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Predicting and Identifying Potato Blight Disease through Deep Learning with Fuzzy Approaches

Debraj Roy[1], Biswapati Jana[2] and Nguyen Kim Sao[3]

Abstract. *Two diseases, early and late blight, put great danger on the potato crop and cause farmers to lose money. Farmers could immediately react to crops that these diseases have impacted be- cause of their early and automatic identification. The deep learning methodology is extensively discussed in the literature and provides various possibilities for diagnosing crop blight diseases. This article uses deep learning to identify the disease in crops. Here, machine learning-based image processing methods have been taken into consideration. We have employed VGG16, ResNet50, and ResNet152V2 models and the fuzzy technique based on deep learning to identify the blight disease stage in potato leaf images. To make pixel-by-pixel forecasts in pictures of specific leaves, the initial instance of the state-of-the-art DeepLabV3+ linguistic segmentation framework, constructed from ResNet152V2, is trained. Then, the features that were extracted, such as ROI and POI. Second, an uncertain rule-based method is created for every characteristic to estimate the severity of disease harm. In the fuzzy logic system, suitable membership functions for the inputs and outputs are also considered for fuzzification and defuzzification processes. Last, potato leaves are labeled Healthy, Mild, Medium, and Severe. However, utilizing ResNet152V2, we were able to reach 98% accuracy, the best result among these techniques.*

Keywords: *Deep learning; Fuzzy Inference System; Blight infection; Potato (Solanum tuberosum L.), Deep learning, Convolutional Neural Networks (CNNs).*

1. Introduction

Both Solanum tuberosum L., the potato plant, and Solanum lycopersicum, L. 1753, the tomato plant are severely at risk from early and late blight, which leaves farmers with no choice but to abandon their crops. Researchers have suggested a ResNet-9 model that farmers can use to identify the blight disease status in potato and tomato leaf images [1]. Researchers have suggested an advanced deep learning classification architecture for hyperspectral pictures, which combines deep cooperative attention networks with 2D and 3D convolutional neural networks for image classification (PLB-2D-3D-A) [2]. Rich spectral space features are first extracted using 2D-CNN and 3D-CNN. Then the attention mechanisms Attention Block and SE-ResNet are employed to highlight the prominent attributes within the characteristics of maps and improve the model's generalizability. To evaluate the piece of work for identifying potato infection, Support vector machines (SVM), random forests (RF), artificial neural networks (ANN), and k-nearest neighbour (k-NN) classifiers were the four model types used.

Gao et al. [3] highlights the viability of deploying deep learning techniques to treat disease lesions segmentation and assessment of severity using diatal radiology, which might help to breed agricultural resistance for crops situations and moreover enhance precise farming techniques. Globally damaging, potato late blight is brought on by Phytophthora

[1] ***Department of Computer Science, Tamralipta Mahavidyalaya, Tamluk, Purba Medinipur,721636, West Bengal, India, debraj545roy@gmail.com***
[2] ***Department of Computer Science, Vidyasagar University, Paschim Medinipur, West Bengal, India, biswapatijana@gmail.com***
[3] ***Department of Computer Science, University of Transport and Communication, Đ. Cầu Giấy, Láng Thượng, Đống Đa, Hà Nội, Vietnamsaonkoliver@gmail.com***

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infectants, which is an oomycete suggested by Fu et al. [4. In a pot experiment, the potato late blight health's prevalence and diagnostic index were reduced by applying FXP04 to wedges of potatoes before seeding and, upon putting down roots, to the soil. For the quick and easy finding of oospores from a species of Phytophthora infestans, the root cause of late potato mildew in the ground, a polymerase chain reaction has been established. In comparison to traditional PCR tests employed elsewhere and for P.infestans screening to verify positive inoculum levels in potato seedlings, the real-time PCR technique described by Hussain, Singh, and Anwar [5] which is very delicate and precise and has a number of upsides. Researchers Bienkowski et al. [6] investigated the use of fractional least squares and models of spectrum calibration using back propagation networks of neurons to analyze light spanning the both graphic and close to the in f (400–1000 nm) sections of the range of possibilities to identify and distinction between many materially significant potato illnesses.

1.1. Objective of the Paper

- Combination of deep learning techniques, specifically the utilization of VGG16, ResNet50, and ResNet152V2 models, with a fuzzy logic-based approach for the identification and severity assessment of blight disease in potato crops.
- The current study introduces the integration of fuzzy logic with deep learning models. Fuzzy logic allows for the incorporation of uncertainty and imprecision in the assessment of disease severity, providing a more comprehensive and nuanced analysis.
- Furthermore, the study employs the enhanced ResNet152V2-based DeepLabV3+ semantic segmentation design for pixels-by-pixels forecasts in individual potato leaf pictures. This advanced model enhances the accuracy and dexterity of disease identification by segmenting and analyzing the leaf images at a finer level.
- The use of deep learning and fuzzy technique in conjunction with image processing techniques and semantic segmentation represents a novel approach in the field of agricultural disease diagnosis. By combining these methodologies, the study offers a promising solution for early and automatic identi- fication of blight diseases in potato crops

Figure 2: Images of blight-affected potato leaves captured in their natural environment.

2. Data Collection

In order to train the system, sample images of disease [12] leaves are gathered. We have taken leaf images from the potato leaf disease data set from Kaggle. The 1500 samples in our hold dataset, including samples with varying degrees of disease, are split between 20% healthy samples and 80% diseased samples. Also, we have taken some potato plant images. Healthy leaf images and more images of diseased [13] leaves are used to train and test the system. Stored the images in a standard format. In Fig.3, the normal and damaged regions of an individual leaf are marked, which also generates the required mask maps for the leaf's location on a grey backdrop. The regions of the infected area ROIs

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(regions of interest) and the POIs (percentages of infections) from pictures are used simultaneously as the benchmarks gained to assess the accuracy.

To determine future fuzzy sets, it is essential to take into account the statistical consistency of ROI and POI. For the estimation of blight disease, fuzzy logic methods are used to compute the ROI and POI as inputs to the system of fuzzy logic inference.

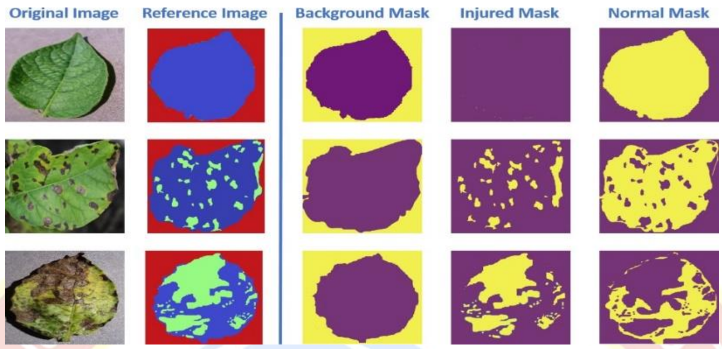

Figure 3: Examples of annotated samples of a potato leaf's background, injured portion, and normal portion, respectively.

2.1 The Blight disease severity analysis technique

The overall procedure used by the suggested technique uses statistical calculation and image analysis to classify the severity of the potato blight diseases shown in Fig4. DeepLabV3+ with ResNet152V2 backbone is introduced in the first step to identify pathological damages and create optimal segmentation masks for the common area and injured area at the same time. In the second step, the features, which include ROI and POI, have been eliminated and taken as supplies for a system of fuzzy inference. It is possible to determine the risk knowledge regarding the different levels of potato blight disease severity through logical reasoning. In order to prevent excessive economic loss, agricultural producers can now immediately implement accurate treatment measures without the need for expert advice, for example, precise methods for reactive pesticide dosing and tailored treatment based on the severity of potato leaf damage.

2.2 Classification using fuzzy logic inference system

When dealing with ambiguous or inaccurate information, fuzzy logic inference systems are frequently employed for classification tasks. By giving membership degrees to each class, these systems can handle data that is difficult to categorize into separate classes. For the purpose of predicting potato blight disease, we utilized ROI and POI as input parameters. These features were extracted by DeepLabV3+. To accomplish this, a fuzzy logic system for potato blight disease was developed. As illustrated in Fig.4, the evaluation is structured in many steps, Fuzzy logic input processing, creating membership functions, formulating fuzzy rules, and outputting defuzzification. The result will indicate the degree of severity of potato blight disease. It is important to note that the fuzzy reference system will only activate when the ROI (POI) is not equal to zero, if the ROI (POI) is equal to zero, the image will automatically be categorized as healthy, and no involvement in the following fuzzy rule-based categorization is necessary.

2.3 Fuzzyfication

The subsets of ROI and POI are categorized as Very Small, Small, Medium, High, and Very High, while the subsets of Very Low, Low, Medium, High, and Very High are used for Fuzzy classification, for fuzzification, depicted in Fig.5.

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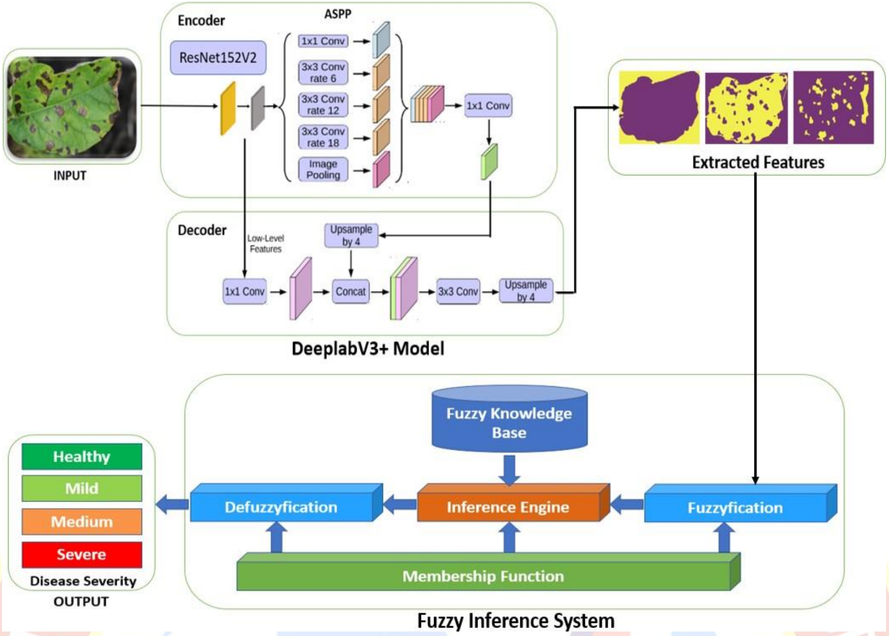
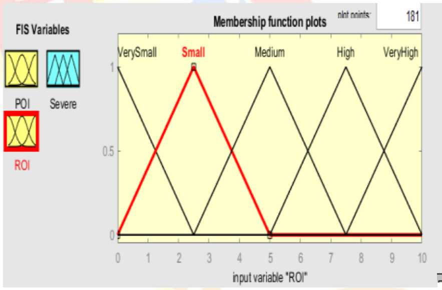


Figure 4: A model has been introduced to categorize the severity grades of potato blight disease...

The severity subset is created as Mild, Medium, and Severe, depicted in Fig.6. For convenience, all of the linked membership functions are built up as triangle functions, A smooth and uninterrupted line that determines the level of each quantitative factor being related to is a linguistic variable.



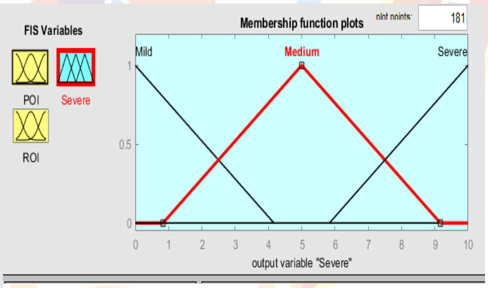
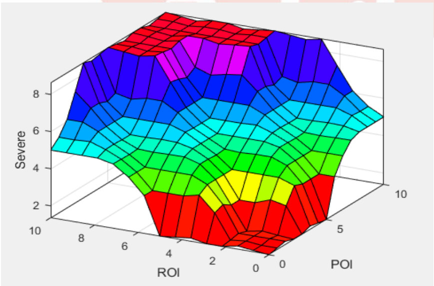


Figure 5: Input mfs for ROI Figure 6: Output mf for Severe.

2.4 Setup and execution of the rule database.



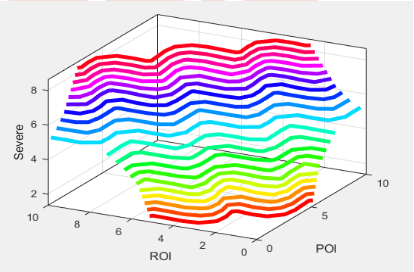


Figure 7: Surface view of Early blight of Potato Figure 8: Contour view of Early blight of Potato

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The fuzzy inference system's rule base or knowledge base is created in the shape of certain 'IF-THEN' commands that establish the connections among the input elements (the IF portion) and outputs (the THEN portion). When the fuzzy reference system is run, all of the fuzzy decision rules are evaluated at the same time and with the same weight. When all decision rules are triggered, the outcomes of the 3-D surfaceevaluations and the outcomes of the fuzzy system for inference are shown in from Fig.7 to Fig.10. This fuzzy-based technique predicts disease severity easily and accurately by combining plant pathologist expertise and experience with statistical analysis.

2.5 Defuzzification

The defuzzifier produces the output as a crisp value. In the defuzzification stage, triangular membership functions are also examined for the output variable severity prediction for potato blight disease severity classes shown in Fig.4. In order to calculate the precise result of the fuzzy inference system, we perform some computations, the center of gravity approach is utilized, which takes the gravity center of the portion contained by the final output value represented by the abscissa and the membership function curve of the fuzzy inference system.

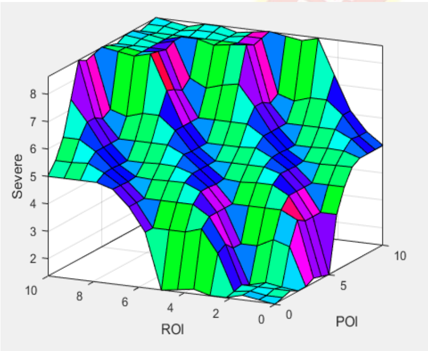

Figure 9: Surface view of potato blight disease

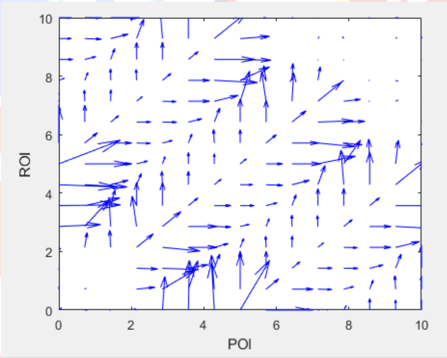

Figure 10: Line view of potato blight disease.

3. Result and analysis

On the hold-out test dataset, the suggested work achieves an overall accuracy of 98%. To be more specific, it achieves 94%, 98%, 98%, and 100% accuracy for Healthy, Mild, Medium, and Severe, accordingly. Samples of moderate risk are frequently erroneously as mild risk. Here are the projected ROI and POI values that are often reduced compared to the reference values, and the underestimating influence is be- ginning to appear as the wounded portion expands, which will be prevented in actual farming activities. With the use of DeepLabV3+ [14] and ResNet152V2, the ability to learn and comprehend a wider range of features from input data is possible. This results in the capability to perform efficiently in diverse image situations. DeepLabV3+ improves the outcome of segmentation, particularly along object borders, by including a module for decoding that is both simple and effective Shown in Fig-4 and Figure11 indicates the correlation between the reference values and the values that would be anticipated by our suggested method.

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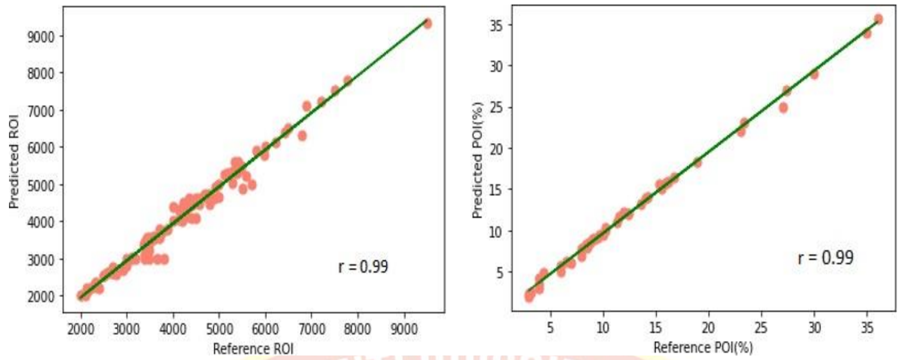

Figure 11: The scatter diagram depicts the connection between expected values obtained from DeepLabV3+ model the images' pixel-level predictions and reference values were manually annotated on the same leaves. The green line is the best-fitting linear regression line.

To determine the link between POI and ROI, we employed linear regression. Predictions for ROI are the closest to the reference values. This approach predicts the coefficient of correlation r is 0.99 and root mean square error (RMSE) is 0.018 and the Confusion matrix for the classification of grade of potato disease severity is shown in Fig-12. Furthermore, the suggested approach has a tendency to incorrectly categorize healthy samples as diseased, which is caused by the DeepLab3+ [15-18] structure. In most cases, Samples that have been classified incorrectly are just conflated by their nearby labels. For instance, samples with low levels of risk are often incorrectly identified as healthy, while those with moderate risk may be misinterpreted as well. The overall error, which is mostly due to segmentation error but is demonstrated to be within the permissible range, is strongly influenced by the misinterpretation between adjacent labels.

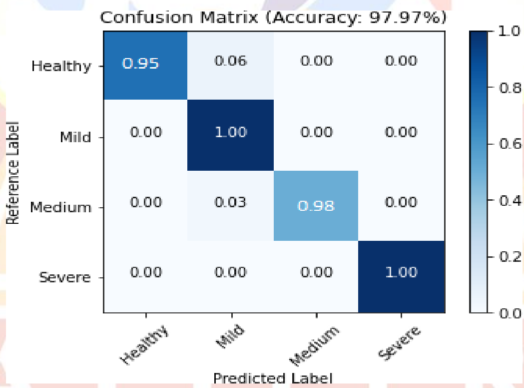

Figure 12: Confusion matrix for the classification of potato disease severity.

4. Discussion

Normally, the artificial categorization of image samples into various severity levels according to prior knowledge or somatosensory perception, CNN-based models were utilized to recognize and assess the severity of plant disease (Manavalan [7]). A multi-task system based on CNNs was developed by certain researchers to be effective and practical for monitoring the level of stress caused by biotic agents on coffee leaves (Esgario, Krohling, and Ventura [8]). The most accurate classification of biotic stress (95.24%) and severity rating (86.51%) were obtained from their ResNet50 architecture investigations. To solve the problem of precisely segmenting powdery mildew on leaves based on visible

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images, several researchers proposed a semantic segmentation approach based on the UNet architecture (Iqbal et al. [9]). Experiment results showed that, in comparison to other segmentation techniques currently in use, their proposed method significantly enhanced perfection with mAS 96.08% and mIOU achieved a score of 72.11% on 20 samples tested. The application of Mask-RCNN and ResNet101 as the core allows for the accurate diagnosis of symptom portion and the severity of disease in wheat spikes. (Su et al. [10]) evaluating the wheat FHB severity value ratio of the forecast over ground truth yielded a prediction accuracy of 77.19%.
With respect to the preceding methods, our suggested potato disease severity analysis method employs a Framework for fuzzy inference after separating the injuries on plant leaves utilizing the DeepLabV3+ model with the ResNet152V2 backbone. For farmers, measuring segmentation outcomes is either abstract or difficult. Reasoning using fuzzy logic offers suitable thinking and also assists in dealing with uncertainty (Pathan et al. [11]). Our proposed potato disease prediction approach is guided by botanists, while it may not al- ways require specialized knowledge. Furthermore, Segmenting pixels with semantic content using image assessment is prone to errors due to technical bottlenecks or the influence of natural noise. Utilizing a fuzzy set can minimize the effect of mistakes, leading to more resilient classification results and, therefore, increasing their reliability.

5. Conclusions

The study aimed to develop a fuzzy-based approach for the identification and severity assessment of blight disease in potato crops. Three deep learning models, namely VGG16, ResNet50, and ResNet152V2, were employed along with a fuzzy technique to analyze potato leaf images. The ResNet152V2-based DeepLabV3+ model was trained for pixel-level forecasts in individual leaf images using semantic seg- mentation. The features extracted, including ROI (Region of Interest) and POI (Point of Interest), were utilized to predict the severity of disease harm. A structure with fuzzy rules was created for every feature, considering appropriate membership functions for fuzzification and defuzzification processes. The severity levels of the disease were separated as Healthy, Mild, Medium, and Severe. Among the techniques utilized, the ResNet152V2 model exhibited the best performance, achieving an accuracy of 98%. This indicates that the suggested method utilizing deep learning coupled with fuzzy logic can effectively identify and classify the stages of potato crop blight disease. The findings of this study have significant implications for potato farmers, as early and automatic identification of blight diseases can help them take timely actions to mitigate crop damage and prevent financial losses. The utilization of deep learning methods in agriculture, specifically for disease diagnosis, showcases the potential of these techniques in improving crop management and ensuring food security. Further research can focus on expanding the dataset, exploring other deep learning architectures, will introduce type-2 fuzzy, and investigating the application of this approach to different crop diseases. These advancements can contribute to the development of robust and accurate systems for disease detection and monitoring in agricultural settings.

Declaration of competing interest

In this research work, the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work.

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