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Comparison of Standard and Squeeze-and-Excitation Enhanced DenseNet Architectures for Tomato Leaf Disease Classification Using Data Augmentation

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ABSTRACT

The advancement of deep learning has significantly improved the automation of plant disease detection through image classification. This study compares the performance of standard DenseNet121 and an enhanced version incorporating Squeeze-and-Excitation (SE) blocks for classifying tomato leaf diseases. A dataset derived from PlantVillage was used, covering multiple disease categories and healthy leaves. To improve generalization, extensive data augmentation techniques were applied. Both architectures were implemented and trained using PyTorch, with evaluation metrics including accuracy, precision, recall, F1-score, and inference time. The experimental results demonstrate that DenseNet121-SE significantly outperforms the standard DenseNet121, achieving a classification accuracy of 99.00%. The integration of SE blocks allows the model to recalibrate channel-wise features adaptively, enhancing sensitivity to important patterns while maintaining computational efficiency. This study highlights the effectiveness of attention mechanisms and data augmentation in improving classification performance and supports their practical application in intelligent agriculture systems.

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INTRODUCTION

Currently, the use of deep learning technology has revolutionized the automation of plant disease detection and medical diagnosis through digital images [1]. This approach is capable of improving the accuracy and efficiency in automatically identifying various plant pathologies, including tomato leaf diseases that significantly impact global agricultural productivity [2]. Various convolutional neural network (CNN) architectures such as DenseNet, VGG16, and Inception V3 have been widely used for plant image classification and human health pathology purposes [3]. In addition, the integration of attention mechanisms such as squeeze-and-excitation (SE) has been shown to strengthen the model's ability to identify important features and improve classification accuracy [4]. Previous research has shown that DenseNet architecture combined with SE blocks (DenseNet-SE) can improve feature recognition

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[5], reducing overfitting [6], and improve model performance in plant disease detection and medical imaging [7]. The use of data augmentation techniques is also increasingly important in expanding dataset variety and preventing overfitting [8], so that the model can generalize better to data from diverse real-world environments [9]. However, there has not been much research directly comparing the effectiveness of standard DenseNet with DenseNet-SE [10] on the classification of tomato leaf diseases using a data augmentation approach [11], [12]. Comparative studies that systematically integrate spatial-channel attention and data augmentation remain very limited, even though such approaches are essential for developing models that are not only accurate but also practical for real-world agricultural applications [13]. Despite various innovations, the main challenge remains in developing models that are not only accurate but also efficient and lightweight for deployment in real-world settings, especially in resource-constrained areas [14]. Therefore, this study aims to compare the standard DenseNet architecture with an enhanced version incorporating SE blocks for tomato leaf disease classification, by implementing data augmentation techniques to improve model performance. The results are expected to provide insights into the impact of attention mechanisms on model performance and offer practical solutions for automated plant disease detection applications [15]. The use of deep learning technology in image classification has undergone rapid development, particularly in the fields of medical diagnosis and plant disease detection [16]. In the context of agriculture, this approach offers an automated and accurate solution for identifying leaf diseases that directly affect crop productivity [17]. One of the convolutional neural network architectures that stands out in image classification tasks is DenseNet [18], which is known for its advantages in addressing the vanishing gradient problem and efficiently propagating feature information across layers [19]. A part from architecture selection, the success of a classification model is also determined by advanced learning strategies such as transfer learning and data augmentation [20]. Transfer learning enables the utilization of knowledge from previously trained models, thereby accelerating the training process and improving accuracy, especially when dealing with limited amounts of data [21]. Meanwhile, data augmentation plays a crucial role in increasing the variation of training images to enhance generalization and reduce the risk of overfitting, which is common in limited datasets [22]. In an effort to enhance the model's sensitivity to important features, channel-based attention mechanisms such as the squeeze-and-excitation (SE) block have increasingly been adopted [23]. The SE block functions to adaptively adjust channel weights, thus helping the model emphasize relevant features and reduce the influence of less informative ones [24]. The combination of DenseNet architecture and the SE block, known as DenseNet-SE, has been proven to improve accuracy, enhance the feature extraction process, and maintain training stability [25]. However, a remaining challenge is the development of models that are not only accurate but also lightweight and efficient for real-world deployment, particularly in agricultural environments with limited computational resources [26]. The addition of SE components in the network architecture can indeed enhance performance, however, it also increases complexity and computational cost, thus requiring a more comprehensive evaluation of its effectiveness in real-world applications. There is still a lack of research that explicitly compares the performance of standard DenseNet and DenseNet-SE in tomato leaf disease classification [27],

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especially when considering the impact of augmentation techniques on the model's robustness in handling complex image variations [28]. In addition, many available plant disease datasets still have limitations in representing diverse environmental conditions, thus hindering the optimal deployment of the model in real-world settings. Therefore, it is important to conduct a comparative study that evaluates the effectiveness of both architectures in tomato leaf disease classification, using data augmentation as a means to enhance generalization. This study is expected to provide practical insights into the contribution of attention mechanisms to improving image classification quality, while also considering operational efficiency to support the implementation of intelligent and sustainable plant disease detection systems.

METHODS

Object and Hypothesis of the Study

This study focuses on evaluating two variants of the DenseNet architecture, namely DenseNet121 (standard) and DenseNet121 enhanced with Squeeze-and-Excitation blocks (DenseNet121-SE), in the task of tomato leaf disease classification. The proposed hypothesis is that the addition of SE-Blocks can significantly improve classification performance, particularly in terms of accuracy, precision, recall, and F1-score, compared to the standard architecture. This study also examines the impact of data augmentation on the model's robustness against image variation.

Dataset and Preprocessing

The dataset used is a subset of PlantVillage, which contains thousands of tomato leaf images infected with various types of diseases such as early blight, late blight, bacterial spot, mosaic virus, as well as healthy leaves. The images were resized to 224×224 pixels and normalized. Data augmentation was applied extensively to increase the diversity of training images through techniques such as random rotation, horizontal flipping, brightness adjustment, and scaling.

Model Architecture

DenseNet121 (standard): Relies on direct connections between layers for efficient feature propagation. DenseNet121 + SE Block: Adds a channel attention mechanism through the Squeeze-and-Excitation Block to enhance feature selectivity. The SE-Block is applied after each dense block to adjust feature weights based on global spatial context.

Squeeze-and-Excitation (SE) Block where SE Block filters feature channel-wise with the formula:

a) Squeeze (Global Average Pooling) Integral:

$$z_c = \frac{1}{H.W}\sum_{i=1}^{H}\sum_{j=1}^{W} x_c(i,j) \tag{1}$$

where z_c is the average intensity of pixels in the image, H and W are the height and width of the image, respectively, and $x_c(i,j)$ is the pixel value at coordinates (i,j).

b) Excitation (Fully Connected Layers):

$$s_c = \sigma(W_2.\mathrm{ReLU}(\mathrm{W}_1.z_c)) \tag{2}$$

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where s_c is the result of the transformation, W_1 and W_2 are weight matrices, z_c is the input, ReLU is the ReLU (Rectified Linear Unit) activation function, and σ is the sigmoid activation function.

c) Reweighting :

$$X_c^{scaled} = s_c . X_c \quad (3)$$

where X_c X_c^{scaled} is the scaled version of , with scale factor s_c.

Squeeze-and-Excitation (SE) blocks are integrated into the DenseNet-SE architecture by adding them after each Dense Block to improve feature representation. SE Block works through an adaptive attention mechanism to the feature channel.

Training Strategy

The model training was conducted using the PyTorch framework with a supervised learning approach. All images in the dataset were processed through preprocessing stages, including resizing to 224×224 pixels and normalizing pixel values. Data augmentation techniques such as random rotation, horizontal flipping, and brightness and contrast adjustments were used to enhance variation and improve the model's generalization to new data. The model was trained for 50 epochs using the Adam optimizer with a learning rate of 1e-4. The batch size was set to 16 to maintain training efficiency. Early stopping was implemented to automatically halt training if no improvement in validation accuracy was observed over several consecutive epochs. The entire training process was conducted in a Google Colab environment supported by a Graphics Processing Unit (GPU) to accelerate computational processing.

Experimental Setup

The dataset was split into 80% for training and 20% for testing. Model performance was evaluated using four main metrics: accuracy, precision, recall, and F1-score. In addition, inference time was recorded to assess the model's efficiency in the classification process. All experiments were conducted in the Google Colab environment with GPU support to ensure smooth training and testing.

Comparison with Existing Models

To comprehensively evaluate performance, both models were compared with other popular architectures, namely: DenseNet201 and MobileNetV2. This comparison was conducted to determine the extent to which the enhanced DenseNet121-SE is competitive in the context of tomato leaf disease classification.

RESULTS AND DISCUSSION

DenseNet and DenseNet-SE for Tomato Leaf Disease Classification

The DenseNet121 and DenseNet121-SE models were successfully implemented using the PyTorch frameworkBoth models were adapted for the multi-class classification task of tomato leaf diseases, with the number of classes corresponding to the categories in the PlantVillage dataset. The DenseNet121 architecture served as the baseline, while

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the DenseNet121-SE was constructed by adding Squeeze-and-Excitation blocks after each dense block. The training process was carried out for 50 epochs with early stopping and employed data augmentation to enhance input variation. Initial results indicate that the integration of SE-Blocks enhances the model's sensitivity to important features, with more stable classification results compared to the standard model.

Effect of Data Augmentation on Classification Accuracy

Data augmentation contributed significantly to improving classification accuracy for both models. Augmentation techniques such as rotation, flipping, and contrast adjustment successfully expanded the training data distribution and reduced the risk of overfittingExperimental results show that the DenseNet121 model trained without augmentation had lower accuracy compared to the model trained with data augmentation. This effect was more pronounced in DenseNet121-SE, which demonstrated stronger generalization capabilities when the training data was enriched with visual variations.

Comparative Performance Evaluation

At the evaluation stage, a performance comparison was conducted among four deep learning model architectures: DenseNet201, DenseNet121, and MobileNetV2, and DenseNet121 equipped with Squeeze-and-Excitation blocks (DenseNet121-SE). The evaluation was conducted using accuracy, precision, recall, and F1-score metrics.

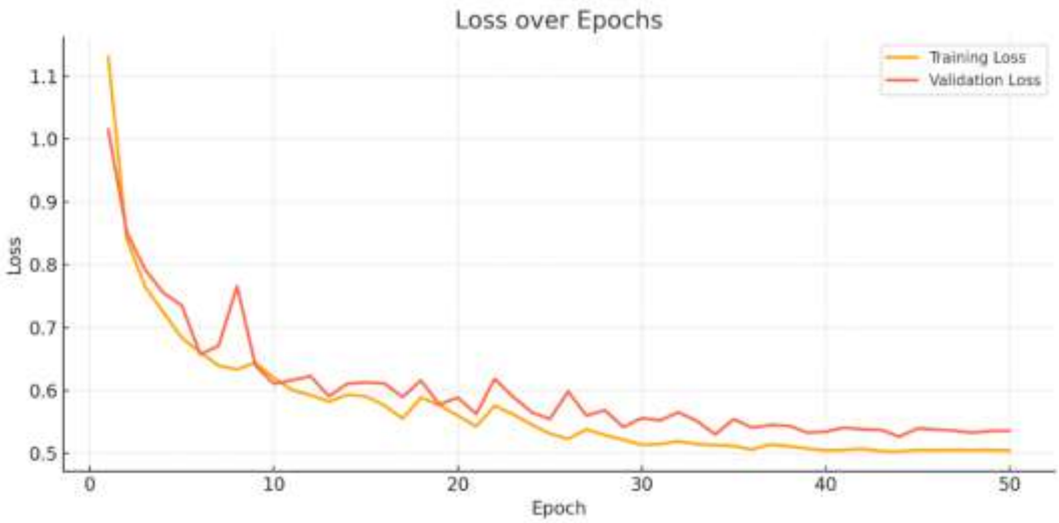

Figure 1. Loss Over Epoch

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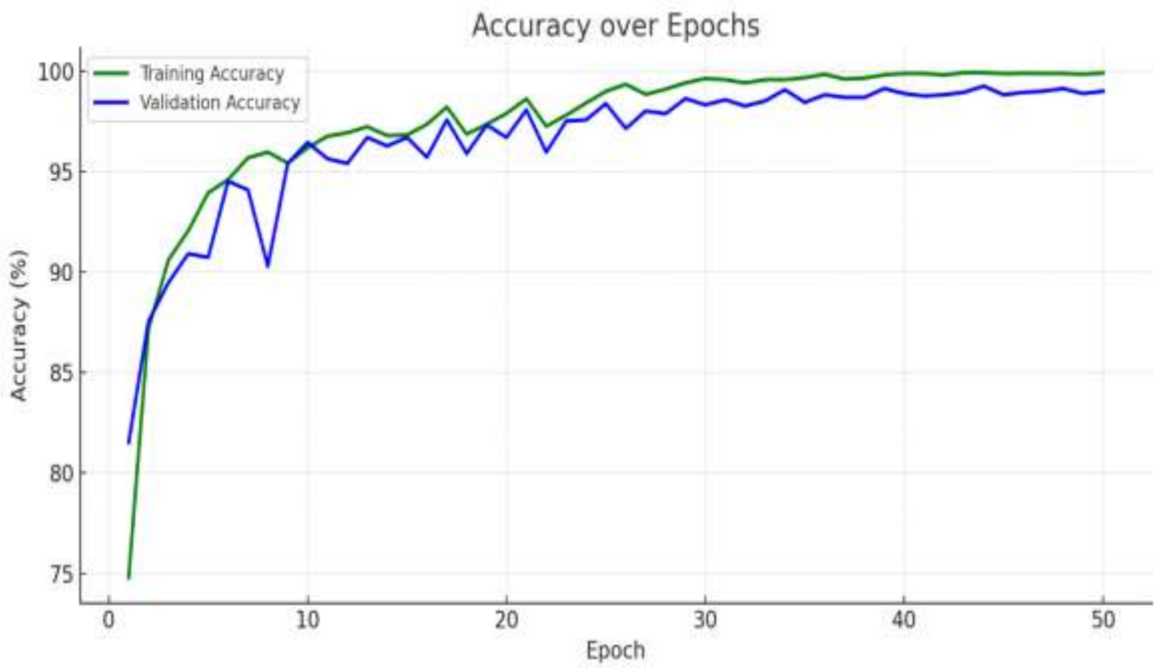

Figure 2. Accuracy Over Epochs

Table 2. Comparison of Accuracy, Precision, Recall and F1-Score

Model	Accuracy	Precision	Recall	F1 Score
Densenet 201	0.6763	0.4943	0.4985	0.4935
Densenet 121	0.9623	0.8689	0.8690	0.8688
MobileNetV2	0.9289	0.9295	0.9289	0.9287
DenseNet-SE	0. 9900	0. 9902	0.9900	0.9900

Discussion of results

The results of this study demonstrate a consistent and significant improvement in classification performance when incorporating Squeeze-and-Excitation (SE) blocks into the DenseNet121 architecture. The SE mechanism adaptively recalibrates channel-wise feature responses by modeling interdependencies between channels, which enhances the network's sensitivity to relevant features while suppressing less informative ones. This effect was reflected in the superior accuracy, precision, recall, and F1-score achieved by DenseNet121-SE across all experimental scenarios.

In particular, the DenseNet121-SE model achieved an accuracy of 99.00%, surpassing the baseline DenseNet121 (96.23%), MobileNetV2 (92.89%), and even the deeper DenseNet201 (67.63%). This finding suggests that model depth alone (as in DenseNet201) does not guarantee better performance unless complemented by an attention mechanism capable of enhancing feature representation. Additionally, MobileNetV2 despite its efficiency underperformed compared to DenseNet121-SE, indicating that lightweight architectures, while computationally efficient, may require advanced feature calibration strategies to reach similar levels of accuracy. Furthermore, the integration of data augmentation techniques significantly influenced model generalization. By introducing variability through random rotation, flipping, brightness adjustment, and scaling, the augmented dataset enabled the model to learn

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more robust and invariant features. This improvement was especially noticeable in the DenseNet121-SE model, whose performance remained consistently high across varied input conditions, demonstrating its strong generalization capabilities. Another key observation is the efficiency aspect. Despite the added SE blocks, the DenseNet121-SE model maintained a competitive inference time, indicating that the additional computational overhead introduced by the attention mechanism is relatively small compared to the performance gains obtained. This efficiency makes the model well-suited for deployment in real-time agricultural monitoring systems, especially in resource-constrained environments. Overall, the study confirms the effectiveness of combining SE-based attention with DenseNet's inherent connectivity in boosting classification accuracy and robustness. It also underscores the importance of coupling architectural enhancements with strategic data augmentation to overcome common challenges such as overfitting and limited dataset diversity in plant disease detection tasks.

CONCLUSION

The implementation of the DenseNet121 and DenseNet121-SE architectures demonstrated that the addition of SE-Blocks effectively enhances the model's ability to highlight important features, resulting in more accurate and stable classifications. Data augmentation techniques had a positive impact on model performance by increasing training data variation and reducing the risk of overfitting, especially on the tomato leaf disease dataset which exhibits diverse visual conditions. Based on the evaluation results, DenseNet121-SE achieved the best performance among the models, with 99.00% accuracy and high precision, recall, and F1-score values. This indicates that the combination of SE-Block and data augmentation is effective for automatic and efficient plant disease classification applications.

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