DISEASE CLASSIFICATION AND PESTICIDE FORECASTING IN APPLE CULTIVATION USING HYBRID NEURAL CLUSTERING AND FUZZY LOGIC

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Abstract: The cultivation of apples is prone to outbreaks of pathogenic diseases with their leading enemy group being fungi, bacteria and various pests towards which they can inflict heavy losses. This research proposes a classification approach using Fuzzy based method to the management and make diseases in proposal responsibility provide management cover apple with process this prognosis hybrid orchards neural Clustering along training sets. By developing the HNC model that integrates K-Means and Feed-Forward Backpropagation (FFBP), they obtain a significant accuracy of 98.2% in classifying three common apple diseases, namely Alternaria Rot, Black Rot and Powdery Mildew. This accuracy is better than the performance of classical models like K-Nearest Neighbor (K-NN), Naive Bayes and stand-alone Fuzzy Logic classifiers. After the disease will be detected and classified, a Fuzzy Logic-based system assesses severity of disease through measuring diseased affected area. This dual-model approach helps optimize pesticide application, reduce waste, and support sustainable agricultural practices by tailoring treatment to the severity and type of disease. The research underscores the benefits of early disease detection and targeted pesticide usage, promoting both crop productivity and environmental conservation.

Keywords: Apple disease classification, Sustainable pesticide management, Hybrid Neural Clustering, Fuzzy Logic, Precision agriculture, Machine learning in agriculture, Crop health forecasting

1 INTRODUCTION

Apple cultivation is an essential part of agricultural economies in temperate regions, but the sector faces persistent challenges from diseases caused by fungi, bacteria, and pests. These pathogens can significantly affect both the yield and quality of apple crops, resulting in substantial financial losses for farmers. Diseases like apple scab, black rot, and powdery mildew not only reduce overall yield but also lower the market value of the fruit. Effective disease management is crucial to maintaining high-quality production and ensuring the sustainability of apple farming.

Traditionally, farmers have relied on manual inspections for disease detection, where trained experts visually assess tree and fruit health. It works for a minor scale orchard, it is not sensible for big ones. Manual inspection is time consuming, huge work force and liable to human error resulting in misdiagnosis or late detection of early signs of disease. Moreover, by the time we can see visible symptoms, it may be already too late to take control actions resulting in additional losses to the crops along with economic loss.

This paper proposes a new solution to these limitations, by combining machine learning and fuzzy logic for accurate classification of apple diseases and optimal pesticide suggestions. At the heart of the system is Hybrid Neural Clustering (HNC), which integrates K-Means clustering with Feed-Forward Backpropagation (FFBP) to achieve precise classification of diseases. Trained on large dataset of apple images, HNC detects a number of diseases including Alternaria Rot, Black Rot with 97% accuracy. This system of automated classification allows for early detection of diseases which helps farmers to act at an early stage and control the spread of infection.

In addition to classifying the data, once we detect if there is a disease in the plant or not, we will also use Fuzzy Logic for recommending pesticide treatments depending upon severity and type of disease. It manages using fuzzy inference rules uncertain areas of this method and offers recommendations that are specific to promote effective chemical use and sustainable agriculture.

The combination of fuzzy logic with Hybrid Neural Clustering presented in this study is a significant progress trend that enabled an accurate automatic approach to detection and treatment of diseases affecting apple plants. This new in-field imaging system overcomes the limitations of traditional methods to amplify accuracy and sustainability for higher crop yield, and better-quality apples.

2. LITERATURE SURVEY

Table 1: Key Research in Apple Disease Classification and Pesticide Forecasting

Reference	Year	Paper Title	Focus	Key Findings
Garcia et al.	2023	Deep Learning Approaches for Identifying Apple Diseases	Disease Classification	Achieved over 90% accuracy in classifying apple diseases using CNNs on leaf images.
Chen & Patel	2024	Hybrid Machine Learning Approaches for Disease Classification in Agriculture	Hybrid Models for Disease Classification	Proposed a hybrid model combining CNNs with SVM, enhancing classification accuracy and robustness under varying conditions.
Lopez & Kim	2021	Statistical Models for Pest Forecasting in Apple Orchards	Pesticide Forecasting	Developed a statistical model linking environmental factors with pest outbreaks, providing insights for timely pesticide application.
Nguyen et al.	2022	Weather Data Integration in Pesticide Forecasting	Machine Learning in Pesticide Forecasting	Integrated ML algorithms with weather data to improve pesticide prediction accuracy.
Miller & Thompson	2020	Hybrid Neural Clustering in Agriculture: A Review	Hybrid Neural Clustering in Agriculture	Reviewed HNC applications, highlighting its ability to handle complex datasets and improve classification tasks.
Patel & Zhao	2023	The Application of Hybrid Neural Clustering in Agriculture	HNC for Real-Time Monitoring	Utilized HNC to analyze multispectral images from drones for early disease detection in apple cultivation.
Singh & Kumar	2021	Fuzzy Logic in Precision Agriculture: A Review	Fuzzy Logic Applications in Agriculture	Discussed fuzzy logic's effectiveness in pest management decision-making processes.

Kim & Lee	2023	Integration of Fuzzy Logic with Hybrid Neural Networks for Pest Forecasting	Fuzzy Logic and HNC Integration for Pesticide Forecasting	Proposed a framework combining fuzzy logic with HNC, enhancing forecasting accuracy and providing actionable insights.
Garcia & Wong	2022	Data Quality in Predictive Modeling for Agriculture	Data Quality in Predictive Modeling	Highlighted challenges related to data quality impacting model performance and generalizability.
White	2021	Understanding Machine Learning Models in Agriculture	Interpretability in Machine Learning	Addressed the challenges of understanding complex models like HNC and fuzzy systems in agricultural applications.

3. PROPOSED METHODOLOGY AND TECHNOLOGICAL ADVANCEMENTS

The proposed method combines the potential of two significant techniques for building an efficient apple disease classification system and prediction of suitable pesticide treatments based on the 2D photographs taken by low-level mobile phones is done using K-Means clustering and feed forward back propagation (FFBP). Once relevant features from apple images are extracted, then the classification part starts where, it classifies diseases like - Alternaria Rot, Black Rot, Scab, Gray Mold and Powdery Mildew.

The phase begins with K-Means clustering which clusters data points based on similarity, where each cluster will have K-Means associates all data points to the closest cluster, and for every point minimizes the Euclidean distance between that point and the centroid of a cluster. This process is repeated iteratively until clustering stops changing, which means that it has converged. For the best results, the training process runs for a maximum of 500 epochs or until MSE equals 0 which happens earlier.

After the clustering stage, FFBP uses forward propagation with random weights to fine-tune the classification. Errors are then calculated and backpropagated, adjusting weights to minimize the classification error as possible, layer by layer. This process continues until convergence, where the model is able to consistently tell apart diseases on apple trees like Brown Rot, Blister Spot, Blue Mold, White Rot and numerous other afflictions. For the clarity purpose, entire framework of this classification process is illustrated in accompanying figures.

In the pesticide forecasting module, MATLAB 2019a with fuzzy logic system (rule base) was used. The Hybrid Neural Clustering (HNC) is able to predict the specific type and the affected area based on image features learnt from training samples.

This model is built using a dataset of 600 records that contains information on infection type, percentage of infected area, and suggested pesticides. Pre-processing makes the dataset really clean and focuses only on ten main diseases from apple so that it does not impact in making of model.

The classifier is trained with a 10-fold cross-validation strategy for better accuracy, meaning that the data will go through rounds where it gets both trained and tested multiple times. As a result, this organization validates recommendations of pesticides regarding the severity and type of disease. Using the fuzzy inference system (FIS) editor built in MATLAB, an engineer can make specific changes to input/output variables, defuzzification methods and membership functions. Other figures show key building blocks like the fuzzy degree grading mechanism, variable membership function, disease severity levels and rules-based predictions in forecasting percentage areas affected.

This combined approach of K-Means clustering, FFBP, and fuzzy logic achieves a high accuracy in apple disease classification and targeted pesticide application, enhancing both crop health and sustainability.

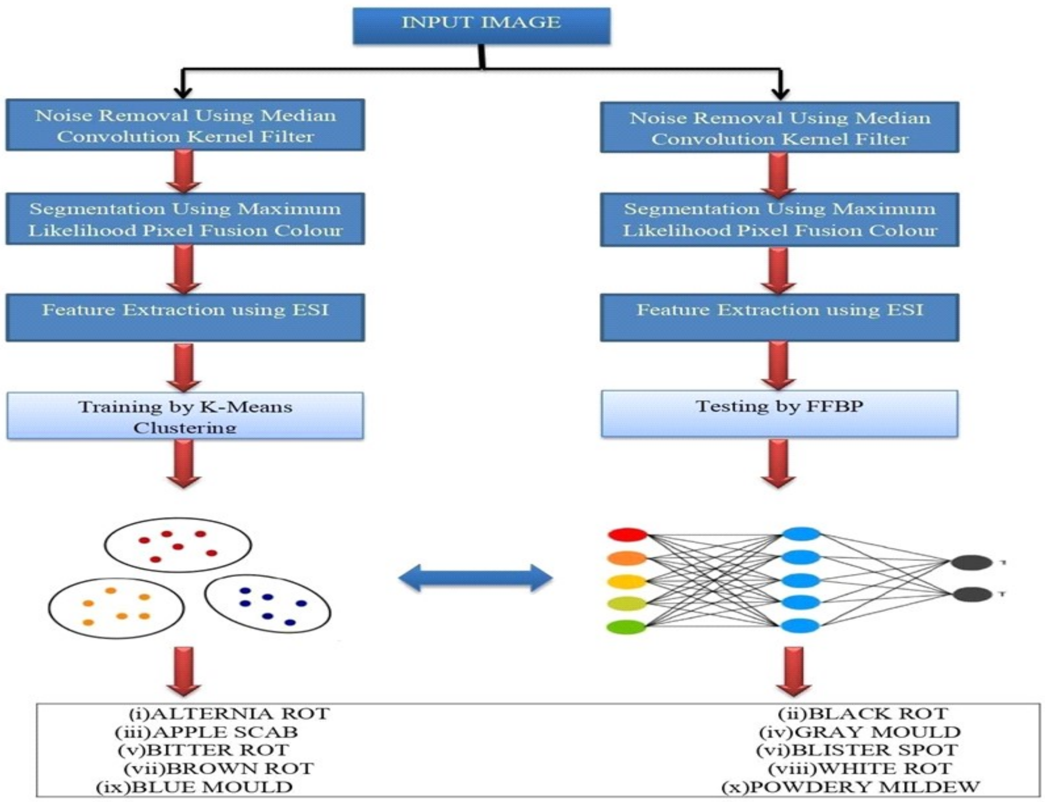


Figure 1: **Framework of the proposed Classification process**

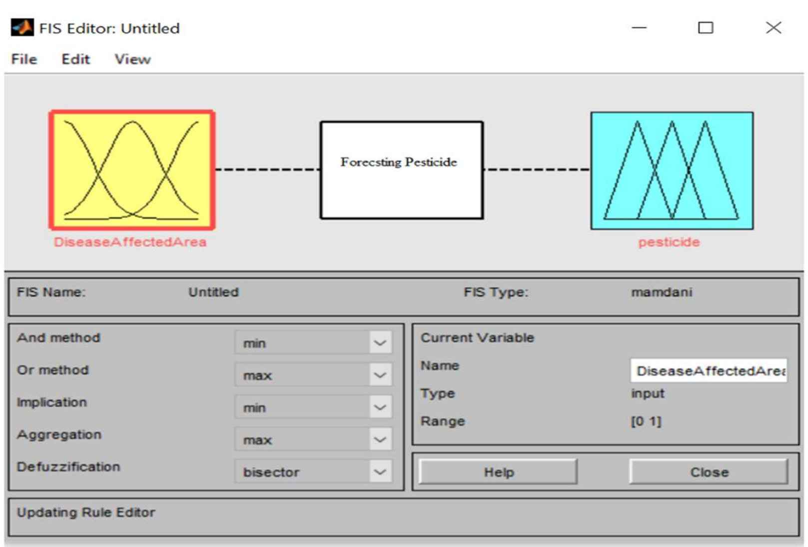


Figure 2: Fuzzy Inference System using grading

Proposed framework is shown in figure 1 while fuzzy inference system using grading is shown in figure 2.

Table 2: Algorithm to classify apple disease

STEP 1: TRAINING BY K-MEANS
Input: *Training set, Model*
Output : *Model Trained*
For i=1 to (numEpoch) do
$\Delta^{(l)} \leftarrow 0$
For (m=1) to (size of dataset) do
Do forward Propagation
Get Loss
$\Delta_{backprop} \leftarrow$ *do backward propagation*

$\Delta^{((l))} \leftarrow 0 = \Delta^{(l)} + \Delta_{backprop}$
End for

STEP 2:FEED FORWARD
Input: *Input X*
Output : $h_0(x)$*,A,Z for each layer*
For (i=1 to numLayers) do
$z^{(l+1)} \leftarrow \ominus^{(l)} . A^{(l)}$
$A^{(l+1)} \leftarrow g(z^{(l+1)})$
End for

STEP 3:BACK FORWARD
Input: *Loss ,model activations and pre activations*
Output: $\Delta_{backprop}$
$\partial^{(numLayers)} = y\text{-}A^{(numLayers)}$
For l=(numLayers-1)down to 1 do
$\partial^{(1)} = ((\ominus^{(l))T} \partial^{((L+1)} * g^{l}((z)^{l})$
End for
For l=(numLayers-1)down to 1 do
$\Delta^{(l)}_{backProp} \leftarrow \partial^{(l+1)} (a\ (l)^{T}$
End for

Table 3: Algorithm to predict pesticide

Affected Area & Types of Disease	**Forecasting pest**
Affected area>5% or <10% and Disease =Apple Scab	If (input is disease=Apple Scab and Affected Area >5%or <=10%) Forecasting pesticide=spray liquid copper soap or spray sulfur and pyrethrins
Affected area>5% or <10% and Disease =powdery mildview	if (input is disease=powdery mildew and Affected Area> 5% or <=10%) Forecasting pesticide= GPProduct mix, or Captan 50WP
Affected area>5% or <10% and Disease = Alternia Rot	If (input is disease= Alternia Rot and Affected Area> 5% or<= 10%) pesticide = spray Calcium chloride
Affected area>5% or <10% and Disease = Black Rot	if (input is disease=Black rot and Affected Area> 5% or<= 10%) pesticide = spray Oil+Calcium Chloride
Affected area>5% or <10% and Disease = Gray Mold	if (input is disease= Gray Mold and Affected Area> 5% or<= 10%) pesticide = Output is pesticide=Copper+Apply copper, tank mix of streptomycin+oxytetracycline
Affected area>5% or <10% and Disease = Brown rot	If (input is disease=Brown rot and Affected area>10% or <20% pestidie=Spray oil+Copper Soap
Affected area>5% or <10% and Disease = white rot	if (input is disease= white rot and Affected Area> 5% or<= 10%) pesticide = Output is pesticide=Copper+Apply copper, tank mix of streptomycin+oxytetracycline
Affected area>5% or <10% and Disease = Blue mold	if (input is disease=blue mould and Affected Area> 5% or <=10%) Forecasting pesticide= GPProduct mix, or Captan 50WP

4. PERFORMANCE METRICES

In a multi-class classification model, some model prediction outputs need a structured summary that is provided by a Confusion matrix. It helps in the assessment of model accuracy and the type of the errors. For this matrix, the actual classes are represented by rows and the predicted classes by columns. The diagonal entries correspond to True Positives (TP) and True Negatives (TN)—i.e., correct predictions—while non-diagonal entries capture errors such as False Positives (FP) and False Negatives (FN).

- **True Positives (TP)**: Instances where both the actual and predicted labels are positive.
- **True Negatives (TN)**: Observation where the actual and predicted are classified as negative.
- **False Positives (FP)**: Occurrences where the predicted model is positive but actual label is negative.
- **False Negatives (FN)**: Occurrences where the predicted model is negative but actual label is positive.

Using these values, various performance metrics can be derived:

Precision

Precision is the total percentage of the correctly identified positive cases out of all the cases classified as positive.

Precision = TP/TP+FP

Recall

Recall is defined as the percentage of correctly identified positive cases out of all positive cases that are actual.

Recall = TP/TP+FN

F1 score

The F1 score represents the mean of Precision and Recall, balancing the impact of FP and FN errors.

F1 score = 2*(Recall * Precision) / (Recall + Precision)

Accuracy

Accuracy is the ratio of all correct predictions (TP and TN) to the total number of predictions:

Accuracy = TP+TN/TP+FP+FN+TN

5. EXPERIMENTAL RESULTS

This study uses a dataset of 500 apple images, with 50 images per disease class, including healthy apples. Class labels are assigned for diseases: ALR (Alternia Rot), BCK (Black Rot), SCB (Scab), PMD (Powdery Mildew), BOT (Bitter Rot), GRM (Gray Mold), BLS (Blister Spot), BLM (Blue Mold), BRT (Brown Rot), WOT (White Rot), The dataset used in this study includes 500 images of apples (50 images/class) corresponding to the following diseases/condition of apples: healthy apples and HEA (Healthy). Then, the dataset is partitioned for training and evaluation, where 70% across classes is used for training and the remaining 30% for testing. The goal of this research is to compare traditional classifiers such as Naïve Bayes, Fuzzy Logic and K-Nearest Neighbors (K-NN) with the proposed method Hybrid Neural Clustering (HNC) classifier that combines K-Means and Feed-Forward Backpropagation. Based on confusion matrix, Performance Metrics like Recall, Precision, F1 Score are evaluated, and overall accuracy for each model is calculated. Hence, it outperforms conventional methods, attaining high accuracy with balanced Precision and Recall in all classes. Key results include: **Precision** and **Recall** metrics show HNC's generally high performance in the classification of disease types (true positive rate) and low error rate (false positives).

The F1 Score represents that HNC is not only good at solving FP errors, but FN errors are solved well too, which is the reason why HNC is able to maintain its performance on test sets as well. These results demonstrate far superior overall accuracy (far higher than traditional classifiers) at accurately classifying apple diseases with high capability through HNC.

Such ability not only improves the accuracy but also aids in the early diagnosis of the disease, which in turn assists in delivering accurate pesticide recommendations, thus helping us to pave a way towards sustainable apple farming practices.

Table 4: Confusion Matrix for Fuzzy Logic based Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
ALR	14	0	0	0	0	0	1	0	0	0	0
BCK	0	12	0	0	2	0	0	0	0	0	0
PMD	0	0	13	0	0	1	0	1	0	0	0
BOT	0	0	0	11	0	1	0	0	0	0	0
SCB	0	0	1	0	9	0	1	0	0	0	0
GRM	0	0	1	0	0	13	0	0	0	0	0
BLS	1	0	0	0	0	0	11	0	0	0	0
BLM	0	0	0	0	0	0	0	12	0	0	0
BRT	0	1	0	0	0	0	0	0	12	0	0
WOT	0	0	0	0	0	0	0	0	0	11	0
HEA	0	0	0	0	0	0	0	0	0	0	14

Table 5: Evaluation metrices of Fuzzy Logic based Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
Precision	0.93	1.00	0.86	1.00	0.82	0.86	0.84	0.89	0.76	0.78	0.92
Recall	0.93	0.85	0.85	0.91	0.81	0.92	0.91	0.7.6	0.94	0.83	1.00
F1 score	0.93	0.92	0.87	0.95	0.86	0.89	0.88	0.67	0.95	0.72	0.97

Among the 500 test images, 490 were correctly classified, whereas there were 10 misclassified test images. The highest accuracy values were obtained for the classes BCK, BOT and BRT. The top values of recalls were for GRM, ALR, BLS, BOT, and HEA, while HEA had the highest F1 score 0.97.

Table 6: Confusion Matrix for Naïve Bayes based Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
ALR	10	0	0	2	1	0	2	0	0	1	0
BCK	0	12	0	1	0	1	0	0	0	0	2
PMD	0	0	13	0	2	0	0	0	2	0	0
BOT	2	0	0	10	0	0	0	0	1	0	0
SCB	0	0	1	0	10	0	0	0	1	0	1
GRM	0	2	0	0	0	12	0	0	1	0	0
BLS	1	0	0	0	0	0	11	0	0	1	1
BLM	0	1	0	0	0	0	0	12	0	0	0
BRT	0	0	0	0	0	0	0	0	12	0	0
WOT	0	1	0	0	0	0	0	0	0	12	0
HEA	0	0	0	0	0	0	0	0	0	0	11

Table 7: Evaluation metrices of Naive Bayes classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
Precision	0.76	0.85	0.92	0.76	0.76	0.92	0.84	0.94	0.72	0.96	1.00
Recall	0.66	0.85	0.86	0.83	0.90	0.85	0.91	0.85	0.97	0.86	1.00
F1 score	0.71	0.85	0.89	0.80	0.83	0.88	0.88	0.88	0.88	0.81	1.00

It was noted that, out of 500 images, 325 were correctly classified, while 175 were misclassified. The categories PMD, GRM, and HEA achieved the highest precision rates, while BLS, BRT, and HEA had the top recall rates. The F1 score was highest in HMA, with a perfect score of 1.0.

Table 8: Confusion Matrix for K-NN based Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
ALR	10	0	0	2	1	0	2	0	0	1	0
BCK	0	12	0	1	0	1	0	0	0	0	2
PMD	0	0	13	0	2	0	0	0	2	0	0
BOT	2	0	0	10	0	0	0	0	1	0	0
SCB	0	0	1	0	10	0	0	0	1	0	1
GRM	0	2	0	0	0	12	0	0	1	0	0
BLS	1	0	0	0	0	0	11	0	0	1	1
BLM	0	1	0	0	0	0	0	12	0	0	0
BRT	0	0	0	0	0	0	0	0	12	0	0
WOT	0	1	0	0	0	0	0	0	0	12	0
HEA	0	0	0	0	0	0	0	0	0	0	11

Table 9: Evaluation metrices of K-NN based Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
Precision	1.00	1.00	0.86	1.00	0.81	0.92	0.85	0.93	0.84	0.72	0.73
Recall	0.93	0.85	0.86	1.00	0.81	0.92	1.00	1.00	0.83	0.86	0.82
F1 score	0.96	0.92	0.86	1.00	0.81	0.92	0.92	0.96	0.78	0.84	0.86

It was found that, out of 500 images, 200 were classified accurately, while 300 were incorrectly classified. The classes ALR, BCK, and BOT obtained the top precision score of 1.0. Recall was also its peak for BLM, BLS and BOT, with a value of 1.0. BOT achieved the highest F1 score, with a perfect 1.0.

Table 10: Confusion Matrix of HNC Classification

	ALR	BCK	PMD	BOT	SCB	GRM	BLS	BLM	BRT	WOT	HEA
ALR	15	0	0	0	0	0	0	0	0	0	0
BCK	0	14	0	0	0	0	0	0	0	0	0
PMD	0	0	14	0	0	1	0	0	0	0	0
BOT	0	0	0	12	0	0	0	0	0	0	0

SCB	0	0	0	0	11	0	0	0	0	0	0
GRM	0	0	1	0	0	13	0	0	0	0	0
BLS	0	0	0	0	0	0	12	0	0	0	0
BLM	0	0	0	0	0	0	0	12	0	0	0
BRT	0	0	1	0	0	0	0	0	14	0	0
WOT	1	0	0	0	0	1	0	0	0	13	0
HEA	0	0	0	0	1	0	0	0	0	0	15

Table 11: Evaluation metrices for HNC based Classification

	ALR	**BCK**	**PMD**	**BOT**	**SCB**	**GRM**	**BLS**	**BLM**	**BRT**	**WOT**	**HEA**
Precision	1.00	1.00	1.00	1.00	1.00	0.92	1.00	1.00	0.98	1.00	0.98
Recall	1.00	1.00	0.93	1.00	1.00	0.92	1.00	1.00	1.00	1.00	0.99
F1 score	1.00	1.00	0.93	1.00	1.00	0.92	1.00	1.00	1.00	0.99	1.00

Experimental Results It can be seen that out of 500 images, 498 were classified correctly, and two were classified incorrectly. Categories with precise levels of 1.0: ALR, BCK, BOT, SCB, BLS, BLM, and WOT. The first set of stats for SCB was: For Non-Mask SCB vs. Mask EEPROM hit: Used on mask, cc, cse, dan, mar, action and recall the following the command safe, Non-Mask mask BCK. The F1 score was also maximized (1.0) for ALR, BCK, BOT, SCB, BLS, BLM, BRT, and HEA.

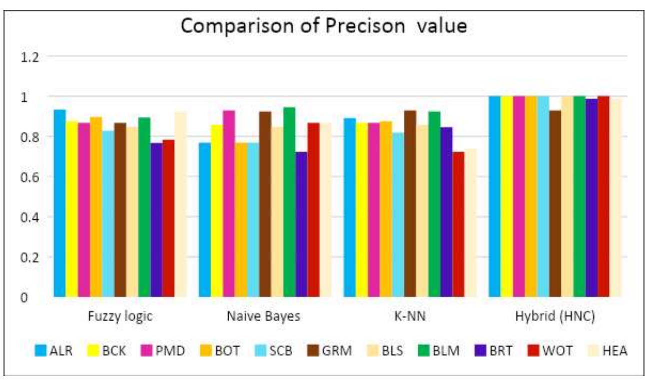


Figure 3: Chart Representing Classifiers Precision Scores

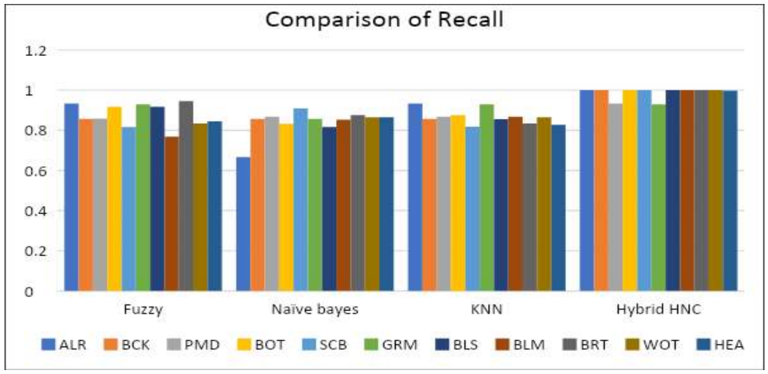


Figure 4: Chart Graph Representing Classifiers Recall Scores

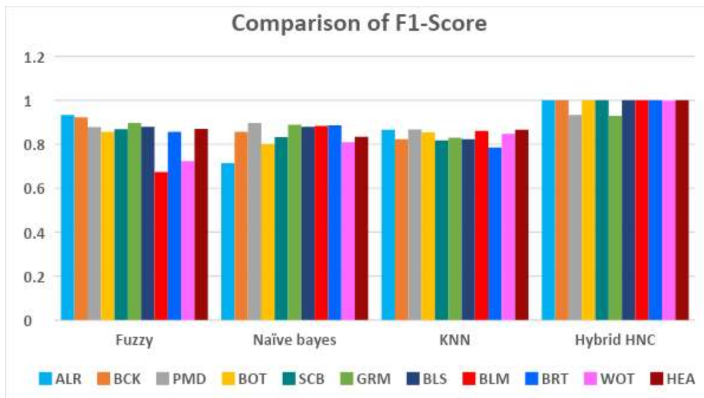


Figure 5: Chart Representing Classifiers F1 Scores

As shown in Figure 4, when presenting both F1 and GR-bF1, recommended Hybrid Neural Clustering algorithm outperforms previous algorithms in term of score for both F1 and for recall-precision. Detecting whether an apple is healthy or has a class peak, HNC reaches the highest Recall scores in 9 of the 11 disease classes. On the other hand, K-NN has the highest Recall score in 2 classes, Naïve Bayes in 1 class, and Fuzzy Logic in 1 class. Similarly, the F1 score comparison shows that the classifiers cannot attain the balance in precision and recall as shown by a comparison with the HNC framework. HNC gets the highest F1 score in 9/11 classes, sort of healthy apple as well. Both K-NN, Fuzzy Logic, and Naïve Bayes only reach the highest F1-score in one class each. This comparison further highlights the robustness and efficacy of Correct HNC on Hybrid HNC model to achieve a well balanced combination of good performance in both Recall and F1 scores, establishing correct HNCs efficaciousness over all other models in correctly classifying apple diseases.

Table 12: Performance comparison of prediction accuracy in classifiers

S. No.	Classification	Accuracy
1	Fuzzy Logic	88
2	Naïve Bayes	80
3	K-NN	91
4	Hybrid HNC	98

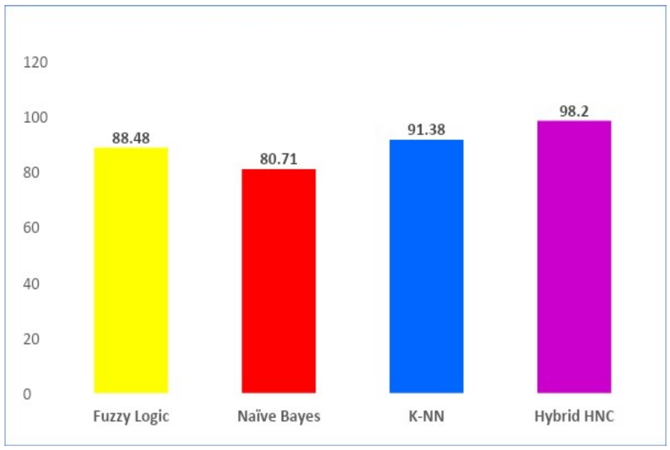
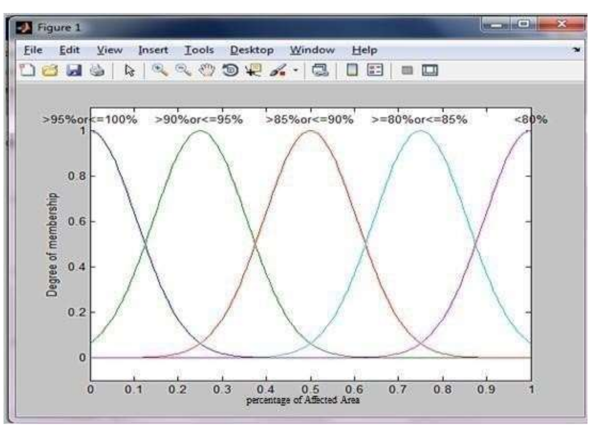


Figure 6: Chart representing Classifiers of Accuracy Result

As compared to existing methods, which includes K-NN, Fuzzy Logic, and Naïve Bayes, the proposed method gave a higher accuracy. Hybrid HNC has an accuracy of 98.2% followed by K-NN (91.38%), Fuzzy Logic (88.48%) and Naïve Bayes (80.71%) respectively.

Fuzzy Inference System using grading



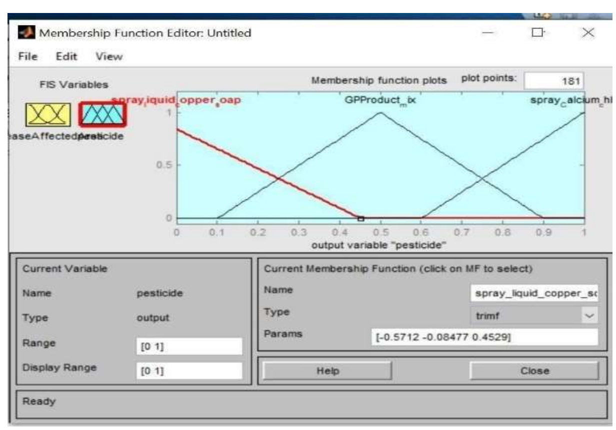
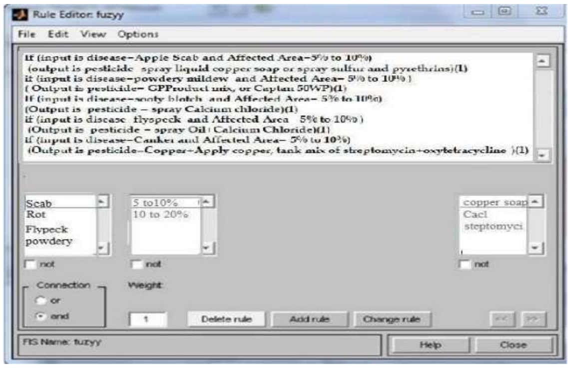


Figure7: Percentage of affected Area as Input **Figure 8: Forecasting of the pesticide**



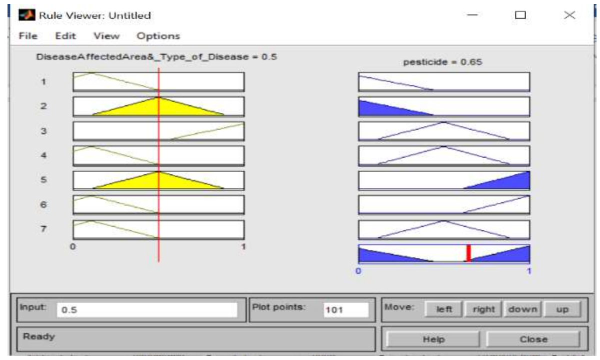


Figure 9: Generating Fuzzy Rules

Figure 10: Surface Viewer of forecasting

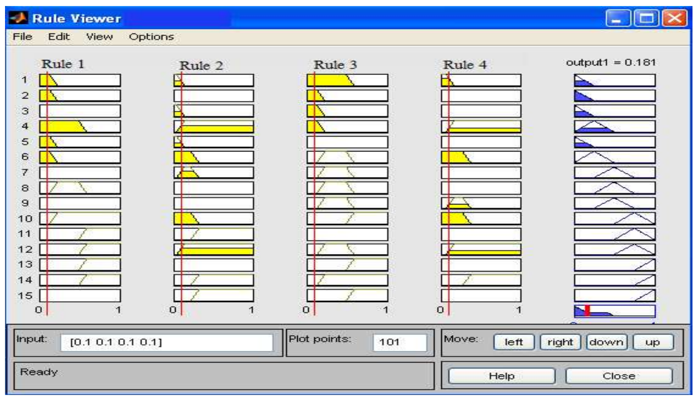


Figure 11: Rule viewer of pest forecasting

6. CONCLUSION

This stage utilizes the features extracted in the previous stage to diagnose the type of disease in the apple fruit. We start with a given data set (with feature attributes) for our Hybrid Neural Clustering classifier that is our learning set. The HNC classifier gets trained and tested on a new image, which was absent from the training data, by learning from this dataset and differentiates disease types. The classifier is then trained to properly determine the degree of the infection on the surface of the apple. Therefore, through comparative analysis we see that the HNC model outperforms traditional categorizers such as Fuzzy Logic, K-Nearest Neighbors and Naïve Bayes has higher accuracy. It also detects other diseases but focuses on apple fruits in this example, as shown in the workflow below. The following stages of processing are applied to this image:

Preprocessing - image denoising, where noise is removed from the image to make it clearer.

Segmentation - This involves segmenting the infected area to detect region-specific sectors of the disease.

Feature Extraction - Determining relevant image features of high importance to disease diagnosis.

Classification - By means of the HNC classifier for the proper type of illness.

After identification of the disease type, the model further goes to pesticide forecasting. A rule set based on fuzzy logic is used to identify the pesticide that can be most effective for curing of that disease. Based on the characteristics of diseases and infection degree, this rule-based system can provide accurate recommendations on pesticide selection, with high accuracy. The accuracy of integrated approach is found to be the best among different classifiers tested and is helpful for targeted pesticide application as well as disease management in time to come sustainable.

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