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Enhancing Precision Agriculture with a Novel AI Framework for Early Crop Health Detection

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Abstract: The Precision agriculture is a groundbreaking approach that leverages advanced technologies to optimize agricultural productivity and sustainability. By integrating data-driven techniques, farmers can monitor and manage their crops more effectively, ensuring better yields and resource efficiency. One of the key challenges in precision agriculture is the early identification of factors that may negatively impact crop health. Microorganisms and environmental stressors can silently affect plants, often remaining undetected until they cause significant damage. This paper presents a novel methodology employing a Logistic Activation function with a Modified Fuzzy-based Convolutional Neural Network (LA-MFCNN) algorithm, designed to enhance the early detection of potential threats to crop health, specifically targeting sugarcane cultivation. Our approach utilizes fuzzy logic principles combined with deep learning techniques to analyze complex data patterns, identifying subtle indicators that may signal emerging issues in crop health. The LA-MFCNN algorithm is specifically engineered to recognize and interpret early warning signs, enabling timely interventions and mitigating potential risks. By leveraging artificial intelligence, this method facilitates more accurate and efficient monitoring, thereby supporting decision-making processes in precision agriculture. The performance of the proposed LA-MFCNN algorithm is rigorously compared against traditional Machine Learning (ML) and Deep Learning (DL) algorithms. Key performance metrics, including accuracy, precision, recall, and F1 score, demonstrate that our approach significantly outperforms existing methods. The results underscore the algorithm's potential to revolutionize precision agriculture by improving crop management strategies and enhancing agricultural productivity. Furthermore, the adaptability of the proposed method allows for its application to various crops, making it a versatile tool for modern agriculture. This research highlights the critical role of advanced AI techniques in transforming traditional farming practices, paving the way for more sustainable and efficient agricultural systems.

Keywords: artificial intelligence; convolutional neural networks; deep learning; fuzzy logic; precision agriculture

1 INTRODUCTION

India will make up about 20% of the world's sugarcane production by 2030 [1]. In the Indian state of Tamil Nadu, sugarcane is cultivated on more than 4 million acres, and the state's annual sugar output averages 67 tons per acre. About 12% of all the sugarcane that is grown in India is grown in the state of Tamil Nadu. Tiruchirappalli, Salem, and Coimbatore all work together to make up 81% of Tamil Nadu's total output. Madurai, Dharmapuri, Thanjavur, and Ramanathapuram comprise the rest of the 19%. Quoc et al. [2] devised a way to determine if sugarcane has white leaf diseases. When polymerase chain reaction (PCR) was used, the results were better than those from methods like restriction fragment length polymorphism (RFLP), which had been used before.

A novel approach was proposed by Rao G. P. et al. [3] in order to gain a deeper comprehension of the photo plasmas that are associated with sugarcane grassy shoot disease and sugarcane white leaf disease. Most of these diseases are common in Asia. In this body of work, the relationships between polymerase sequence analysis, ribosomal DNA (rDNA) analysis, and Restriction Fragment Length Polymorphism (RFLP) approaches were investigated for their potential relevance. Germany was where the tests for this study were done. The authors of [4] discuss the Support Vector Machine (SVM) algorithm as a possible way to find sugarcane borer disease and figure out what it is. For identifying diseases, segmentation and classification algorithms are used. The regularisation and kernel function parameters are written as C and are used. At the Sugarcane Research Institute in Shahjahanpur, which is located in Uttar Pradesh, India, Kour et al. conducted their research on sugarcane grassy shoot disease and the photo plasma that was connected with it. In the training set, disease detection was shown to have an accuracy of 96%, whereas in the test set, it only had an accuracy of 95%. [4]. It has been discovered that sugarcane COS7250 is afflicted with grassy shoot disease. In order to find out if the disease was present, direct amplification of the phytoplasma ribosomal gene was done, and then a nested PCR was done after that. When compared to traditional methods, this approach showed better results. X.'s research shows that Huang et al. [5] gives a complete analysis of the system for finding and treating sugarcane diseases. This research has revealed various diseases that can affect sugarcane, some of which are red rot, smut, wilt, rust, leaf scald, and yellow leaf. Sugarcane is susceptible to a broad variety of illnesses, and this research has uncovered several of them. Nested polymerase chain reaction (PCR) arrays, conventional PCR, and reverse transcription PCR are all utilized in the diagnostic process of many diseases [6].

SVI is used in certain places and situations. Statistical modeling was used to find diseases like orange rust in sugarcane in the region of Mackay, in the Australian state of Queensland. Function coefficients were used in the modeling process, and correlation rankings were determined. The proposed method was 96% accurate when it came to classifying. Agriculture is an essential part of the economy, and it employs many people who grow different crops based on the weather conditions where they live [7]. The agriculture industry is a big part of the economy's growth. Still, farmers have to deal with several problems, the most important of which is that plant diseases are prevalent. One new area of study in agriculture is using leaf images to identify and classify plant diseases. This topic pertains to a novel area of investigation within the realm of agriculture. The amount of work needed to ensure safe agricultural products is expected to decrease due to the project. This will happen because farmers use image processing to find and diagnose plant diseases. Chernov et al. use a new framework to look for diseases that affect paddy leaves and put them into groups [8]. With this method, both the Jaya algorithm and a deep neural network must be optimized. In an agricultural setting, the rice crop's leaves are photographed to be used in later steps of the image acquisition process. It is very obvious that brown spot, sheath rot, and blast, in addition to bacterial blight, are all present. In order to get rid of the background in RGB photographs, a technique is utilized to convert them into their HSV equivalents. This is done by taking the RGB values and inverting them. This action aims to keep the original color scheme as close as possible [9].

2 RELATED WORKS

Bacterial blight, brown spot, sheath rot, and blast occur. After converting RGB images to HSV, background elements can be removed. This preserves the color scheme. Saturation and color temperature are used to generate binary images [10]. Low-resolution images are analyzed to identify pathology and normal tissue. Clustering separates background elements from normal and diseased backgrounds, simplifying analysis. Post-processing feedback loops strengthen the method [11]. The agricultural sector is vital to the economic development of many nations, contributing significantly to their income. The agricultural sector now drives economic growth where farmers carefully choose edible plants that suit their climate and farming needs. Various diseases are diagnosed using medical imaging. Image capture, pre-processing, segmentation, feature extraction, and classification are just a few of the many processes that are included in multi-step approaches. Other steps include the processing of raw data [12-14]. Treatments only work on the plant's exterior, where the disease's symptoms are visible.

The foliage of a plant is the best indicator of its disease status, say experts [15]. Rice plants can get sheath rot, leaf blast, leaf smut, brown spot, and bacterial blight. Brown spots are another common problem. Brown leaf spots plague rice plants. Haridasan et al. agree that a professional physical examination is needed to confirm a manual plant disease diagnosis [16]. Large farms require significant time and financial investment. Misdiagnosis increases with excessive information. The decline in rice production is due to a lack of knowledge and understanding about rice plant leaf disease management. The lack of information reduced rice production. A reliable and efficient rice leaf disease detection system is needed to resolve this issue. This study aims to develop a new photographic analysis method for rice plant disease detection. The current strategy prioritizes image composition. This study found that brown spots, leaf blasts, bacterial blight, and sheath rot kill rice plants [17] insects, fungi, and nematodes damage sunflower crops, reducing productivity. Disease detection is feasible. This may not detect epidemics in large agricultural operations. Immune system testing can help identify diseases based on symptoms. Image segmentation divides it into similar regions that do not overlap [18].

Image quality affects an object's appearance. Image quality is improved by noise reduction and contrast enhancement algorithms. This condition ensures no homogeneity between adjacent regions. Recent image segmentation studies have shown promise using evolutionary algorithms. Implementing an automated plant disease diagnosis and prevention system could help farmers. A system to diagnose plant diseases is needed due to its difficulty. This is due to a labor shortage in the industry. The prevention of ten diseases could boost food production without specialized expertise. Automation is an efficient and cost-effective way to streamline processes, reduce costs, and reduce manual labor, helping to achieve this goal. The authors' main goal is to present a novel method for identifying and diagnosing many plant diseases [19].

Jha et al. used fuzzy set theory and neutrosophic logic to develop a segmentation method called a segmentation strategy [20]. The ROI calculation method was made just for this task. Three separate membership functions were used to reach the needed segmentation level. Plant leaf diseases can be found by looking at feature subsets within segmented regions, which leads to conclusions based on the collected data. Different classifiers were used in the presentation, but the random forest technique worked best in the end [21]. In their dataset, they looked at 400 images of leaves. Two hundred showed signs of leaf disease, and the other 200 showed signs of health.

Fifty percent of the pictures in the set were of leaves with signs of disease. Malik et al. used image processing techniques to come up with a way to figure out what kind of disease was hurting paddy leaves [22]. This plan of action was made possible by the efforts of the people who were involved. To determine the disease outbreak, it was essential to determine how much of the affected area had been affected. Diseases like bacterial blight, brown spots, and rice blasts significantly reduce the amount of rice that can be grown in paddy fields. This is why pesticides are used. When deciding whether or not to use pesticides, the disease's severity was considered. Pathogens can spread to rice plants in many different ways. However, Ting Li et al. recently devised a new way to find and classify these infectious agents. Image processing techniques that used a proportion of the RGB value of the part of the body that was sick were used to find and identify diseases [23]. These methods can be used to find diseases and determine what they are. The researchers put the illness into different groups using a simple classification method called the Naive Bayes classifier. Even though the researchers only used one distinguishing feature, they could correctly classify and group the three most common rice plant diseases. The method used after that showed a significant speed boost and a big improvement in how well it worked. Using various image processing tools, the authors worked together to devise a method for automating the diagnosis of paddy leaf diseases [24]. Different things were used during the feature extraction phase, such as hybridized gray-scale co-occurrence matrices, discrete wavelet transforms, and selective iterative feature transformations. The process involved taking plant features and using different classifiers to tell the difference between sick and healthy plants.

A CNN was used to analyze images to identify grass and broadleaf weeds in soybean crops. A comprehensive photo collection includes over 15000 soil weeds, soybeans, broadleaf plants, and grasses. People can find photos in this collection. Photos formed a new database with Convolutional neural networks, a famous Deep Learning architecture, assisted with identification. This was chosen because image recognition was so important. Traditional leaf disease diagnosis relies on the observer's leaf observation skills. In this case, professional help is costly and time-consuming and expensive.

The research gap lies in the need for an efficient, automated plant disease detection system that can accurately identify multiple diseases, such as bacterial blight and brown spot, using advanced image processing and machine learning techniques. Current methods face challenges with misdiagnosis, data overload, and the need for large-scale applicability in agricultural settings.

3 PROPOSED WORK

In general, the farmer acknowledges symptoms of disease in crops by using naked eye observations, involving continuous evaluation; however, this method is costlier in large agricultural land and might be less precise at times. Farmers in other countries, like India, might be required to show samples to specialists, which adds time and costs. The parts that follow in this paper cover the essential steps of a plant disease identification system and a machine survey.

3.1 Convolutional Neural Network

Deep Learning is critical in the development of artificial intelligence for humans and computerized systems. DL is made up of a large number of networks that communicate and employs a computer's processor or video embedded processor to operate in a neural network, each neuron, that is referred to as only one node. The images were utilized to train Artificial Neural Network (ANN) [25] and Neuro-fuzzy models [26]. This paper presents a Logistic activation function with modified fuzzy based convolutional neural networks. Image-based computer vision challenges have high memory and processing needs. Fig. 1 depicts the elements of a LA-MFCNN model: an input image, convolutional layers, pooling layers, fully connected layers, and an output.

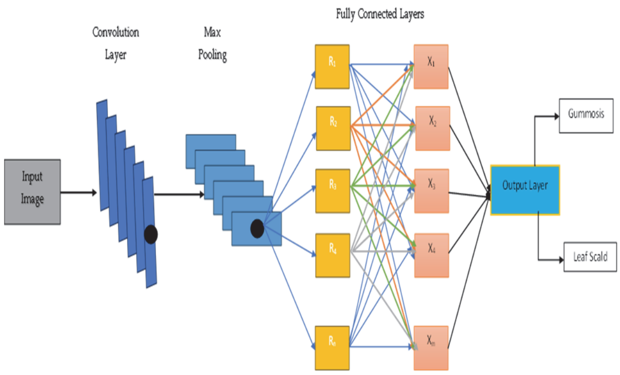

Figure 1 Proposed Neural Network architecture

Fig.2. illustrates many phases in sugarcane disease prediction utilizing a design of MFCNN. The construction is explained in the suggested work.

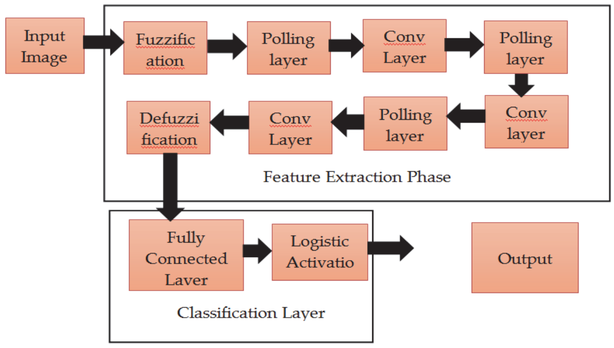

Figure 2 Disease Prediction using LA-MFCNN architecture

Convolution layers save the result of the preceding layers; it includes biases and weights to be learned. kernels were developed for representing the data. The optimization function's goal is to avoid errors. This layer contains a series of mathematical methods for extracting the image's feature map. The Conv layer output can be calculated using formula.

$$Conv(n,k)=\left(\left[\frac{n_w-f_w}{s}+1\right],\left[\frac{n_h-f_f}{s}+1\right],f_c\right) \tag{1}$$

The first convolutional layer's input width (n_w) and height (n_h) are 128 and 128 correspondingly. Furthermore, the f_w, f_h, and f_c indicate the width, height, and channels of the convolutional layer's kernel filter. This convolutional layer has a stride (S) value of one.

Activation Layer: This layer contains a non-linear Logistic Activation (LA), utilized in each convolution layer continuously.

Pooling Layer: After applying filters, data is transferred from the LA layer. LA uses the max (a, 0) function to set all negative convolution matrix values to zero while maintaining positive numbers. The processed information is fed into the pooling layer, which is the next layer. The pooling layer compresses inputs and improves processing.

The LA-MFCNN model's pooling layer the hyper-parameter includes stride, filter size, max pooling, and average pooling. A MFCNN model could have 'n' layers of convolution and pooling.

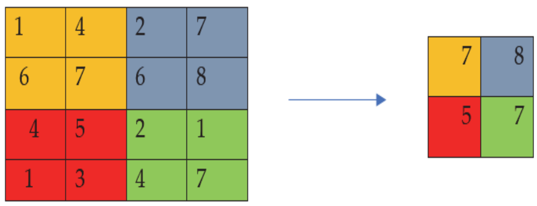

Figure 3 2 × 2 filters of max pooling applied with stride 2

The max-pooling layer output was calculated using.

$$Conv(n,k)=\left(\left[\frac{n_w-f_w}{s}+1\right],\left[\frac{n_h-f_f}{s}+1\right],n_c\right) \tag{2}$$

n_c represents channel of filter.

Fully Connected Layers: In the output layer, a fully connected layer conducts the process of classifying the image into multiple classes. To accomplish image categorization [27], the MFCNN model's completely linked layers are referred to as dense layers. The dropout layer is utilized for preventing overfitting in a neural network.

Pre-processed images: [28] have been minimized in dimensions and improved. For additional processing, coloured and scaled photo of 96 × 96 resolution is employed in this research. The RGB image was converted into a grayscale image using the normalization technique.

$$GS(p,q)=\frac{R(p,q)+G(p,q)+B(p,q)}{a} \tag{3}$$

where p and q are the rows and columns values respectively; $GS(p, q)$ is the image in grayscale. $G(p, q)$ is the green colour pixel value. $R(p, q)$ is the red colour pixel value. $B(p, q)$ is the blue colour pixel value. Median filtering techniques were utilised to remove salt and pepper noise from the input image while also improving it.

Feature Extraction: After an image has been preprocessed, the procedure of feature extraction is applied to it in order to extract the information that is most relevant. Extraction of color characteristics, shape features, and texture features are the three procedures that are utilized the most frequently in the process of gleaning information from photographs. The colour extraction on the basis of a threshold value was applied in this study. The accuracy of the system is determined by the characteristics chosen; thus, picking the threshold value is critical. The value of the selection thresholds is based on the training picture data. Tab. 1 shows the threshold values for gummosis and Leaf scald disease [29]. Tab. 2 shows the neuro fuzzy output of gummosis and Leaf scald disease.

Logistic Activation Function: The rules corresponding to the fuzzy based system [30] are indicating its prevalence with the help of its pixel value. When it is less than 15% then it is assumed that no disease is identified. If it is in between 15% to 60% then it is indicating that fertilizer is to be provided and if the pixel value is more than 55% then the plant should be removed from the field.

The logistic activation function may be utilized to include fuzzy logic into modified fuzzy-based CNNs [31]. It is mathematically expressed as

$$\sigma(x)=1/\left(1+\exp(-x)\right) \tag{4}$$

To do this, support must be added for fuzzy inputs and fuzzy outputs to the sigmoid function. The introduction of ambiguity by fuzzy logic depends heavily on the fuzzy member functions. Consider the fuzzy sigmoid function for a single value for input x given as:

$$(x)=1/\left(1+\exp\left(-\mu(-x)\right)\right) \tag{5}$$

where (x) is the input x's fuzzy membership value. The value of (x) indicates how likely it is that the input belongs to a specific fuzzy set. Domain expertise or data-driven methods, such as fuzzy logic techniques, may be employed to determine the membership function (x).

The fuzzy output of each neuron in a CNN can similarly be affected by the fuzzy membership functions for Logistic activation function with modified fuzzy based convolutional neural networks. For a given input x, a neuron's fuzzy output can be expressed as (y), where y is the output value.

The fuzzy output can be calculated as follows for a Logistic activation function with modified fuzzy based convolutional neural networks:

$$Fuzzy\ Output=1/\left(1+\exp\left(-\mu(-x)\right)\right) \tag{6}$$

where (y) is the fuzzy membership value of the neuron's output y. Again, $\mu(y)$ should be computed using appropriate fuzzy membership function.

Consider a fuzzy convolutional layer in the context of a Logistic activation function with modified fuzzy based convolutional neural networks to demonstrate this.

$$Fuzzy\ Output=1/\left(1+\exp\left(-\mu\left(conv_{output}\right)\right)\right)$$

where $conv_{output}$ is the non-fuzzy output of the convolution operation, and $\mu(conv_{output})$ is the fuzzy membership value corresponding to the $conv_{output}$.

Algorithm for Logistic activation function with modified fuzzy based convolutional neural networks

```
    Define: fuz_conv(input_data, fuz_filters,
fuz_membership_functions):
    Define:  fuz_pool(input_data):
    Define: fuz_fully_connected(input_data, weights,
biases):
    Define:  fuz_cnn(input_data, num_filters_1,
num_filters_2, num_neurons_fc1, num_classes,
filter_size):
        fuz_filters_1 = randomly_initialize(num_filters_1,
filter_size, filter_size)
        fuz_membership_functions_1 =
define_membership_functions()
        fuz_output_1 = fuz_conv(input_data,
fuz_filters_1, fuz_membership_functions_1)
        fuz_pool_output_1 = fuz_pool(fuz_output_1)
        fuz_filters_2 = randomly_initialize(num_filters_2,
filter_size, filter_size)
        fuz_membership_functions_2 =
define_membership_functions()
        fuz_output_2 = fuz_conv(fuz_pool_output_1,
fuz_filters_2, fuz_membership_functions_2)
        fuz_pool_output_2 = fuz_pool(fuz_output_2)
    flat_output = fuz_pool_output_2.flatten()
        fuz_weights_1 =
randomly_initialize(num_neurons_fc1,
flat_output.shape[0])
        fuz_biases_1 =
randomly_initialize(num_neurons_fc1)
        fuz_output_fc1 =
fuz_fully_connected(flat_output, fuz_weights_1,
fuz_biases_1)
        fuz_weights_2 =
randomly_initialize(num_classes, num_neurons_fc1)
    fuz_biases_2 = randomly_initialize(num_classes)
```

```
        fuz_output_fc2 =
fuz_fully_connected(fuz_output_fc1, fuz_weights_2,
fuz_biases_2)
            return fuz_output_fc2
        define:  logistic_activation(x):
            return 1 / (1 + np.exp(−x))
        deftrain_fuz_cnn(training_data, training_labels,
epochs, num_filters_1, num_filters_2, num_neurons_fc1,
num_classes, filter_size):
            for epoch in range(epochs):
                for input_data, label in zip (training_data,
training_labels):
                    fuz_output = fuz_cnn(input_data,
num_filters_1, num_filters_2, num_neurons_fc1,
num_classes, filter_size)
        output = logistic_activation(fuz_output)
                    # Calculate loss and gradients
                    loss = calculate_loss(output, label)
                    gradients = calculate_gradients(loss)
        update_parameters(gradients)
        deftest_fuz_cnn(test_data, num_filters_1,
num_filters_2, num_neurons_fc1, num_classes,
filter_size):
            for input_data in test_data:
                fuz_output = fuz_cnn(input_data,
num_filters_1, num_filters_2, num_neurons_fc1,
num_classes, filter_size)
        output = logistic_activation(fuz_output)
        predicted_label = np.argmax(output)
                print(predicted_label)
        train_fuz_cnn(training_data, training_labels, epochs,
num_filters_1, num_filters_2, num_neurons_fc1,
num_classes, filter_size)
        test_fuz_cnn(test_data, num_filters_1,
num_filters_2, num_neurons_fc1, num_classes,
filter_size)
```

4 RESULTS AND DISCUSSION

Python 3.7.10 is offered as a tool for use in the implementation and assessment of the suggested approach for the detection of plant diseases in conjunction with Well-known and extensively used state-of-the-art machine learning classification algorithms. This study proposes and evaluates the usage of Python 3.7.10 for this purpose. The evaluation was carried out on a platform that was based on Linux-5.4.109+−x86_64 with Ubuntu-18.04-bionic. The GPU acceleration was supplied by a Tesla P100-PCIE-16GB that was run through Google Colab. The Gummosis dataset and the Leaf Scald dataset each have their own set of models constructed for them, which are then assessed and compared with regard to their performance metrics. The CNN model that was proposed in this research performed better than other classifiers that were tested.

Each of these models has been trained separately for Gummosis and Leaf Scald datasets, and the model's performance metrics is then analyzed and compared. The proposed Logistic activation function with modified fuzzy based convolutional neural networks outperformed then existing classifiers for both Gummosis and Leaf Scald datasets. Tab. 1 shows the CNN model architecture's hyper-parameter setups.

Table 1 Parameters used in CNN architecture

Parameter	Value
Optimizer	Learning rate l_r = 0.001
Sample Size	34
Parameters	Accuracy
Activation feature	Softmax

Deep Neural Network predicts accurately by extracting valuable information from the picture input. Each layer of the CNN model applies filter to an input image to generate activation maps or feature maps. Analysing the resulting activation maps of each of the layers can assist to understand the features retrieved from an input image. Filter and activation maps might be viewed to get a sense of the internal representation of the framework for a particular input at an individual layer.

Fig. 4 to Fig. 7 illustrate the training graph for the proposed Logistic activation function with modified fuzzy based convolutional neural networks on gummosis and leaf scald datasets, respectively, and each graph indicates accuracy and loss for the associated model.

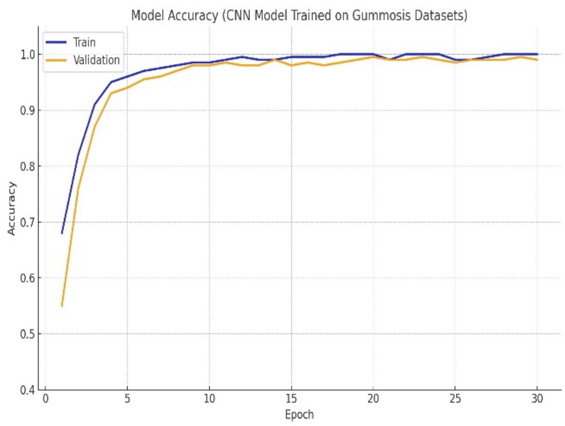

Figure 4 Model Accuracy Training graphs (CNN model trained on the Gummosis datasets)

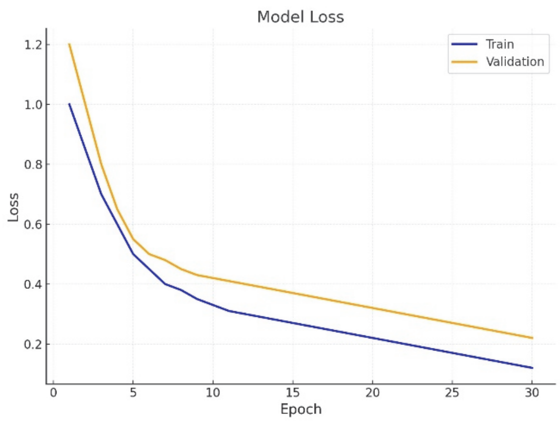

Figure 5 Model Loss Training graphs (CNN model trained on the Gummosis database)

As seen in the figures (Fig. 7 - Fig. 10), increasing the number of iterations improves accuracy while decreasing model loss. To minimise overfitting, both training and validation accuracy are maintained. The model is trained over a period of 30 epochs.

Logistic activation functions with modified fuzzy based convolutional neural networks while executing the 19th epoch, a trained model utilizing the Gummosis dataset achieved 99.5% accuracy.

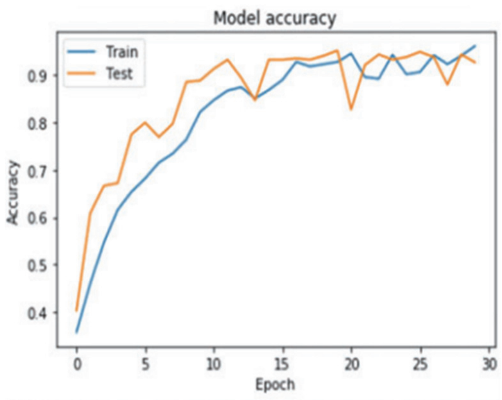

Figure 6 Model Accuracy Training graphs (CNN model trained on the Leaf Scald database)

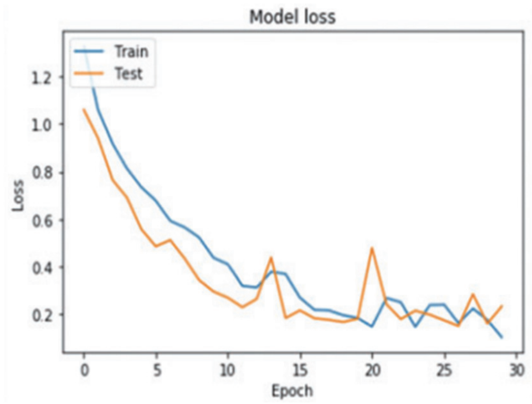

Figure 7 Model Loss Training graphs (CNN model trained on the Leaf Scald datasets)

Performance Evaluation: The performance of several image categorization methods for gummosis and Leaf scald disease datasets is examined in this work. The parameters that follow are used to assess the performance of the system that is proposed. Accuracy, recall or sensitivity, precision or specificity and $F1$-score are all measures of accuracy. These performance indicators were as follows.

Accuracy: The accuracy of image classification is quantified as a percentage, calculated by dividing the total number of correctly identified pixels by the total number of pixels present in the image. It computes the total number of pixels in a picture that are appropriately pixeled. The proposed work handles noisy or incomplete data in precision agriculture by leveraging convolutional layers for localized, noise-resistant feature extraction and applying techniques like data augmentation, pooling, and transfer learning to enhance robustness. These methods ensure accurate crop health detection even under challenging field conditions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In the context of binary classification, TP represents the number of true positive instances, TN represents the number of true negative instances, FP represents the number of false positive instances, and FN represents the number of false negative instances.

Sensitivity or recall: The calculation involves the division of the aggregate magnitude of accurate data by the magnitude of accurately approximated data.

$$Sensitivity\ or\ recall = TP / \left(TP + FN\right)$$

Specificity or Precision: The determination of the proportion of successfully estimated negative values is achieved by dividing the count of accurately assessed negative values by the total count of negative values.

$$Specificity\ or\ Precision = \frac{TN}{TN + FP}$$

$F1$-Score: The F - measure is computed by utilizing the values of recall and precision.

$$F1\text{-}Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

In this study, the performance of various picture categorization models for Logistic activation function with modified fuzzy based convolutional neural networks is utilized to analyse Gummosis and Leaf Scald disease datasets. The accuracy, precision, recall, and $F1$ score of these models are shown in Tab. 6 and Tab. 7 and performance evaluation is shown in Fig. 11 and Fig. 12.

Table 2 Performance result

Classifiers	Accuracy	Precision	Recall	$F1$-Score	Computational Complexity
CNN	99.5	99.7	99.7	99.89	28.9×10^9
SVM	93.5	92.3	93.2	92.4	35.6×10^{12}
KNN	70.5	73.4	69.6	69	33.2×10^9
Decision Tree	89	95.3	90.4	93.4	41.7×10^9

CNNs reduce computational complexity by using shared weights (kernels) across input regions, drastically lowering the number of parameters compared to fully connected layers. Integrating this AI approach with existing agricultural management systems can streamline data flow, enabling seamless analysis and decision-making for early crop health detection. This fosters broader adoption by enhancing compatibility with current workflows, tools, and IoT devices in precision agriculture. The proposed LA-MFCNN algorithm can be integrated with real-time sensor data to continuously monitor crop health by analyzing multispectral and environmental inputs for precise disease detection and stress prediction. However, challenges include managing high-dimensional data streams in real-time, ensuring robust connectivity in field conditions, and addressing computational constraints in resource-limited agricultural environments.

5 CONCLUSION

By merging a modified fuzzy-based convolutional neural network model with a Logistic activation function, this study presents a novel way for accurately diagnosing plant leaf diseases. The method was developed as a result of this research. In order to diagnose gummosis and leaf scald, a modified version of a fuzzy-based convolutional neural network model that utilizes the Logistic activation function has been developed. Diseases such as gummosis have a detection rate of 99.5%, whereas leaf scale has a detection rate of 97.5%, according to the available documentation. In this particular research project, we examined a total of 13,842 pictures of sugarcane leaves, which included both damaged and healthy specimens. The Logistic activation function displayed greater performance versus state-of-the-art machine learning image classifiers such as SVM, KNN, Decision Tree, and Random Forest across a variety of evaluation metrics when it was paired with a modified fuzzy-based convolutional neural network model. This was the case regardless of the evaluation metric being used. Comparisons were done using a wide range of performance indicators, including recall, accuracy, and precision, as well as the F1 score. Different models may be incorporated in future work to determine the model's performance on the training set. Several learning rates and optimizer are also possible to test the proposed model. The major potential challenge of the proposed work in the handling of diverse environmental conditions and variations in image quality may require extensive data augmentation and domain-specific fine-tuning. As a future scope of enhancement, incorporating additional deep learning models and testing with various learning rates and optimizers can further enhance the model's robustness and generalizability.

6 REFERENCES

[1] Kour, V. & Arora, S. (2019). Particle swarm optimization based support vector machine (P-SVM) for the segmentation and classification of plants. *IEEE Access*, *7*, 29374-29385. https://doi.org/10.1109/ACCESS.2019.2901900

[2] Huang, N., Ling, H., Liu, F., Su, Y., Su, W., Mao, H., Zhang, X., Wang, L., Chen, R., & Que, Y. (2018). Identification and evaluation of PCR reference genes for host and pathogen in sugarcane-Sporisorium scitamineum interaction system. *BMC Genomics*, *19*, 1-13. https://doi.org/10.1186/s12864-018-4854-z

[3] Atheeswaran, A., Raghavender, K. V., Chaganti, B. N. L., Maram, A., & Herencsar, N. (2023). Expert system for smart farming for diagnosis of sugarcane diseases using machine learning. *Computers & Electrical Engineering*, *109*, 108739. https://doi.org/10.1016/j.compeleceng.2023.108739.

[4] Kannan, S., Prabakaran, D, Dhenesh Kumae, S., & Sivaraj, S. (2023). A Deep Learning-Based Convolution Neural Networks to Forecast Wind Energy. *International Conference on Recent Trends in Electronics and Communication* (ICRTEC), Mysore, India, 1-6. htps://doi.org/ 10.1109/ICRTEC56977.2023.10111917

[5] Alfred, R., Obit, J. H., Chin, C. P. Y., Haviluddin, & Lim, Y. (2021). Towards paddy rice smart farming: a review on big data, machine learning, and rice production tasks. *IEEE Access*, *9*, 50358-50380 https://doi.org/10.1109/ACCESS.2021.3069449

[6] Chernov, V., Alander, J., & Bochko, V. (2015). Integer-based accurate conversion between RGB and HSV color spaces. *Computers & Electrical Engineering*, *46*, 328-337. https://doi.org/10.1016/j.compeleceng.2015.05.008

[7] Glorindal, G., Arun Mozhiselvi, S., Kumar, T.A., Kumaran, K., ChisomoKatema, P., & Kandimba, T. (2021). A simplified approach for melanoma skin disease identification. *International Conference on System, Computation, Automation and Networking (ICSCAN)*, 1-5. IEEE. https://doi.org/10.1109/ICSCAN53069.2021.9526454

[8] Gayathri Devi, T. & Neelamegam, P. (2019). Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu. *Cluster Computing*, *22*, 13415-13428. https://doi.org/10.1007/s10586-018-1949-x

[9] Zamani, A. S., Anand, L., Rane, K. P., Prabhu, P., Buttar, A. M., Pallathadka, H., Raghuvanshi, A., & Dugbakie, B. N. (2022). Performance of machine learning and image processing in plant leaf disease detection. *Journal of Food Quality*, 2022, 1-7. https://doi.org/10.1155/2022/1598796

[10] Bi, Y., Xue, B., Mesejo, P., Cagnoni, S., & Zhang, M. (2022). A survey on evolutionary computation for computer vision and image analysis: past, present, and future trends. *IEEE Transactions on Evolutionary Computation*, *27*(1), 5-25. https://doi.org/10.1109/TEVC.2022.3220747

[11] Sabapathy, S., Maruthu, S., Krishnadhas, S. K., Tamilarasan, A. K., & Raghavan, N. (2022). Competent and affordable rehabilitation robots for nervous system disorders powered with dynamic CNN and HMM. *Intelligent Systems and Rehabilitation Engineering*, 57-93. https://doi.org/10.1002/9781119785651.ch3

[12] Jain, S., Sahni, R., Khargonkar, T., Gupta, H., Verma, O. P., Sharma, T. K., Bhardwaj, T., Agarwal, S., & Kim, H. (2022). Automatic rice disease detection and assistance framework using deep learning and a Chatbot. *Electronics*, *11*(14), 2110. https://doi.org/10.3390/electronics11142110

[13] Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. *Environmental Monitoring and Assessment*, *195*(1), 120. https://doi.org/10.1007/s10661-022-10656-x

[14] Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. *Environmental Monitoring and Assessment*, *195*(1), 120. https://doi.org/10.1007/s10661-022-10656-x

[15] Sundaresan, S., Suresh, K., Kishore, V., & Jayakumar, A. (2021). Insight into various algorithms for medical image analysis using convolutional neural networks (deep learning). *Handbook of Deep Learning in Biomedical Engineering and Health Informatics*. *Apple Academic Press*, 137-164. https://doi.org/10.1201/9781003144694-6

[16] Barbedo, J. G. A. (2013). Digital image processing techniques for detecting, quantifying and classifying plant diseases. *SpringerPlus*, *2*(1), 1-12. https://doi.org/10.1186/2193-1801-2-660

[17] Jha, S., Kumar, R., Priyadarshini, I., Smarandache, F., & Long, H. V. (2019). Neutrosophic image segmentation with dice coefficients. *Measurement*, *134*, 762-772. https://doi.org/10.1016/j.measurement.2018.11.065

[18] Balyan, A. K., Ahuja, S., Lilhore, U. K., Sharma, S. K., Manoharan, P., Algarni, A. D., Elmannai, H., & Raahemifar, K. (2022). A hybrid intrusion detection model using ega-pso and improved random forest method. *Sensors*, *22*(16), 5986. https://doi.org/10.3390/s22165986

[19] Malik, A., Vaidya, G., Jagota, V., Eswaran, S. P., Sirohi, A., Batra, I., Rakhra, M., & Asenso, E. (2022). Design and evaluation of a hybrid technique for detecting sunflower leaf disease using deep learning approach. *Journal of Food Quality*, 2022, 1-12. https://doi.org/10.1155/2022/9211700

[20] Li, T., Wang, Z., Guo, J., de la Fuente-Nunez, C., Wang, J., Han, B., Tao, H., Liu, J., & Wang, X. (2023). Bacterial resistance to antibacterial agents: mechanisms, control strategies, and implications for global health. *Science of the Total Environment*, *860*, 160461. https://doi.org/10.1016/j.scitotenv.2023.160461.

[21] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. *Sensors*, *17*(9), 2022. https://doi.org/10.3390/s17092022

[22] Bouguettaya, A., Zarzour, H., Kechida, A., & Taberkit, A. M. (2023). A survey on deep learning-based identification of

plant and crop diseases from UAV-based aerial images. *Cluster Computing*, *26*(2), 1297-1317. https://doi.org/10.1007/s10586-022-03627-x

[23] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, 1-11. https://doi.org/10.1155/2016/3289801

[24] Papadopoulos, N. T., Blaauw, B. R., Milonas, P., & Nielsen, A. L. (2023). Biology and management of insect pests. *In: Peach*, 366-420. https://doi.org/10.1079/9781800620990.0366

[25] Chen, Y., Wang, X., Chen, Z., Wang, K., Sun, Y., Jiang, J., & Liu, X. (2023). Classification of Camellia oleifera diseases in complex environments by attention and multi-dimensional feature fusion neural network. *Plants*, *12*(14), 2701. https://doi.org/10.3390/plants12142701

[26] Hu, G., Du, B., Wang, X., & Wei, G. (2022). An enhanced black widow optimization algorithm for feature selection. *Knowledge-Based Systems*, *235*, 107638. https://doi.org/10.1016/j.knosys.2021.107638

[27] Kalimuthu, V. K. & Pelavendran, M. J. P. (2024). Blockchain-based secure data sharing in precision agriculture: A comprehensive methodology incorporating deep learning and hybrid encryption model. Brazilian *Archives of Biology and Technology*, *67*, e230858. https://doi.org/10.1590/1678-4324-2024230858

[28] Jing, X., Nugroho, H., Eswaran, S., & Siang, T. F. (2024). Effective edge solution for early detection of rice disease on ARM-M microcontroller. *IEEE Access*, *12*, 148267-148280. https://doi.org/10.1109/ACCESS.2024.3470970

[29] Alves Nogueira, E. (2024). Enhancing corn image resolution captured by unmanned aerial vehicles with the aid of deep learning. *IEEE Access*, *12*, 149090-149098. https://doi.org/10.1109/ACCESS.2024.3476232

[30] Kalimuthu, V. K. & Pelavendran, M. J. P. (2025). Blockchain-integrated deep reinforcement learning for secure data sharing in precision agriculture. *Technical Gazette*, *32*(1), 196. htps://doi.org/10.17559/TV-20240404001447

[31] Tussupov, C. J. (2024). Analysis of formal concepts for verification of pests and diseases of crops using machine learning methods. *IEEE Access*, *12*, 19902-19910. https://doi.org/10.1109/ACCESS.2024.3361046

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