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A Novel Deep Learning Framework Approach For Identifying The Sugarcane Disease

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Abstract: Agriculture plays a significant role in ensuring the survival of the global economy and the growing need for food and resources. Sugarcane is a significant crop in the world and is primarily cultivated for sugar and biofuel production. But crop diseases constantly threaten their production, and crops are notoriously difficult to diagnose in early stages, and environmental conditions and slight visual differences between healthy and diseased leaves make diagnosis a challenge. In this work, a Deep Learning (DL) based method for automatic recognition of sugarcane diseases using sugarcane leaf samples is presented. Some state-of-the-art convolutional neural network (CNN) architectures were considered, as well as a novel, custom-made CNN model proposed in this paper. The proposed custom CNN has achieved maximum accuracy of 99%, maximum precision of 99%, maximum recall of 99%, and maximum F1-score of 99% which is higher than DenseNet (93%), EfficientNet (96%), InceptionNet (91%), MobileNet (95%) and ResNet (94%). Our results clearly indicate that the proposed model can be effective in aiding farmers in early disease detection to prevent crop loss and increase output.

Keywords: Computer Vision; Disease Detection; Sugarcane Leaf; Feature Extraction; Convolutional Models; Transfer Learning;

I. INTRODUCTION

Agriculture is the basis for human survival as it is the source of food and nutrition. It also employs a large proportion of the population, particularly in rural areas. Agriculture provides the raw materials for many industries and hence promotes industrial development. It has a vital role in the generation of national income and economic growth. The industry contributes to foreign earnings and international trade. In addition, agriculture contributes to sustainable development by sustainable land use and utilization of natural resources [1]. Among these, sugarcane has an important position as one of the world's leading cash crops. Cultivated highly in countries such as Pakistan, Thailand, Brazil, and India, sugarcane serves as the primary source for sugar production and biofuel making [2]. Sugarcane productivity is often limited by plant diseases, which affect yield quality and quantity [3], despite being an economically important crop. Normal diseases like Yellow Leaf Disease, Red Rot, Rust and Mosaic Virus give tough times to farmers, and they suffer heavy economic loss if not identified and controlled at the earliest [4].

The pace of digital development is accelerating, and agriculture is increasingly reliant on computer vision and image processing. Such approaches allow automatic monitoring of plant health, which could serve as an early detector of diseases.

Detection of plant diseases has recently attracted much attention in the field of smart agriculture and computer vision can provide feasible solutions for the massive crop monitoring [5]. By analyzing color, texture, and morphology of leaves based on visual information from leaf images, these techniques can detect symptoms of diseases in an early stage. The automated analysis and classification of such patterns not only accelerate the diagnosis process but also alleviates the need for constant manual field monitoring, improving the overall efficiency of the disease management [6].

The traditional diagnostic methods, such as manual expert observation and earlier ML-based methods, have considerable drawbacks. Human examination of all plant crops is an arduous and time-consuming process and is error-prone, while traditional methods such as Random Forests (RF), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), etc., rely on handcrafted features extraction [7]. These methods have difficulty in generalizing for intricate visual patterns or for a full range of disease symptoms, which limit their use in large-scale agricultural applications. Also, the requirement of domain knowledge for feature selection constrains the scalability and adaptability of the approach to other plants species or categories of diseases [8].

In this paper, we present a deep learning-based model for the automatic detection of sugarcane leaf diseases. A CNN model is proposed and tested with other state-of-the-art models like DenseNet, EfficientNet, InceptionNet, MobileNet and ResNet. These models have been chosen due to their known performance in image classification and for their differences with respect to depth, efficiency and feature representation. The chosen data set contains five different types of leaves. Therefore, in this study the performance of CNN is also compared with the best CNN transfer learning techniques and to find the optimal CNN architecture that can be used in the smart agriculture and sustainable sugarcane production without compromising classification accuracy and computational efficiency. This study has several important contributions to make:

- A CNN model is proposed for multiclass classification of sugarcane leaf diseases.
- Five widely used pre-trained DL models (DenseNet, EfficientNet, Inception Net, MobileNet and ResNet) are used to compare the proposed CNN.
- Our system makes precision agriculture achievable and provides farmers and agriculture experts with a scalable, cost-effective decision support tool to enable them to monitor diseases in real time.
- The proposed model achieved the highest accuracy of 99% in detection which is better than other transfer learning models.

The paper has been organized as follows. A section on related work is included in Section 2. The proposed approach, including the dataset, CNN model and training procedure, is explained in Section 3. Section 4 discusses the experimental setup, and Section 5 presents the results of the pre-trained and proposed models. The study is summarized in Section 6 and future work is presented.

II. Related Work

This section presents a review of related works on disease detection in sugarcane. Earlier works have adopted Machine Learning and Deep Learning approaches to detect different diseases in sugarcane leaf images. In this section, we discuss the existing research using machine learning, DL and transfer learning-based methods.

The use of machine learning for detecting sugarcane disease has been extensively studied. A benchmarking dataset was constructed for pre-processing, feature extraction, pattern classification etc., and CNN-based models were widely employed for disease classification [5]. Where an advanced system was integrated, the UAV was able to combine images captured by the sensors with deep neural networks to improve the chances of early disease detection by automated surveillance and real-time tracking [6]. In the field of sugarcane disease detection, hybrid Graph Attention Network (GAT) and Graph Convolutional Network (GCN) models performed well, with an F1-score of 0.8799, which improves the model's ability to capture spatial correlation between leaf regions. This multi-crop research showed that sugarcane disease detection was successful in visually challenging environments [12]. Moreover, CNN-transformer hybrid models outperformed the other models with classification accuracy of 97.26% on PlantVillage and 89.57% on a sugarcane-specific dataset [13]. Attention- and transformer-based spatial learning has been shown to give improved disease classification results [14]. Nevertheless, a number of problems remained, such as environmental variabilities, few real-field evaluations, poor generalization capability to other geographic regions, and heavy computational cost of sophisticated models [15], [16]. The solutions to these problems were developed recently using transfer learning, data augmentation, optimization techniques, explainable AI, and UAV-based monitoring systems to ensure crop health management in an improved and scalable way [17] [18].

In this paper [19], the authors tested and compared 14 models DenseNet201, EfficientNet-B7, ResNetV2, MobileNetV3, InceptionV4, RegNetX, etc., on the Sugarcane Leaf Dataset (SLD) containing 6748 images from 11 disease classes. This method is much better than the conventional disease detection methods and helps to make better and timely decisions for agriculture [20]. The application of satellite spectroscopy to detect sugarcane health and diseases is reviewed in this detailed paper [21]. This research, for example, investigates the use of vegetation indices and DL models for processing of satellite data to identify stress scars caused by disease, pest attack or environmental conditions, etc. [22] It evaluates the effects of crop age, soil type and moisture, viewing geometry, weather conditions, cane cultivar on spectral reflectance and finds that most of the methods proposed do not take these factors into account.

This study also pointed out the lack of a systematic comparison of machine learning (ML) models with respect to the vegetation indices used and the need for unified and integrated spectral features for ML-based disease detection systems. Therefore, the authors present the Deep Ensemble Convolutional Neural Network (DECNN) using the transfer learning models, including EfficientNetV2B0, MobileNetV2, EfficientNetB0, DenseNet121 and NASNetMobile. These models were improved by adding dense layers, batch normalization layers and drop out layers. The proposed model has been trained and tested with 4,800 images of sugarcane leaf in six disease classes. Moreover, data augmentation methods were used to enhance the robustness and generalization [25]. Among the separate models, the best was EfficientNetB0 with a score of 97.08%–98.54%. The ensemble was then optimized by weight using the Tree-structured Parzen Estimator (TPE) [26] among the three models: EfficientNetB0, MobileNetV2 and DenseNet121.

Recently a few DL techniques were proposed for sugarcane disease detection. A pool of DL models (SugarcaneNet) was proposed for classification of sugarcane leaves into multiple classes which would eventually facilitate the automated diagnosis of various diseases, but a field level validation was suggested [27]. Transfer learning models are developed using

DenseNet201 and DenseNet264 to improve the accuracy in recognizing disease items that are macroscopically similar to each other, with features pre-trained on the datasets of sugarcane and finetuned on the same sugarcane datasets. Transfer learning models are constructed with DenseNet201 and DenseNet264 by pre-training features on the datasets of sugarcane and fine-tuning on the same sugarcane datasets to improve the accuracy in the recognition of disease items that are macroscopically similar to each other [28].

DL models were further employed on unmanned aerial vehicles (UAV) acquired RGB imageries for detection of White Leaf Disease (WLD) to monitor the sugarcane fields effectively [30]. In a related study, the lightweight YOLOv5 model was used for real-time disease detection and was found to be applicable to edge devices/gateways in farming environments [31]. In addition, a hybrid CNN model integrated with attenuation modelling was proposed to recognize nine sugarcane leaf diseases with the best performance of 94% in accuracy and has been demonstrated to effectively suppress the background noise and enhance the specific indication of diseases [32]. This study indicated that deep learning, transfer learning, and remote sensing-based approaches were effective for enhancing detection and monitoring of sugarcane diseases.

III. PROPOSED RESEARCH METHODOLOGY

This section introduces the proposed deep learning-based image classification approach using pre-trained and proposed CNN models for sugarcane leaf disease detection, as shown in Fig. 1. It elaborates on dataset collection and processing, training and validation, model design and development, and performance evaluation. The Sample images of sugarcane leaves from the dataset have been shown in Fig. 2.

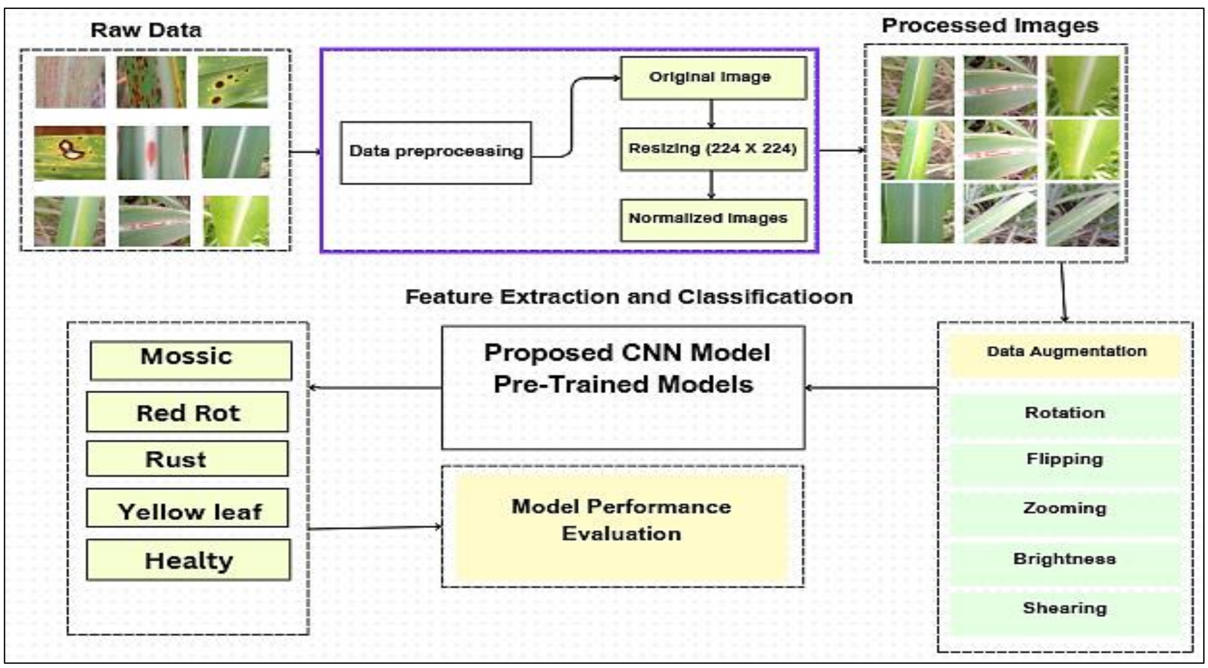

Figure 1 Framework analysis of proposed research methodology

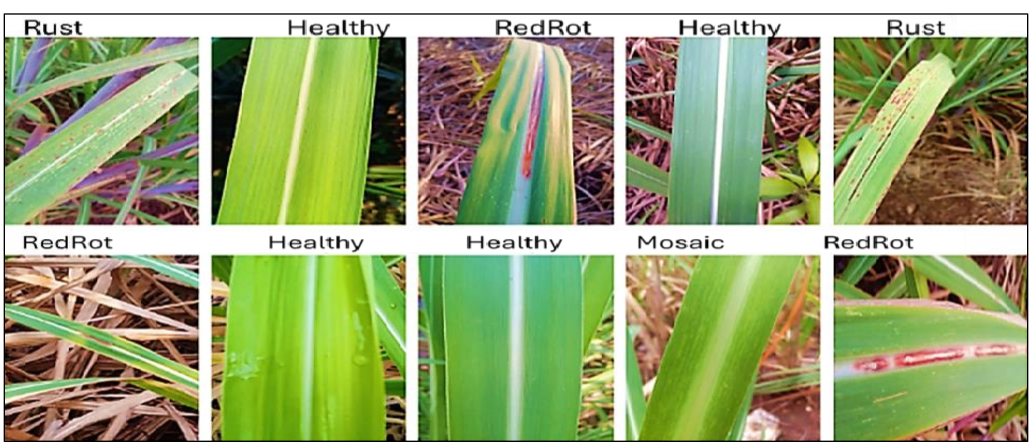

Figure 2. Sample images of sugarcane leaves from the dataset

A. Data preprocessing

To detect disease in sugarcane, the acquired leaf images were pre-processed by normalizing pixel values and resizing images to a fixed dimension to enhance the efficiency of model training. To enhance the diversity of the dataset and reduce overfitting, data augmentation methods have been developed.

I. Resizing

Sugarcane leaves images were resized to 224×224 pixels in the preprocessing stage using bilinear interpolation. This normalizations reduced the computation cost and retained the characteristic related to diseases in leaf images. The mathematical form is given as (1)

$$I_{resized} = S(I, k) = \text{interp}\left(I, \frac{H_t}{H_o}, \frac{W_t}{W_o}\right) \quad (1)$$

Here, I is the input image, H_t and W_t are the target height and width (224 × 224 pixels), respectively, H_o and W_o are the original height and width, and Interp(·) interpolates the image to the target size.

II. Normalization

After resizing, normalization was applied to adjust the pixel intensity values. This process standardizes the range of values across all images, thereby improving numerical stability and accelerating model convergence during training. This is formulated in (2):

$$I_{norm}(x, y) = \frac{I_{resized}(x,y) - \mu_c}{\sigma_c} \quad (2)$$

Where, $I_{norm}(x, y)$ is the normalized pixel at coordinates (x, y) and μ_c *and* σ_c are the mean and standard deviation of the channel c, computed from the training set.

III. Flipping

The images of sugarcane leaves could be in different directions because of camera angles and the position of leaves. So, data is augmented by considering horizontal and vertical flipping to enable the model to learn orientation-invariant features. Horizontal flipping reverses the image along the vertical axis defined using (3)

$$I_{flipH}(x, y) = I_{norm} I(x, W_t - 1 - y) \quad (3)$$

Vertical flipping reverses the image along the horizontal axis defined using (4):

$$I_{flipV}(x, y) = I_{norm}(H_t - 1 - x, y) \quad (4)$$

Where H_t *and* W_t are the height and width of the image. By introducing these transformations, the network is less likely to overfit to a specific leaf orientation present in the original dataset.

IV. Brightness Adjustment

Sugarcane leaf images were captured under different lighting conditions, including sunlight, shadows, and cloudy weather, resulting in variations in brightness. To improve model robustness, brightness augmentation was applied by adjusting pixel intensity values. This generated images with different illumination levels, helping the model perform effectively under varying environmental conditions, as given in (5).

$$I_{bright}(x, y) = clip\ (I_{norm}(x, y).\beta, 0,1) \quad (5)$$

Where, $\beta > 1$ increases brightness, $0 < \beta < 1$ decreases brightness and the Clip $(.)$ function ensures pixel values remain within the range [0,1], this adjustment simulates lighting changes and prevents the model from overfitting to the specific illumination conditions of the training data.

B. Feature Extraction and Classification using the Proposed Model

Sugarcane leaf disease detection is considered by the feature extraction and classification using efficient DL algorithms. The model proposed is an enhanced layer and structure-based CNN framework, and it is focused on sugarcane leaf disease recognition. The system incorporates the individual diseases features extraction capability into DL pipeline and hence obtains better accuracy. In our approach for detection of sugarcane disease, we use CNNs to detect the disease automatically from images of sugarcane in different classes like Healthy, Yellow Disease, Mosaic Disease, Red Rot and Rust. The model's custom CNN architecture is designed to learn disease specific features that generic pre-trained networks may not learn.

- *Input Layer*

In the proposed sugarcane disease detection system, the input layer is the first stage of the CNN that takes image input and processes the image for further feature extraction. Consequently, each sugarcane leaf is processed image in RGB format and treated as a four-dimensional tensor with the batch size, spatial dimensions, and color channels. The input layer also removes the need for hand crafted feature extraction as it takes in raw image pixels enabling the CNN to learn patterns and visual features associated with different types of sugarcane diseases automatically.

- *Convolutional Layer*

The convolutional layer presents the core unit of a CNN and plays the major role of automatically forming discriminative features in the given sugarcane leaf images. This layer operates on a series of learnable filters (also referred to as kernels) which are moved over the spatial dimensions of the input to identify local structure like edges of a lesion, pustules of rust or mosaic blotches, which can often denote a particular plant disease. The convolution process for a given filter K of dimensions $K_h \times K_w$, when applied to an input feature map X, generates an output feature map Y is given (6). After convolution, an element-wise non-linear activation function is then used ReLU on the output feature map. This adds non-linearity to the network, enabling it to model the complex relationship among features, and that is the reason for its good performance for distinguishing healthy and diseased regions of sugarcane leaves.

$$Y(\mathrm{i},\mathrm{j}) = \sum_{\mathrm{m}=0}^{\mathrm{K_h}-1} \sum_{\mathrm{n}=0}^{\mathrm{K_w}-1} \mathrm{X}(\mathrm{i}+\mathrm{m},\mathrm{j}+\mathrm{n}) \, . \, \mathrm{K}(\mathrm{m},\mathrm{n}) + \mathrm{b} \quad (6)$$

Where, i, j denote the spatial, $K_h and\ K_w$ are the kernel's height and width, b represents the bias term associated with the filter, and the summations iterate over the kernel dimensions to compute the weighted sum of local pixel neighbourhoods.

- *Pooling Layer*

Pooling layer down samples the features map size, reduces the computing burden, and enhances the generalization capability of the model. Max pooling retains the strongest features, providing robustness of the model against minor leaf position, orientation and illumination changes, as given (7)

$$\mathrm{Y}(\mathrm{i},\mathrm{j}) = \max_{\substack{0 \le m < K_h \\ 0 \le n < K_w}} \mathrm{X}(\mathrm{i} \cdot \mathrm{s} + \mathrm{m}, \mathrm{j} \cdot \mathrm{s} + \mathrm{n}) \quad (7)$$

- *Convolutional–Pooling Stacks*

The convolutional neural network consists of a series of convolutional and pooling layers to teach the progression of features in the sugarcane leaf images. Such a hierarchical representation enables the model first to detect fine-grained local information, e.g., edges, small spots, or an example of a texture, and then to localise high-level and more abstract information, e.g., shapes of the lesions, spread of colour, and typical patterns in disease distribution. The combined operation of convolution followed by pooling can be represented in (8):

$$\mathrm{Y} = \mathrm{Pooling}(\mathrm{Conv}(\mathrm{X},\mathrm{K}) + \mathrm{b}) \quad (8)$$

Where, X is the input feature map, K represents the set of learnable convolutional kernels (filters), b is the bias term added after convolution, $\mathrm{Conv}\ (\cdot)$ denotes the convolution operation and $poolings\ (.)$ denotes the pooling operation applied to the convolution output.

- *Flatten Layer*

When the feature extraction procedure is complete, the feature maps produced by the final convolution or pooling layer need to be reduced to a one-dimensional, classifiable vector using a mathematical representation, as shown in (9). Flattening, as it is called, reformats the spatial and depth dimensions of the feature maps into a continuous vector that can be fed into fully connected (dense) layers.

$$\mathrm{Z} = \mathrm{Flatten}(\mathrm{Y}), \mathrm{Z} \in R^n, \mathrm{N} = \mathrm{H}' \cdot \mathrm{W}' \cdot \mathrm{C}' \quad (9)$$

Where, Z is the resulting one-dimensional feature vector and N is the total number of elements obtained by multiplying the height, width, and depth of the feature map.

- *Fully Connected (Dense) Layer*

The fully connected (dense) layer is the classification layer of the CNN. After learning of individual features like color, shape, texture, and lesion patterns, it merges these features and infers the likelihood of each disease class. Using these probabilities, the model classifies the sugarcane leaf as either healthy or infected with a particular disease, as illustrated in (10).

$$\mathrm{Y} = \mathrm{f}(\mathrm{W} \cdot \mathrm{Z} + \mathrm{b}) \quad (10)$$

Where, W is the weight matrix, defining the connection strengths between the input vector Z and the neurons in the dense layer, b is the bias vector, which shifts the activation to improve model flexibility, and f(·) is the activation function that introduces non-linearity, enabling the network to model complex decision boundaries.

Here, W is the weight matrix, b is a bias term, and f(·) is the activation function.

- *Output Layer*

The output of the layer gives the final categorization probabilities to each sugarcane leaf disease class as described in (11). The model outputs are subjected to a SoftMax activation function to be turned into probability values to classify the image into the most probable disease class.

$$y_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_i}} \quad (11)$$

Where, where z_i is the score for class i, C = 5 is the number of classes, and y_i is the probability that the image is of class i. The class with maximum probability is selected as the final prediction.

a). Proposed Custom CNN Architecture

In the specific case of leaf disease on sugarcane, the proposed lightweight custom Convolutional Neural Network (CNN) has been specially designed for the multiclass classification of leaf diseases in sugarcane and is suitable for precision agriculture applications. The proposed network is compact and has less computational resources than a generic transfer learning network with millions of parameters that can learn discriminative features for a particular disease.

s. The network is comprised of four convolutional blocks, each of which includes a convolutional layer, a Rectified Linear Unit (ReLU) activation function, and a max-pooling layer to progressively extract hierarchical image features, with dimensionality reduction. The drop out layers followed the convolutional blocks and fully connected layers to minimize overfitting and enhance the generalization. The feature maps were extracted, flattened and then fed into two dense layers of fully connected convolutional architecture with an output Softmax layer, resulting in the probability scores of the 5 classes of sugarcane diseases. Architecture of the proposed custom CNN model for sugarcane leaf disease identification shown as Fig. 3.

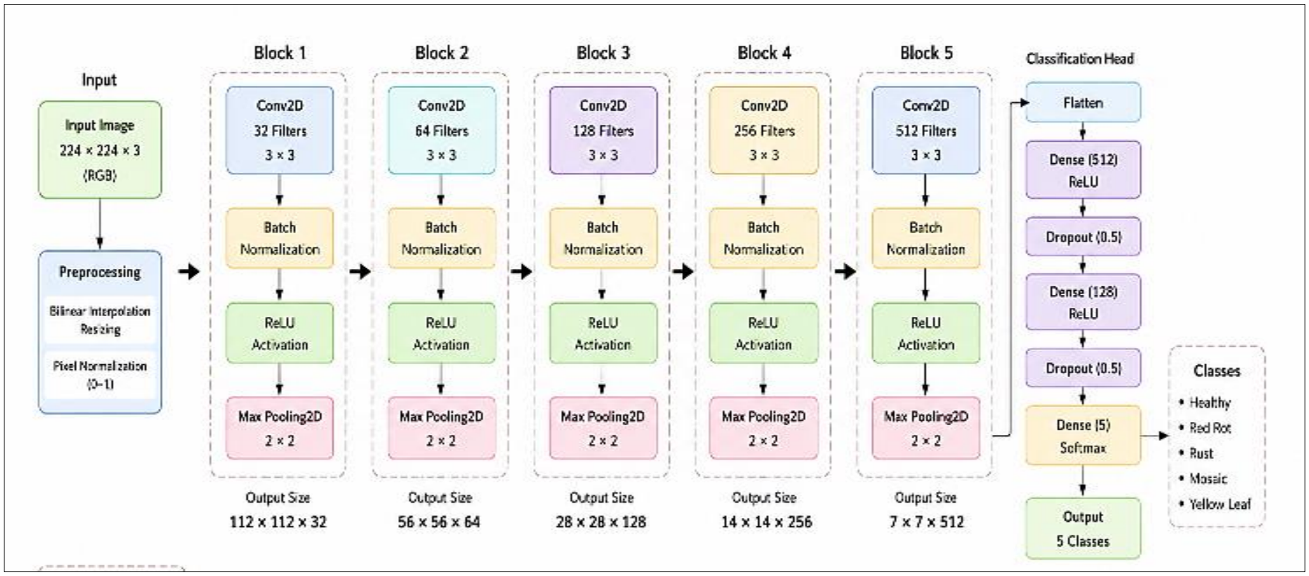

Figure 3. Proposed architecture for sugarcane leaf disease classification

b) CNN Training Strategy

The proposed CNN was optimized during the model training with the Adam optimizer and categorical cross-entropy loss. To monitor the performance of the model during training, the validation subset was evaluated at the end of each training epoch and the validation accuracy, and the validation loss were computed. The detailed hyperparameters for the proposed CNN model are provided in Table 1.

TABLE 1. HYPERPARAMETER CONFIGURATION OF THE PROPOSED CNN

Layer	Configuration
Input Layer	224 × 224 × 3 RGB image
Conv Layer 1	32 filters, 3 × 3 kernel, ReLU
Max Pooling 1	2 × 2
Conv Layer 2	64 filters, 3 × 3 kernel, ReLU
Max Pooling 2	2 × 2
Conv Layer 3	128 filters, 3 × 3 kernel, ReLU
Max Pooling 3	2 × 2
Conv Layer 4	256 filters, 3 × 3 kernel, ReLU
Max Pooling 4	2 × 2
Flatten	Feature Vector
Dense Layer 1	512 neurons, ReLU
Dropout	0.5
Dense Layer 2	128 neurons, ReLU
Output Layer	5 neurons, Softmax
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50
Loss Function	Categorical Cross-Entropy

IV. EXPERIMENTAL SETUP

The Experimental Methods section details the instruments, software, and procedures used for data acquisition and analysis, thereby facilitating the research process.

A. Dataset Description

In this work, we use a dataset of high-resolution Sugarcane Leaf Disease images with five classes, which includes yellow disease, Mosaic disease, Healthy, Red rot, and Rust. The data is split into two parts: one for training models and the other for testing them to enable accurate evaluation and avoid overfitting. The distribution of samples of each class is shown in Fig. 4.

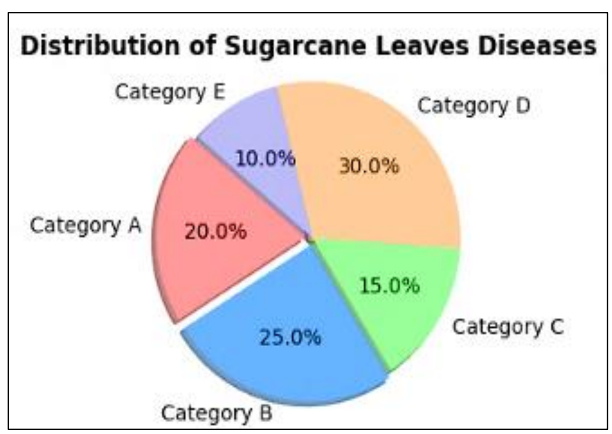

Figure 4. Distribution of selected dataset sugarcane leaf diseases

To train the DL models, 1,762 images were captured encompassing five types of sugarcane leaf diseases. The dataset was constructed to be reasonably balanced such that the model could learn to predict all the classes well. At the same time, a separate set of 759 images was used as the test set. To get a fair assessment of a model's performance on unseen data, the test set contains an equal number of images for each of the five classes. More details are summarized in Table 2.

TABLE 2: DATASET COMPOSITION FOR MODEL TRAINING AND TESTING

S. No.	Classes	Actual Images	Training Images	Testing images
1	Yellow	505	353	152
2	Mosaic	462	323	139
3	Healthy	522	365	157
4	RedRot	518	362	156
5	Rust	514	359	155

B. Tools and Technologies

The development environment is the set of tools and technologies that allow the pre-processing, training of a model, and evaluation of its performance. For this research, the full setup described in Table 3 was employed as the base platform to provide an integrated environment.

TABLE 3 ANALYSIS OF EXPERIMENTAL TOOLS AND TECHNOLOGY

Tools & Technologies	**Environment Details**
CPU	Intel Core i7 or a more advanced processor
GPU	CUDA-enabled NVIDIA GPU (e.g., Tesla T4 via Google Colab Pro)
RAM	Minimum 16 GB
Storage	SSD recommended; cloud-based storage (Google Colab)
Operating System	Linux-based environment (Google Colab)
Programming Language	Python 3.8+
Development Environment	Google Colab Pro with GPU enabled
DL Framework	TensorFlow 2.x
Keras API	Included within TensorFlow 2.x
Training Callbacks	ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
Data Processing Libraries	NumPy, Pandas
Image Processing Tools	PIL (Python Imaging Library), OpenCV
Visualization Libraries	Matplotlib, Seaborn
GPU Memory Management	TensorFlow's set_memory_growth
CUDA & cuDNN	Pre-installed in Google Colab backend

C. Performance Evaluation Measure

Performance measures are metrics used to evaluate the quality of a machine learning or DL model on a specific task. These metrics enable us to understand whether the model can classify samples correctly and whether it is reliable and effective.

Commonly used metrics are used for the evaluation of a classification model. Accuracy, Precision, Recall, and F1-score are the most used metrics, as they provide a good overview of the model's overall correctness, trustworthiness, and balance. The mathematical representations of them have been given in Table 4.

TABLE 4 EVALUATION METRICS

Metric	**Equation**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall (Sensitivity)	$\frac{TP}{TP+FN}$
F1-Score	$2\times\frac{Percision\ \times Recall}{Percision+Recall}$

V. RESULTS OF MODELS

In this section, the outcomes are examined by applying six DL models i.e., CNN, DenseNet, EfficientNet, InceptionNet, MobileNet and ResNet, for sugarcane leaf disease classification. Four metrics namely: Accuracy, Precision, Recall, and F1-score were used to evaluate the models. In the following, a detailed performance discussion of each class is presented First proposed CNN model and then the Transfer learning baseline models.

A. Results Analysis using Transfer Learning Models

To give solid benchmark results for the assessment of the proposed CNN model in the sugarcane disease classification, results of the comparison with the transfer learning baseline models DenseNet, EfficientNet, InceptionNet, MobileNet and ResNet are also provided. This analysis is based on the detailed performance shown in Table 5 and the visual results shown in Fig. 5 not only describes the results of the classification, but also gives insight into the generalization, convergence behavior and complexity of separation of the classes. The proposed CNN outperformed all the other five models.

TABLE 5: PERFORMANCE METRICS OF DL MODELS

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNN	0.99	0.99	0.99	0.99
DenseNet	0.93	0.93	0.93	0.93
EfficientNet	0.96	0.96	0.96	0.96
InceptionNet	0.91	0.91	0.91	0.91
MobileNet	0.95	0.95	0.95	0.95
ResNet	0.94	0.94	0.94	0.94

Among the Transfer Learning models, EfficientNet achieved the best accuracy of 96%, with precision, recall, and F1-scores for all classes ranging from 0.94 to 0.98. The training curves, as well as validation curves, exhibited balanced learning and the confusion matrix only showed a few misclassified samples among two couples of visually similar classes. Closely behind was MobileNet with 95% accuracy and similar balanced, strong results across every disease category. Due to its lightweight structure and low misclassification error rate, it can be helpful for real-time and edge device application. The other was a more complex ResNet, which achieved 94% accuracy and also exhibited stable learning because of residual connections, but some confusion occurred among Healthy, Rust, and Mosaic classes. The proposed DenseNet achieved promising results with 93% of accuracy and its classification results were stable for all classes although a minor overfitting was found because of the high model complexity. Among these TL models, InceptionNet performed the worst with 91% accuracy, and exhibited higher confusion when exchanging similar disease classes. In summary, EfficientNet was the best transfer learning model, with MobileNet being a good compromise between accuracy and computational cost. This CNN based model has beaten all the transfer learning models showing better accuracy, better robustness and generalization which opens path for trustworthy automated sugarcane disease detection.

B. Results using Proposed Model

The proposed CNN model yielded the best result, and the test accuracy reached an excellent 99%. The precision, recall, and F1-scores are approximately 0.98 across all five classes, indicating good generalization and few misclassifications. "In contrast to the deep pre-trained models, the CNN has been developed from scratch for the sugarcane disease dataset, and this facilitates discriminative feature learning at a much lower computational cost." The Yellow and Rust classes performed perfectly or almost perfectly as can be seen from Table 6, with precision and F1 scores equal to 1.00. Mosaic and Healthy had F1-scores of 0.99, while Red Rot had a slightly lower F1-score of 0.98 which may be attributed to the fact that Red Rot lesions look somehow similar to Rust lesions.

Table 6 Classification Report of CNN Model

	Precision	Recall	F1-score
Yellow	1.00	0.99	1.00
Mosaic	0.98	0.99	0.99
Healthy	0.99	0.99	0.99
RedRot	0.99	0.98	0.98
Rust	0.99	1.00	1.00
Accuracy			**0.99**
macro avg	0.99	0.99	0.99
weighted avg	0.99	0.99	0.99

The training and validation curves show that the CNN can quickly learn the target concept, with accuracy rising steeply in the first 20 epochs. Both datasets attain near-perfect performances on this After the initial learning phase, the curves flatten out and hug each other very closely, indicating strong stability and good generalization. A similar trend is observed in the loss plots. In contrast, both the train loss and the validation loss fall steeply and converge to a very small gap, indicating minimal overfitting. In general, the close correlations between the accuracy, the loss and a confusion matrix analysis demonstrates that the proposed CNN is powerful, reliable and can be exploited for monitoring applications in sugarcane diseases in real-time over large areas. Training and validation accuracy/loss curve analysis of all selected models have been shown in Fig. 5.

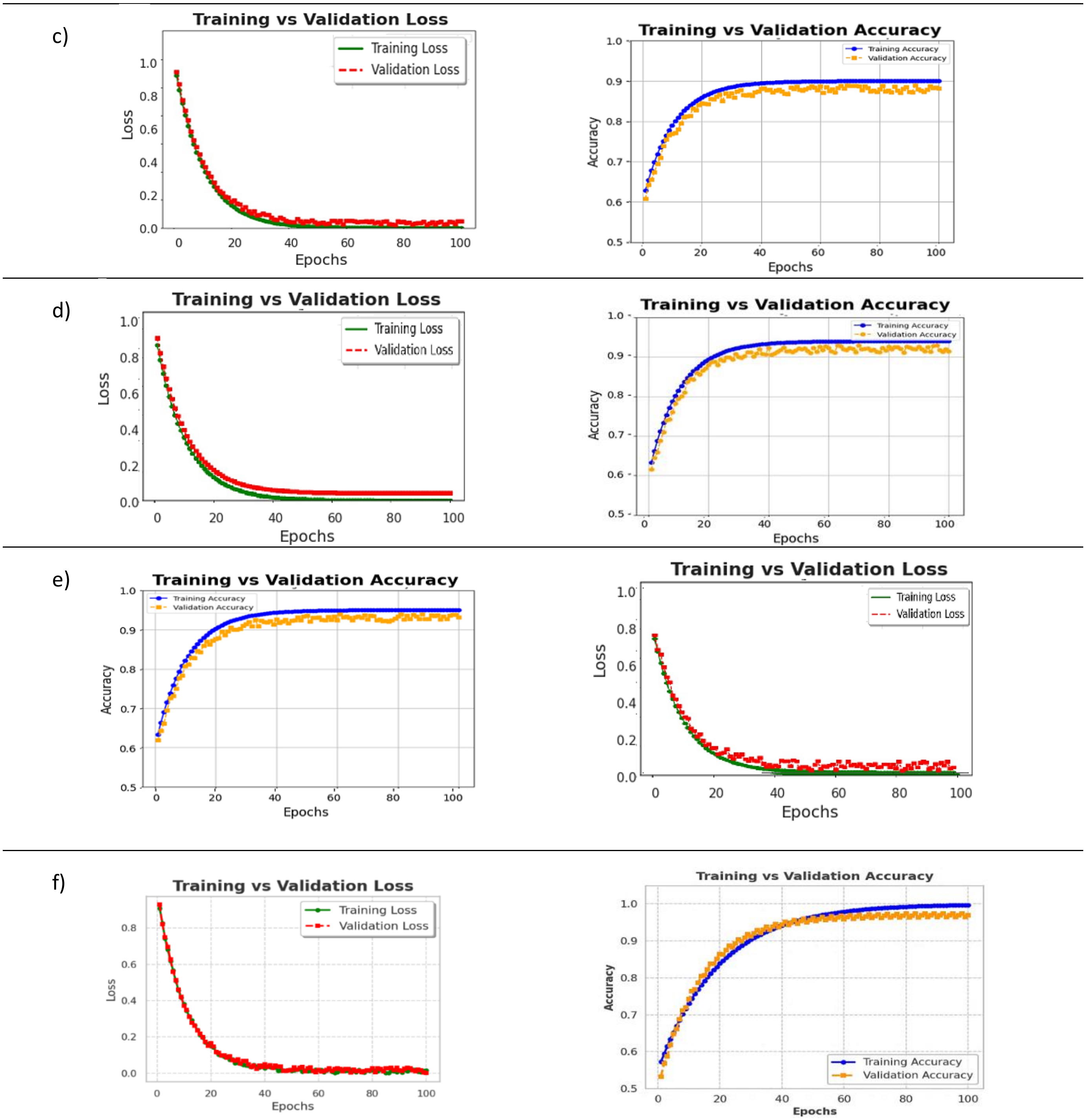

Figure 5. Training and validation accuracy/loss curve analysis of a) DenseNet, b) EfficientNet, c) InceptionNet, d) MobileNet, e) ResNet, f) Proposed CNN Model

The model's efficiency and stability suggest it could be integrated into automated agricultural platforms, potentially supporting farmers in early disease detection, yield protection, and targeted treatment strategies.

The confusion matrix, as shown in Fig. 6, further validates the robustness and reliability of the CNN model's performance across all sugarcane diseases. The diagonal entries representing correct predictions consistently exceed 98%, indicating very high class-wise precision and recall. Only a minimal number of off-diagonal entries are observed, indicating very few misclassifications.

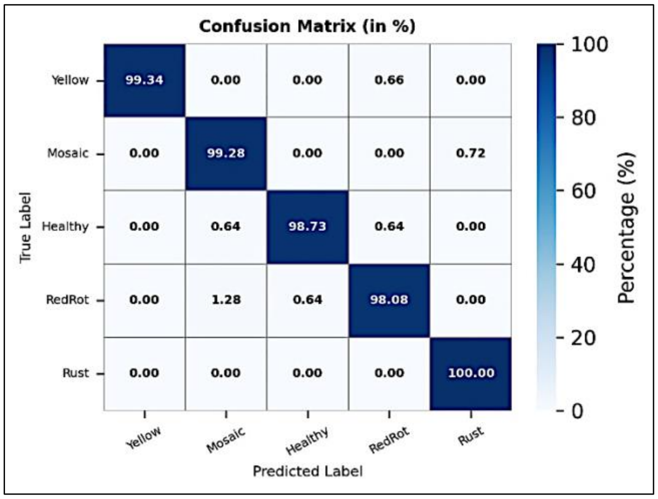

Figure 6. Confusion Matrix of the Proposed Model

C. Performance of All Applied Models

The proposed CNN achieves excellent performance in sugarcane disease classification, combining minimal architectural complexity with exceptionally high predictive accuracy. CNN's better performance over transfer learning models is not limited to predictive accuracy. It also exceeds them in stability, speed of convergence and ease of deployment. This combination of a compact yet optimized network architecture, balanced class-wise performance, almost no overfitting, and real-time inference capability indicates that a task-specific CNN can match or outperform more sophisticated transfer learning methods and is therefore better suited for scalable, real-time sugarcane disease monitoring systems. Comparative Performance Analysis of all selected models are given in Figure 7.

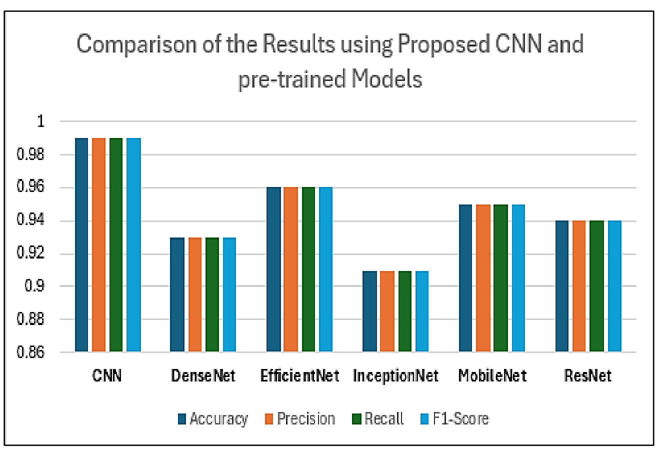

Figure 7. Comparative Performance Analysis of CNN, DenseNet, EfficientNet, InceptionNet, MobileNet, and ResNet using Accuracy, Precision, Recall, and F1-Score

The classification performance of DL models evaluated is presented in Comparative Performance of the evaluated DL models as presented in fig 7 with Accuracy, Precision, Recall and F1-Score. The proposed CNN with customization consistently achieved the highest accuracy of 99% and the highest precision, recall and F1 scores of 99%. EfficientNet and MobileNet were next with 96% and 95% accuracy respectively followed by ResNet, DenseNet, and InceptionNet, which gave comparatively lesser results. The outcomes indicate that the proposed CNN has performed well for proper classification of the five types of sugarcane diseases with its light weight design suitable for precision agriculture in real world.

VI. Conclusion

In this paper, present an automated sugarcane leaf disease classification system using 1762 images belonging to five classes: yellow disease, Mosaic disease, Healthy leaf, Red Rot and Rust. The proposed custom CNN achieved the best results among all tested networks with significantly high precision, recall and F1-scores as well, which all together indicate the robustness and strong generalization of the proposed model for both inter-subject and intra-subject scenarios (even between very similar diseases). Following EfficientNet and MobileNet were 96% and 95% respectively which also performed well in terms of construct complexity and time consumption and could be considered as candidates for case with limited resources. ResNet and DenseNet achieved 94% accuracy and 93% respectively, suggesting good, but somewhat less accurate results and over-fitting in some instances; InceptionNet achieved 91% accuracy, which was acceptable but not as good, and did not overfit in any instances. Based on the results, it can be concluded that the learning-based methods are suitable for automated detection of sugarcane disease which can be considered as Fig. 7. Future work will involve further diversity of datasets and the implementation of explainable AI techniques for real-world applications.

Data Availability

The dataset is freely available at: https://www.kaggle.com/datasets/nirmalsankalana/sugarcane-leaf-disease-dataset [34]

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