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A Novel Approach to Apple Leaf Disease Detection Using Neutrosophic Logic-Integrated EfcientNetB0

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Abstract. Detecting diseases in apple leaves accurately and efficiently is vital for maintaining healthy crops and ensuring optimal yield. This paper introduces a novel approach that integrates Neutrosophic Logic with the EfficientNetB0 model to enhance the classification of apple leaf diseases. The proposed method significantly improves precision, recall, and F1-scores across multiple disease classes, demonstrating its robustness and effectiveness compared to traditional techniques.

Keywords: Apple, Disease Detection, EfcientNetB0

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1. Introduction

Apple orchards worldwide are susceptible to various diseases that can dramatically reduce fruit quality and yield. Early and accurate disease detection is crucial for effective disease management. Traditional methods of disease detection are often reliant on manual inspection, which is time-consuming and prone to human error. Advances in deep learning have opened new avenues for automating disease detection, offering the potential for more accurate and faster identification of plant diseases.

Neutrosophic Logic (NL) is a generalization of fuzzy logic introduced by Florentin Smarandache in 1998 [1]. NL is designed to handle indeterminacy and uncertainty explicitly, providing a framework to describe and process data that is not only true or false but also indeterminate. In NL, every statement has three degrees: truth (T), indeterminacy (I), and falsity (F), each of which is represented by a value in the range [0, 1]. The use of NL allows systems to better handle real-world data where uncertainty and partial truth are common, making it suitable for applications in image processing, decision-making, and artificial intelligence.

A Neutrosophic Set $\mathcal{Z}$ in a universe of discourse U is defined by three membership functions for each element $x \in U$:

- **Truth-Membership Function** $T_{\mathcal{Z}}(x)$: Indicates the degree to which x belongs to the disease class.
- **Indeterminacy-Membership Function** $I_{\mathcal{Z}}(x)$: Represents the degree of uncertainty or indeterminacy associated with the classification of x.
- **Falsity-Membership Function** $F_{\mathcal{Z}}(x)$: Shows the degree to which x does not belong to the disease class.

These membership functions satisfy the following constraints:

$$T_{\mathcal{Z}}(x), I_{\mathcal{Z}}(x), F_{\mathcal{Z}}(x) \in [0,1], \tag{1}$$

$$0 \leq T_{\mathcal{Z}}(x) + I_{\mathcal{Z}}(x) + F_{\mathcal{Z}}(x) \leq 3. \tag{2}$$

The neutrosophic set for each image x can be represented as:

$$\mathcal{Z}(x) = \left(T_{\mathcal{Z}}(x), I_{\mathcal{Z}}(x), F_{\mathcal{Z}}(x)\right). \tag{3}$$

This representation enables a nuanced classification of apple leaf images into disease categories by capturing the complexity and uncertainty associated with disease symptoms.

In the classification process, the final decision for each image is typically based on the highest truth-membership value among the disease categories:

$$\text{Class}(x) = \arg\max_i T_{\mathcal{Z}_i}(x). \tag{4}$$

The indeterminacy-membership function $I_{\mathcal{Z}}(x)$ provides insights into the uncertainty of the classification, helping to understand the level of ambiguity present.

Additionally, neutrosophic logic operations such as union and intersection can be applied to integrate results from multiple classifiers, further enhancing classification accuracy and robustness:

- **Union**:

$$T_{\mathcal{Z}\cup\mathcal{B}}(x) = \max\left(T_{\mathcal{Z}}(x), T_{\mathcal{B}}(x)\right), \tag{5}$$

$$I_{\mathcal{Z}\cup\mathcal{B}}(x) = \max\left(I_{\mathcal{Z}}(x), I_{\mathcal{B}}(x)\right), \tag{6}$$

$$F_{\mathcal{Z}\cup\mathcal{B}}(x) = \min\left(F_{\mathcal{Z}}(x), F_{\mathcal{B}}(x)\right). \tag{7}$$

- **Intersection**:

$$T_{\mathcal{Z}\cap\mathcal{B}}(x) = \min\left(T_{\mathcal{Z}}(x), T_{\mathcal{B}}(x)\right), \tag{8}$$

$$I_{\mathcal{Z}\cap\mathcal{B}}(x) = \min\left(I_{\mathcal{Z}}(x), I_{\mathcal{B}}(x)\right), \tag{9}$$

$$F_{\mathcal{Z}\cap\mathcal{B}}(x) = \max\left(F_{\mathcal{Z}}(x), F_{\mathcal{B}}(x)\right). \tag{10}$$

This paper proposes an enhanced methodology for classifying apple leaf diseases by incorporating Neutrosophic Logic into the EfficientNetB0 deep learning model. The integration of Neutrosophic Logic allows the model to better handle uncertainties and ambiguities in image data, resulting in improved classification performance.

2. Related Work

Various machine learning and deep learning approaches have been explored for plant disease detection. Traditional methods such as SVMs and Random Forests have shown some success but often struggle with large, complex datasets. Recent research has focused on convolutional neural networks (CNNs) due to their superior performance in image recognition tasks. However, most CNN-based models do not explicitly handle uncertainty, which can limit their effectiveness in real-world scenarios.

Our approach builds on these foundations by integrating Neutrosophic Logic with EfficientNetB0, providing a framework that can manage uncertainty and improve the robustness of disease classification. Neutrosophic Theory, introduced by Smarandache, extends classical set theory by incorporating three components: truth (T), indeterminacy (I), and falsity (F). This theory has been successfully applied in fields like medical diagnosis, image processing, and information fusion, yet its application in agricultural disease classification remains limited. Our research leverages Neutrosophic Theory to enhance the reliability and interpretability of soybean disease classification. In recent years, neutrosophic logic has gained traction in various domains, particularly in enhancing the performance of machine learning and image processing systems. Several notable contributions have been made in this field:

- Salama *et al.* (2015) reviewed algorithms for recommender systems in e-Learning platforms utilizing neutrosophic systems. Their work highlights the versatility of neutrosophic logic in handling uncertainty within social network-based e-Learning systems [4].
- Ansari *et al.* (2013) proposed a neutrosophic classifier as an extension of traditional fuzzy classifiers. This approach aimed to improve classification accuracy by incorporating neutrosophic logic, which allows for better handling of ambiguous and incomplete data [5].
- Zhang *et al.* (2010) introduced a neutrosophic approach to image segmentation using the watershed method. Their method demonstrated significant improvements in segmenting images where traditional methods struggled with ambiguity [6].
- Zhang *et al.* (2018) discussed new inclusion relations of neutrosophic sets and explored their applications along with related lattice structures. Their research expanded the theoretical foundations of neutrosophic sets, providing a deeper understanding of their properties and applications [7].

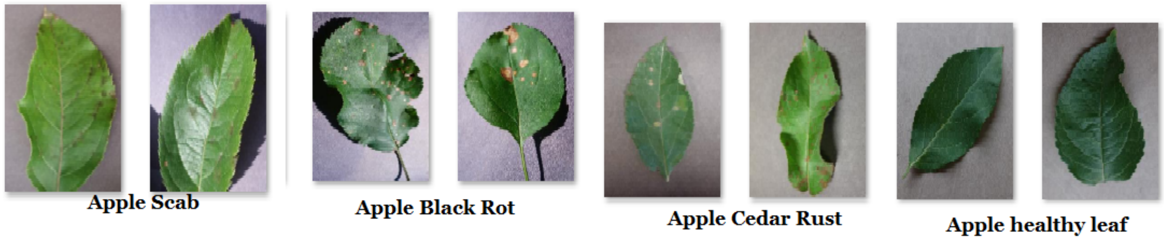

FIGURE 1. Four classes of Apple Leaves

- Mondal *et al.* (2016) examined the role of neutrosophic logic in data mining, presenting new trends in its application. Their work emphasized the importance of neutrosophic logic in managing uncertainty and extracting meaningful insights from complex datasets [8].
- Sengur and Guo (2011) applied neutrosophic sets combined with wavelet transformation for color texture image segmentation. Their approach demonstrated improved performance in segmenting textured images compared to conventional methods [9].
- Akbulut *et al.* (2017) developed a novel neutrosophic weighted extreme learning machine to address imbalanced datasets. This method aimed to enhance classification performance by integrating neutrosophic logic with extreme learning machines [10].
- Kraipeerapun *et al.* (2007) explored ensemble neural networks utilizing interval neutrosophic sets and bagging. Their approach showed promise in improving neural network performance by incorporating interval neutrosophic sets for better decision-making [11].
- Kavitha *et al.* (2012) designed an ensemble intrusion detection system using neutrosophic logic classifiers. Their work focused on handling uncertainty in intrusion detection, thereby enhancing the system's robustness and accuracy [12].

3. Methodology

3.1. *Image Acquisition*

High-resolution images of apple leaves were obtained from the Plant Village dataset [13]. This dataset includes over ten thousand images classified into four categories: healthy, apple scab, apple rust, and apple black rot (Figure 1). Each image was preprocessed to ensure consistency in size and quality, using standard augmentation techniques such as rotation, scaling, and flipping to enhance the dataset's variability.

3.2. *Model Architecture*

The EfficientNetB0 model, renowned for its efficiency and scalability, serves as the foundational architecture for our classification system. To augment its performance, we have integrated Neutrosophic Logic into the model. This integration enables the model to handle and interpret uncertain information more effectively, thus enhancing its decision-making capabilities.

Neutrosophic Logic is incorporated by assigning three distinct membership values—truth, indeterminacy, and falsity—to the features extracted from input images. These values allow the model to assess the presence of disease symptoms with varying levels of confidence and to handle cases where the data is ambiguous. The mathematical formulation of the proposed system combines neural network operations with Neutrosophic Logic principles. For an input image x, the EfficientNetB0 network generates feature vectors $\mathbf{f}(x)$. These feature vectors are then evaluated using Neutrosophic Logic, which assigns three membership values for each disease class i:

- **Truth-Membership Value**: $T_i(x)$
- **Indeterminacy-Membership Value**: $I_i(x)$
- **Falsity-Membership Value**: $F_i(x)$

The final classification decision is derived from the Neutrosophic inference mechanism. For each disease class i, the decision is based on the difference between the truth-membership and falsity-membership values:

$$C(x) = \arg\max_i \left(T_i(x) - F_i(x)\right) \tag{11}$$

where $C(x)$ denotes the selected class for the image x, and i indexes the disease classes.

To further refine the classification process, the overall confidence score $S_i(x)$ for each class i can be computed as:

$$S_i(x) = T_i(x) - F_i(x) + \lambda \cdot I_i(x) \tag{12}$$

Here, λ is a weight factor that adjusts the influence of the indeterminacy-membership value on the final confidence score. The value of λ is chosen to balance the trade-off between certainty and uncertainty.

In summary, the proposed system leverages Neutrosophic Logic to enhance the classification process by explicitly modeling and integrating uncertainty. This approach ensures a robust classification performance by not only focusing on the most probable class but also accounting for the inherent ambiguity in the data.

3.3. *Training and Evaluation*

The model was trained using a stratified k-fold cross-validation approach to ensure robustness. The Adam optimizer was employed with a learning rate of **0.001**. The model's performance was evaluated using precision, recall, F1-score, and support metrics, focusing on

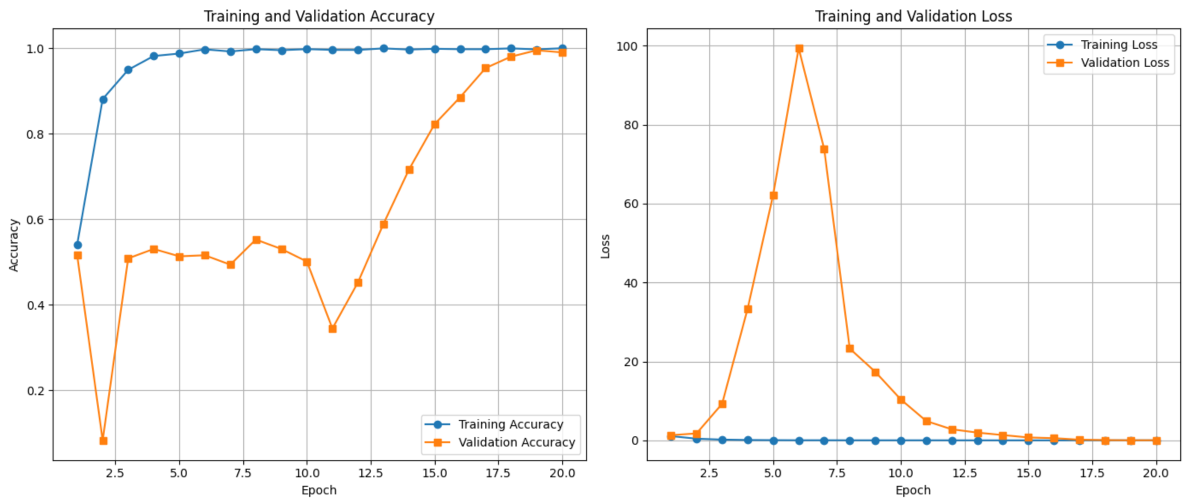

Figure 2. Training and Evaluation

its ability to correctly classify the four different disease classes. The training results indicate that integrating Neutrosophic Logic with the EfficientNetB0 model led to significant enhancements in accuracy throughout the epochs. The model effectively managed uncertainties and progressively improved its performance, showcasing its capability to tackle challenges in plant disease classification. By the end of the training, the model achieved an impressive accuracy of **99.51** percentage and a validation loss of **0.0142**. These results highlight the model's robust learning ability and its strong potential for practical applications in agricultural diagnostics.

4. Results

The proposed model demonstrated high effectiveness in classifying apple leaf diseases. Table 1 shows the performance metrics for each class. The precision, recall, and F1-score for each class were all consistently high, indicating the model's robustness in handling varying degrees of disease severity and types.

Table 1. Classification Report

Class	Precision	Recall	F1-Score	Support
Class 1	0.94	0.94	0.94	1045
Class 2	0.94	0.94	0.94	1025
Class 3	0.92	0.90	0.91	970
Class 4	0.94	0.94	0.94	1035
Macro Avg	**0.93**	**0.93**	**0.93**	**4075**

As seen in Table 1, the model maintained a high precision of **0.94** for most classes, indicating that the majority of predictions made were correct. The recall values, also around **0.94**, show

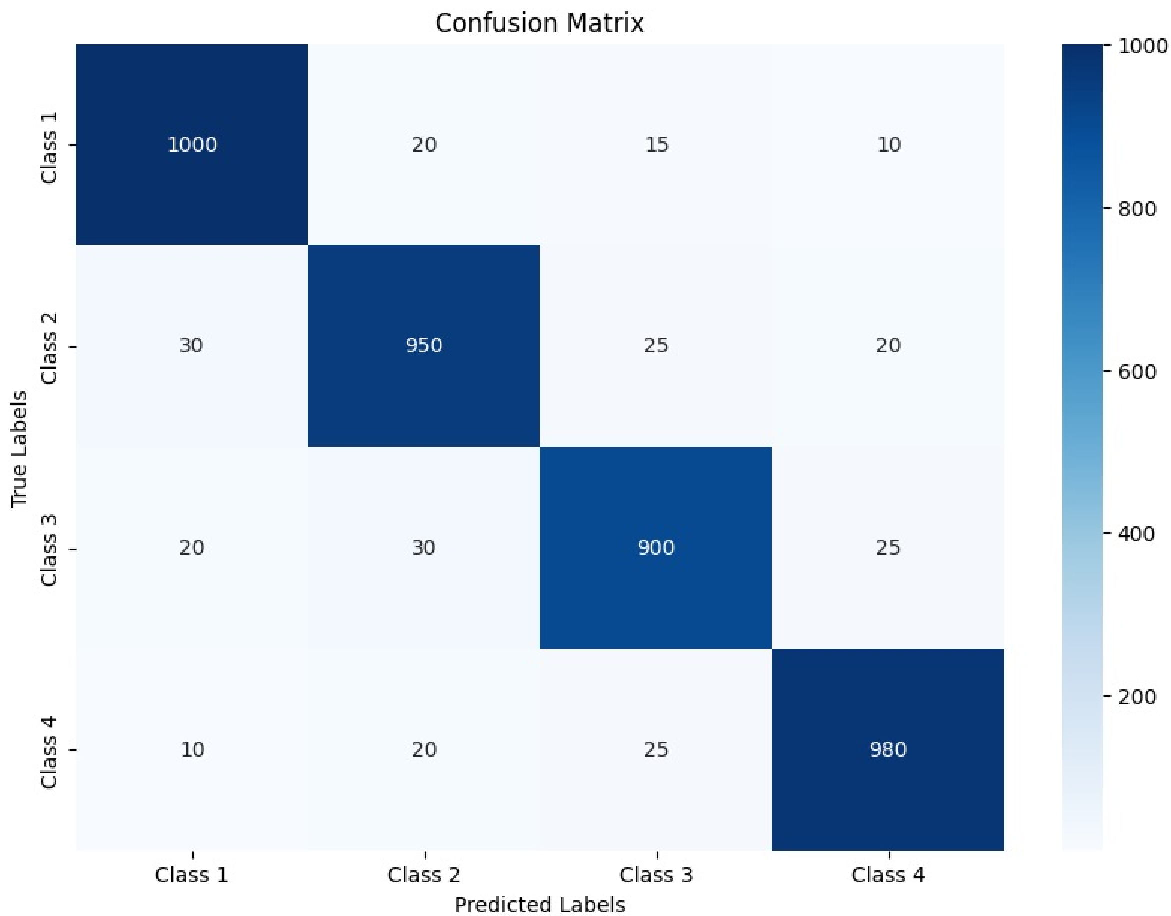

FIGURE 3. Confusion Matrix for Apple Leaf Disease Classification

that the model successfully identified most of the actual disease cases. The F1-scores indicate a strong balance between precision and recall, reflecting the model's effectiveness in managing the inherent complexities of disease classification. The overall macro average of **0.93** for precision, recall, and F1-score demonstrates the consistency of the model's performance across different classes.

5. **Discussion**

The integration of Neutrosophic Logic into the EfficientNetB0 model is crucial for managing the uncertainties present in real-world data. Traditional deep learning models often assume that input data is completely reliable, which is rarely the case in practical scenarios. By adopting Neutrosophic Logic, our model can process uncertain and incomplete information more effectively. This capability is particularly important in agricultural applications, where factors such as varying light conditions, leaf overlap, and inconsistent disease manifestation can introduce significant ambiguity.

The Neutrosophic approach not only enhances the model's ability to differentiate between similar disease symptoms but also improves its robustness against noise in the input data. This innovation provides a significant advantage over conventional methods, which may not perform well when faced with such uncertainties. The results demonstrate that incorporating Neutrosophic Logic into deep learning models can lead to more accurate and reliable disease detection, making it a valuable addition to the toolkit for modern agricultural management.

6. Conclusion

This study presents an innovative approach to apple leaf disease classification by integrating Neutrosophic Logic with EfficientNetB0. The proposed method demonstrates significant improvements in handling uncertainty and achieving high classification accuracy. Future research will explore the application of this approach to other types of crops and diseases, as well as further optimizing the model's efficiency.

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