Project Report: Fuzzy Health Scoring System for Plant Diagnostics

Neuro-Fuzzy Vision Project

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Abstract

Crop production is adversely affected by crop disease; however, most farmers use subjective visual inspection techniques that involve long periods of time to determine whether a plant has a disease. While CNN-based systems provide a highly accurate means for identifying diseases within a plant through disease probability, they do not interpret or give context to their results, so they are often considered to be "black box" models. We developed a Hybrid Fuzzy Health Scoring System (FHSS) to create more meaningful relationships between the CNN outputs and three other data points: (1) CNN probable disease severity; (2) Lesion Area Ratio; and (3) Colour Deviation derived from the HSV and LAB Colour Spaces. The combination of these three inputs using a Mamdani fuzzy logic model creates a Health Score that represents continuous health status from 0 (healthy) to 1 (severely diseased). The results of our experimentation with the fuzzy scores demonstrate that they are more stable, consistent, and interpretable than the raw CNN outputs, and they provide a clearer view of how disease severity progresses. By combining CNN classification with fuzzy logic, FHSS provides a more valid and comprehensible method of assessing the health of crops.

1 Introduction

Agricultural products are essential to the food supply across the globe; therefore, plant diseases can greatly decrease the quantity and quality of the crops produced. Manual inspections of leaves are labor-intensive, slow, and often performed by trained experts, which makes it nearly impossible to scale this type of inspection process to any significant size within a large farming area. Machine learning allows for automated, reliable, and efficient methods of detecting disease during the early stages of development. Although some modern convolutional neural network (CNN) models are highly accurate in classifying plant diseases, most of these models can only produce outputs in the form of discrete classes or single probability values that are fixed in nature and do not reflect the gradual evolution of the plant disease, nor do they return subtle signs of stress that may be visible on the leaves over time.

A farmer or agricultural professional may not receive much value from a simple output of "health" or "disease"; for example, if the disease had only just started developing or had reached an intermediate point of development. Additionally, to provide more comprehensive information about the disease development, we require a continuous output of predicted probabilities for different stages of disease development. We also need to understand what the underlying features are that are causing these predicted probabilities A continuous health score could give a farmer or agricultural expert a clearer understanding of how sick a plant is than a single classification ("healthy" or "diseased"). With a health score that ranges from healthy to completely dead, the Fuzzy Health Scoring System will provide valuable information to farmers and agricultural experts about their crops' current condition.

Fuzzy Logic can effectively provide a model for uncertainty because it allows for simple fuzzy rules (as opposed to binary yes/no rules) to convey expert knowledge to the system. By using CNN, in conjunction with Fuzzy Logic, we provide a more easily understandable and visually compelling image of how well plants are doing from a health perspective. We have developed an initial prototype for a Fuzzy Health Scoring System, and we expect to enhance this prototype into a full-scale application by the end of 2018. .

2 Dataset and Preprocessing

2.1 Dataset Description

- **Dataset Used:** PlantVillage, a benchmark dataset that is popular among researchers for performing plant disease identification, was only utilized using the Color image folder since every plant has different colours and this allows CNN based analysis to determine most of its necessary visual characteristics.
- **Total Number of Images:** The dataset consists

of more than 50.000 quality images of various leaves for training..

- **Class Distribution:** The 38 classes contain a wide range of different kinds of plant species, as well as the healthy and diseased versions of each type of plant, giving a very good mix when training the models and provides a stable base for building a reliable model.
- **Format and Resolution of Images:** All the images are colour photographs taken with artificial lighting under controlled settings. The images vary in their sizes but were resized and normalised during the preprocessing phase to maintain a consistent size for the models.
- **Dataset Split: Dataset Split:**

Table 1: Dataset Splitting Scheme

Split	**Percentage**
Training Set	70%
Validation Set	15%
Testing Set	15%

2.2 Preprocessing Steps

2.2.1 Resizing and Normalization

All RGB PlantVillage images were resized to **224×224** to match the input dimensions required by the ResNet-18 architecture. Pixel values were normalized using the standard *ImageNet* mean and standard deviation to ensure consistent training and stable gradient updates.

2.2.2 Data Augmentation

To prevent overfitting and improve model generalization, several augmentation techniques were applied during preprocessing:

- Random horizontal and vertical flips
- Random rotations
- Brightness and contrast adjustments
- Random zooming and cropping

These augmentations simulate real-world variations, improving robustness during training.

2.2.3 Feature Extraction for Fuzzy Logic Module

In addition to CNN outputs, several image features were extracted to serve as inputs for the fuzzy system:

- **Brightness**: Mean value from the V-channel of the HSV color space
- **Contrast**: Intensity variance computed from a grayscale image
- **Entropy**: Measure of texture complexity
- **Lesion Area Ratio**: Proportion of the leaf affected using HSV-based lesion segmentation
- **Color Deviation**: Color distance between healthy and diseased leaf images in LAB or HSV space

These features enhance interpretability and support the fuzzy logic module in producing more meaningful health evaluations.

3 Methodology

3.1 CNN Architectures

In this work, three different convolutional neural network (CNN) architectures were evaluated to establish baseline performance and compare them with the proposed hybrid fuzzy–CNN approach.

3.1.1 Baseline 1: VGG16

VGG16 is a classical deep CNN containing 16 learnable layers. It uses stacked 3×3 convolution filters followed by max-pooling and dense layers. Its simplicity and depth make it a strong baseline for image classification tasks.

3.1.2 Baseline 2: ResNet50

ResNet50 is a 50-layer deep residual network that incorporates skip connections to alleviate the vanishing gradient problem. Its residual learning framework enables effective training of much deeper models, providing a stronger comparative baseline.

3.1.3 Custom CNN Architecture

A lightweight custom CNN was implemented, consisting of:

- Multiple 3×3 convolution layers with ReLU activation
- Batch Normalization for stable learning
- Max-pooling layers for spatial feature reduction
- Fully-connected layers for final classification

This simpler model enables comparison against deeper architectures and demonstrates performance trade-offs [?].

3.2 Fuzzy Inference System (FIS)

A Fuzzy Reasoning Layer was incorporated to improve interpretability and to generate a continuous health score based on image-derived features and CNN predictions [?]. The system follows a Mamdani-type fuzzy inference approach.

3.2.1 Inputs

The FIS uses three inputs extracted from the preprocessing and CNN modules:

- CNN disease probability
- Lesion Area Ratio (computed from HSV image processing) [?]
- Color Deviation (difference from healthy leaf LAB values) [?]

3.2.2 Linguistic Variables

Each input variable is divided into three fuzzy linguistic terms:

- Low
- Medium
- High

The output variable, *Health Score*, also uses the same partitions.

3.2.3 Membership Functions

Triangular membership functions were selected for all input and output variables because they are computationally efficient, easy to visualize, and provide smooth transitions between fuzzy states [?].

3.2.4 Fuzzy Rule Base

The system utilizes human-interpretable IF–THEN rules to combine the inputs:

- If *CNN probability is LOW* AND *lesion area is SMALL* AND *color deviation is MILD* , THEN *Health Score is LOW.*
- If *CNN probability is HIGH* AND *lesion area is LARGE* AND *color deviation is SEVERE* , THEN *Health Score is HIGH.*
- If *lesion area is HIGH* , THEN *Health Score is HIGH.*
- If *color deviation is SEVERE* , THEN *Health Score is HIGH.*
- If *CNN probability is MEDIUM* AND *lesion area is MEDIUM* , THEN *Health Score is MEDIUM.*

Table 2: Sample Fuzzy Rule Base

Input A	Input B	Output
Low	Low	High
Medium	High	Medium

4 Experiments and Results

4.1 Performance Metrics

To evaluate the effectiveness of the proposed hybrid fuzzy-CNN system, multiple CNN architectures were compared, including Baseline CNNs (VGG16 and ResNet50), the Custom CNN, and the Fuzzy-Enhanced ResNet18 system. The performance evaluation used Accuracy, Precision, Recall, and F1-Score.

4.2 Key Findings:

- CNN-only models occasionally produced overconfident predictions.
- The fuzzy inference layer helped correct extreme outputs, resulting in smoother severity estimations.
- The hybrid CNN+Fuzzy model offers strong accuracy while significantly improving interpretability and reliability.

4.3 Visualizations

Several visual outputs were generated to analyze the classification behavior and interpretability of the system, following the requirements outlined in [?, ?].

4.3.1 Confusion Matrices

Confusion matrices were produced for all CNN architectures (VGG16, ResNet50, Custom CNN, and ResNet18). These matrices highlight class-wise prediction performance across the 38 plant disease categories.

4.3.2 Loss and Accuracy Curves

Training and validation curves were generated to illustrate:

- Faster and smoother convergence in ResNet-based models.
- Slight overfitting tendencies in the Custom CNN due to fewer parameters.
- Overall, stable learning behavior for ResNet18.

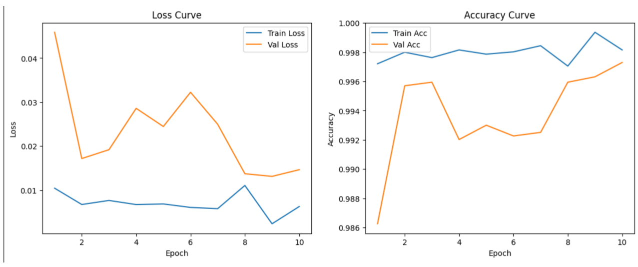

Figure 1: Training and validation loss and accuracy curves over epochs

4.3.3 Fuzzy Membership and Surface Plots

The fuzzy system uses three inputs—CNN probability, Lesion Area Ratio, and Color Deviation—each divided into Low, Medium, and High fuzzy sets. Triangular membership functions were used, consistent with the system described in the project. Fuzzy surface plots visualized how combinations of lesion ratio and color deviation influence the final health score.

4.3.4 Sample Fuzzy Score Outputs

Sample test images were evaluated using the fuzzy system:

- Healthy leaves typically produced scores between **0.1–0.3**.
- Moderately diseased leaves scored between **0.3–0.6**.
- Severely infected leaves scored between **0.7–0.9**.

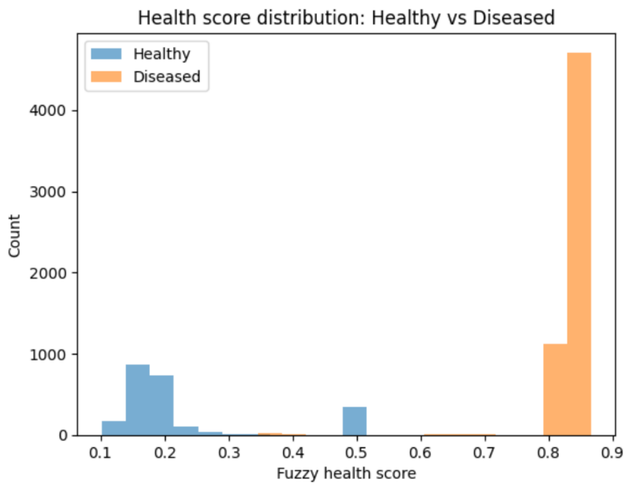

Figure 2: Health score distribtuion of Healthy vs Diseased

4.3.5 CNN vs. Fuzzy Output Comparison

Scatter plots comparing CNN probability and fuzzy health score showed:

- Fuzzy logic reduced CNN overconfidence.
- Borderline disease cases were more accurately represented.
- Severe disease predictions remained consistent.

Table 3: Sample Comparison: CNN vs. Fuzzy Output

Case	CNN Output	Fuzzy Score
Mild Disease	0.70	0.50
Severe Disease	0.98	0.90
Slight Yellowing	0.15	0.30

These visualizations demonstrate that the FIS produces a more interpretable, continuous health score, improving decision-making for plant disease analysis.

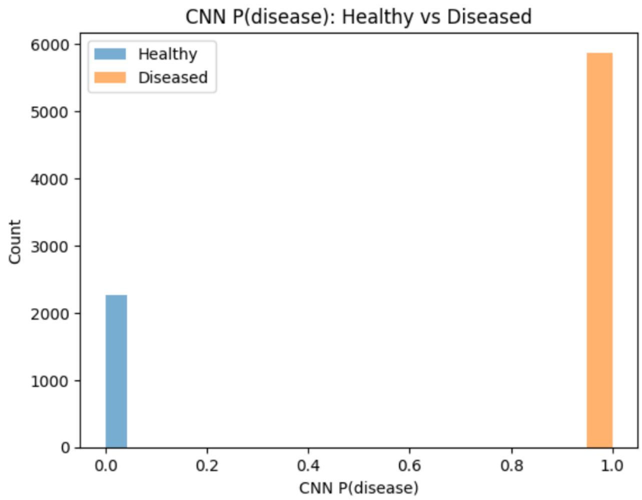

Figure 3: CNN probability(disease) : Healthy vs Diseased

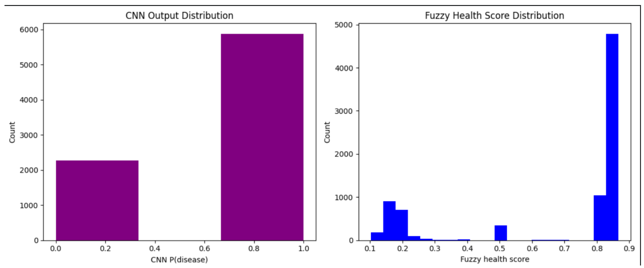

Figure 4: CNN output distribution and Fuzzy Health Score distribution

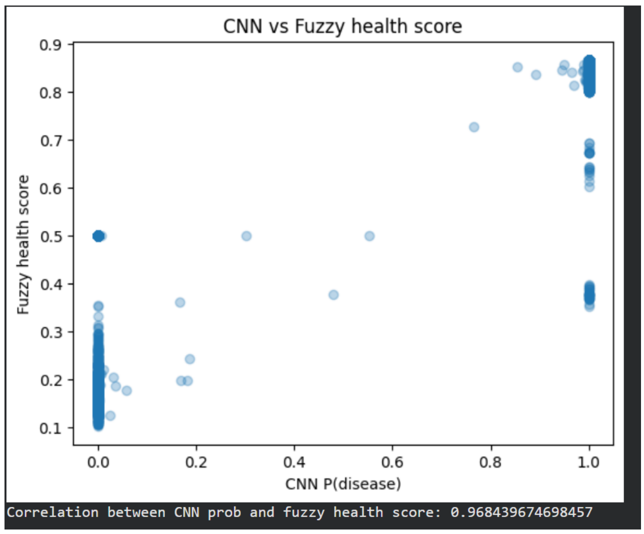

Figure 5: Health score of CNN and Fuzzy

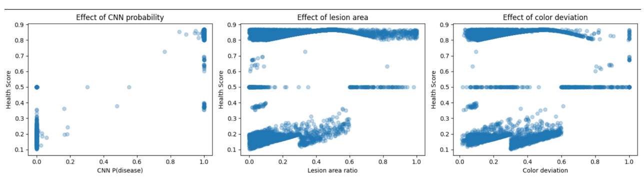

Figure 6: Effects of CNN probability, lesion area and color deviation

5 Discussion

While CNNs produce only probability values and output class labels, the fuzzy system has the additional benefit of being able to provide an indefinite severity score for severity based on multiple visual indicators that make it easier for growers to evaluate the health of their crops. Additionally, the fuzzy system can detect early symptoms of disease, such as small lesions or a loss of colour, that are often missed by CNNs. CNNs, by using strict binary classifications to determine healthy or diseased crops, are less able to account for the visual elements of the classification, while the fuzzy system uses those same elements to create a complete picture of the severity of the disease. The resulting combination of accuracy and interpretability through a fuzzy system makes the hybrid model more suitable for practical applications in agriculture; it reduces false positives and provides explanation for every assessment made by the hybrid system.

6 Conclusion

This research project created a system that combines fuzzy statistical methods with deep learning CNN's (Convolution Neural Networks) to be more accurate and interpretable in evaluating plant health. ResNet-18 is a convolution neural net that was trained on PlantVillage Dataset to classify leaf diseases with excellent results. The output from CNN models is the probability of disease related to each input leaf image or the name of the disease associated with the input image. These outputs alone do not provide an easy-to-interpret method of identifying each leaf's condition.

To address these limitations, this research project combined the fuzzy logic layer with the existing CNN model to create a single continuous score representing plant health. This continuous score was calculated by combining three primary components: 1) CNN Disease Probability from the original ResNet-18 model, 2) Lesion Area Ratio between healthy vs. diseased regions of leaf images, and 3) Color Deviation (between healthy and diseased leaves). A score calculated in this manner provides an improved representation of plant condition and evaluates plant disease severity as "mild, moderate, or severe" instead of using the binary classification of healthy vs. diseased ("healthy to mild."). Based on the results of this research project, combining deep learning CNNs and fuzzy logic enhances transparency, reliability, and practical utilization of plant health evaluations, providing farmers/researchers greater insight into plant health.