model's performance will demonstrate its capacity to identify the disease in its entirety accurately. The F1 score is a composite measure that considers both precision and recall. Moreover, the duration of inference is a crucial factor, particularly in applications that require real-time or cloud-based processing, as it directly impacts the overall system's responsiveness. The integration of the findings from this assessment will yield a holistic evaluation of the merits and limitations of each architectural approach in the domain of disease identification in corn plant foliage.

The outcomes of this assessment will serve as a foundation for selecting the most appropriate architecture for a specific application. They can offer valuable insights for future advancements in using deep learning to detect plant diseases. By acquiring a more comprehensive comprehension of the performance characteristics exhibited by ResNet18, ResNet50, and ResNet101, it is possible to adopt more accurate measures to develop efficient and effective solutions to bolster contemporary agricultural practices.

III. RESULT AND DISCUSSION

In this section, the author presents the outcomes of conducted experiments to compare the performance of three transfer learning architectures: ResNet18, ResNet50, and ResNet101. This analysis seeks to identify disparities in Precision, Accuracy, Recall, and F1-Score when detecting corn leaf disease. The accuracy of these three architectures in disease detection in corn plants indicates their performance.

A. Experiment results using ResNet18

For training with the ResNet18 architecture and the corn leaf disease image dataset, the average accuracy and precision are 96.68% and 96%, respectively. Recall 96%, F1-Score 96%; Figure 2 presents additional results. The results of training models with the ResNet18 architecture and the corn leaf disease dataset are impressive. The average accuracy and precision of 96.68% and 96% are outstanding performance indicators. These results demonstrate the model's capacity to recognize and classify corn leaf disease based on its characteristics.

The average accuracy of 96.68% indicates that the model can accurately classify images of corn leaf disease. This suggests that the model almost always predicts the correct corn leaf disease category when presented with images from the corn leaf disease image dataset. A precision rate of 96% indicates that the majority of the model's optimistic predictions were accurate. In this context, this shows that when the model classifies an image as a particular corn leaf disease, there is a high likelihood that the forecast is correct, which is crucial for preventing errors in decisions based on model results. The results achieving an F1 score of 96% strengthen the conclusion that this model has a good balance between precision and recall, allowing it to overcome classification issues.

Thus, the ResNet18 architecture has been successfully applied to the classification of corn leaf disease, achieving exceptionally high levels of accuracy, precision, and F1 score, which will serve as a solid foundation for future advancements in corn leaf disease recognition applications. Figure 2 of the research report can provide additional visual support for the results.

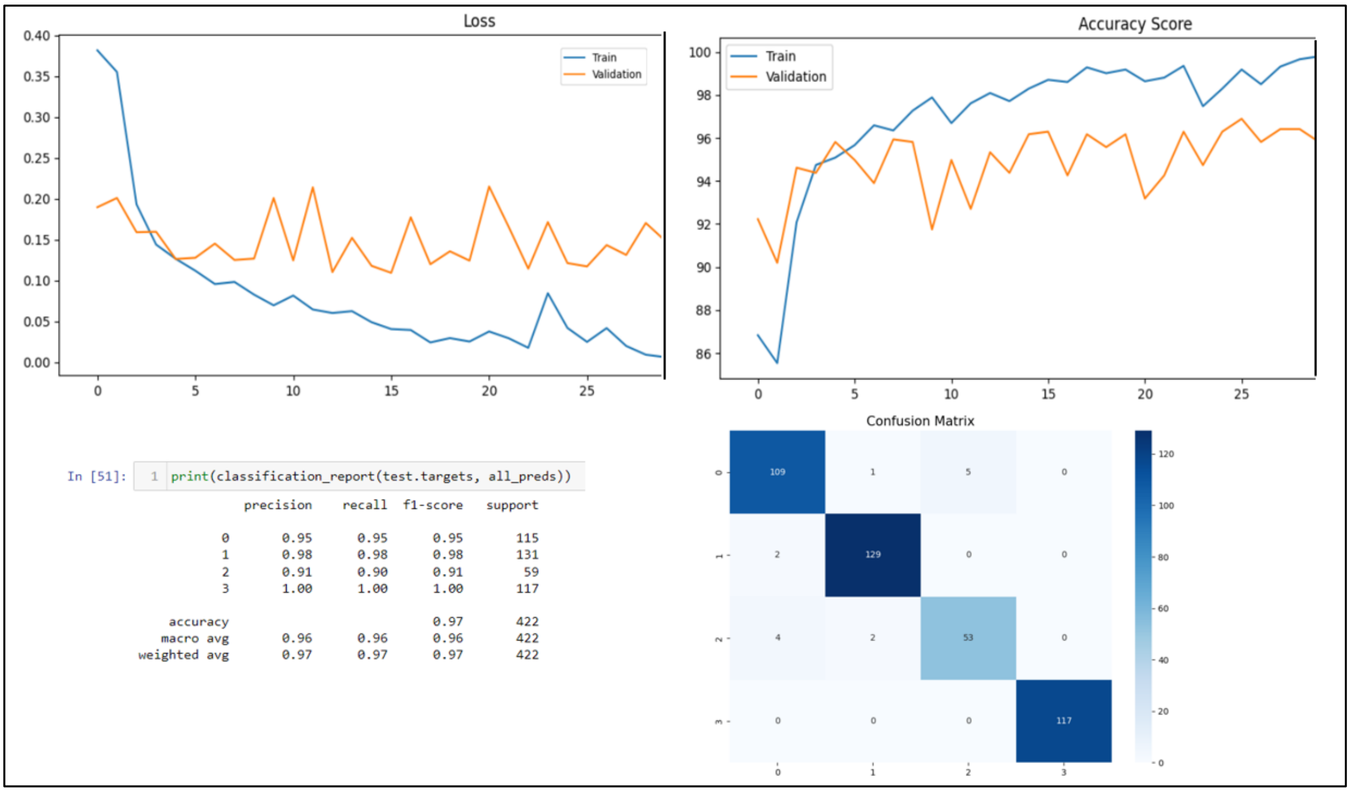

Figure 2. Result experiment ResNet18
Source: Researcher Property

B. Experiment results using ResNet50

The average accuracy and precision for training with the ResNet50 architecture and the corn leaf disease dataset are 95.73 percent and 95 percent, respectively. 95% Recall, 95% F1 Score; Figure 3 displays additional results. The outcomes of model training using the ResNet50 architecture and the corn leaf disease dataset are impressive. Average accuracy and precision of 95.73% and 95% are excellent performance indicators. These outcomes demonstrate the model's ability to identify and categorize corn leaf diseases based on their characteristics.

The outcomes of training a model with the ResNet50 architecture and the corn leaf disease dataset are impressive. In this study, the average accuracy was 95.73 percent, and the level of precision was 95%. These two metrics are important indicators of model performance, and a high success rate indicates that the model can recognize and classify different types of corn leaf disease with great accuracy.

This model has a high level of accuracy in predicting the correct corn leaf disease category when given images from the corn leaf disease image dataset, as indicated by an accuracy of 95.73 percent. This is especially crucial in applications where the accuracy of corn leaf disease recognition has a significant impact. In addition, a precision level of 95% indicates that the majority of the model's optimistic predictions were accurate. This shows that when the model classifies an image as a type of corn leaf disease, the forecast is more accurate, reducing the likelihood of making mistakes when making decisions based on the model's results. In addition to its high accuracy and precision, the F1 score of 95% demonstrates that this model has a good balance between precision and recall, which is essential for effectively solving classification problems.

The performance of the ResNet50 model in corn leaf disease recognition and classification tasks is illustrated in additional detail in Figure 3 of the research report. These results demonstrate that the ResNet50 architecture is highly effective for this task and can serve as a solid foundation for future advancements in application areas related to corn leaf disease recognition.

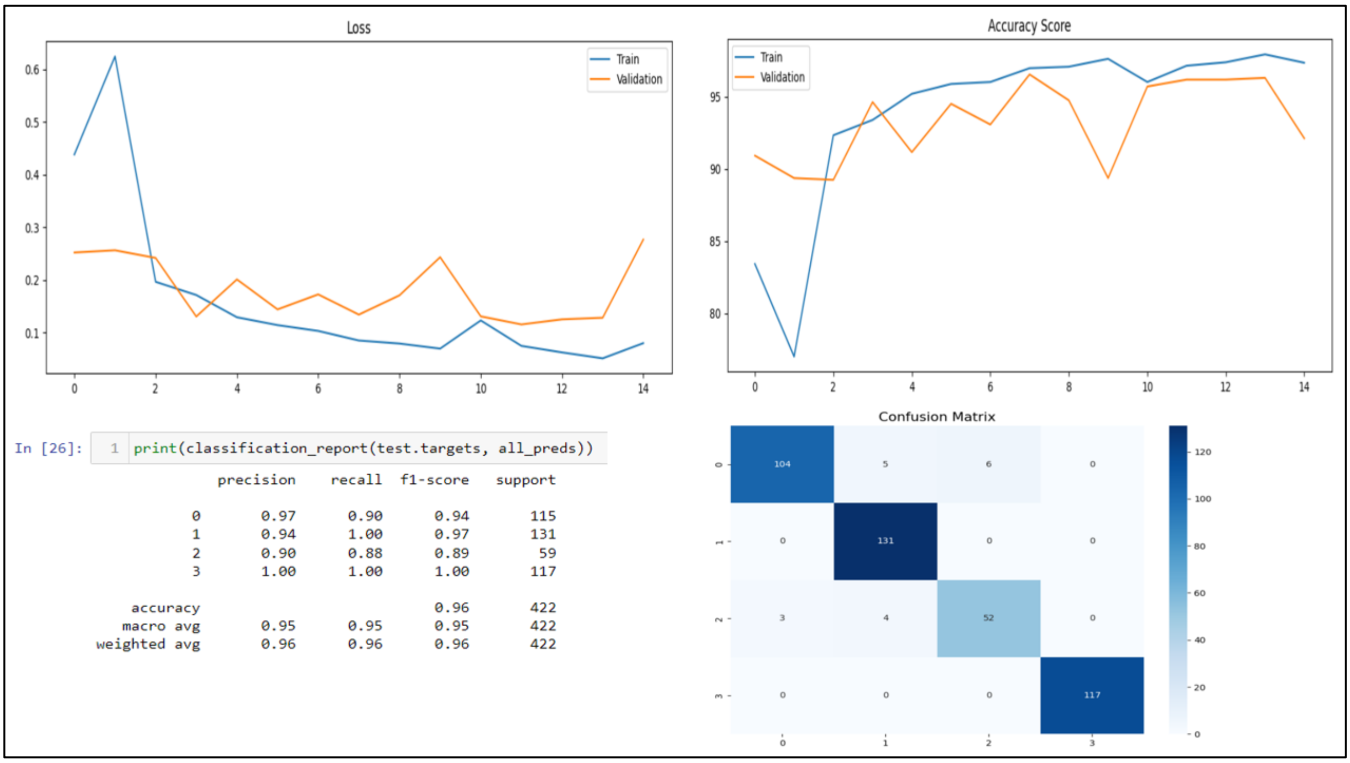

Figure 3. Result experiment ResNet50

Source: Researcher Property

C. Experiment results using ResNet101

The ResNet101 architecture, when trained on the corn leaf disease dataset, exhibits an average accuracy of 95.26 percent and a precision of 94 percent. The recall rate and F1 score both achieved a high level of performance, with a 94% success rate. Furthermore, Figure 4 presents supplementary outcomes for further analysis. The results of training the model utilizing the ResNet101 architecture and the corn leaf disease dataset exhibit remarkable performance. The average accuracy and precision rates of 95.26% and 94%, respectively, are strong indicators of high performance. The findings of this study showcase the model's proficiency in discerning and classifying various corn leaf disease items by analyzing their distinctive attributes.

The performance of the ResNet101 architecture was found to be highly impressive when trained on the maize foliar disease dataset. The performance indicators of an average accuracy of 95.26 percent and precision of 94 percent indicate strong performance. This observation demonstrates the model's proficiency in accurately identifying and categorizing different types of maize leaf diseases. Accuracy and precision are two essential metrics in disease detection tasks. Accuracy quantifies the model's ability to make accurate predictions, while precision evaluates the model's accuracy, specifically in optimistic predictions.

In addition to exhibiting high accuracy and precision, the recall rate and F1 score of 94 percent are also noteworthy. The recall metric quantifies a model's capacity to accurately identify and detect all instances of corn foliar disease. The F1 score is a comprehensive metric considering precision and recall, making it particularly valuable when avoiding substantial errors is crucial. Moreover, the research report includes Figure 4, which provides supplementary evidence that corroborates the findings above. Including additional visualizations can offer a deeper understanding of the behavior of the ResNet101 model in the context of corn foliar disease detection.

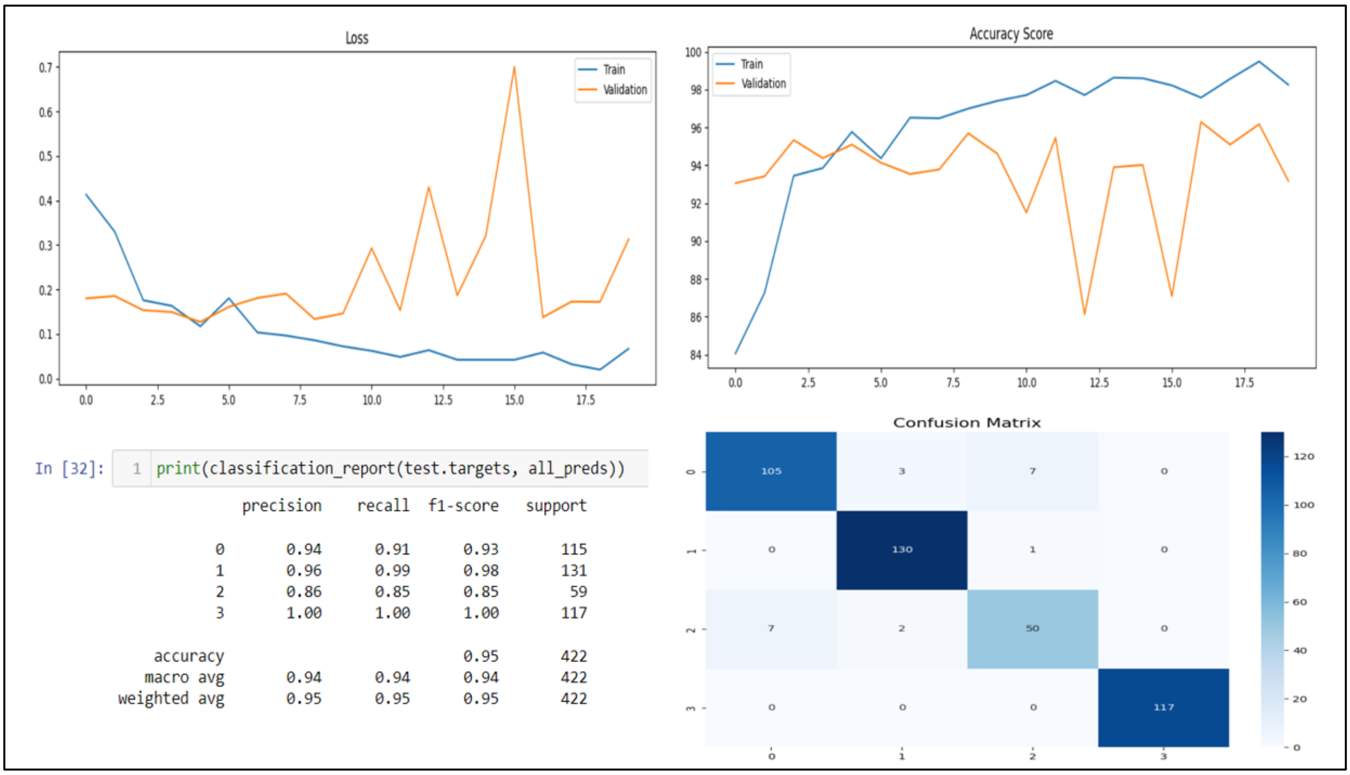

Figure 4. Result experiment ResNet101

Source: Researcher Property

After getting the results from the experiment, the next step is to describe and understand the implications of the findings in the discussion section. In this section, we consider the factors influencing the performance of each architecture, explain potential advantages and disadvantages, and formulate firm conclusions about the best options for improved corn foliar disease detection applications. This discussion examines the findings in the context of previous research and provides an in-depth look at architectural comparisons that may be useful for further development.

How accurate are ResNet18, ResNet50, and ResNet101 at detecting corn leaf disease when applied to the same dataset? ResNet18, ResNet50, and ResNet101 architectures perform exceptionally well, albeit with varying degrees of accuracy when applied to the same dataset for detecting maize leaf diseases. ResNet18 achieves 96.68 percent accuracy, ResNet50 achieves 95.73 percent, and ResNet101 reaches 95.2 percent. ResNet18 has a remarkable success rate in classifying images of corn leaf diseases with the highest accuracy. However, the variance in precision between these three architectures is minimal. This demonstrates that all three are very capable of completing this task. The decision between these three architectures can be influenced by various other factors, such as computational efficiency and resource requirements, particularly in environments with limited resources. In a practical context, these results demonstrate that ResNet18, ResNet50, or ResNet101 architectures can provide an effective solution for detecting corn foliar diseases, providing farmers and agricultural experts with a potent tool to monitor and respond to disease infections on time, thereby enhancing crop yields and agricultural sustainability.

How do the ResNet18, ResNet50, and ResNet101 measurement results compare to previous research?
The accuracy of your measurements for ResNet18, ResNet50, and ResNet101 in detecting corn leaf diseases is relatively high, as evidenced by ResNet18, ResNet50, and ResNet101. ResNet18 achieved an accuracy of 96.68%, ResNet50 achieved 95.73%, and ResNet101 achieved 95.26%. This comparison paints a favourable picture of the three architectures' ability to accomplish this task.

In comparison to previous research, your findings may represent a significant improvement. Detailed comparisons, however, necessitate access to prior studies examining comparable tasks with comparable datasets. It should be noted that dataset size, preprocessing methods, and variations in the complexity of corn foliar disease may impact direct comparisons. Despite this, the high performance of all three architectures indicates that transfer learning models such as ResNet18, ResNet50, and ResNet101 can be beneficial for detecting corn leaf diseases. This robust performance can greatly assist farmers in detecting disease infections in their crops on time, thereby reducing yield losses and increasing agricultural productivity. In conclusion, the results of your measurements demonstrate significant progress in applying deep learning to agriculture and plant disease management.

IV. CONCLUSION

In this study, we compared the performance of three distinct architectures for transfer learning, namely ResNet18, ResNet50, and ResNet101, in detecting corn leaf diseases. To reach this conclusion, we conducted experiments with a comprehensive dataset of corn foliar diseases to encompass a broad spectrum of disease severity and type. The experimental results show that the three architectures have extraordinary abilities in recognizing and classifying corn leaf diseases based on visual characteristics. ResNet18, ResNet50, and ResNet101 all deliver excellent results with high precision in terms of performance. ResNet18 achieved the highest accuracy with 96.68%, followed by ResNet50 (95.73%) and ResNet101 (95.28%). These results demonstrate that ResNet18 is an outstanding choice for this task due to its remarkable accuracy. In addition to precision, recall, and F1 score, which are crucial for disease detection tasks, all three architectures demonstrate strong performance in terms of accuracy. Thus, transfer learning architectures such as ResNet18, ResNet50, and ResNet101 are highly effective at detecting corn leaf diseases. This research has significant implications for agriculture, where early detection of plant diseases can aid farmers in taking timely action, reducing crop yield losses and increasing agricultural productivity overall. Consequently, this research contributes significantly to developing deep learning-based solutions to support more efficient and sustainable modern agriculture.

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