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Empowering Artificial Intelligence Techniques with Soft Computing of Neutrosophic Theory in Mystery Circumstances for Plant Diseases

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Abstract

Plant diseases are one of the factors that lead to yield and economic losses, which have a direct effect on national and international food production systems. One of the most essential ways to avoid agricultural product loss or reduction in amount is to diagnose plant diseases promptly and accurately. Hence, the diagnosis process for plants is crucial and should be conducted accurately. Moreover, this study focuses on this process by constructing an Artificiality Diagnostics Framework (ADF) to serve the study's objectives which entailed conducting diagnosis for plants in a professional and precise manner over uncertain environments. Thus, neutrosophic theory is considered the principal ingredient in our ADF. Due to the ability of neutrosophic to divide images into Truth (T), Falsity(F), and Indeterminacy (I). Also, deep learning (DL) is considered another principal ingredient in treating vast samples of datasets. Our comparative analysis of the leaves of potatoes is conducted whether leveraging neutrosophic and without utilizing Neutrosophic. ResNet50, ResNet152, and Mobile Net are the principal ingredients for the training dataset. The findings of implementing these networks indicated that ResNet50 achieved the highest accuracy of 0.915 in the T domain, ResNet152 achieved the highest accuracy of 0.905 in the True(T) domain, and Mobile Net achieved the highest accuracy of 0.915 in Truth(T) domain. Accuracy of 0.863 in Indeterminate(I).

Keywords: Neutrosophic theory, Deep Learning, plant disease

1. Introduction

Economic losses arise from yield losses caused by plant diseases, which have a direct effect on national and international food production systems. Oerke et al. [1] estimated that 13% of the loss in agricultural productivity worldwide is attributed to plant diseases. From the perspective of [2] comprehension of the causes of plant diseases is mandatory. A conducive habitat, the pathogen, and the host are the three elements that help diseases develop in plants. Also, drought and plant disease[3] are factors that impact agricultural productivity. As a result of the spread of many plant diseases throughout the crop after infection, [4] regular crop monitoring is necessary since prompt disease control will stop the disease's progress.

In this evolving context [5], the need to accurately and promptly identify illnesses, including early impediments, has never been higher. For decades[6], computer vision technology has been used in agriculture to identify weeds, assess crop geometric sizes, diagnose nutritional deficiencies, and predict crop yields.

Overall, plant phenotyping and precision agriculture need the diagnosis of plant diseases. While diagnosing and monitoring plant diseases is important [7], conventional approaches that require a human visual inspection are costly, time-consuming, dependent on specialists, and unsuitable for precision agriculture. Furthermore, human prejudice is likely to have an impact on these methods, reducing their accuracy. Hence [2], solved these issues by examining the utilization of image processing methods with images of plants.in the same vein [8] that employed image processing techniques to measure corn stripe disease, and it was shown that computer-based approaches outperformed traditional visual analysis in terms of accuracy.

Nevertheless [9] decided that the degree of uncertainty in the image's data increases when two-dimensional images are converted from three-dimensional ones through image processing. Furthermore, many of the concepts in the image are also vague and ambiguous. Whilst a crucial part of image processing and pattern recognition [10], image segmentation is one of the trickiest processes which has many uses and uncertainties [9] that contribute to the difficulty of segmenting images.

Wherefore fuzzy theory is used to the field of image segmentation[11] , to effectively express fuzzy concepts and information. In the discipline of image segmentation [12] , fuzzy image segmentation has grown in importance and popularity as a study area. Subsequently [13] established neutrosophic fuzzy clustering algorithm within the conventional fuzzy C-means clustering techniques. In the same vein, the study of [14] confusing data in the diagnosis of skin cancer are grouped using neutrophilic c-means clustering (NCMC). On the other hand, the notion of Neutrosophic theory is highlighted by [15] which proposed by Smarandache, where the basic distinction between fuzzy and intuitionistic fuzzy logic and set is represented by the neutral concept that is known as Neutrosophy [16].

In the realms of artificial intelligence (AI) and deep learning (DL), Neutrosophic theory (NTh)[17] offers the necessary ability to serve as a universal framework for uncertainty analysis in data sets, particularly with images.

Overall, all of these studies are considering catalyst for implementing neutrosophic theory in field of diagnosis the plant and classify it [18] into three sets as Truth (T), Falsity (F),and Indeterminacy (I).Although, we are leveraging ML especially DL [19] for the identification of diseases as a result of enhanced computing power, larger storage capabilities, and the accessibility of enormous datasets.

Herein, Plant diseases can be diagnosed by merging NTh with DL toward establishing Artificiality Diagnostics Framework (ADF). We applied the established ADF to real problem through implementing the framework on dataset consisting of around 4000 images of potato. The findings of ADF are recorded and analyzed into the results and discussion section.

2. Realm of Neutrosophic Theory

In the context of vague and ambiguity about data and circumstances, the notion of neutrosophic was founded by Smarandache[15] which extended to fuzzy logic.

2.1 Preliminary

This theory described in field of image processing [9, 16] as :

- Assum $\Re$ be a universe in this study. A group of image pixels represent as $\vartheta = \omega * \omega$.whilst $\omega \subseteq \Re$, and ω is an argument.
- Herein, neutrosophic image can be described as ∂ , F, ℓ are symbols of truth, false and indeterminacy.
- Each pixel $p(\chi, \nu)$ in the neutrosophic image can be described as $p_{Neu}(\chi, \nu) = \{\partial(\chi, \nu), \ell(\chi, \nu), F(\chi, \nu)\}$.

  $\partial(\chi, \nu) = \frac{\bar{\kappa}(\chi,\nu) - \bar{\kappa}\min}{\bar{\kappa}\max - \bar{\kappa}\min}$ (1)

  Where: $\bar{\kappa}(\chi, \nu)$is the region mean value of $\kappa(\chi, \nu)$

  $$\bar{\kappa}(\chi, \nu) = \frac{1}{\omega * \omega} \sum_{m=i-\omega/2}^{i+\omega/2} \sum_{n=i-\omega/2}^{i+\omega/2} \kappa(m, n) \quad (2)$$

  $\ell(\chi, \nu) = \frac{\wp(\chi,\nu) - \wp_{\min}}{\wp_{\max} - \wp_{\min}}$ (3)

  where: $\wp(\chi, \nu)$is the absolute value of the difference between intensity $\kappa(\chi, \nu)$ and its local mean value at $\kappa(\chi, \nu)$.whilst ℓ is indeterminacy degree of p_{Neu}

  $\wp(\chi, \nu) = \text{abs}(\kappa(\chi, \nu) - \bar{\kappa}(\chi, \nu))$ (4)

  where: $\kappa(\chi, \nu)$ is the gray value of $p(\chi, \nu)$

  $F(\chi, \nu) = 1 - \partial(\chi, \nu)$ (5)

- whereas, in interval neutrosophic, p_{INeu} described according to interval number set as:

  $p_{INeu} = \{[\partial_1(\chi, \nu), \partial_2(\chi, \nu)], [\ell_1(\chi, \nu), \ell_2(\chi, \nu)], [F_1(\chi, \nu), F_2(\chi, \nu)\}$ (6)

2.2 Applications of Neutrosophic

According to bibliometrics analysis [20], we are conducted analysis based on web of science (WoS) database for prior studies and terms which related to our scope. VoS viewer software is utilized for showcases the findings of queries conducted on WoS for applying neutrosophic in various domains.

2.2.1 Neutrosophic in Agriculture

We conducted bibliometric analysis based on certain keywords such as ("Agriculture" AND "Neutrosophic") The findings of this process showcase as following Figure 1 where query conducted for Co-citation based on Co-Sources for mentioned key words. The findings indicated that 14 items which classified into two clusters. Cluster 1 has seven items with red color and cluster 2 has seven items with green color.

2.2.2 Neutrosophic in Healthcare

Figure 2 illustrated bibliometric analysis which conducted certain keywords such as ("Healthcare" AND "Neutrosophic") for Co-citation based on Co-Sources for mentioned key words. The findings indicated that 12 items which classified into two clusters. Cluster 1 has six items with red color and cluster 2 has six items with green color.

2.2.3 Neutrosophic in Climate

The conducted bibliometric analysis for Co-citation based on Co-Sources for utilizing neutrosophic in climate has been represented in Figure 3. According to this Figure, there are two clusters. Each cluster has 6 items. Overall, there are 12 items resulted of query ("Climate" AND "Neutrosophic") for Co-citation based on Co-Sources.

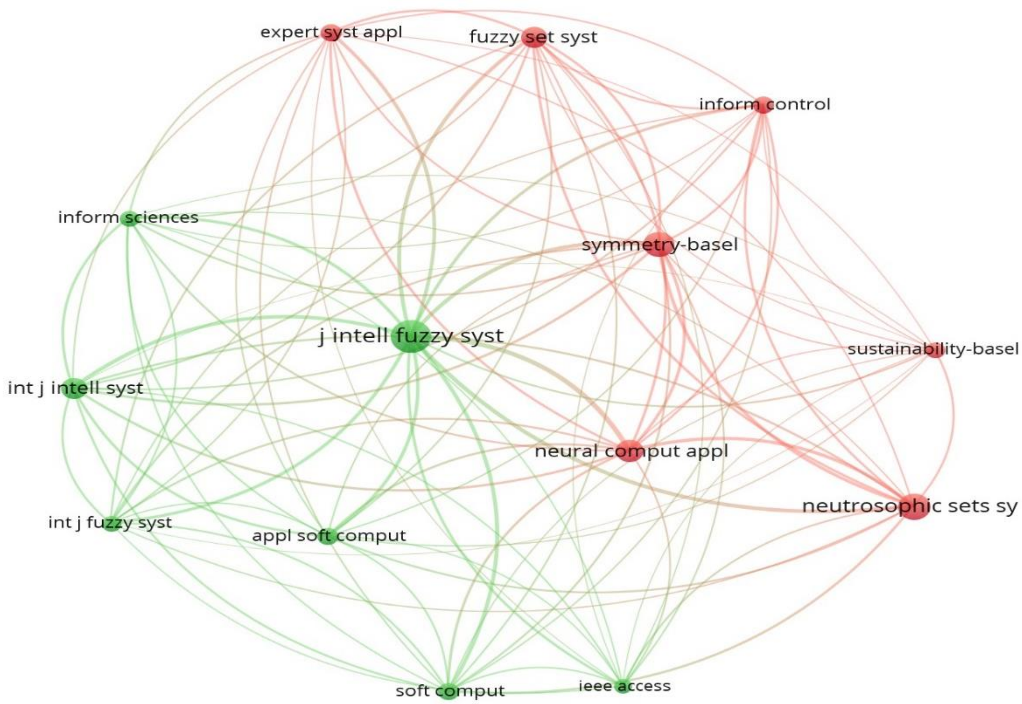


Figure 1. Visualization network for Co-citation based on Co-Sources in agriculture.

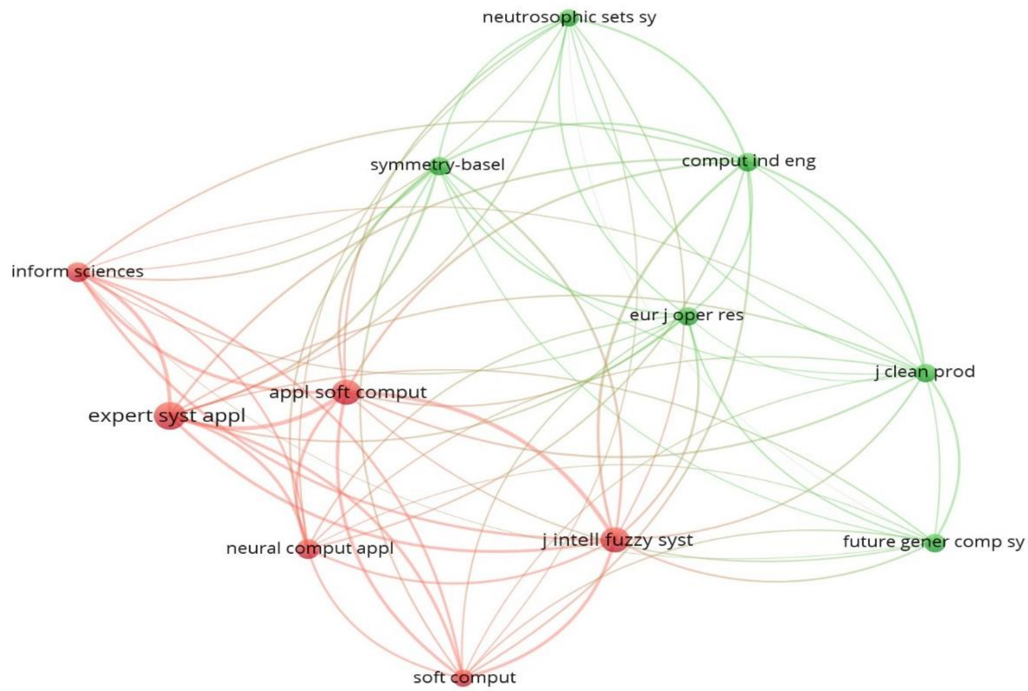


Figure 2. Visualization network for Co-citation based on Co-Sources in healthcare.

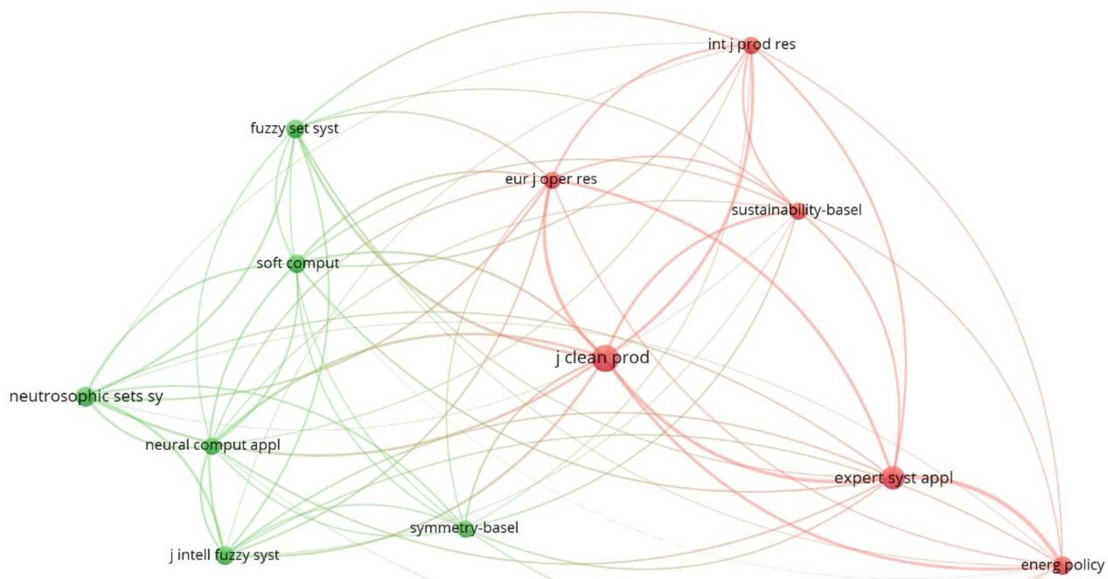


Figure 3. Visualization network for Co-citation based on Co-Sources in climate.

3. Related Work

Herein, we attempted to ensemble the prior studies which related to our scope; through surveys have been conducted. The surveys' findings indicated that not many literary works treat uncertainty and incomplete data. Thereby, this study covered this issue through merging Neutrosophic with DL and established ADF. Table 1 illustrates a set of related studies.

Table 1. previous literary studies

Ref #	**Methodology**	**Objectives**	**Dataset**	**Findings**
Paul et al. [21]	In this study, the author built a custom lightweight CNN model and compared it with some CNN models based on the transfer learning principle.	Tomato disease detection and classification	The dataset, called multi-source tomato disease, was collected from a single source consisting of 11 varieties and containing 32,535 images.	The proposed model achieved the best with data augmentation accuracy 95% and without 89%.
Memon et al.[22]	Build Meta DL Model and Compare Accuracy it With Custom CNN Model, Vgg16 Transfer learning and ResNet50 Model	Identify and detect cotton leaf diseases	The cotton data set with 2384 samples. The utilized data divided into seven classes: nutrient deficiency, healthy, leafspot, powdery mildew, target spot, verticillium, and leaf curl)	The Proposed Model achieve 98.53%
Rangarajan et al.[23]	Train two Deep learning Model Vgg16 and Alex Net based of Transfer Learning and Compare accuracy of them	Detect Tomato Leaves Disease	The dataset consists of seven categories, including the health category, which consists of 13,262 images extracted from the plant Village Dataset.	Alex Net achieved best Accuracy 97.49 With better performance
Bi et al.[24]	Scholars build mobile phone-based models based on Mobile Net and compare it with InceptionV3 and ResNet152 in terms of speed in image prediction.	Detecting diseases of apple leaves by low-cost model	The data set consists of two categories (Alternaria leaf spots and rust leaves) and contains 334 images. The data set was collected by a group of experts.	The best model in terms of image processing speed is Mobile Net with the fastest speed of .22 seconds
Dahiya et al.[25]	In this research, the author trained a group of the most famous types of deep learning models on plant diseases Dataset such as Google Net and ResNet18 and compared them in terms of accuracy.	Analysis of some deep learning models in terms of accuracy in detecting plant leaf diseases	Plant Village data set consists of 18 classes of 2064 images, divided into 70% for training, 20% for validation, and 10% for testing	The best models achieved Accuracy is ResNet50 and ResNet101
Wei et al.[26]	In this work, the author made a comparison between a group of models such as Alex Net, VGG16, Res Net50, and DenseNet121) on more than one endpoint device (CPU, GPU, VPU).	plant leaf disease identification	The Plant Village dataset, which consists of 55,446 images, is divided into 38 classes	The Best Model archive accuracy is DenseNet121 96.4

Rao et al.[27]	authors implemented pre trained Model Alex Net	Detect Diseases Grape and Mango Leaves	The dataset consists of 7,222 grape leaves from plant Village and 1,216 self-acquired mango leaves	Model archive accuracy in Grape Dataset 99.03% and 89% for Mango Dataset
Belay et al.[28]	proposed model has been built by combining CNN with LSTM and Compare it with server models such a InceptionV3 s VGGNet16 and	Chickpea disease detection	Chickpea Data Set which it consists of 3 Class and contain 1399 image and after augmenting 8391	The Proposed Model achieved highest with 92.55 accuracy

4. Data and Methods

In this study, Potato Dataset has been utilized to compare the performance of a group of models before and after applying the neutrospheric technique to the data. Potato Dataset consists of around 4000 images divided into 3 we used Sample of It in training Model. Table 2 show Statistics of Sample.

The methodology which is employed in this study is to correctly classify potato plant diseases, and this is done in two steps. The first step is to apply the Neutrosophic Domains as an image processing step. The second step is to train the data on deep learning models using the Transfer learning principle. Establised ADF is highlighted in Figure 4.

We used three models for training data ResNet50, ResNet152, and Mobile Net. We trained models with Adam optimizer and lr = .0001.Model training with 50 epochs and evaluate models after each epoch with metrics.

Table 2. Statistics of utilized samples

Classes		Images	Percentage	Total
Diseased	Early Blight	325	0.349%	638
	Late_Blight	313	0.336%	
Healthy	Healthy leaf (C2)	292	0.313 %	930

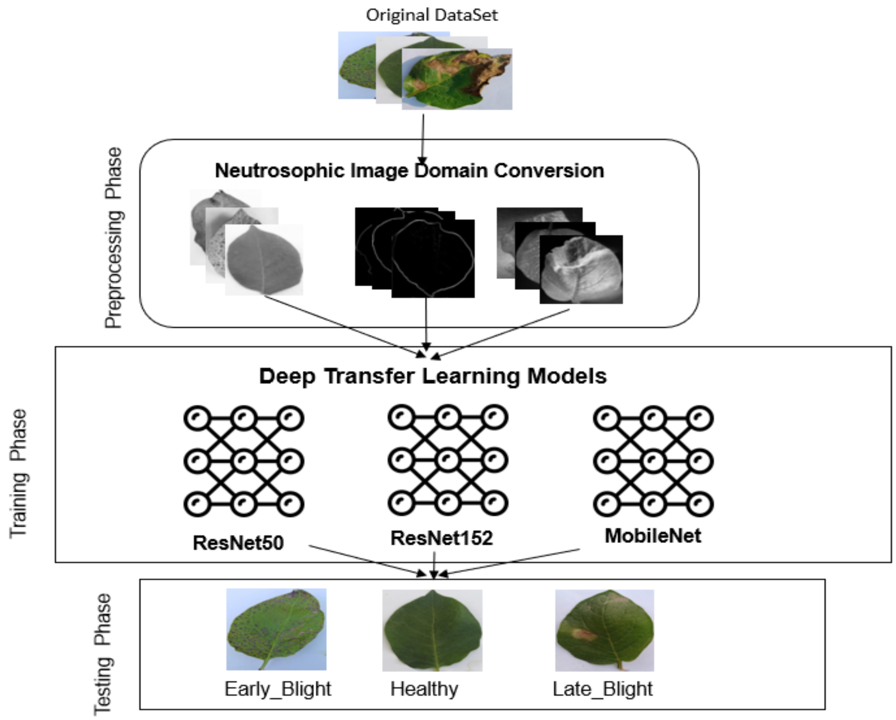


Figure 4. Proposed ADF

5. Result and Discussion

Herein, we illustrate the ADF'S findings and discuss it.

5.1 Performance parameter

Comparison Analysis between models with some matrices has been conducted. We evaluated the model's performance through recall, F1Score, Precision, and Accuracy

5.1.1 Accuracy

This metric is calculated from the number of correct predictions for all categories to the total number of predictions according to Eq.(7).

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{FP}+\text{TN}+\text{FN})} \qquad (7)$$

5.1.2 Precision

This measure is calculated from the number of correct predictions for a category to the total number of predictions in the same category through implementing Eq.(8).

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \qquad (8)$$

5.1.3 Recall

This metric is calculated by harmonic mean based on Eq.(9).

$$\text{F1 Score } = 2 \times \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}} \quad (9)$$

We ustilized Kaggle to train all Models that has GPU Nvidia Tesla P100 With Ram 16 GB.We use Python Version 3.7.6 and Keras Version 2.3.1.

5.2 Hyperparameters For Models

All Models train with Adam optimizer through learning rate .0001, batch size 32, number of epoch 50.

5.2.1 Original Dataset Experiment

Summary performance of models for original dataset are listed in Table 3 without Neutrosophic Domain. We observed that ResNet 50 achieved highest accuracy with .873.

Table 3. Performance o various models based on original dataset

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.842	0.842	0.841	0.840
ResNet50	0.873	0.871	0.870	0.870
ResNet152	0.831	0.841	0.841	0.826

5.2.2 Neutrosophic Domains Experimental Results

- In table 4, summary performance of models for True(T) NS Domain has been showcased. whilst ResNet152 achieved highest accuracy with .0.905.
- Whereas performance of models for Falsity(F)has been showcased and listed in Table 5. Therefore, ResNet50 achieved highest accuracy with 0.905.
- Table 6 summary performance of models for Indeterminate (I) has been summarized. Moreover, NS Domain Mobile Net achieved highest accuracy with .863%.
-

Table 4. Dataset True(T)

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.852	0.854	0.852	0.853
ResNet50	0.852	0.850	0.848	0.846
ResNet152	0.905	0.907	0.901	0.901

Table 5. Dataset Falsity (F)

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.694	0.701	0.693	0.694
ResNet50	0.915	0.914	0.913	0.9134
ResNet152	0.905	0.912	0.900	0.899

Table 6. Dataset (I)

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.863	0.862	0.861	0.861
ResNet50	0.778	0.777	0.776	0.776
ResNet152	0.831	0.841	0.827	0.826

5.3 Comparative Result of Neutrosophic Domain with the Original Dominant

Table 7 shows best accuracy of models achieved Mobile Net achieved best accuracy in Indeterminate (I) domain with accuracy .863. ResNet50 and ResNet152 achieved best accuracy in True(T) domain with accuracy 91.5 and 0.905. Figure 5 summarized comparison of models' accuracy.

Table 7. Accuracy of various Models

Model	Accuracy	Precision	Recall	F1 Score
MobileNet	0.863	0.862	0.861	0.861
ResNet50	0.915	0.914	0.913	0.9134
ResNet152	0.905	0.912	0.900	0.899

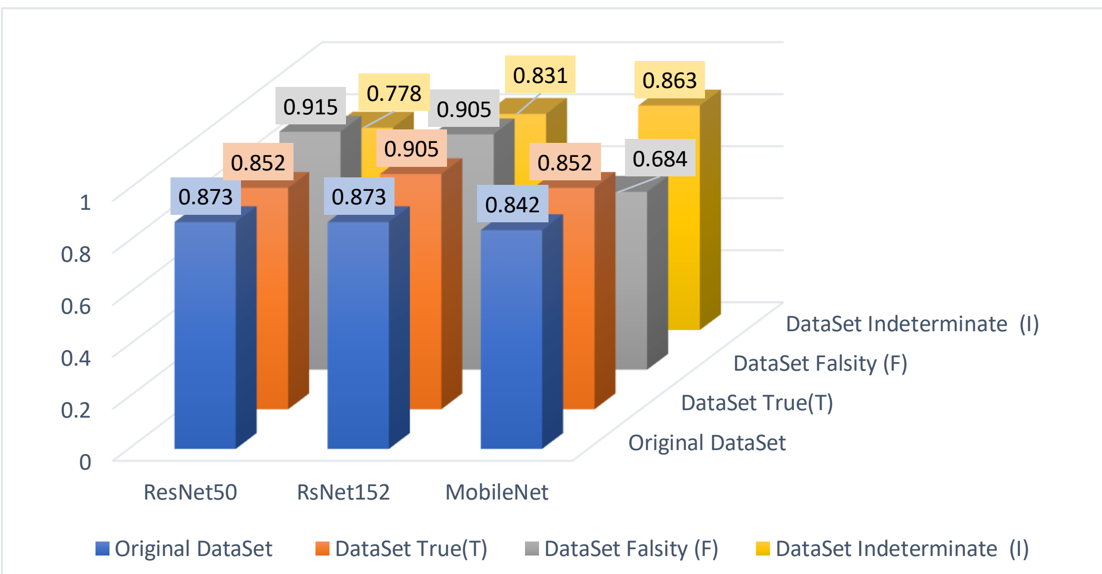
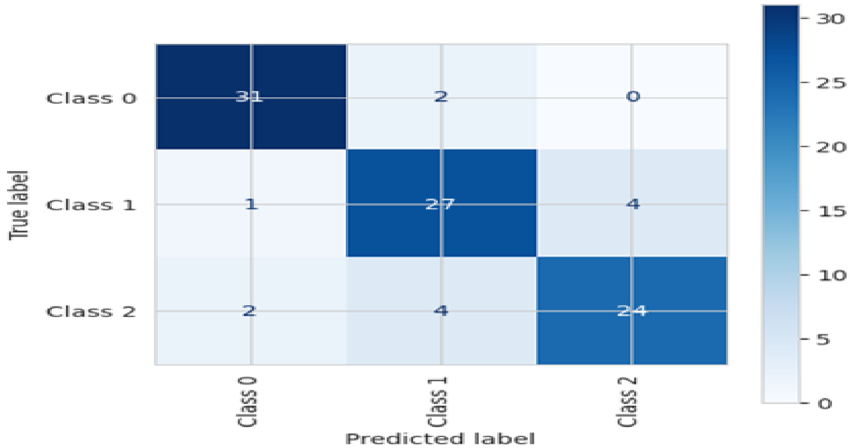


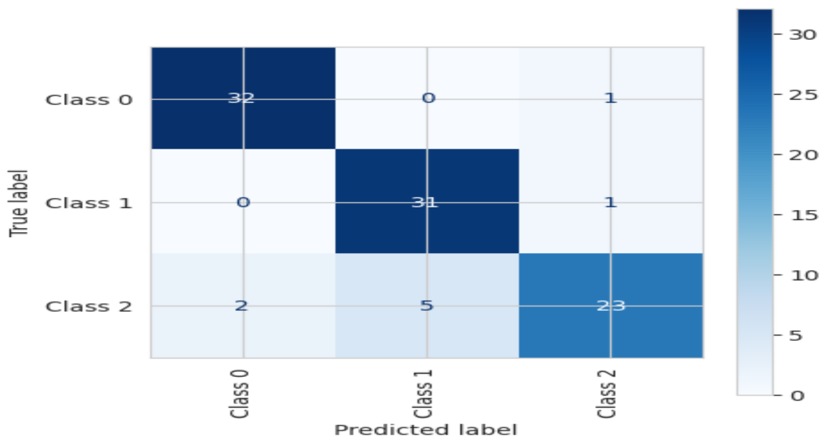
Figure 5. Accuracy of comparative models

5.4 Confusion Matrix of MobileNet

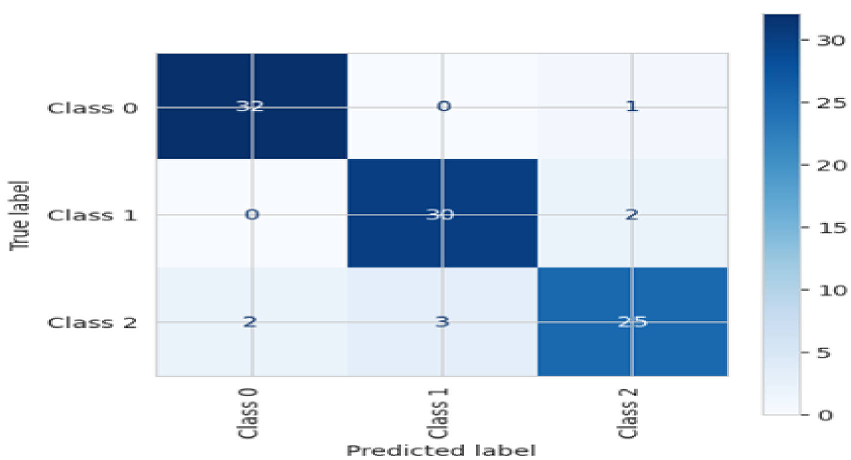
Figure 6. aggregated the confusion matrix for each measurement for truth (T), Indeterminate (I), and Falsity (F).



Confusion Matrix of MobileNet in domain Indeterminate (I)



Confusion Matrix of ResNet152 in domain True(T)



Confusion Matrix of ResNet50 in domain False (F)

Figure 6. Confusion Matrix of Mobile Net for True, False, and Indeterminate

6. Conclusion

This study attempted to cover some of the issues mentioned and determined in the prior studies. One of these issues was incorrect diagnosis for plant diseases. A misdiagnosis might shorten the crop's life or even eradicate it. Moreover, agriculture is diminishing.

Another issue entailed in not many literary studies discuss the uncertainty and incomplete data.

Thereby, these issues are catalysts for developing our ADF which depends on theory which characterized with uncertainty and has ability to treat with ambiguity circumstances. This theory is Neutrosophic which treats with image through three possibilities are T, I, and F. Also, we combined this theory with ML especially DL. Due to the ability of DL to treat with large volume of data. Hence, commenced acquiring an interest in diagnosing diseases especially plants in agriculture domain.

Overall, we applied our constructed ADF potato dataset. Whereas the utilized dataset trained by ResNet50, ResNet152, and Mobile Net models Also, we conducted comparison between the performance of the models before and after applying Neutrosophic theory. The findings of this experiment indicated that Neutrosophic theory proved very effective in improving the accuracy of the models.

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