Hybrid Deep Learning Framework for Real-Time Sugarcane Disease Detection

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Abstract. Sugarcane is a vital crop in global agriculture, yet it is highly susceptible to diseases that can drastically affect crop productivity and disrupt agricultural planning. Traditional methods for identifying and diagnosing diseases in sugarcane leaves rely heavily on manual inspections, which are labor-intensive, slow, and prone to human error. To overcome these limitations, this study introduces a dynamic, real-time disease detection framework that integrates convolutional neural networks (CNNs) with Gated Recurrent Units (GRUs). Using a publicly available dataset from Kaggle containing a diverse range of sugarcane disease images, this hybrid model architecture was trained and evaluated to provide accurate and efficient disease classification.

Three hybrid models—DenseNet201 + GRU, Inception v3 + GRU and InceptionResNetv2 + GRU— were implemented and compared. The DenseNet201 + GRU model achieved the highest performance, with an accuracy of 96.49%, precision of 96.53%, recall of 96.49% and F1-score of 96.49%. These results emphasize the advantages of combining CNNs and GRUs: CNNs excel at extracting spatial features from complex disease patterns in leaf images, while GRUs effectively capture sequential dependencies, enhancing the model's ability to classify diseases with high precision. The proposed hybrid approach provides a scalable and reliable solution for automated sugarcane disease detection. By incorporating this system into disease management workflows, agricultural stakeholders gain access to timely and accurate diagnostic insights, enabling proactive measures to reduce crop loss and enhance overall yield. This framework exemplifies the potential of advanced deep learning architectures in precision agriculture, offering a sustainable and practical tool for improving disease management in sugarcane cultivation.

Keywords: Sugarcane Plant Disease (SPD), Deep learning(DL) , Machine Learning(ML) , Convolutional Neural Networks(CNNs) , Gated Recurrent Unit (GRU), Precision Agriculture.

1 Introduction

Sugarcane, a globally significant crop, is fundamental to various industries, from sugar production to biofuels. However, it is susceptible to a range of diseases that can drastically impact crop health, yield, and, consequently, the economic stability of regions dependent on its cultivation. In areas with extensive sugarcane farming, particularly in developing economies, disease outbreaks can lead to major production losses and financial setbacks for local communities and economies. Diseases in sugarcane are often difficult to detect early because many display similar visual symptoms, such as leaf discoloration, spot formation, or wilting, which can easily be misidentified or overlooked. Traditional disease detection relies heavily on manual inspections conducted by agricultural experts, which are time-consuming, labour-intensive, and require specialised knowledge. Moreover, the geographic vastness of sugarcane plantations further complicates timely inspections, leaving fields vulnerable to disease progression before effective intervention can take place. These manual inspections, while effective for small areas, are neither scalable nor efficient for the large-scale monitoring required in modern agriculture. As a result, farmers may not receive the necessary insights in time to take preventive or remedial actions, leading to reduced crop yields, higher production costs, and increased risks of disease spread across regions. Given these challenges, there is an urgent need for automated, real-time disease detection solutions that can monitor crop health continuously, enabling prompt responses to disease threats, safeguarding agricultural productivity, and promoting sustainable farming practices.

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addition to the CNN framework. By combining these two architectures, the hybrid CNN-GRU model is able to accurately capture both spatial and sequential patterns in sugarcane disease data, leading to more robust and precise disease detection. We used a publicly available dataset from Kaggle containing 6 labelled classes of sugarcane disease images, ensuring that the model was trained on a diverse set of disease conditions. Three hybrid models—DenseNet201 + GRU, Inception v3 + GRU and InceptionResNetv2 + GRU—were implemented and evaluated in this study. Among these, DenseNet201 + GRU achieved the highest classification performance, with an accuracy of 96.49% and strong metrics across precision, recall, and F1-score, demonstrating its effectiveness as a real-time disease detection tool. The novel methodology proposed in this research not only enhances disease detection accuracy but also offers a practical application in the agricultural sector. By incorporating this hybrid model into regular disease monitoring systems, farmers can gain insights into crop health with high precision and on a continuous basis. This capability is critical for decision-making at the field level, enabling farmers to detect disease onset early and respond promptly with targeted interventions. The scalable design of the model also means that it can be adapted to monitor multiple large fields at once, methods. CNNs are widely recognized for their ability to capture and process spatial features, making them highly effective at identifying complex patterns in visual data, such as those in diseased sugarcane leaves. However, static models alone may lack the ability to capture sequential or contextual information that could enhance classification accuracy. GRUs excel at processing sequential data and identifying temporal dependencies, making them an ideal making it an invaluable tool for both individual farmers and large-scale agricultural operations. Additionally, this framework holds potential for integration into automated agricultural platforms or drones, which could monitor crops in real-time and send alerts to farm managers. With timely and actionable insights, farmers can reduce the risk of disease-related crop loss, optimise resource use, and enhance overall productivity, ultimately contributing to the sustainability and economic resilience of sugarcane agriculture.

The organisation of the remaining paper is as follows. Section 2 reviews related work and highlights the limitations of existing approaches. Section 3 presents the proposed methodology, detailing the structure of the hybrid CNN- GRU models and explaining the experimental setup. Section 4 offers a comprehensive analysis of results and model performance across various metrics. Finally, Section 5 concludes the study with the results obtained.

2 Related Work

Recent developments in the field of plant disease detection have harnessed advancements in DL, specifically targeting crop diseases that threaten yield. Sugarcane, as a vital cash crop, has been subject to various ML techniques aimed at early and accurate disease detection. Militante et al. [1] implemented DL models for sugarcane disease recognition, highlighting that CNN models such as VGGNet achieved promising accuracy in distinguishing diseased from healthy sugarcane leaves. Similarly, Kumar and Tiwari [2] proposed image processing techniques specifically for detecting sugarcane diseases, using various preprocessing methods to improve classification accuracy. Their approach showcased the potential of segmentation and feature extraction in isolating symptomatic areas for analysis. Building on this, Thilagavathi et al. [3] developed a detection framework that used image processing to identify disease symptoms in sugarcane leaves. Their study introduced a novel way of integrating texture analysis, which increased detection precision. Srivastava et al. [4] applied a DL framework with enhanced feature extraction to boost disease detection capabilities, finding significant improvements with CNN architectures tailored for sugarcane datasets. Hossain et al. [5] focused on the red rot disease, examining detection and management strategies for Colletotrichum falcatum through extensive analysis of disease spread and control mechanisms. Additionally, Malik et al. [6] explored DL for recognizing sugarcane crop diseases, underscoring the efficiency of pretrained CNN models. Lu et al. [7] conducted a comprehensive study on sugarcane mosaic disease, offering insights into its characteristics, identification, and control using ML techniques. Nguyen et al. [8] applied hyperspectral imaging and DL for early viral disease detection in plants, which has promising applications for sugarcane due to its susceptibility to multiple viral infections. Remote sensing has also played a crucial role in sugarcane disease detection. Som-Ard et al. [9] reviewed the potential of remote sensing for sugarcane cultivation, discussing its application in crop health monitoring and stress detection. This review highlighted the promise of using multispectral and hyperspectral data in conjunction with ML. Bhuiyan et al. [10] reviewed sugarcane smut disease, emphasizing that early detection is key in managing outbreaks. Rajput et al. [11] discussed current knowledge on managing sugarcane smut, indicating a shift toward more predictive, image-based diagnostics for disease monitoring. Hemalatha et al. [12] applied DL models to detect sugarcane leaf diseases, advocating for automated solutions in agriculture. Amarasingam et al. [13] utilized UAV-derived RGB imagery and DL models for detecting white leaf disease in sugarcane, showcasing how aerial imagery can facilitate large-scale monitoring. Tamilvizhi et al. [14] proposed a novel DL model based on Quantum Behaved Particle Swarm Optimization (QPSO), combined with transfer learning, to classify sugarcane leaf diseases, achieving notable results in classification accuracy. Murugeswari et al. [15] developed a faster R- CNN model with an Android application, demonstrating the feasibility of mobile platforms for real-time disease diagnostics. Huang et al. [16] evaluated data augmentation techniques to improve recognition of sugarcane leaf spot disease, demonstrating that augmented datasets yield higher model accuracy and robustness. Sharma and Kukreja [17] integrated segmentation with multi-layer perceptrons for multi-class classification of sugarcane diseases, which proved effective for diverse symptom manifestations. For sustainable agricultural practices, Atheeswaran et al. [18] devised an expert system for smart farming that diagnoses sugarcane diseases using ML, optimizing resource use and reducing response times for intervention. Daphal and Koli [19] conducted a comparative study of ensemble DL techniques, evaluating the effectiveness of transfer learning to enhance sugarcane disease classification. Banerjee et al. [20] developed an intelligent framework for detecting and classifying the severity of Grassy Shoot Disease in sugarcane, leveraging AI to accurately assess disease intensity for targeted treatments. Tanwar et al. [21] proposed a DL approach for predicting red rot disease in sugarcane, emphasizing the value of CNN-based architectures in disease prediction. Li et al. [22] investigated the role of technological innovations in disease detection and management for sugarcane planting, underscoring how sensor- based approaches are advancing disease diagnostics. Rajput et al. [23] implemented a hybrid model combining CNNs and SVM for sugarcane leaf disease classification, achieving high classification accuracy by fusing features extracted from CNNs with SVM classifiers. Yead et al. [24] employed DL techniques for sugarcane leaf disease classification, emphasizing the efficiency of multi-class classification models for this purpose. Bao et al. [25] advanced early detection techniques for sugarcane smut and mosaic diseases, combining hyperspectral imaging with spectral-spatial attention mechanisms to enhance model accuracy. Finally, a Kaggle dataset on sugarcane diseases [26] has served as a valuable resource for training and validating DL models, providing researchers with a diverse range of symptomatic images for sugarcane disease classification.

3 Proposed Methodology

The proposed methodology (Fig 1.) for detecting sugarcane diseases involves a hybrid model that integrates CNNs with GRUs to improve classification accuracy. Initially, images of sugarcane leaves are processed through the CNN layers, which are responsible for identifying and extracting critical spatial features and patterns in the images. These features are then passed through pooling layers to reduce data complexity while preserving essential information. The refined feature set is subsequently fed into the GRU layer, which captures temporal relationships within the data, enhancing the model's ability to recognize sequential patterns. Finally, the output is passed to a fully connected layer, which categorises the image based on disease type. This approach combines CNN’s strength in spatial feature extraction with GRU’s capability for sequential analysis, resulting in an efficient and accurate disease detection framework.

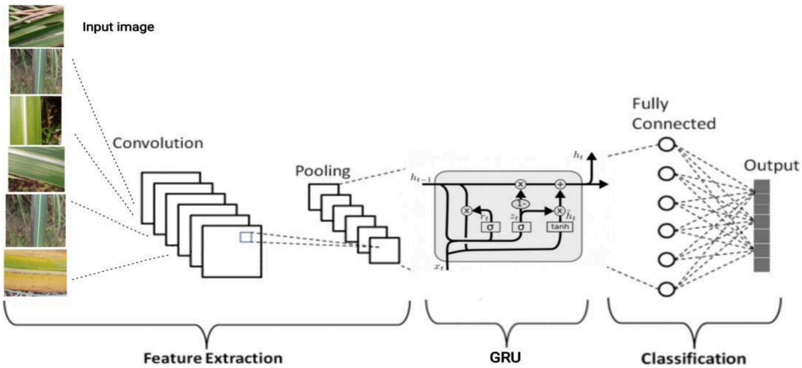

Fig 1. Proposed Methodology

3.1 DenseNet201 + GRU

The proposed approach for real-time sugarcane disease detection integrates DenseNet201 and GRU in a combined architecture to capture both spatial and temporal patterns effectively. In this setup, sugarcane leaf images are preprocessed and resized to meet the input specifications for DenseNet201. This model then serves as a feature extractor, leveraging its dense block structure to identify detailed spatial features that reveal unique disease characteristics. These extracted features are subsequently transformed into a 1D vector, which retains critical spatial information necessary for classification. To account for sequential patterns, the spatial feature vectors are reshaped and passed to a GRU layer. The GRU’s gated mechanism allows it to effectively learn temporal dependencies, emphasizing disease-relevant patterns while minimizing irrelevant details. Finally, a fully connected layer translates these fused features into distinct disease classes, with a softmax activation function providing probabilistic outputs for each category. Model training is achieved using categorical cross-entropy loss optimized by the Adam algorithm. By combining DenseNet’s spatial insights with GRU’s temporal learning, this architecture enables rapid and accurate disease detection, offering timely support for sugarcane disease management efforts. The model summary of the proposed model is in Fig 2.

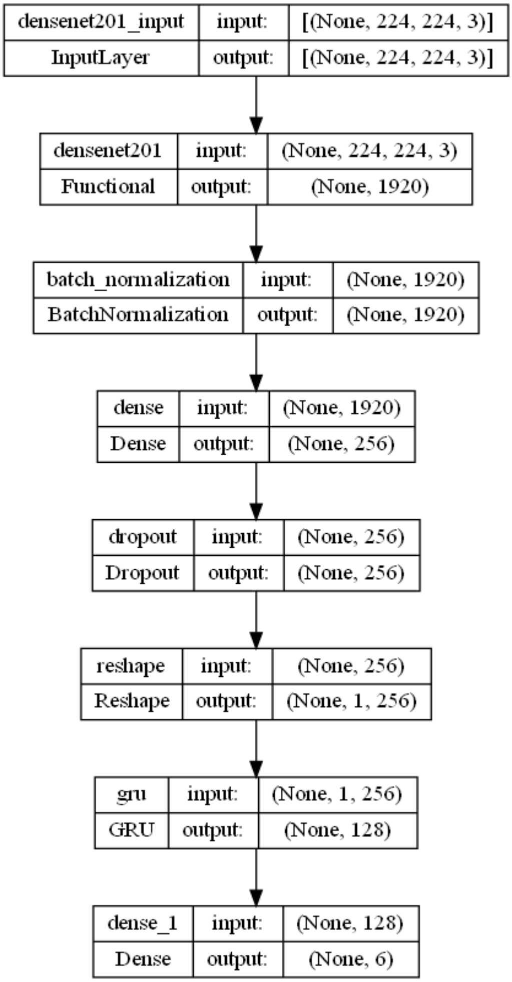

Fig 2. Model summary using DenseNet201 + GRU

3.2 Inception v3 + GRU

The proposed methodology utilizes a hybrid model that synergizes Inception v3 and GRU to enhance real-time detection of diseases in sugarcane by merging spatial and temporal features. The process began with preprocessing the sugarcane image dataset, where images were resized and pixel values were normalized to improve model efficiency. We employed Inception v3, a CNN previously trained on ImageNet, as a feature extractor. By removing the top layers, we derived 2048-dimensional feature vectors for each input frame, effectively capturing critical spatial patterns associated with disease manifestations. These feature vectors were subsequently processed by a GRU layer, which excels in handling sequential data, allowing the model to learn temporal dependencies and monitor disease progression over consecutive frames. Classification was conducted using a dense output layer that provided probabilities for different disease classes. Throughout training, we fine-tuned the weights of both Inception v3 and GRU with categorical cross-entropy loss and the Adam optimizer to maximize classification accuracy. Additionally, we established a real-time inference pipeline for dynamic frame processing and classification, enabling timely responses in sugarcane crop management. This approach successfully leverages the spatial strengths of Inception v3 alongside the temporal learning capabilities of GRU, resulting in an effective system for real-time disease detection. The model summary of the proposed model is in Fig 3.

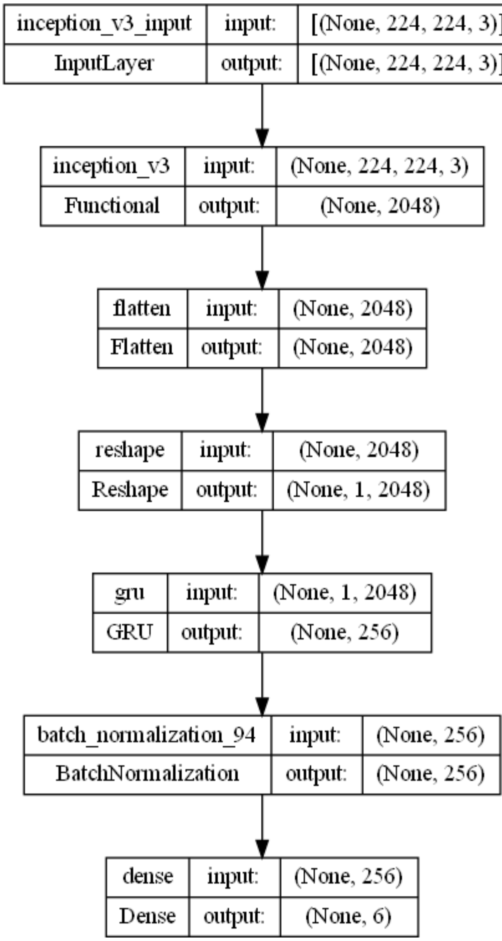

Fig 3. Model Summary using Inception v3 + GRU

3.3 InceptionResNetV2 + GRU

The methodology designed for real-time sugarcane disease detection leverages a hybrid InceptionResNetV2 + GRU model to improve feature extraction and classification precision. Initially, sugarcane leaf images are preprocessed and resized to meet the input specifications of the InceptionResNetV2 architecture. This pre-trained network, equipped with advanced inception modules, captures a diverse range of spatial features at multiple scales within each image. A global average pooling layer then compresses these features into a unified vector, offering a compact representation of key image characteristics. These feature vectors are subsequently processed by a GRU layer, where each image's features are treated as sequential data to uncover patterns that differentiate disease types. This temporal analysis enriches the model's capability to capture subtle variations in feature sequences relevant to disease classification. The GRU output is fed into a dense layer with softmax activation to classify the image into specific disease categories. To optimize performance, the model uses a categorical cross-entropy loss function with the Adam optimizer, enabling efficient convergence during training. By combining InceptionResNetV2's spatial feature extraction with GRU's sequential learning, this model achieves enhanced accuracy in detecting sugarcane diseases in real-time, adapting effectively to field conditions. The model summary of the proposed model is in Fig 4.

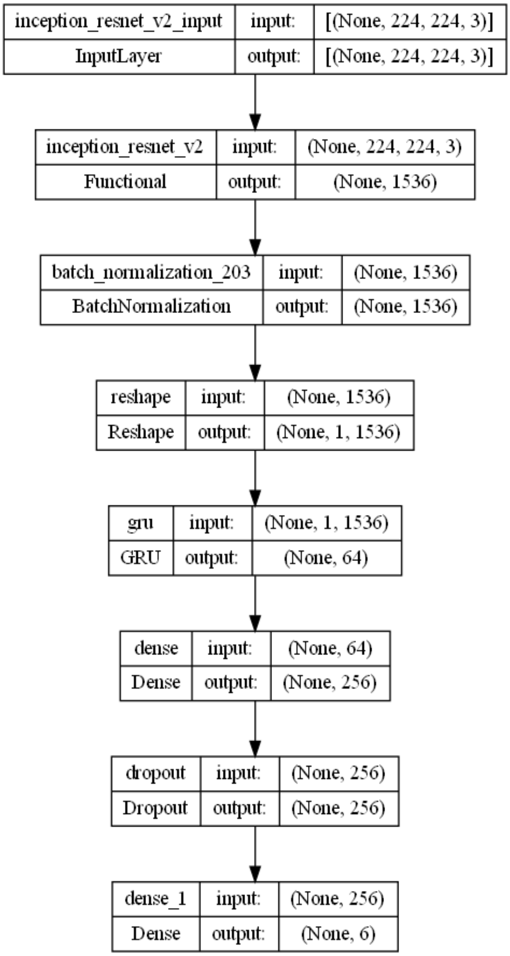

Fig 4. Model summary using InceptionResNetV2 + GRU

3.4 Dataset Description

The Sugarcane Plant Diseases Dataset comprises 19,926 images of sugarcane leaves, organized into six classes representing both healthy and diseased conditions. Each class corresponds to a distinct leaf health status: Healthy, Bacterial Blight, Mosaic Disease, Red Rot, Rust, and Yellow Disease. The Bacterial Blight class includes leaves with necrotic lesions, while the Mosaic Disease class displays characteristic mosaic-like discoloration. Red Rot is represented by leaf samples exhibiting reddened and decayed tissue, and Rust disease is identified by brown to orange fungal spots. The Yellow Disease class consists of leaves showing chlorosis and yellowing.This well- balanced dataset offers substantial training value for machine learning applications focused on automated disease detection and plant health monitoring in sugarcane agriculture. The sample dataset image is given in Fig 5.

Fig 5. Sample Dataset Image

4 Results Analysis

The Sugarcane Disease detection models were implemented in a Jupiter environment with a hardware configuration featuring an AMD Ryzen 7 5800H processor boasting 8 cores, 16 GB of RAM for efficient memory handling, and a storage setup comprising a 256 GB SSD for quick data access and a 1 TB HDD for ample storage capacity. The graphics processing unit (GPU) utilized for computational tasks was the Nvidia GeForce RTX 3060. Meticulous evaluation of Sugarcane Disease detection models across various classifiers, as depicted in table 1:

Table 1: Results based on Sugarcane Leaf Disease Dataset

Classifier	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
DenseNet201 + GRU	96.49	96.53	96.49	96.49
Inception v3 + GRU	94.78	94.81	94.78	94.78
InceptionResNetv2 + GRU	95.18	95.23	95.18	95.17

The results of our proposed hybrid models underscore the effectiveness of combining CNN and GRU architectures for accurate sugarcane disease detection. Among the models tested, DenseNet201 + GRU emerged as the best performing model, achieving an impressive accuracy of 96.49%, along with precision, recall, and F1-score values of 96.53%, 96.49%, and 96.49%, respectively. This model's high accuracy can be attributed to DenseNet201's unique architecture, which efficiently captures intricate spatial features through dense connections. These connections enable each layer to access gradients from preceding layers, preserving detailed information that enhances feature extraction, especially in complex disease patterns. Paired with the GRU, which processes sequential dependencies, DenseNet201 + GRU excels in identifying disease characteristics in real-time. The Inception v3 + GRU model, while achieving a respectable accuracy of 94.78%, precision of 94.81%, and balanced recall and F1-score of 94.78%, falls slightly behind, likely due to its reliance on a more traditional inception-based feature extraction approach, which may not capture as detailed patterns as DenseNet201. Similarly, InceptionResNetv2 + GRU performed well with an accuracy of 95.18% and similar precision, recall, and F1-score values, reflecting its robust feature extraction abilities but slightly less effectiveness than DenseNet201 in preserving intricate spatial relationships. Overall, DenseNet201 + GRU's superior performance highlights its potential as an optimal model for practical, real-time disease detection in large-scale sugarcane farming applications. The Confusion matrix of the DenseNet201 + GRU model is given in Fig 6.

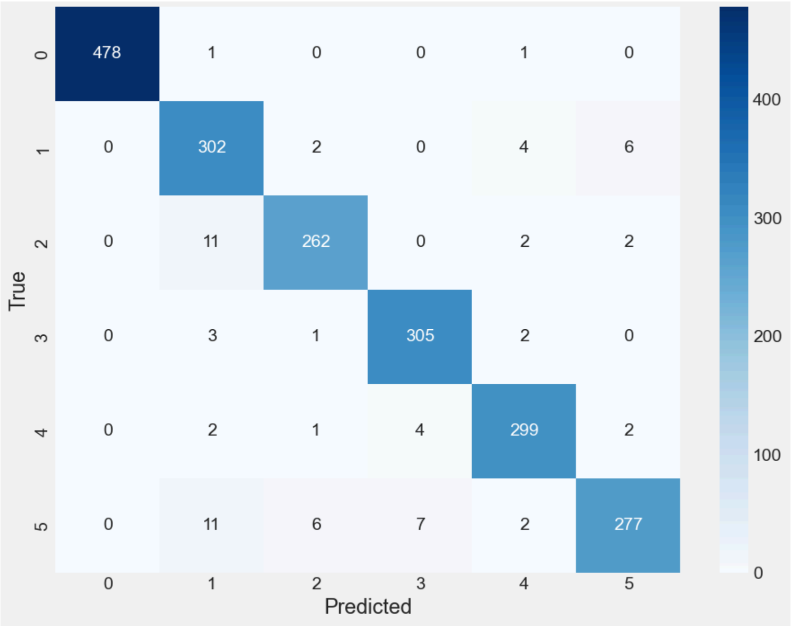

Fig 6. Confusion matrix using DenseNet201 + GRU

5 Conclusion & Future Work

In conclusion, this study presents a robust approach for real-time sugarcane disease detection by integrating CNN and GRU architectures, leveraging the unique strengths of each model component. Our hybrid models effectively capture spatial patterns and sequential dependencies in leaf images, enabling precise disease classification. Among the tested models, DenseNet201 + GRU demonstrated the highest accuracy at 96.49%, making it the most effective for recognizing diverse disease features. This approach has significant practical implications, as it can provide farmers and agricultural stakeholders with timely, accurate insights to manage disease outbreaks efficiently, reduce crop loss, and enhance overall yield. By implementing this model in real-world settings, sugarcane growers can streamline disease management, enabling better crop planning and sustainable agricultural practices.

For future work, this methodology could be further developed into a comprehensive, mobile-based application, allowing real-time disease diagnosis in the field using smartphone cameras. Expanding the dataset to include a broader variety of diseases and environmental conditions could make the model more resilient to diverse field scenarios. Additionally, integrating this system with IoT-based monitoring platforms could provide continuous surveillance and early warning systems for large-scale farming operations. This hybrid CNN-GRU framework could also be adapted for other crops, promoting broader applications in agriculture and empowering farmers with advanced AI-driven tools to safeguard crop health and productivity in the face of growing agricultural challenges.

References

[1] Militante, Sammy V., Bobby D. Gerardo, and Ruji P. Medina. "Sugarcane disease recognition using deep learning." *2019 IEEE Eurasia conference on IOT, communication and engineering (ECICE)*. IEEE, 2019.

[2] Kumar, Arpan, and Anamika Tiwari. "Detection of Sugarcane Disease and Classification using Image Processing." *Int J Res Appl Sci Eng Technol* 7.5 (2019): 2023-30.

[3] Thilagavathi, K., et al. "Detection of diseases in sugarcane using image processing techniques." *Bioscience Biotechnology Research Communications, Special Issue* 11 (2020): 109-115.

[4] Srivastava, Sakshi, et al. "A novel deep learning framework approach for sugarcane disease detection." *SN Computer Science* 1 (2020): 1-7.

[5] Hossain, Md Imam, et al. "Current and prospective strategies on detecting and managing colletotrichumfalcatum causing red rot of sugarcane." *Agronomy* 10.9 (2020): 1253.

[6] Malik, Hashmat Shadab, et al. "Disease recognition in sugarcane crop using deep learning." *Advances in Artificial Intelligence and Data Engineering: Select Proceedings of AIDE 2019*. Springer Singapore, 2021.

[7] Lu, Guilong, et al. "Sugarcane mosaic disease: Characteristics, identification and control." *Microorganisms* 9.9 (2021): 1984.

[8] Nguyen, Canh, et al. "Early detection of plant viral disease using hyperspectral imaging and deep learning." *Sensors* 21.3 (2021): 742.

[9] Som-Ard, Jaturong, et al. "Remote sensing applications in sugarcane cultivation: A review." *Remote sensing* 13.20 (2021): 4040.

[10] Bhuiyan, Shamsul A., et al. "Sugarcane smut, caused by Sporisorium scitamineum, a major disease of sugarcane: a contemporary review." *Phytopathology®* 111.11 (2021): 1905-1917.

[11] Rajput, Muhammad Aslam, et al. "Sugarcane smut: current knowledge and the way forward for management." *Journal of Fungi* 7.12 (2021): 1095.

[12] Hemalatha, N. K., et al. "Sugarcane leaf disease detection through deep learning." *Deep Learning for Sustainable Agriculture*. Academic Press, 2022. 297-323.

[13] Amarasingam, Narmilan, et al. "Detection of White Leaf Disease in Sugarcane Crops Using UAV-Derived RGB Imagery with Existing Deep Learning Models." *Remote Sensing* 14.23 (2022): 6137.

[14] Tamilvizhi, T., et al. "Quantum Behaved Particle Swarm Optimization‐Based Deep Transfer Learning Model for Sugarcane Leaf Disease Detection and Classification." *Mathematical Problems in Engineering* 2022.1 (2022): 3452413.

[15] Murugeswari, R., et al. "Automated sugarcane disease detection using faster RCNN with an android application." *2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE, 2022.

[16] Huang, Yiqi, et al. "Evaluating data augmentation effects on the recognition of sugarcane leaf spot." *Agriculture* 12.12 (2022): 1997.

[17] Sharma, Rishabh, and Vinay Kukreja. "Segmentation and multi-layer perceptron: an intelligent multi-classification model for sugarcane disease detection." *2022 International Conference on Decision Aid Sciences and Applications (DASA)*. IEEE, 2022.

[18] Atheeswaran, Athiraja, et al. "Expert system for smart farming for diagnosis of sugarcane diseases using machine learning." *Computers and Electrical Engineering* 109 (2023): 108739.

[19] Daphal, Swapnil Dadabhau, and Sanjay M. Koli. "Enhancing sugarcane disease classification with ensemble deep learning: A comparative study with transfer learning techniques." *Heliyon* 9.8 (2023).

[20] Banerjee, Deepak, et al. "An Intelligent Framework for Grassy Shoot Disease Severity Detection and Classification in Sugarcane Crop." *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*. IEEE, 2023.

[21] Tanwar, Vishesh, et al. "Red rot disease prediction in sugarcane using the deep learning approach." *2023 2nd International Conference for Innovation in Technology (INOCON)*. IEEE, 2023.

[22] Li, Ameng. "Technological Innovation in Disease Detection and Management in Sugarcane Planting." *Bioscience Methods* 15 (2024).

[23] Rajput, Kapil, et al. "Transforming Sugarcane Leaf Diseases Pathology with Convolutional Neural Networks and SVM." *2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*. IEEE, 2024.

[24] Yead, Md Asadur Rahaman, et al. "Deep Learning-Based Classification of Sugarcane Leaf Disease." *2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT)*. IEEE, 2024.

[25] Bao, Dong, et al. "Early detection of sugarcane smut and mosaic diseases via hyperspectral imaging and spectral-spatial attention deep neural networks." *Journal of Agriculture and Food Research* 18 (2024): 101369.

[26] (https://www.kaggle.com/datasets/akilesh253/sugarcane-plant-diseases-dataset/data) (Kaggle Dataset)