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# A Comprehensive Review of Machine Learning and Deep Learning Models for Sugarcane Disease Detection

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***Abstract*—The agricultural sector plays a pivotal role in global economies, with sugarcane being a significant cash crop in many countries. However, sugarcane production is often severely impacted by various diseases, leading to substantial economic losses. In this paper we provides a comprehensive review of current advancements in machine learning (ML) and deep learning (DL) methodologies applied to the detection and diagnosis of sugarcane diseases. We thoroughly investigate a wide range of ML and DL algorithms, from traditional classifiers like Support Vector Machines (SVM) and Random Forest (RF) to Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Our evaluation covers the important components of data gathering, preprocessing, feature extraction, and model tuning, providing insights into the strengths and limits of each method. This survey aims to showcase the potential of advanced ML and DL models in transforming sugarcane disease prediction techniques. Our survey paper emphasizes the importance of interdisciplinary collaboration and the development of strong, scalable solutions to the problems posed by sugarcane diseases.**

***Index Terms*— Sugarcane Disease Detection, Machine Learning, Deep Learning, Convolutional Neural Networks.**

## I. INTRODUCTION

Sugarcane is one of the most important cash crops globally, contributing significantly to the economy of many countries by serving as a primary source of sugar, ethanol, and other by-products [1]. However, sugarcane cultivation faces substantial challenges due to various diseases, which can severely impact crop yield and quality, leading to considerable economic losses. Diseases such as rust, mosaic, red rot, and yellow leaf pose serious threats to sugarcane plantations (Figure 1)[2]. Traditional methods of disease detection rely on manual inspection by experts, which is time-consuming, labour-intensive, and prone to human error. This highlights the need for automated, accurate, and efficient disease detection systems.

Recent advancements in machine learning (ML) and deep learning (DL) offer promising solutions for detecting and diagnosing plant diseases through leaf image analysis[3]. These models excel in image recognition and classification, processing large data quickly to provide reliable results, crucial for timely agricultural interventions[4,5,6]. However, their application in sugarcane disease detection is still emerging, facing challenges like limited annotated datasets, variability in disease symptoms, and complex environmental factors. More advanced models are needed to accurately detect diseases under diverse conditions and offer actionable insights for farmers.

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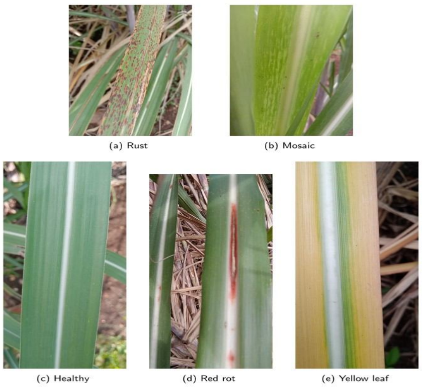


Figure 1. Types of Sugarcane diseases (1a) Rust, (1b) Mosaic, (1c) Healthy, (1d) Red rot, (1e) Yellow leaf

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This survey paper aims to explore and review the current state of ML and DL techniques for sugarcane disease detection. By examining state-of-the-art algorithms, the paper seeks to highlight the strengths and limitations of existing methods and identify opportunities for enhancing accuracy, efficiency, and scalability in disease detection systems.

The rest of the paper is organized as, Section II presents deep literature survey on sugarcane diseases detection and other plants diseases detection using machine learning and deep learning models. Section III discusses provided comparative analysis and discuss limitations of state of art systems. Section IV concludes the paper with future directions

## II. Literature Survey

This research evaluates the classification performance for seven sugarcane leaf diseases, highlighting precision, recall, F1-score, support, and overall accuracy. Precision rates range from 94.34% to 94.86%, demonstrating high accuracy. Recall values align closely, indicating effective identification of true positives. The F1-score is consistently 94.57%, balancing precision and recall. Support metrics (795-875) show the model's adaptability across different disease instances. With an overall accuracy of 94.57%, this study offers a reliable tool for early disease detection in sugarcane, aiding in reducing crop losses and boosting productivity[7]. Authors in [8] highlight the efficiency of convolutional neural networks (CNN), specifically the VGG-16 architecture, in accurately detecting sugarcane smut. Utilizing a dataset of 160 images, the model achieved a precision and recall of 94.74\% and an overall accuracy of 95\%. This surpasses previous machine learning techniques by achieving higher accuracy and lower false discovery rates. The study underscores the VGG-16 model's reliability for early disease detection through effective feature extraction and image recognition.

The authors in [9] used Convolutional Neural Networks (CNN) to predict and classify diseases in sugarcane, focusing on the Red Stripe virus. They used secondary data sources like Kaggle to improve disease management strategies. In [10], the authors recommend the Inception Nadam L2 Regularized Gradient Descent (NLRGD) CNN model for classifying sugarcane diseases such as red rot, smut, mosaic, yellow leaf, and red-orange rust. This model, trained on a dataset of 3,000 images from Kaggle, achieved an accuracy of 96.75%, precision of 96.62%, recall of 96.25%, and F-Score of 96.76%, outperforming other CNN models.

Researchers in [11] developed a model combining CNN and SVM techniques to predict the severity of Grassy Shoot Disease in sugarcane. Their process includes data preprocessing, CNN-based feature extraction, and SVM-based classification, achieving 81.53% accuracy with precision, recall, and F1-scores between 65.71% and 85.37%. Researchers in [12] created a sugarcane classification system using CNNs and image processing to evaluate crop quality by analyzing color, texture, and shape, achieving high accuracy and outperforming traditional methods. Authors in [13] highlight farming's critical role in India's economy, focusing on sugarcane cultivation and the challenges posed by natural disasters and diseases. They propose using the MobileNet v2 model for disease detection.

In [14], a deep learning model using ConvNet (CNNs) accurately identified sugarcane diseases, showing the effectiveness of deep learning in disease management. A study in [15] compared transfer learning methods VGG-16 and ResNet on a dataset of 1,470 images, with ResNet achieving approximately 91% accuracy.Authors in [16] propose an IoT and machine learning system to help farmers identify crop diseases and provide fertilizer information. Research in [17] applied advanced machine learning and image processing to monitor coconut tree health. Authors in[18] focuses on using CNNs for sugarcane disease prediction, effectively distinguishing between healthy and infected leaves and aiming to enhance predictive model performance. A study on tomato disease images utilized the Modified U-net along with Efficient B0, Efficient B4, and Efficient B7 models for meticulous segmentation and classification [19]. In [20], researchers introduce a real-time crop disease detection model that employs image analysis to identify rodents. The approach integrates computer-aided segmentation and employs various classification methods, including the k-means algorithm. The proposed model focuses on disease identification for pomegranate plants and envisions potential applications for different crops in the future. In [21], a mobile application for paddy crops, employing machine learning techniques such as CNN and SVM classifiers to identify diseases, is proposed. The model also offers remedies for detected diseases, providing a comprehensive solution for crop management.

Authors in [22] introduce a smart system using IoT and machine learning for predicting potato and tomato diseases. The system issues warning messages and employs support vector machines (SVM) and logistic regression (LR) for effective yield prediction. Authors in [23] employ data mining techniques to predict sugarcane leaf diseases. Utilizing automated processes for disease prediction, the study employs algorithms such as J48, Multilayer Perceptron, and K-means. Future work includes further analyses to enhance prediction accuracy.The paper [24] proposes a model focusing on grass grub insects that infect crops, utilizing various classification techniques and an ensemble design. Future work involves hybridizing algorithms to improve model performance. Authors in [25] present a model for predicting sugarcane diseases using a decision tree model (DTM) and the Random Forest algorithm. The approach aims to increase crop yield, and the study concludes that Random Forest exhibits the best results. The paper [26] explores the prediction of sugarcane diseases using the Discrete Wavelength Transfer algorithm, incorporating image processing for disease detection.

Authors in [27] introduce a mobile application for detecting crop yield, predicting diseases, and providing crop recommendations. Future work includes the creation of a website and linguistic feature enhancements. Authors in [28] propose a method that utilizes Wireless Sensor Networks (WSN) and ML techniques, such as the Naïve Bayes Kernel algorithm, for disease detection. The paper provides foundational material for further research. In the context of chili, a study compared traditional methods for detecting pests and diseases with deep learning-based models for feature extraction [29]. The analysis involved chili leaves affected by five diseases, two pest attacks, and one healthy leaf. Six traditional feature-based methods were compared to six deep-learning feature-based frameworks to assess their efficiency. In the context of rice plant disease classification and identification, a model utilizing Hybrid Deep CNN Transfer Learning was presented [30]. This model categorized and identified various rice plant diseases. Preprocessing involved geometric transformation procedures for three types of disease images, resulting in an accurate Resilient Distributed Dataset.

Another research effort proposed an enhanced Yolo v3 model for multi-scale object detection through varying image resolutions, aiming to achieve efficient and accurate detection of tomato pests and diseases [31]. This approach integrated different layers to increase filters, optimizing computational efficiency and processing speed. For detecting and recognizing rice pests and diseases, a framework featuring a non-consecutive VGG16 and Inception-V3 architecture was meticulously fine-tuned [32]. Internal representation techniques like MobileNet, NasNet Mobile, and Squeezenet were compared to multi-step convolution neural network frameworks. For hot pepper pest and disease diagnosis, a fine-tuning-based transfer learning approach was advocated [33]. Pre-trained VGG16, VGG19, and ResNet50 techniques were used, providing knowledge from the ImageNet datasets to enhance the convolutional features within the vector space.

Yan Guo et al. introduced an efficient model for plant disease prediction, improving generality, accuracy, and training efficiency [34]. Their framework includes three key steps: leaf localization, segmentation, and disease identification. Using a dataset of 1000 leaf images, the first step detects diseased leaves in complex environments using the Region Proposal Network (RPN) algorithm. The Chan-Vese Algorithm is then applied for precise leaf segmentation. Finally, disease types are identified by feeding the segmented leaves into a pre-trained learning model. A. A. Sarangdhar and V. Pawar utilized a hybrid approach combining regression and Internet of Things (IoT) technologies to detect diseases in cotton plant leaves by assessing soil quality [35]. They employed a Support Vector Machine (SVM)-based regression method to classify five types of cotton leaf diseases: Alternaria leaf spot, gray mildew, bacterial blight, fusarium wilt, and cercospora leaf spot. An Android application provided information about the identified disease and its treatment. K. P. Panigrahi employed several supervised machine learning techniques to analyze maize plant leaves [36]. The dataset for detecting maize leaf diseases was sourced from the PlantVillage website [37]. O. Kulkarni conducted a study utilizing computer vision techniques to identify plant diseases based on leaf characteristics [38]. The dataset consisted of 54,306 crop leaf images across 38 categories. These images underwent preprocessing and segmentation before being processed through Convolutional Neural Network (CNN) models. Performance was enhanced using transfer learning from the ImageNet dataset. Two CNN models, MobileNet and InceptionV3, were implemented.

TABLE I: COMPARATIVE ANALYSIS OF SUGARCANE DISEASE DETECTION MODELS

| **Methodology** | **Key Findings** | **Limitations** |
|---|---|---|
| CNN, evaluation of classification performance [7] | High precision (94.34%-94.86%), recall, and F1-score (94.57%) for identifying seven sugarcane leaf diseases. | Requires extensive preprocessing and a large dataset; potential overfitting despite high accuracy. |
| CNN (VGG-16 architecture)[8] | High precision and recall (94.74%) in detecting sugarcane smut, with overall accuracy of 95%. | Dataset limited to 160 images, leading to potential overfitting and limited generalizability; accuracy might drop with larger dataset. |
| Deep learning (ConvNet/CNNs)[14] | Efficient and accurate identification of sugarcane diseases, enhancing disease management practices. | General performance metrics provided; lacks specific breakdown of disease categories; potential variability in accuracy. |
| Transfer learning (VGG-16, ResNet)[15] | VGG-16 achieved 83.00% accuracy, ResNet 91.00%, showing promising outcomes with transfer learning. | Limited dataset (1470 images); accuracy might not scale well with larger datasets. |
| Deep learning (CNN)[18] | Accurate prediction of sugarcane diseases, distinguishing between infected and non-infected leaves. | Current model may be computationally intensive; accuracy needs validation with more diverse datasets. |
| Data mining (J48, Multilayer Perceptron, K-means)[23] | Automated processes for predicting sugarcane leaf diseases, with potential for accuracy enhancement. | Initial accuracy not detailed; further analyses needed to enhance prediction accuracy. |
| Decision tree model (DTM), Random Forest[25] | Effective prediction of sugarcane diseases, with Random Forest showing the best results. | Model comparison limited to specific algorithms; overall accuracy not extensively validated. |
| Discrete Wavelength Transfer algorithm, image processing[26] | Effective sugarcane disease prediction using image processing techniques. | Performance metrics and dataset details not extensively covered; accuracy could vary with more data. |
| Mobile application, disease prediction, crop recommendations[27] | Comprehensive tool for detecting crop yield, predicting diseases, and providing recommendations. | Current scope limited; future work includes validation for accuracy and development of a website. |
| Wireless Sensor Networks (WSN), ML techniques (Naïve Bayes Kernel)[28] | Foundational material for disease detection using WSN and machine learning techniques. | Limited to foundational material; accuracy needs extensive validation for specific crops. |

TABLE II: MACHINE LEARNING AND DEEP LEARNING MODEL FOR PLANT DISEASE PREDICTION

| **Crop/Disease** | **Methodology** | **Key Findings** | **Future Scope / Limitations** |
|---|---|---|---|
| General crop diseases[39] | CNN, fully connected networks | Achieved 89.7% accuracy using CPU; improved diagnosis process using smartphone images. | Could explore GPU-based models for faster processing and higher accuracy. |
| Various plant diseases[40] | ML techniques | Average classification accuracy of 93.79%. | Scalability to larger datasets and different crop diseases needs exploration. |
| Multiple species/diseases[41] | CNN | Achieved 96.5% accuracy in real-time identification. | Further research needed on robustness across diverse environmental conditions. |
| Tea leaf infections[42] | Enhanced DL models | 92.5% identification accuracy; outperformed traditional methods. | Future work could focus on optimizing the model for real-time applications. |
| Tomato diseases[43] | Deep CNNs (VGGNet, AlexNet, GoogleNet) | Highlighted efficacy of deep architectures for early detection. | Exploration of more complex architectures and larger datasets recommended. |
| Sugarcane diseases[44] | LeNet, StridedNet, VGGNet | VGGNet showed highest accuracy among the three models. | Could investigate the impact of integrating additional data sources for improved accuracy. |
| Wheat yellow rust[45] | Hyperspectral imaging, PRI | Effective disease detection; potential for aerial application. | Requires further testing in diverse climatic conditions and scaling to larger fields. |
| General (bank cheques)[46] | Graph Transformer Networks (GTNs) | High accuracy in commercial applications; minimized need for | Application in agricultural disease detection could be an area of future |

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|---|---|---|---|
| | | manual heuristics. | research. |
| Grapevine Leafroll[47] | ACCA | Accurate early-stage disease detection and classification. | Need for validation across more diverse grapevine varieties and regions. |
| Various plant diseases[48] | Comparison of ML algorithms | CNNs demonstrated highest accuracy in disease identification. | Future studies should address scalability and integration with IoT devices. |
| Tea Leaf Blight (TLB)[49] | Four-step segmentation procedure | Higher accuracy and robustness compared to conventional methods. | Potential for real-time monitoring systems; scalability to other tea diseases. |
| Sugar beet diseases[50] | ML classification models | Achieved 95.48% accuracy in disease detection. | Could benefit from larger datasets and integration with remote sensing technologies. |
| Potato diseases[51] | Various ML models | Accuracy ranged from 83% to 96%, depending on dataset size. | Future research should focus on cross-domain adaptability and robustness. |
| Various crops[52] | Expanded dataset diversity | Enhanced model accuracy with varied environmental data. | Needs further validation on additional crops and in diverse geographic locations. |
| Maize[53] | Decision trees, ML algorithms | High performance in soil fertility and crop yield prediction. | Incorporating disease impact analysis could enhance prediction accuracy. |
| Barley[54] | ML and DL methods for price forecasting | Traditional methods more efficient; neural networks provided good results with additional factors. | Could integrate disease forecasting for comprehensive agricultural planning. |

## III. DISCUSSION

The literature analysis emphasizes significant advances in sugarcane disease detection using machine learning and deep learning approaches, demonstrating the excellent accuracy and usefulness of CNN-based models such as VGG-16 and ResNet. These models have outstanding precision, recall, and F1-scores, demonstrating their capacity to effectively recognize and categorize numerous sugarcane illnesses. However, there is much room for improvement in the accuracy of present approaches. Combining deep learning with machine learning techniques may produce stronger outcomes by harnessing the benefits of both approaches. Furthermore, ensemble approaches, which combine many models to improve prediction performance, represent a promising route for increasing accuracy and robustness.Current limitations include dependency on small datasets, which may result in overfitting and reduced generalizability, as well as the computational intensity of deep learning models, which can be challenging in resource-constrained environments. Addressing these limitations with larger datasets, scalable models, and hybrid approaches has the potential to significantly enhance disease detection systems' reliability and usefulness in a variety of agricultural situations.

## IV. CONCLUSIONS

In this paper, we provide a comprehensive evaluation of various machine learning and deep learning methodologies for the detection and classification of sugarcane diseases. The study demonstrates that advanced techniques such as Convolutional Neural Networks (CNNs) and transfer learning models like VGG-16 and ResNet can achieve high accuracy in identifying and classifying sugarcane leaf diseases. Despite the promising results, there is significant scope for increasing accuracy in existing methods by addressing challenges such as overfitting, limited datasets, and computational demands. Integrating machine learning with deep learning approaches and employing ensemble methods could further enhance prediction accuracy and robustness. This study significantly contributes to the field of agricultural disease detection, offering valuable insights for developing more effective and scalable disease management solutions. Future research should focus on expanding datasets to include a more diverse and comprehensive range of images, helping to mitigate overfitting and improve the generalizability of the models. Exploring hybrid approaches that combine the strengths of machine learning and deep learning techniques is a promising direction. Ensemble methods, which integrate multiple models, could be employed to further enhance prediction accuracy and robustness.

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