Sugercane Leaf Disease Detection

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***Abstract*—Sugarcane disease poses a substantial risk to crop production, necessitating proactive detection measures. This research harnesses the power of Convolutional Neural Networks (CNN) to accurately identify sugarcane diseases. Training on a comprehensive dataset of 6,725 images, including both healthy and diseased sugarcane leaves, the models achieved an impressive maximum accuracy rate of 93.01%. Among the three CNN architectures employed—DenseNet121, MobileNetV2, and Custom CNN—DenseNet121 emerged as the top performer, showcasing its potential in disease recognition.To facilitate practical implementation, an Android application interface was developed, enabling farmers to easily capture or upload images of sugarcane leaves using their smartphones. The application processes the images on a server, providing timely disease predictions directly to the farmer's device. This streamlined approach empowers farmers to swiftly intervene and mitigate potential crop losses. By integrating advanced machine learning techniques with user-friendly mobile technology, this solution offers a promising avenue for enhancing crop productivity, promoting agricultural sustainability, and bolstering food security in sugarcane-producing regions worldwide.**

***Index Terms*—sugarcane leaf disease recognition, image classification, convolutional neural network**

I. Introduction

Sugarcane is a crucial renewable agricultural resource with extensive applications, including the production of sugar, biofuel, fiber, and fertilizer. The processing of sugarcane juice results in various products such as white sugar, brown sugar (Khandsari), Jaggery (Gur), and ethanol. Additionally, byproducts like bagasse and molasses play significant roles in the paper industry and alcohol 1 production, respectively. Despite its economic importance, sugarcane cultivation faces considerable challenges due to various diseases that not only reduce yield but also deteriorate the quality of sugarcane varieties. Effective disease management in sugarcane cultivation is vital to mitigate these impacts. Diseases such as rust spots, yellow spots, and ring spots are among the most damaging, identifiable by distinct spots on the leaves. Although farmers can detect these diseases through visual inspection, this method is often inconsistent and prone to errors. An automated system for disease detection offers a more reliable and precise solution. Traditional automated systems rely on high-definition digital images to identify diseases, but such resources are not always accessible to all farmers. To address this challenge, we propose an innovative detection and classification system utilizing a hidden Markov model and an anisotropic diffusion algorithm. This system allows users to capture images using a mobile camera or select images from their gallery, making it both practical and accessible. Our proposed system aims to provide a robust and user-friendly tool for the early detection of sugarcane diseases, thereby enhancing disease management practices. By ensuring timely intervention, this system can help maintain high crop productivity and sustain the economic viability of sugarcane cultivation in major producing countries.

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A. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) are pivotal in deep learning, particularly for image recognition. They mimic the human visual cortex, extracting hierarchical visual features from raw data. CNNs consist of convolutional, pooling, and fully connected layers, enabling them to automatically learn complex patterns from data without handcrafted feature engineering. This adaptability makes them ideal for tasks with large datasets. CNNs have widespread applications, including healthcare, autonomous driving, and agriculture. In agriculture, CNNs facilitate disease detection, crop monitoring, and yield prediction, revolutionizing farming practices. This paper provides an overview of CNNs, emphasizing their role in transforming agriculture through image-based tasks.

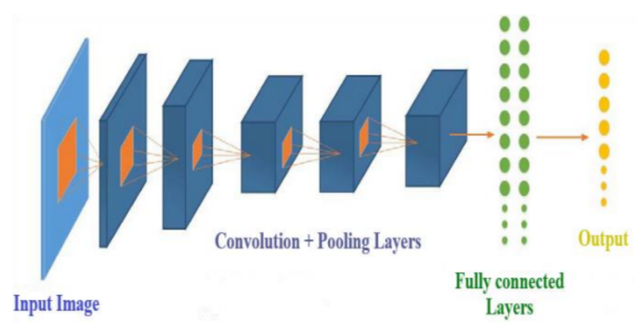

Fig. 1. CNN Architecture.

In this study, we focus on the application of CNNs in identifying diseases in sugarcane plants based on leaf images. Specifically, we analyze three CNN architectures—MobileNetV2, DenseNet121, and Custom CNN model leveraging machine learning frameworks like Keras and OpenCV for computational support. By evaluating the performance of these architectures, DenseNet121 achieves remarkable accuracy in classifying plant diseases, reaching an impressive 93.53% accuracy on a dataset of 6,548 images.

II. Methology

The methodology for detecting sugarcane leaf diseases using deep learning involves several key steps, with a particular focus on preprocessing images to ensure the dataset's quality and uniformity. Initially, a diverse dataset of sugarcane leaf images was collected, encompassing various disease categories. The images were then resized to 224x224 pixels to match the input requirements of the deep learning model. Pixel values were normalized to a range of 0 to 1 by dividing by 255, which aids in faster and more stable convergence during training. To enhance the dataset's diversity and prevent overfitting, data augmentation techniques such as rotation, width and height shifts, shear, zoom, and both horizontal and vertical flips were applied. These preprocessing steps are crucial as they help the model generalize better by simulating variations and distortions that might occur in real-world scenarios. The prepared dataset was then used to train a MobileNetV2 model, a convolutional neural network known for its efficiency and performance in image classification tasks. By employing transfer learning and fine-tuning pre-trained weights from the ImageNet dataset, we adapted the model to our specific classification task. The model was compiled using the Adam optimizer and categorical cross-entropy loss function. Throughout the training process, early stopping and model checkpoint callbacks were utilized to prevent overfitting and save the best-performing model. The performance of the model was evaluated using accuracy, precision, recall, and F1-score metrics, demonstrating its effectiveness in accurately detecting sugarcane leaf diseases.

A. Pre-processing of Images

The preprocessing phase ensures high-quality, uniform inputs for the deep learning model. Images are resized to a standard resolution of 64x64 pixels to reduce computational complexity while preserving essential features. They are then cropped to focus on regions of interest, eliminating unnecessary background details. The images are processed to maintain and enhance the RGB color scale, which provides a richer and more detailed representation crucial for accurate disease identification. These steps optimize the dataset for training, improving the model's performance in detecting sugarcane leaf diseases.

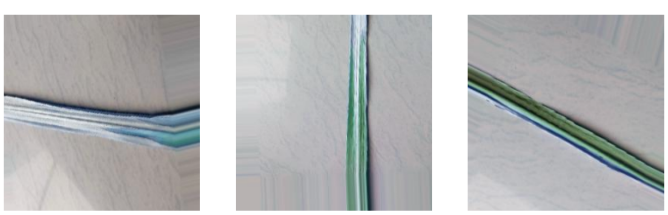

Fig. 2. Preprocessed leaf.

B. Feature Extraction

The convolutional layers of the MobileNetV2 model extract features from the 64x64 RGB images. Unlike traditional handcrafted extractors like SIFT or Gabor filters, CNNs autonomously learn feature map weights and biases through training. The Rectified Linear Unit (ReLU) activation introduces non-linearity, enhancing the model's ability to capture complex patterns. Average Pooling operations, to reduce feature map dimensions while preserving crucial information. Convolution and pooling layers together generate robust feature representations, crucial for accurately classifying sugarcane leaf diseases.

C. Flowchart

The workflow diagram illustrating the experimental design of the CNN used to predict whether a sugarcane plant is infected by analyzing leaf images is presented in Fig. 3. The various stages in the processing include the following:

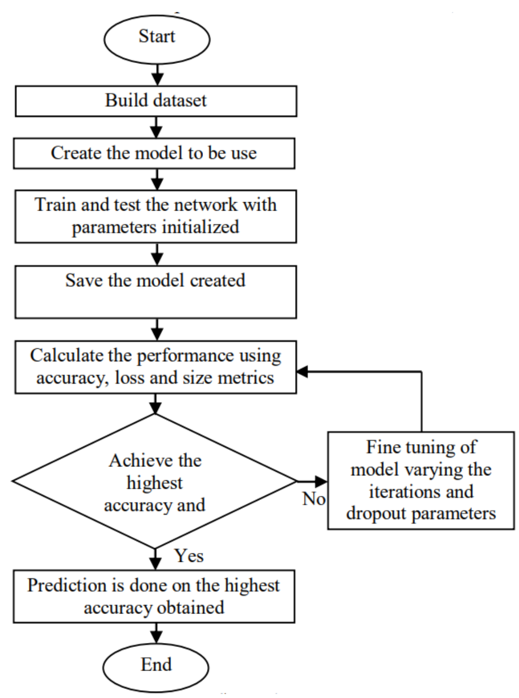

Fig. 3. Workflow diagram for prediction.

D. Classification

The architecture uses three main blocks: convolutional, activation, and Average-pooling layers, followed by fully connected layers and a softmax activation layer. Feature extraction is performed using the convolutional and pooling layers. The classification of sugarcane leaves, determining if they are infected with the disease or not, is done in the final layers.

E. Compile and Train the Model

The dataset is divided into a training set and a testing set in a ratio of 80:20, with 80% of the data used for training and 20% used for testing.

III. EXPERIMENTAL SETTINGS

The dataset comprised three primary categories: diseased, dry, and healthy. Within the diseased category, there were 9 subclasses, resulting in a total of 11 classes. To ensure a balanced dataset, data augmentation techniques were employed, including random rotations by 25 degrees, horizontal flipping, and vertical and horizontal shifting of images. This approach adjusted the number of images in each class, scaling them up or down to 800 images per class.

The model training utilized the Adam optimizer with categorical cross-entropy as the loss function. Training was conducted over 50 epochs with a batch size of 32 across three different models. To further enhance model accuracy, training continued for a total of 220 epochs, with an early stopping mechanism in place to halt the training process once optimal accuracy was achieved.

IV. RESULTS AND ANALYSIS

In the evaluation of models for classifying sugarcane leaf diseases, the DenseNet121 model emerged as the most effective, achieving a remarkable validation accuracy of 93.01% after 50 epochs of training. This performance underscores its robust capability in disease identification. Close on its heels, the MobileNetV2 model demonstrated a strong performance with an accuracy of 86.76% while the Custom CNN model achieved a commendable 83%. Figures 4 and 5 illustrate the accuracy and loss metrics for the MobileNetV2 and DenseNet121 models, respectively, highlighting their training progression and validation performance. Meanwhile, Figure 6 presents the accuracy and loss trends for the Custom CNN model, offering insights into its learning dynamics over the training period. These visualizations and results collectively highlight the efficacy of all three models in accurately classifying sugarcane leaf diseases, with DenseNet121 yielding the highest validation accuracy.

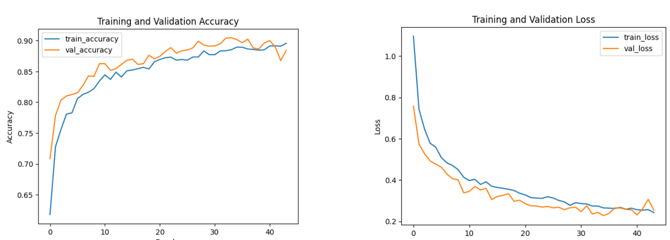

Fig. 4. MobileNetV2 model plot of accuracy and loss against epochs

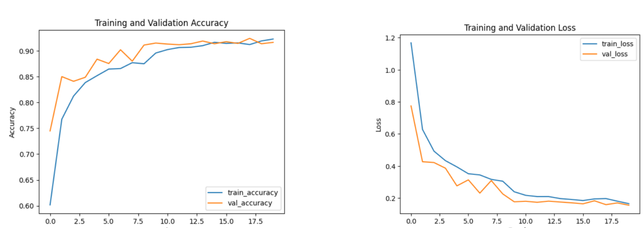

Fig. 5. DenseNet121 model plot of accuracy and loss against epochs

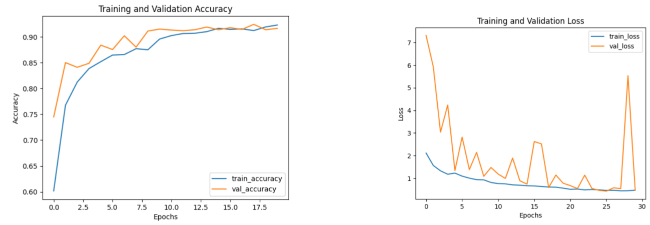

Fig. 6. Custom CNN model plot of accuracy and loss against epochs

A. *Confussion Mattrix*

A confusion matrix is a powerful tool for evaluating the performance of a classification model. It provides a detailed breakdown of the model's predictions compared to the actual labels. It provides insight into not just the overall accuracy but also the performance of each class individually. This allows for a more granular understanding of where the model performs well and where it needs improvement.

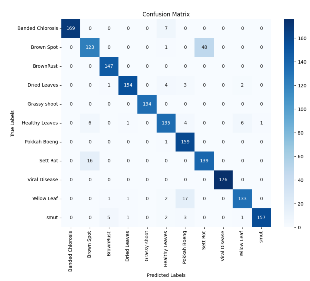

Fig. 7. DenseNet121 Confusion Matrix Plot

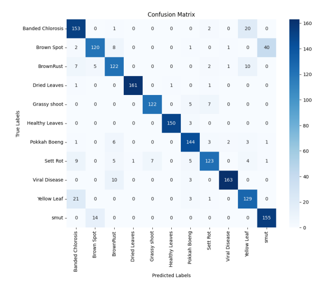

Fig. 8. MobileNetV2 Confusion Matrix Plot

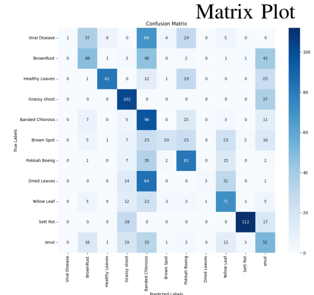

Fig. 9. Custom CNN Confusion Matrix Plot

Observations

1) Overall Performance:
   - DenseNet121 achieved higher overall accuracy compared to MobileNetV2 and Custom CNN, with fewer misclassifications across most classes.
2) Class-Specific Performance:
   - **DenseNet121** shows better performance in identifying "Sett Rot," "Healthy Leaves," "Yellow Leaf" and "Viral Disease" with higher correct predictions.
   - **MobileNetV2** has more misclassifications, particularly in "BrownRust" and "Yellow Leaf" but still less than Custom CNN.

- **Custom CNN** Better performance in classes like ”Sett Rot” and ”Grassy Shoot”.Struggles with ”Viral Disease” and ”Yellow Leaf” where there are significant misclassifications.

3) Misclassification Patterns:
   - **DenseNet121** ”Yellow Leaf” is occasionally confused with ”Healthy Leaves” and ”Viral Disease”. Few misclassifications across other classes.
   - **MobileNetV2** ”BrownRust” is sometimes misclassified as ”Brown Spot”. ”Yellow Leaf” also shows some confusion with ”Healthy Leaves” and ”Viral Disease”.
   - **Custom CNN** ”Viral Disease” is often misclassified as ”Grassy Shoot” and ”Dried Leaves”. ”Healthy Leaves” are often misclassified as ”Yellow Leaf”.
4) Consistency::
   - DenseNet121 demonstrates more consistent predictions, reflected by fewer off-diagonal elements in its confusion matrix.

B. *Classification*

Classification is a type of supervised learning in machine learning where the goal is to predict the categorical class labels of new instances based on past observations. Each instance is assigned to one of two or more predefined classes. We use classification in various fields due to its ability to make predictions about the category to which new data points belong, assisting in decision-making by providing data-driven insights.

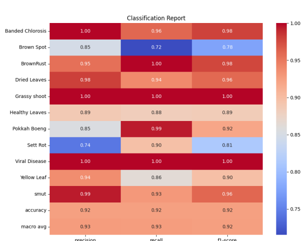

Fig. 10. DenseNet121 classification ploting

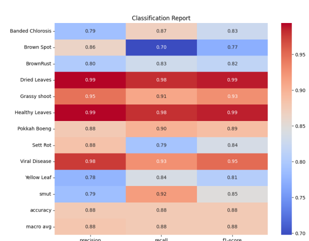

Fig. 11. MobileNetV2 classification ploting

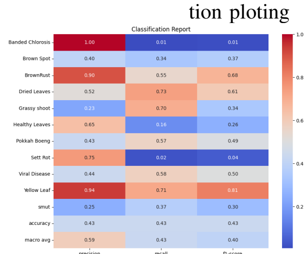

Fig. 12. Custom CNN classification ploting

1) Overall Performance:
   - **DenseNet121** exhibits the highest overall performance with accuracy, precision, recall, and F1-score all above 0.90.
   - **MobileNetV2** also performs well but slightly lower than DenseNet121 in all metrics.
   - **Custom CNN** has significantly lower overall performance compared to the other two models, with metrics around the 0.40 mark.
2) Class-Specific Performance:
   - **DenseNet121:** Performs exceptionally well across most classes, especially ”BrownRust” (Recall: 1.00, F1-Score: 0.98), ”Grassy shoot” (Precision, Recall, F1-Score all 1.00), and ”Viral Disease” (Precision, Recall, F1-Score all 1.00).
     Slightly lower performance on ”Sett Rot” (Precision: 0.74, Recall: 0.90, F1-Score: 0.81).
   - **MobileNetV2:** High performance in most classes with notable scores for ”Dried Leaves” (Precision: 0.99, Recall: 0.98, F1-Score: 0.99) and ”Healthy Leaves” (Precision: 0.99, Recall: 0.98, F1-Score: 0.99).
     Lower performance on ”Yellow Leaf” (Precision: 0.78, Recall: 0.84, F1-Score: 0.81) and ”Sett Rot” (Precision: 0.88, Recall: 0.79, F1-Score: 0.84).
   - **Custom CNN:** Struggles particularly with ”Banded Chlorosis” (Recall: 0.01, F1-Score: 0.01) and ”Sett Rot” (Recall: 0.02, F1-Score: 0.04).
     Performs relatively well with ”BrownRust” (Precision: 0.90, Recall: 0.55, F1-Score: 0.68) and ”Yellow Leaf” (Precision: 0.94, Recall: 0.71, F1-Score: 0.81).
3) Consistency::
   - DenseNet121 demonstrates more consistent performance across most classes. It has fewer significant drops in performance compared to MobileNetV2 and Custom CNN, which shows some variability with notably lower performance in certain classes such as Viral Disease and BrownRust.
   - The Custom CNN has less consistency, with lower scores in precision, recall, and F1-score across many classes.

Observations DenseNet121 outperforms MobileNetV2 and Custom CNN in overall accuracy and consistency, with higher recall and F1 scores, indicating better generalization and robustness. However, MobileNetV2 excels in specific classes, achieving perfect scores in Brown Spot and Smut. The choice between models depends on application needs: DenseNet121 is preferable for consistent performance across classes, while MobileNetV2 is better for high precision in specific classes. The Custom CNN, while showing potential in classes like ”Grassy Shoot,” generally underperforms compared to the other two models. Future work for Custom CNN should focus on improving its robustness and overall accuracy, potentially by exploring different architectures, data augmentation techniques, and hyperparameter tuning.

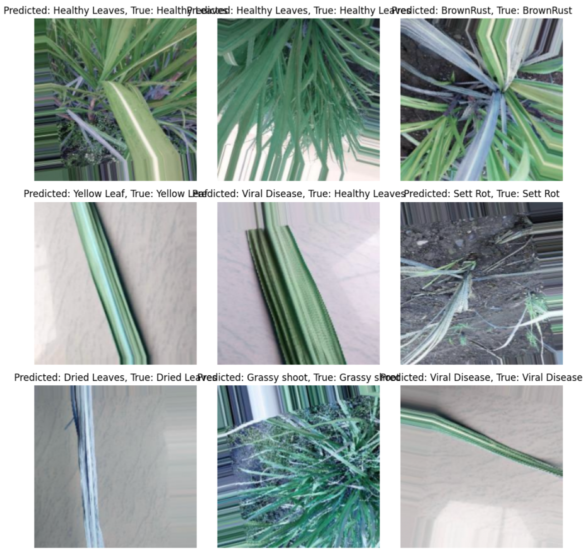

Fig. 13. Shows the DenseNet121 model evaluation result of an image recognized 93.01% accuracy

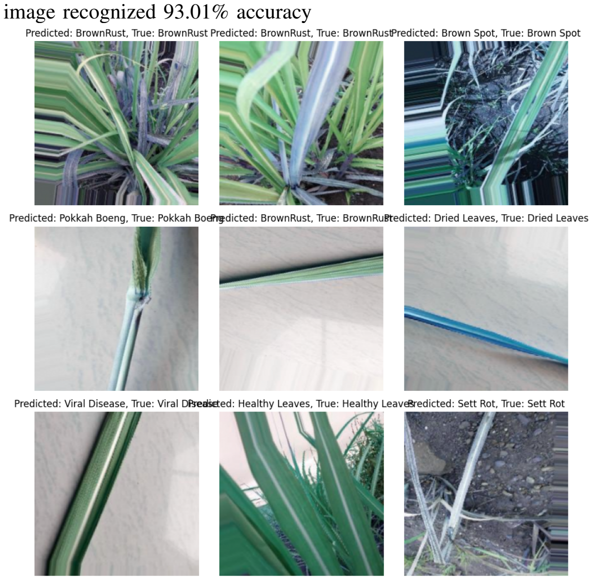

Fig. 14. Shows the MobileNetV2 model evaluation result of an image recognized 86.76% accuracy

Fig. 15. Shows the Custom CNN model evaluation result of an image recognized 83% accuracy

V. Conclusion

The implementation of deep learning techniques, specifically convolutional neural networks (CNNs), in the detection and classification of sugarcane leaf diseases has shown promising results. Through the comparison of three CNN architectures—DenseNet121, MobileNetV2, and Custom CNN—on a dataset comprising 6,725 images, DenseNet121 emerged as the top performer, achieving an impressive accuracy of 93.01%. This outperformance highlights its efficacy in accurately identifying various sugarcane leaf diseases compared to the other models.

Moreover, the proposed approach not only aids in disease detection but also streamlines the process for farmers, reducing the time and effort required. The application, developed using Streamlit, allows for easy image input, resizing to 224x224 pixels, and standardization before feeding it into the model for prediction using Softmax. Additionally, the application provides prevention and treatment methodologies, and it can be used online or offline, catering to the diverse needs and technological access of farmers.

Future enhancements could involve experimenting with different models, adjusting learning rates, and exploring newer architectures to further improve accuracy. Moreover, expanding the dataset and incorporating support for multiple languages would enhance accessibility and usability for farmers worldwide. Additionally, integrating features such as contact details for nearby agricultural offices could offer further assistance and guidance to farmers in need.

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