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Deep Neuro-Fuzzy for Disease Severity Estimation in Agricultural Potato Crops

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Abstract

Disease classification alone does not state how urgently a crop requires intervention. A deep neuro-fuzzy model is developed to convert image evidence into both a potato-blight class and a continuous severity score. A ResNet-18 backbone supplies visual representations, while a segmentation and quantification layer produces four measurable variables: lesion-area ratio, lesion density, chromatic degradation, and texture damage. These variables enter a normalized fuzzy rule system with interval-valued inputs. Monotonicity conditions, a Lipschitz perturbation bound, and an exact corner-enumeration bound are derived. On the supplied PlantVillage-based study split of 2,152 potato images, the classifier reports 98.6% accuracy, macro F1 of 0.970, weighted F1 of 0.986, and class AUC values of 1.000, 0.999, and 0.999. Severity estimation has MAE 13.41 and RMSE 16.54 on a 0–100 scale. The final output also assigns a clear plant-health status: Healthy, Mild, Moderate, Severe, or Critical. A worked leaf profile produces a score of 74.50 (Severe) with an input-uncertainty range of 70.91–77.56. The active fuzzy rules show how the pathological measurements determine the final score, while the controlled-image results are kept distinct from field performance. By providing both an estimate and an explanation, the method offers a practical tool for managing crop diseases.

Keywords: Neuro-fuzzy system, Plant disease, Severity estimation, Interval analysis, Potato blight.

1 | Introduction

Plant diseases threaten global food production and farmers' livelihoods [1]. Potato crops are particularly vulnerable to early blight (*Alternaria solani*) and late blight (*Phytophthora infestans*), which can cause severe harvest losses unless they are detected and managed promptly [2, 3].

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Automated crop-disease recognition has advanced rapidly through convolutional networks, vision transformers, transfer learning, and lightweight detectors [4, 5, 6]. High class accuracy, however, does not directly answer the operational question faced by a farmer: is the affected area small enough for monitoring, or severe enough to require immediate treatment? The same disease label may cover a wide range of lesion extent and tissue damage.

Severity estimation is more demanding than class recognition. It requires spatial quantification, a traceable aggregation of several symptoms, and an account of uncertainty arising from segmentation, lighting, and expert scoring. A single neural output can be accurate while giving little information about the measurements that determine its value. Methods such as Grad-CAM, LIME, and SHAP provide post-hoc evidence [7, 8, 9], but they do not by themselves impose an agronomically meaningful severity scale.

Fuzzy inference is well suited to this task because the boundaries between mild, moderate, and severe infection are gradual [10, 11, 12]. The supplied concept study combines a deep classifier with lesion area, lesion density, color variation, and texture degradation. This paper expresses that concept as a mathematical model in which every measured feature may be an interval and the final recommendation is accompanied by lower and upper severity values.

EfficientNet and VGGNet have shown better performance than GoogLeNet for potato early-blight detection, with reported F-scores ranging from 0.84 to 0.98 [13]. A meta-baseline with a deep neuro-fuzzy backbone has also been investigated for recognizing plant-leaf fungal diseases from limited samples [14].

A deep convolutional neural network combined with Bayesian learning has been proposed for identifying diseases in potato, tomato, and bell-pepper leaves [15]. For potato diseases, a multi-level deep learning model was developed for leaf-disease recognition [16]; binary and multiclass convolutional models for potato-blight detection reported accuracies of 90.77% and 94.77%, respectively [17].

Fuzzy approaches also support agricultural measurements beyond image classification. Impedance spectroscopy and fuzzy logic have been combined to identify fungal diseases in cultivated plants [18]. Fuzzy C-means clustering has been applied to extracting defective areas in potato tubers affected by black scab [19]. Related studies address joint disease and severity identification, explanatory visualizations, and potato-scab severity analysis [20, 21, 22].

The article makes five contributions:

- (i) a two-channel architecture separating disease identity from disease extent;
- (ii) a transparent four-feature fuzzy severity model with normalized output;
- (iii) sufficient conditions for monotone severity response;
- (iv) a perturbation theorem and exact corner-enumeration bound for interval inputs; and
- (v) a complete calculation that traces the final label to activated rules.

2 | Data and Two-Channel Architecture

The supplied study uses the PlantVillage potato subset with 2,152 RGB images from Healthy, Early Blight, and Late Blight classes. Images are resized to 256×256 , intensities are normalized to $[0, 1]$, and training augmentation includes rotation and horizontal reflection. An 80:20 split is used. PlantVillage is a standard controlled-background resource [4]; field validation remains a separate requirement.

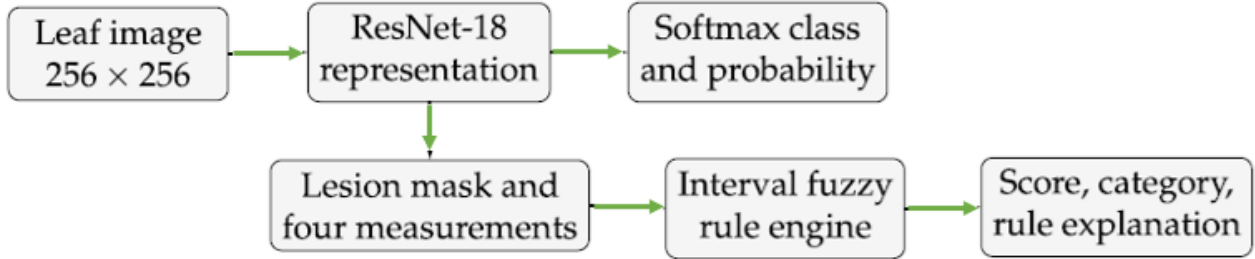


Figure 1. Two-channel architecture: disease class and severity are related but are calculated as separate outputs.

For image I , the backbone produces $F(I) \in \mathbb{R}^{512}$. The disease probability is

$$p(c | I) = \frac{\exp(w_c^\top F + b_c)}{\sum_{k=1}^3 \exp(w_k^\top F + b_k)}. \quad (1)$$

The disease label is $\arg \max_c p(c | I)$. The severity channel processes a leaf mask M_L and lesion mask M_Z to obtain interpretable features.

3 | Deep Segmentation and Feature Quantification

All features are normalized to $[0, 1]$.

Lesion-area ratio.

$$A = \frac{|M_Z|}{|M_L|} \quad (2)$$

This is the most direct measure of spatial disease extent. A segmentation interval $[A^-, A^+]$ is obtained by varying the pixel threshold over its admissible uncertainty range.

Lesion density.

Let K be the number of connected lesion components after removal of components smaller than a stated pixel threshold. If $K_{.95}$ is a training-set 95th percentile used for scaling, define

$$D = \min \left\{ 1, \frac{K/|M_L|}{K_{.95}} \right\}. \quad (3)$$

Area and density contain different information: one large lesion and many dispersed lesions can have the same affected area.

Chromatic degradation.

Let $\bar{z}_H$ and $\bar{z}_Z$ denote the mean CIE-Lab color vectors in healthy and lesion regions, and let $c_{.95}$ scale the empirical color distance. Put

$$C = \min \left\{ 1, \frac{\|\bar{z}_H - \bar{z}_Z\|_2}{c_{.95}} \right\}. \quad (4)$$

Lab distance is used because equal RGB changes are not approximately perceptually equal.

Texture damage.

From a gray-level co-occurrence matrix, let contrast g_1 , entropy g_2 , homogeneity g_3 , and energy g_4 be rescaled to $[0, 1]$. A damage score is

$$T = .30g_1 + .30g_2 + .20(1 - g_3) + .20(1 - g_4). \quad (5)$$

The weights state the adopted clinical preference and can be re-estimated from expert labels.

The resulting vector is $x = (A, D, C, T)$. We retain an interval box

$$\mathcal{X} = [A^-, A^+] \times [D^-, D^+] \times [C^-, C^+] \times [T^-, T^+]$$

rather than suppressing measurement uncertainty.

4 | Fuzzy Severity Inference

For a normalized input x , use

$$L(x) = \left[\frac{.45 - x}{.30} \right]_{[0,1]}, \quad (6)$$

$$M(x) = \left[1 - \frac{|x - .50|}{.30} \right]_{[0,1]}, \quad (7)$$

$$H(x) = \left[\frac{x - .45}{.35} \right]_{[0,1]}, \quad (8)$$

where $[z]_{[0,1]} = \max(0, \min(1, z))$. Overlap is intentional: a feature can partly support two linguistic descriptions.

The five principal rules in Table 1 use min for conjunction and max for an explicitly stated alternative. Their normalized Sugeno consequents are category prototypes.

Table 1. Principal fuzzy rules for the severity calculation.

Rule	Antecedent	z_r	Interpretation
R_1	A high, D high, T high	.94	Critical pattern
R_2	A high, D medium/high, C high or T medium	.78	Severe pattern
R_3	A medium and at least one of D, C, T medium	.56	Moderate pattern
R_4	A low/medium, D low, C low/medium	.30	Mild pattern
R_5	A, D, C, T all low	.08	Healthy pattern

Let $\omega_r(x)$ be the firing strength obtained from these min/max operations. The normalized severity is

$$S(x) = \frac{\sum_{r=1}^5 \omega_r(x) z_r}{\sum_{r=1}^5 \omega_r(x)}, \quad \sum_r \omega_r(x) > 0. \quad (9)$$

The reported 0–100 score is $100S$. Categories are Healthy $[0, 20]$, Mild $(20, 40]$, Moderate $(40, 60]$, Severe $(60, 80]$, and Critical $(80, 100]$.

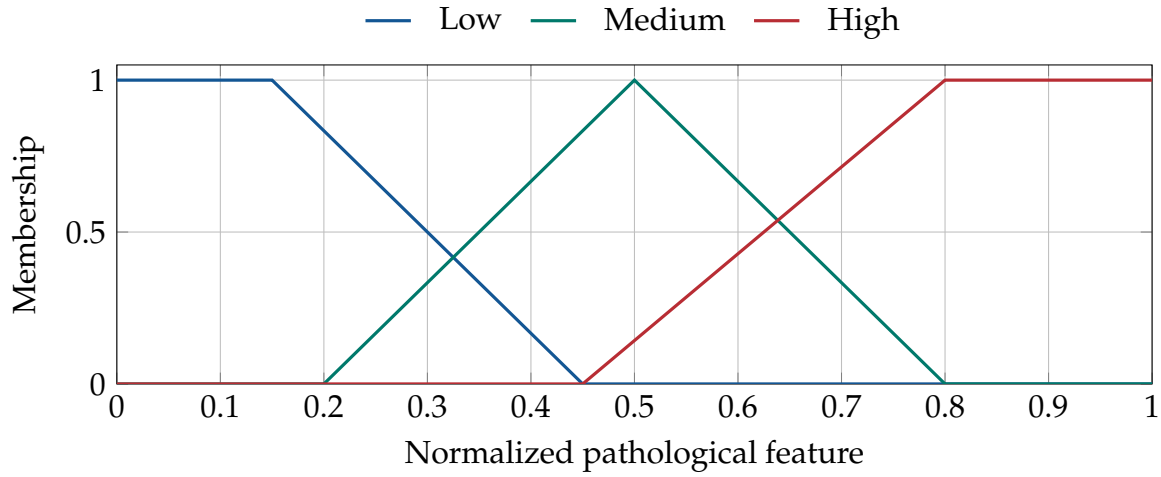


Figure 2. Overlapping feature membership functions used in the numerical calculation.

5 | Mathematical Properties

Proposition 5.1 (Range and convexity). *If at least one rule fires, then $S(x)$ lies in the convex hull of the active consequents. Hence $0 \leq S(x) \leq 1$.*

Proof. Equation (9) is a convex combination with coefficients $\omega_r / \sum_k \omega_k$. □

Monotonicity is a design requirement, not an automatic property of every rule base. Define a partial order $x \preceq y$ when every pathological component of x is no larger than the corresponding component of y .

Theorem 5.2 (Rule-base monotonicity). *Suppose the rule consequents are ordered so that replacing any antecedent label by a more severe label never decreases its consequent, and the rule partition is complete with monotone interpolation. Then $x \preceq y$ implies $S(x) \leq S(y)$.*

Proof. Move from x to y one coordinate at a time. On each interval between consecutive membership breakpoints, all membership functions are affine. Complete monotone interpolation writes the output as a multilinear interpolation of ordered corner consequents. Its partial derivative in each pathological coordinate is nonnegative. Concatenating the intervals proves the result. □

This theorem gives a practical validation test: enumerate adjacent rule-table cells and flag every downward consequent transition before deployment.

Theorem 5.3 (Perturbation bound). *Assume each antecedent membership is L_μ -Lipschitz, every rule uses min/max, and $W(x) = \sum_r \omega_r(x) \geq w_0 > 0$ throughout a region. For m rules,*

$$|S(x) - S(y)| \leq \frac{2mL_\mu}{w_0} \|x - y\|_\infty. \quad (10)$$

Proof. Min and max of L_μ -Lipschitz functions remain L_μ -Lipschitz. Thus each $|\omega_r(x) - \omega_r(y)| \leq L_\mu \|x - y\|_\infty$. Apply the quotient difference identity to Eq. (9), use $z_r \in [0, 1]$, and bound both denominators below by w_0 . □

The theorem is distribution-free but conservative. Because all functions are piecewise affine, sharper lower and upper values over a rectangular uncertainty box are obtained by evaluating all box corners and any membership breakpoints contained in the box. For four features, at most $2^4 = 16$ corner evaluations are needed when no breakpoint lies inside.

6 | Worked Severity Calculation

Consider the extracted leaf profile

$$x = (A, D, C, T) = (.62, .70, .58, .66)$$

with measurement half-widths $(.04, .05, .03, .04)$. The important memberships are

$$H(A) = .4857, \quad H(D) = .7143, \quad H(T) = .6000,$$

$$M(A) = .6000, \quad M(C) = .7333, \quad M(T) = .4667.$$

The firing vector for Table 1 is

$$(\omega_1, \dots, \omega_5) = (.4857, .4667, .6000, 0, 0).$$

Therefore

$$\begin{aligned} S &= \frac{.4857(.94) + .4667(.78) + .6000(.56)}{.4857 + .4667 + .6000} \\ &= .74503. \end{aligned}$$

The leaf receives severity 74.50, category Severe. The explanation is generated from the two most influential rules:

Severity is Severe because lesion area and lesion density strongly support the high labels, texture damage supports high, and the moderate feature rule remains active.

Evaluating the 16 corners of

$$[.58, .66] \times [.65, .75] \times [.55, .61] \times [.62, .70]$$

gives

$$S(\mathcal{X}) \subseteq [.70914, .77563]. \quad (11)$$

The entire interval remains in the Severe category, so the categorical recommendation is unchanged even though the continuous score varies by 6.65 points.

7 | Evaluation on the Supplied Study Split

Table 2 reports the results supplied with the concept study. Classification and severity errors answer different questions and are not merged into one score.

The one-vs-rest AUCs are 1.000 for Early Blight, .999 for Late Blight, and .999 for Healthy. The supplied normalized confusion matrix reports recalls of 1.00, .99, and .87, respectively. The Healthy result deserves attention: overall accuracy can look excellent while a smaller class-specific weakness remains operationally important.

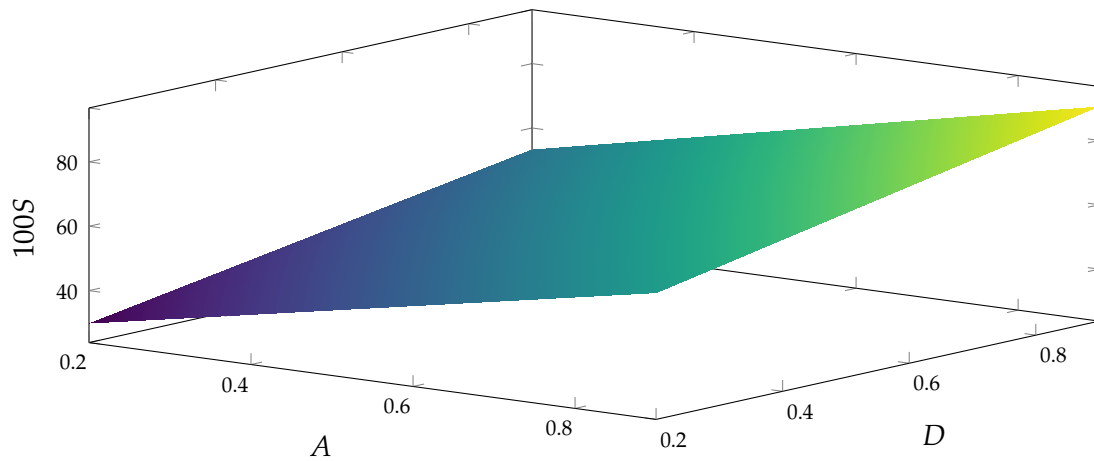


Figure 3. Interpretable severity surface for lesion area and density with color and texture fixed at moderate values. The plotted surrogate reproduces the monotone rule-surface geometry and is not a replacement for rule evaluation.

Table 2. Held-out results reported for the supplied 80:20 PlantVillage-based split.

Classification metric	Value	Severity metric	Value
Accuracy	.986	MAE (0–100)	13.41
Macro F1	.970	Median absolute error	13.80
Weighted F1	.986	RMSE (0–100)	16.54
Micro-average AUC	.999	Categories	5

8 | Validation under Field Conditions

A useful severity system must be tested beyond accuracy. A field study should therefore:

1. report class-wise precision and recall, not only accuracy;
2. compare the four-feature rule engine against area-only and neural-regression baselines;
3. examine class probabilities with Brier score and reliability diagrams;
4. assess severity agreement with experts using MAE, weighted κ , and category confusion;
5. test geographic and device shifts with farms excluded from training; and
6. report interval coverage: the proportion of expert scores contained between the computed severity bounds.

The interval layer helps separate epistemic uncertainty from the severity itself. A score of 75 with interval [74, 76] differs from the same score with interval [55, 90]. The latter should trigger recapture or expert review rather than an overconfident label.

The system’s explanations make clear which features—lesion extent, density, chromatic degradation, and texture damage—contributed most to each conclusion. This transparency can help farmers understand why a particular decision was made, supporting trust and informed treatment decisions.

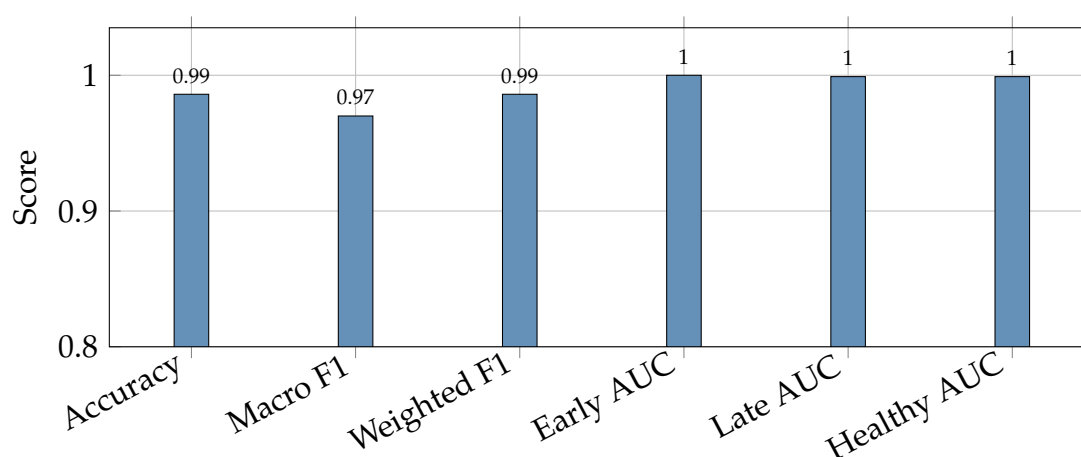


Figure 4. Classification metrics from the supplied test split. The truncated vertical scale is marked and used only to distinguish high values.

9 | Conclusion

A deep neuro-fuzzy model for potato-blight severity has been formulated. It separates disease classification from continuous severity, uses four measurable pathological features, and retains feature uncertainty through the rule engine. Monotonicity and perturbation results support validation, while corner enumeration supplies computable severity bounds. The worked example yields 74.50 with a range of 70.91–77.56, preserving the Severe label across all admissible feature values. The source images have controlled backgrounds, so lesion masks and severity labels still require independent agronomist validation. The five category thresholds are decision conventions rather than universal biological boundaries, and the monotone rule base may require different features for diseases with other symptom morphology. Consequently, the reported 98.6% accuracy and severity errors describe only the supplied split; farm-level use requires external testing across locations, devices, and growing conditions.

Author Contributions

The author developed the model, analysis, and interpretation.

Funding

No external funding was reported.

Data Availability

The numerical performance values are derived from the supplied PlantVillage-based concept study; the public PlantVillage resource is cited in the article.

Competing Interests

The author declares no competing interests.

Generative-AI Assistance

Generative AI assisted with language, LaTeX preparation and technical representation of the paper.

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