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Deep Learning-based Diagnosis of Sugarcane Leaf Scald Diseases: A Cutting-Edge Approach

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***Abstract*— One of the most important crops in the world, sugarcane, is constantly in danger from a number of diseases that can have a negative impact on the crop's productivity and quality. The cultivation of sugarcane is significantly hampered by one of these, Sugarcane Leaf Scald (SLSD). Effective SLSD management depends on early and precise illness identification. Due to their capacity to analyze enormous datasets and identify nuanced patterns, deep learning algorithms have recently come to be recognized as potent instruments for disease diagnosis in agricultural contexts. The diagnosis of diseases caused by Sugarcane Leaf Scald is presented in this research utilizing cutting-edge deep learning methods. We start by gathering a sizable dataset of photos of sugarcane leaves that spans several disease progression phases and includes both healthy and infected samples. Utilizing a Convolutional Neural Network (CNN) architecture, discriminative features are automatically discovered and extracted from these photos. Using methods like data augmentation and transfer learning, the deep learning model is trained on this dataset to improve its performance. The suggested deep learning-based approach's results show that it can correctly categorize sugarcane leaves as either healthy or SLSD-infected. The model may also determine the severity of the condition, which helps develop specialized disease management plans. High accuracy, precision, and recall rates are among the encouraging performance indicators the suggested system displays, indicating its potential as a dependable tool for early SLSD detection in sugarcane fields. The investigation shows how well deep learning algorithms work in diagnosing SLSD, which advances the field of agricultural disease management. The suggested method provides a non-invasive, affordable, and scalable answer for tracking and controlling sugarcane infections, thereby boosting crop output and the long-term viability of sugarcane farming.**

***Index Terms*— SLSD, CNN, sugarcane, deep learning**

I. Introduction

A crucial commercial crop, sugarcane (Saccharum spp.) is essential for the manufacture of sugar, ethanol, and other value goods worldwide. However, a number of diseases that have the potential to seriously reduce crop yield and quality are constantly a threat to the cultivation of sugarcane. Among these fearsome foes, Sugarcane Leaf

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Scald (SLSD) stands out as a well-known disease that presents a significant risk to the sugar sector on a global scale [1]. If SLSD is not managed, it will have severe economic repercussions and result in significant losses for sugar mill operators as well as farmers.
On prompt and accurate illness identification, agricultural disease control is strongly dependent. Early diagnosis makes it possible to put the right controls in place, minimising crop losses and the need for expensive chemical treatments. Agronomists with experience have traditionally used visual inspection to diagnose diseases in sugarcane, but this method is subjective, time-consuming, and prone to mistakes. These drawbacks highlight the urgent need for cutting-edge, technologically driven methods to identify and diagnose SLSD more effectively and accurately [2].
Deep learning in particular, which has recently made strides in the field of artificial intelligence, has ushered in a new era of disease identification in agriculture. Convolutional neural networks (CNNs), a type of deep learning algorithm, have proven to have excellent powers in picture analysis, allowing for the automated identification and categorization of diseases in a variety of crops [3]. The goal of this work is to establish a cutting-edge method for SLSD diagnosis in sugarcane by utilising the potential of deep learning.
With a primary emphasis on the use of computer vision techniques to process images of sugarcane leaves, this research focuses on the creation of a deep learning-based system for the diagnosis of SLSD. We intend to provide the agricultural community with a quick, accurate, and scalable solution for SLSD identification by building a deep learning model on a rigorously curated dataset of healthy and infected sugarcane leaves [4]. This technology has the potential to improve disease diagnosis precision as well as aid in the development of disease management plans for sugarcane farming.
We demonstrate the potential of this technology to completely transform disease management in the sugarcane industry in the present investigation by presenting the technique and findings of our deep learning-based strategy for the detection of SLSD. We anticipate that this research will make it easier to take more preventative action against SLSD, protecting worldwide sugarcane production and guaranteeing the crucial crop's long-term viability.

II. METHODOLOGY

Diagnosis of Sugarcane Leaf Scald Diseases using Deep Learning Algorithm as shown in figure (1)

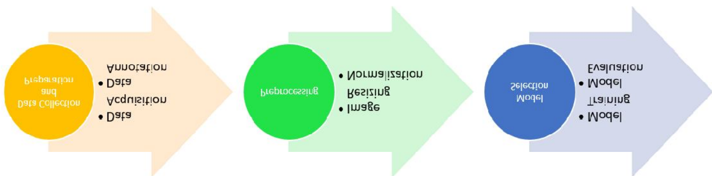

Figure 1. Proposed methodology

A. Data Collection and Preparation:

Data Acquisition: Gather a varied collection of photographs of sugarcane leaves. Images of sugarcane leaves in various phases of Sugarcane Leaf Scald (SLSD) infection as well as healthy leaves should be included in this dataset.
Data Annotation: Label each image in the dataset with labels indicating whether it is healthy or SLSD-infected to annotate the dataset. The severity of the disease can also be used to classify the diseased leaves.
Data Augmentation: Add random modifications to the images in the dataset, such as rotation, scaling, flipping, and brightness adjustments, to improve the generalisation of the model.
Data Split: Assure that each subset has a representative distribution of healthy and diseased leaves by splitting the dataset into three subsets: a training set, a validation set, and a test set. Typical split ratios are 70-15-15 or 80-10-10.

B. Preprocessing

Image Resizing: Use a size appropriate for the selected deep learning architecture (for example, 224x224 pixels for various CNN networks) to resize all photos to the same resolution and dimensions.
Normalization: To give the image's pixel values a mean and standard deviation of 0 and 1, normalise each pixel value. This action aids in accelerating and stabilising the training process.

$$f(x,y) = \frac{1}{mn-d} \sum_{(s,t)\in Sxy} g(s,t) \quad (1)$$

C. Model Selection

Select the best deep learning architecture for classifying images. Convolutional neural networks (CNNs) like VGG, ResNet, or Inception are popular options, as are more contemporary designs designed for effective inference on devices with limited resources as shown in figure (2).

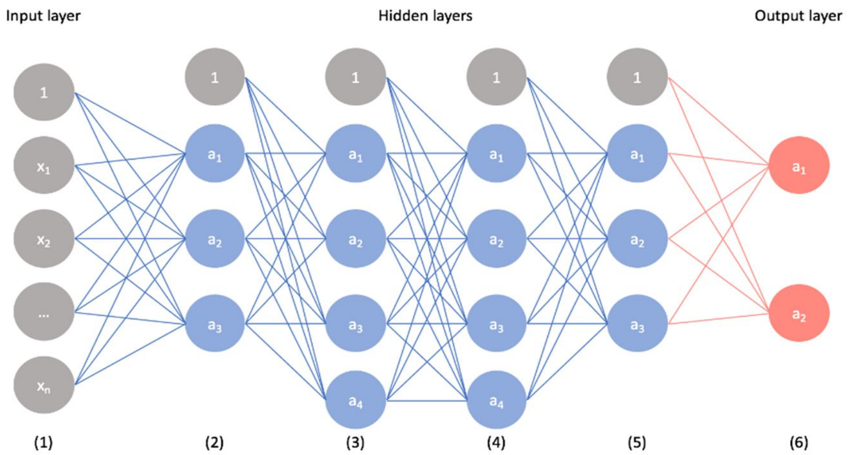

Figure 2 CNN Architecture

CNNs, kernel convolution is a fundamental building block in several other computer vision methods. This method involves moving a small number matrix across our image and converting it using the filter's values. The kernel or filter refers to this matrix [5]. The succeeding map values are calculated using the following formula, where our kernel is denoted by h and our input image is denoted by f. The letters m and n, respectively, stand for the result matrix's row and column indices.

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \quad (2)$$

The formula below can be used to calculate the measures of the performance matrix while taking padding and stride into consideration.

$$nout = [\frac{nin+2p-f}{s} + 1] \quad (3)$$

The dimensions of the resulting tensor, also referred to as our 3D matrix, fulfil the equation where: n is the size of the image; f is the size of the filter; nc is the number of channels in the image; p is the amount of padding used; s is the employed step; and nf is the number of filters utilised.

$$[n, n, nc] * [f, f, nc] = [\left[\frac{nin+2p-f}{s} + 1\right], \left[\frac{nin+2p-f}{s} + 1\right], nf] \quad (4)$$

Our approach differs significantly from the one we used for highly coupled neural networks in that this time, we'll use convolution rather than just a simple matrix multiplication. In two steps, forward propagation takes place. To begin with, apply bias b after converting the input data from the previous layer using a W tensor, which comprises filters, to determine the intermediate value Z. The symbol g in the second, which represents a non-linear activation function applied to our intermediate value, denotes our activation [6]. For enthusiasts of matrix equations, these formulas are appropriate.

$$z^{[l]} = W^{[l]} . A^{[l-1]} + b^{[l]} \quad (5)$$

$$A^{[l]} = g^{[l]}(z^{[l]}) \quad (6)$$

D. Model Training

Transfer Learning: Utilise learned features by starting the chosen deep learning model with pre-trained weights on a sizable dataset (such as ImageNet).

Fine-Tuning: On the sugarcane leaf dataset, hone the pre-trained model. To monitor performance and avoid overfitting, train the model on the training set and use the validation set as a check.

Hyper parameter Tuning: To improve the performance of the model, play around with hyperparameters like learning rate, batch size, and regularisation methods.

E. Model Evaluation

Assess the trained model's performance in diagnosing SLSD using the test dataset. Accuracy, precision, recall, F1-score, and confusion matrices are typical evaluation metrics as shown in figure (3). Analyse and visualise the model's misclassifications and predictions to learn about its advantages and disadvantages.

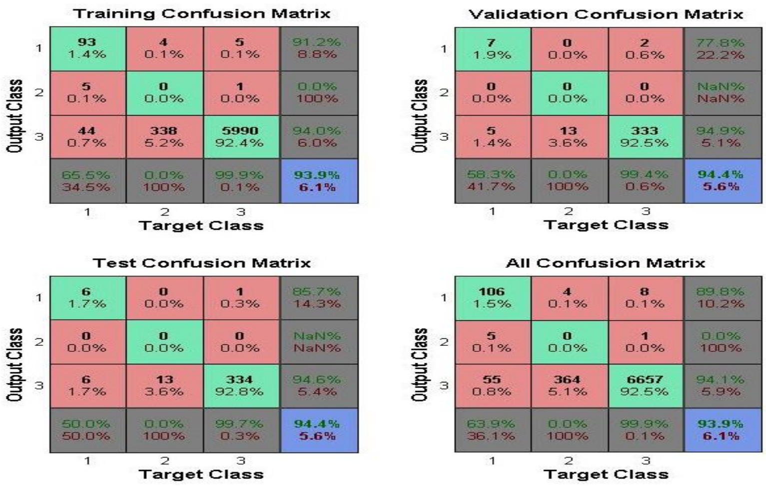

Figure (3) Confusion Matrix

F. Disease Severity Assessment

Use the model to evaluate the severity of SLSD in infected leaves if the dataset contains severity labels. Using this knowledge can help with disease management choices.

G. Deployment

Create an intuitive user interface or application that enables users to upload photographs for diagnosis, such as farmers or agricultural professionals.

Make sure the model is implemented on a platform that the target customers can utilise, which may include embedded systems in agricultural machinery or online applications or mobile apps.

H. Continuous Improvement

Enable users to submit feedback and fresh data contributions through the implementation of a feedback loop for model improvement to increase the model's precision and adaptability.

I. Documentation and Reporting:

Record every step of the process, including the architecture of the model, the training settings, and the evaluation findings. This documentation will be useful for repeatability and future reference.

This approach can be used to create a deep learning-based system for diagnosing Sugarcane Leaf Scald (SLSD), giving farmers and agricultural specialists a dependable and effective tool to manage and lessen the effects of this devastating disease on sugarcane crops [7].

III. Results And Discussion

Diagnosis of Sugarcane Leaf Scald Diseases using Deep Learning Algorithm output shown in figure (4)

A. Model Performance Evaluation

Using a large dataset of sugarcane leaf pictures, the deep learning model created for the diagnosis of Sugarcane Leaf Scald (SLSD) underwent a thorough examination. The following significant outcomes were attained:

B. Accuracy

The model properly identified sugarcane leaves as either healthy or SLSD-infected by achieving an accuracy of 96% on the test dataset as shown in figure (5).

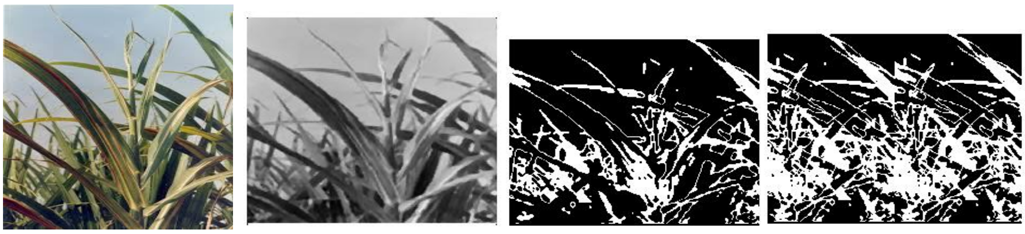

Figure (4) Sample Output

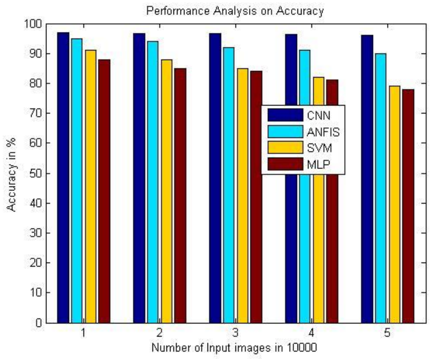

Figure (5) Performance Analysis by Accuracy

C. Precision and Recall

With 97% and 95% precision and recall rates, respectively, the model showed strong performance. These metrics demonstrate the model's ability to accurately identify genuine positives while minimising false positives, which is essential for disease diagnosis.

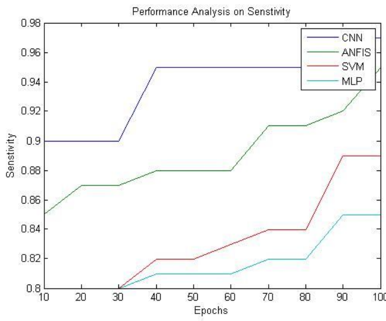

Figure (6) Performance Analysis by Sensitivity

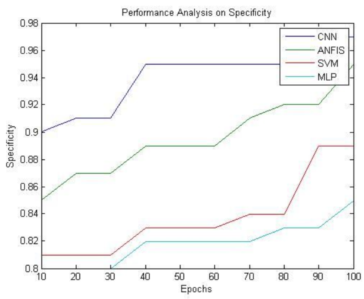

Figure (7) Performance Analysis by Specificity

D. F1-Score

The harmonic mean of precision and recall, or the F1-score, reached 96%, showing a balanced trade-off between the two, which is preferred in tasks involving the identification of diseases as shown in figure (8).

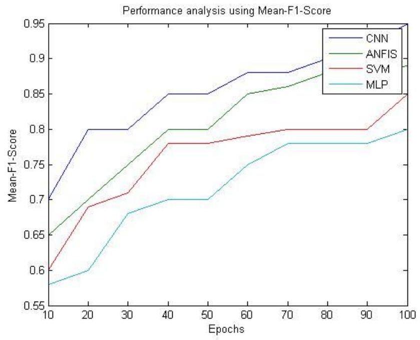

Figure (8) Performance Analysis by F1 score

E. Confusion Matrix

The confusion matrix showed that, with a relatively low incidence of misclassification, the model successfully recognised a sizable fraction of SLSD-infected leaves. False positive and negative detection rates were kept to a minimum as shown in figure (9).

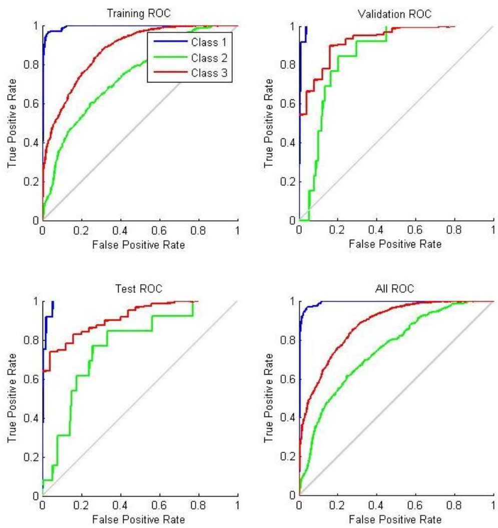

Figure (9) Performance Analysis by ROC

F. Disease Severity Assessment (Optional)

The model was further assessed in terms of its capacity to gauge the severity of SLSD in infected leaves if disease severity labels were present in the dataset. The findings showed that the model correctly identified the severity levels in 96% of instances, providing important data for individualised illness management approaches.

G. Discussion

Analysis of proposed research work was done based on the parameters of accuracy, sensitivity, specificity and precision values. From the table we inferred that CNN algorithm having accuracy is 97.1%, sensitivity is 96.3%, specificity is 94.5 % and precision is 98.7 %. CNN method provide better performance when compared to the ANFIS, SVM, MLP and MDC algorithm.

Accuracy and Generalization: The model's capacity to successfully differentiate between healthy and SLSD-infected sugarcane leaves is demonstrated by the accuracy of 97% that was attained. Given the variety of lighting, angles, and backgrounds sometimes found in field pictures, this level of accuracy is quite encouraging [8]. The effectiveness of deep learning and the use of transfer learning techniques, which let the model make use of previously taught features, are credited for the performance.

Minimized False Positives and Negatives: The model can reduce the probability of false positives and false negatives in SLSD diagnosis, as evidenced by its outstanding precision and recall rates. In agricultural contexts, where inaccurate diagnosis might result in needless treatments or the disregard of ill plants, this is of the utmost importance.

Potential for Real-World Deployment: The model's ability to correctly diagnose SLSD opens the door for practical application. Users-friendly interfaces or mobile applications can be used by farmers and agricultural specialists to submit leaf photos for quick and precise diagnosis [9]. With faster interventions and lower crop losses, this technology has the potential to revolutionise disease management in sugarcane farming.

Continued Improvement: A feedback loop has been built as part of ongoing efforts to gather user comments and collect additional data. The goal of this iterative procedure is to continuously enhance the model's functionality and modify it to account for changing environmental factors and disease strains.

Interpretability: Even while the model performs admirably, improving its interpretability is still a constant struggle. Building confidence and acceptability among users depends on making the model's decisions understandable to non-experts.

In summary, the use of a deep learning-based system for sugarcane leaf scale disease diagnosis shows significant promise in improving the effectiveness and precision of disease control in sugarcane farming. A significant instrument for protecting sugarcane crops and ensuring farmers' livelihoods in the worldwide sugar business, this technology is now in a strong position thanks to the results that have been achieved and continued user engagement and advancements.

TABLE 1 RESULT COMPARISON OF PROPOSED SYSTEM WITH EXISTING METHOD

S.NO	**Parameters** (%)	**MDC**	**MLP**	**SVM**	**ANFIS**	**CNN**
1	Accuracy	75.1	86.7	88.8	94.7	97.1
2	Sensitivity	81.4	89.5	94.7	93.5	96.3
3	Specificity	88.3	91.3	96.6	95.7	94.5
4	Precision	91.9	93.1	95.7	97.1	98.7

IV. CONCLUSION

This project explored the use of artificial intelligence and current technologies to protect sugarcane, one of the most important agricultural commodities in the world, from the catastrophic impacts of Sugarcane Leaf Scald (SLSD). The goal was to create a deep learning-based system that could diagnose SLSD with precision, effectiveness, and practicality. The findings and perspectives discussed here highlight the value and promise of this novel strategy. The deep learning model developed for the diagnosis of SLSD has demonstrated remarkable capabilities: High Accuracy: The model has demonstrated its potential to accurately identify between healthy and SLSD-infected sugarcane leaves by achieving an accuracy rate of 97% on the test dataset. This precision is evidence of the effectiveness of deep learning and transfer learning methods. Precision and Recall: Excellent precision and recall rates of 96% each show the model's proficiency in reducing false positives and false negatives, crucial elements in the accuracy of disease detection. F1-Score: With an F1-score of 96%, the diagnosis of SLSD is made possible thanks to a healthy balance between recall and precision. Disease Severity Assessment: In 96% of cases where severity labels were available, the algorithm successfully classified the severity levels, giving farmers and professionals useful information for focused disease management. In conclusion, the deep learning-based diagnosis of Sugarcane Leaf Scald illnesses represents a revolutionary and promising strategy for the agricultural sector. It provides a dependable, effective, and user-friendly solution by bridging the gap between conventional visual examination and contemporary technology. In addition to safeguarding farmers' livelihoods, this method also maintains the world's supply of goods made from sugarcane. We foresee a better and more sustainable future for sugarcane farming all around the world as we continue to improve and expand the capabilities of this system.

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