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Classification of Sugarcane Leaf Disease with AlexNet Model

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***Abstract*—This study evaluates the influence of activation functions on the performance of the AlexNet deep learning model in classifying sugarcane diseases. Two popular activation functions, ReLU and LeakyReLU, were compared in terms of classification accuracy and computational efficiency. The ReLU function, known for its simplicity and speed, achieved an accuracy of 87.90% with a total training and testing time of 47 minutes. In contrast, LeakyReLU, which allows a small gradient when the input is negative and hence provides continuity in the learning process, obtained a higher accuracy of 90.67%, albeit at a higher computational cost, taking 54 minutes for the training and testing phase. These results highlight the trade-off between model accuracy and computational time in the deployment of deep learning models for agricultural applications. The study suggests that while LeakyReLU can lead to more accurate models, ReLU remains a competitive choice when efficiency is paramount. Future research should focus on optimizing the balance between accuracy and speed, potentially through the tuning of LeakyReLU parameters or the development of hybrid models.**

***Keywords*— Sugarcane disease, AlexNet, Activation Function, ReLU, LeakyReLU.**

I. INTRODUCTION

Estimating disease severity is crucial in the sugarcane breeding process to develop varieties that are resistant to disease. Diseases not only decrease the yield of sugarcane but also degrade the quality of the varieties.

The production quality of sugarcane depends on its resistance to diseases. With an estimated 15% of sugarcane leaves affected by disease, significant losses in production are experienced. Early identification and treatment of these diseases are essential to minimize infections across entire sugarcane fields [1].

Sugarcane, belonging to the Poaceae family, is rich in sucrose and accounts for 75% of global sugar production. Its main by-products include white sugar, jaggery, molasses, and bagasse. India stands as the largest consumer of sugar and the second-largest producer worldwide. The alkaline water of sugarcane can reduce the risk of cancer and support organ health, while the plant is susceptible to diseases that threaten production [2].

In agriculture, diseases and pests in crops like sugarcane can drastically reduce yields. Often these diseases are not easily detectable, leading to severe losses for farmers. Identifying and managing these diseases is essential, yet traditional chemical control methods can be environmentally damaging and costly. Precision agriculture provides a remedy by applying treatments specifically to affected areas. Additionally, deep learning technologies, utilizing artificial neural networks, play a crucial role in detecting and monitoring plant diseases through image analysis, enhancing efficiency and reducing environmental harm in the agricultural sector [3, 4].

The aim of this study is to compare the impact of using ReLU (Rectified Linear Unit) and LeakyReLU activation layers in the AlexNet model. Specifically, the study will explore how ReLU, which zeroes out negative inputs thereby accelerating the learning process and mitigating the vanishing gradient problem, contrasts with LeakyReLU, which allows a small, non-zero gradient when the input is negative, preventing neuron death and information loss from negative values. This investigation seeks to determine if LeakyReLU offers a more balanced learning process and potentially superior performance in scenarios where negative inputs are significant.

II. RELATED WORKS

In a study conducted on a dataset comprising images of five different diseases of sugarcane plants from various regions of Karnataka, India, captured under diverse resolutions and lighting conditions, the performance of CNN-based classification models was investigated. These models achieved a top accuracy of 93.40% on their own dataset and 76.40% on images sourced from different reliable online platforms. Furthermore, object detection algorithms such as YOLO and Faster R-CNN were utilized to accurately localize infected regions, achieving a top mean average precision score of 58.13% on the test set. These findings underscore the effectiveness of CNN-based approaches in automated disease recognition systems even under diverse conditions encountered in realistic scenarios [5].

[6]The proposed system employs Adaptive Histogram Equalization (AHE) and k-means clustering for image processing and segmentation. Statistical features including variance, skewness, standard deviation, mean, and covariance are extracted using Gray Level Co-occurrence Matrix (GLCM) and Principal Component Analysis (PCA). Detection and classification utilize Support Vector Machine (SVM), achieving an average accuracy of 95%. Additionally, the system suggests control measures upon disease identification [6].

This study addresses the challenge of detecting sugarcane diseases by utilizing the MobileNet v2 model. The proposed model, once trained, is integrated with mobile device software, aiming to classify the diseases observed in sugarcane [7].

Jiang et al., explore the extraction of disease features from tomato leaves using deep learning. A dataset comprising 1,000 images for three disease types is utilized in their experiments. The Resnet-50 model serves as the basis, with modifications including the use of a Leaky-ReLU activation function and an 11x11 kernel size in the convolutional layer. Following these adjustments, the training accuracy reached 98.3% (an increase of 0.6 points) and the test accuracy improved to 98.0% (an increase of 2.3 points) [8].

The study introduces a novel approach for detecting plant leaf diseases, termed the Leaky Rectified Residual Network (LRRN) model. This model is designed to classify plant diseases by incorporating the ResNet architecture and Leaky ReLU activation function. Experimental evaluations conducted on the Plant Village dataset demonstrate that the LRRN model achieves superior performance, with an accuracy of 94.56%, precision of 93.48%, an F1 score of 92.83%, a recall of 93.12%, and a specificity of 92.58%. These results confirm the effectiveness of the LRRN model in accurately diagnosing plant diseases [9].

This study proposes a convolutional neural network model named rE-GoogLeNet for accurately identifying rice leaf diseases in natural settings. rE-GoogLeNet is a modification of GoogLeNet, enhanced with the Leaky ReLU activation function and E-Inception modules. Experiments demonstrate that rE-GoogLeNet outperforms both traditional and advanced models in terms of classification performance, achieving an average accuracy of 99.58%, which represents a 1.72% improvement over the original GoogLeNet model. These evaluations confirm that rE-GoogLeNet is robust, stable, and highly accurate for detecting rice leaf diseases [10].

Convolutional neural networks have been successfully employed in the field of visual data processing. They utilize various perceptrons, which typically possess a multi-layered structure, generally requiring minimal preprocessing. Another study explored their effects using the MNIST dataset, employing ReLU and LeakyReLU activations in the CNN’s internal layers, and a softmax activation function in the output layer [11].

The reviewed studies indicate that diseases in sugarcane are classified using various machine learning and deep learning architectures. Additionally, different methods have been adopted in various studies to enhance the models. This study aims to investigate the impact of the activation function on the model's performance.

III. MATERIALS AND METHODS

The objective of this study is to classify diseases in sugarcane using the deep learning model AlexNet. The study employs a five-class dataset comprising images of healthy sugarcane as well as those affected by Mosaic, Redrot, Rust, and Yellow diseases. Initially, the AlexNet model was utilized with the ReLU activation function to classify the dataset. Subsequently, the activation function in the AlexNet model was switched to LeakyReLU for a reclassification. Finally, the results of both models were compared. The block diagram of the study is detailed in Fig. 1.

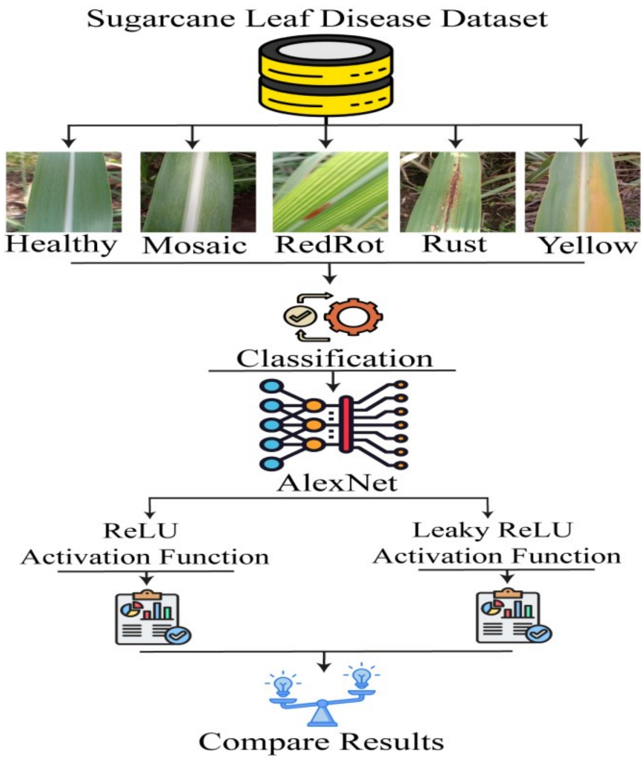
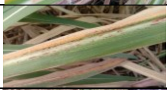


Fig. 1 Block diagram of the study

A. Dataset

The dataset used in this study was obtained from the Mendeley Data website. It comprises manually collected images of sugarcane leaf diseases from India. The primary categories include Healthy, Mosaic, Red Rot, Rust, and Yellow disease. This dataset contains a total of 2,569 images across these five classes. The dataset is both balanced and diverse [12]. Detailed information about the dataset is provided in Table I.

TABLE I.
DETAILS OF THE DATA USED IN THE STUDY

Categories	Count	Image
Healthy	522	
Mosaic	462	
RedRot	518	
Rust	514	
Yellow	505	

B. *Deep Learning Models*

Deep learning models are a subset of machine learning characterized by their ability to learn from large amounts of data using architectures inspired by the human brain. These models are designed to capture complex patterns and relationships within data through the use of layers of artificial neurons [13, 14]. Common architectures such as CNNs (Convolutional Neural Networks) and RNNs (Recurrent Neural Networks) are particularly effective in the areas of image and sequence processing, respectively. Deep learning has revolutionized fields such as image recognition [15], image classification [16], and AI-based mobile applications [17] by providing a level of accuracy previously unachievable.

C. *Transfer Learning and AlexNet Models*

Transfer learning is a method within machine learning that enables the application of knowledge gained from one problem to a different but related problem [18]. This approach is particularly beneficial in scenarios where labeled data is scarce for the target task but plentiful for a similar task. It leverages features learned from models pre-trained on large datasets, thereby enhancing learning efficiency and prediction accuracy for new tasks. Successfully applied in areas such as computer vision and natural language processing, transfer learning reduces the need for extensive data collection and training from scratch [19, 20].

Krizhevsky and his team developed AlexNet, which achieved significant success in the 2012 ILSVRC competition. Structurally similar to LeNet, AlexNet is one of the foremost architectures that incorporates multiple convolutional layers. It consists of five convolutional layers and three fully connected layers [21].

The AlexNet architecture incorporates several key elements that contribute to its success. It utilizes the ReLU (Rectified Linear Unit) activation function, which significantly accelerates training compared to traditional activation functions like tanh. Additionally, the use of multiple GPUs in training AlexNet allows for the development of larger models and facilitates faster training times [22].

D. *Activation Functions*

Activation functions are functions used in artificial neural networks that take inputs and produce a specific output, enabling the model to solve complex non-linear problems [23]. ReLU (Rectified Linear Unit) is one of the most popular activation functions; it outputs zero for negative values and the input itself for positive values. This characteristic accelerates the training process and facilitates the development of deeper networks [24]. LeakyReLU is a variant of ReLU that uses a small slope instead of zero for negative inputs, thus mitigating the problem known as "neuron death" and allowing the network to retain information from negative inputs [25]. Both functions are widely used in deep learning models, especially preferred in image processing and classification tasks.

E. *Confusion Matrix and Performance Metrics*

A confusion matrix is a tool used to assess the performance of classification models. It is a table that visualizes the success of an algorithm by displaying both actual and predicted classifications. The matrix compares actual values against predicted values, indicating the number of correct and incorrect predictions. The primary components are true positives, true negatives, false positives, and false negatives. These metrics are essential for calculating performance indicators such as accuracy, precision, recall, and the F1 score. Analyzing a confusion matrix is crucial for understanding classifier errors and the overall performance of the model, which can assist in improving the model and adjusting its parameters [26-28]. Fig. 2 shows the confusion matrix of the 5-class data set used in the study.

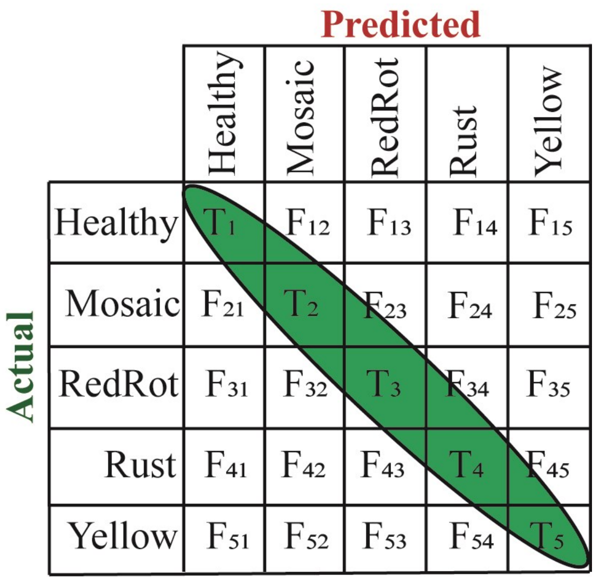


Fig. 2 The 5-class confusion matrix

Different metrics can be calculated from the confusion matrix to evaluate the performance of the models. Accuracy, recall, and precision, metrics were used in the study.

Accuracy:

Accuracy is the ratio of all correct forecasts (both positive and negative) to the total forecasts and indicates the overall success of the model [16]. It is mathematically expressed as:

$$Accuracy = \frac{Total\ accurate\ estimates}{Total\ estimates} \quad (1)$$

Here, the total correct estimates are the sum of the values in the diagonal of all classes (i.e. TP_1, TP_2, TP_3, TP_4, TP_5), while the total estimates are the sum of the values in all cells of the matrix.

Recall:

Recall shows how well the model predicted correctly for a particular class. It is calculated separately for each class and the overall recall value of the model can be found by taking an overall average [29]. The recall for a class is calculated as follows:

$$Recall_{Class\ i} = \frac{TP_i}{TP_i + FN_i} \quad (2)$$

Here TP_i are the correct positives for class i, and FN_i are the false negatives for class i.

Precision:

Precision measures how many of the predicted positive cases are actually positive [30]. Calculated separately for each class:

$$Precision_{Class\ i} = \frac{TP_i}{TP_i + FP_i} \quad (3)$$

Here TP_i are the correct positives for class i, and FP_i are the false negatives for class i.

Calculating the recall and precision values of a model specific to each class is important to understand the effects of class imbalances and how the model performs in certain classes. An overall value can be obtained by using different methods of these metrics, such as macro-average (calculating and averaging the values for each class) or micro-average (summing the TP, FP, FN values of all classes and calculating these total values).

IV. Experimental results and findigs

The aim of the study is to evaluate the performance of the activation functions ReLU and LeakyReLU. Initially, the AlexNet model, a transfer learning model, was chosen to classify a sugarcane dataset. The data set is divided into 80% training and 20% test data. The ReLU activation function operates without any special parameters; it sets negative inputs to zero and leaves positive inputs unchanged. The confusion matrix obtained at this stage and the performance metrics obtained are given in Fig. 3.

The confusion matrix given illustrates the performance of a classification model across various classes. The diagonal elements (green boxes) represent the true positive rates, indicating correct classifications for each class, while the off-diagonal elements (pink boxes) indicate misclassifications, comprising both false positives and false negatives.

• For the Healthy class, the model has correctly classified 71 instances, resulting in an accuracy of 68.3%, and misclassified 33 instances, leading to a 31.7% error rate.

• The Mosaic disease class shows a high accuracy rate with 95.7% correctly classified and only 4.3% misclassified.

• The RedRot class exhibits an accuracy of 88.5% with a misclassification rate of 11.5%.

• In the Rust class, the model performs notably well with an accuracy of 96.1%.

• For the Yellow class, the model achieves an accuracy of 92.1% and an error rate of 7.9%.

Additionally, precision and recall values for each class are displayed below the columns and alongside the rows, respectively. For instance, the precision for the Healthy class is 100% (meaning everything the model predicted as 'Healthy' was indeed healthy), but the recall is lower at 75.9% (indicating that the model correctly predicted 75.9% of the actual 'Healthy' instances).

Overall, the matrix's representation indicates that the classification model performs better in certain classes, particularly excelling in the 'Rust' category, while encountering some challenges in the 'Healthy' class. Such insights can be employed to refine the model and target improvements in areas where it is underperforming.

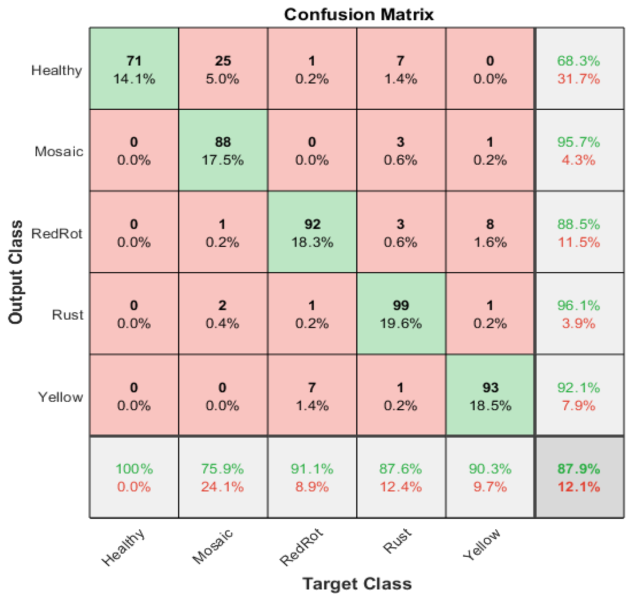


Fig. 3 The confusion matrix obtained as a result of classification with the ReLU activation function

Later, the activation functions were replaced with the LeakyReLU activation function in the AlexNet model and the data set was reclassified. The LeakyReLU activation function is an extended version of ReLU and contains a parameter. This parameter is usually called "alpha" and specifies a value beyond the zero of negative inputs. Usually, the alpha parameter is determined as a very small positive value, and the value of 0.01 was selected in the study. This, in turn, allows negative inputs to pass with a small slope towards zero. The confusion matrix obtained as a result of this classification and the calculated performance metrics are given in Fig. 4.

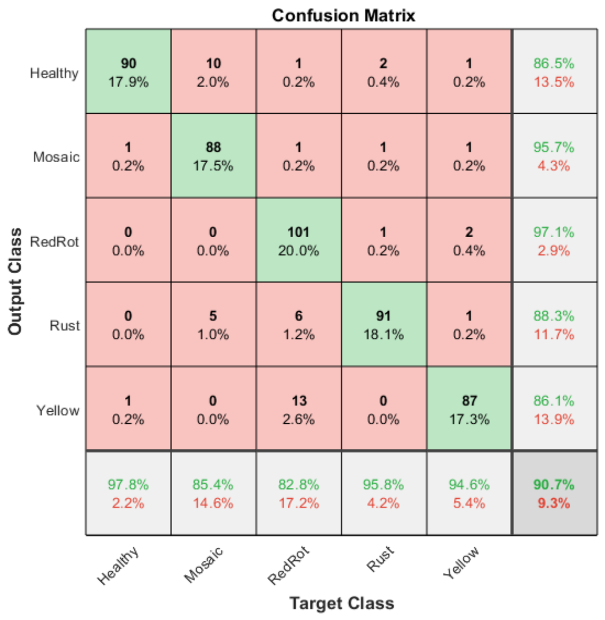


Fig. 4 The confusion matrix obtained as a result of classification with the LeakyReLU activation function.

When the given confusion matrix is examined;

• For the Healthy class, the model has correctly predicted 90 instances, achieving an accuracy rate of 86.5%. The false positive rate stands at 13.5%.

• In the Mosaic disease class, the model accurately classified 88 instances, resulting in a precision rate of 95.7%, with a false positive rate of 4.3%.

• The model excels in the RedRot disease classification with a remarkable accuracy of 97.1% and a low false positive rate of 2.9%.

• For the Rust disease category, the model has correctly identified 91 instances, yielding an accuracy of 88.3% and an 11.7% rate of misclassification.

• In identifying the Yellow disease, the model has reached an accuracy of 86.1% with 87 correct predictions and a false positive rate of 13.9%.

The columns at the bottom of the matrix display precision for each class, while the rows on the right indicate the recall rates. These figures detail how well the model performs for each class. For example, in the Healthy class, the model's precision is 97.8%, and the recall rate is 85.4%.

The accuracy and training-test times obtained at both classification stages are given in Table II.

TABLE II.
ACCURACY AND WORKING TIMES IN BOTH PHASES

Models	Accuracy	Time
AlexNet with ReLU	87.90%	47 min 37 sec
AlexNet with LeakyReLU	90.67%	54 min 11 sec

Upon reviewing Table 2, it is observed that ReLU's simple, parameterless structure provides computational speed and efficiency. Notably, in deep neural networks, ReLU has been shown to accelerate the learning process. Hence, ReLU, operating solely based on the input values without the use of parameters, is often the preferred activation function.

The primary advantage of LeakyReLU is its prevention of complete zeroing out of negative inputs, which can contribute to a more stable training process. Consequently, LeakyReLU is deduced to perform better, particularly in deep neural networks. However, it is understood that it may slow down the learning process in terms of speed.

V. Conclusions

In conclusion, the classification of the sugarcane dataset using the AlexNet deep learning model has yielded informative results concerning the impact of activation functions on the accuracy and training duration. The application of the ReLU activation function resulted in a classification accuracy of 87.90% with a training and testing duration of 47 minutes 37 seconds. This demonstrates the efficacy of ReLU in achieving a high level of accuracy in a relatively short time frame, which can be particularly advantageous in scenarios where computational resources or time are limited.

On the other hand, the implementation of the LeakyReLU activation function achieved a higher classification accuracy of 90.67% but required a longer duration of 54 minutes 11 seconds for training and testing. This increment in accuracy points to LeakyReLU's capability to capture more complex patterns in the data, potentially leading to a more robust model. However, this comes at the cost of increased computational time.

Considering these findings, it is recommended for future work to investigate strategies for optimizing the LeakyReLU activation function to reduce training time while maintaining its accuracy benefits. This could involve adjusting the parameter that governs the slope for negative inputs or experimenting with hybrid models that combine the strengths of both ReLU and LeakyReLU. Moreover, further analysis could include a cost-benefit comparison of training time against accuracy in various operational environments to better inform the choice of activation functions under different constraints. The ultimate objective should be to develop a model that not only provides high accuracy but also maintains efficiency in training and operational deployment.

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Data Availability

The dataset pertinent to this study is accessible through the following hyperlink:
https://data.mendeley.com/datasets/9424skmnrk/1

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