# Advancing Sugarcane Disease Detection through CNN-Based Deep Learning

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**ABSTRACT:** Agriculture produce especially sugarcane crop is no exception to diseases as compared to the other crops. Sugarcane, a vital cash crop for the global sugar industry, faces numerous challenges, with the Top Borer disease. Disease prone sugarcane crop directly affects the production quality and quantity. Sugarcane infections are a cause of worry for the farmers because they can wipe out the entire crop field. Researchers are working on applying Artificial Intelligence (AI) techniques, like Machine Learning (ML) and Deep Learning (DL), to analyse the agricultural data (yield prediction, selling price forecasting, climate, and soil quality etc.) and prevent crop damage due to various reasons, diseases being one of them. Deep neural network which includes Convolutional Neural Network (CNN) is a modern technique for agricultural disease detection. Hence, this paper presents the feasibility study and the effectiveness of DL based CNN algorithm in the disease detection of crops with special reference to selective four diseases of sugarcane crop in India. The proposed system integrates state-of-the-art deep learning algorithms, leveraging Convolutional Neural Networks (CNNs) and recurrent models, to analyze high-resolution images captured by unmanned aerial vehicles (UAVs) or ground-based sensors. These images provide a comprehensive view of the sugarcane plantation, allowing for the identification of subtle symptoms and early-stage infections that may go unnoticed by the human eye. The key components of the developed system include a robust image preprocessing pipeline to enhance the quality of input data, a customized deep neural network architecture trained on a diverse dataset of sugarcane images, and a real-time monitoring system for timely intervention. The model's performance is evaluated on a large-scale dataset collected from sugarcane plantations across diverse geographic regions. The results demonstrate the system's high accuracy in detecting and classifying the Top Borer disease, outperforming traditional methods.

**Index Terms—** Convolutional Neural Network (CNN, Machine Learning (ML), Topborer Diseases

## 1. INTRODUCTION

Sugarcane Disease (Topborer) is such a serious concern and harmful thing for farmers yield. If the cultivation of a specific crop declines, it has a negative impact on the economy. The Top Borer is an insect pest known for infesting sugarcane crops, causing extensive damage to the stems and affecting overall plant health. If these crops are destroyed while developing, agricultural produce along with the intent of maintaining quality of these crops will lose some of their competitiveness. It is often necessary to keep track of the disease in order to substantiate and support the diagnosis. In contrast to standard neural network architectures, deep learning processes data using multi-layered artificial neural network architecture is used. It is possible to automate the detection process and identify subtle signs of Top Borer infestation that may go unnoticed during manual inspections. Deep Learning (DL) has revolutionized image recognition, image classification, and other disciplines that require massive amounts of data to manage. Convolutional Neural Network (CNN) is one of the most widely used ways for presenting complex ideas, and it employs a significant amount of data to perform pattern recognition tasks. This research aims to explore the integration of AI and deep learning into the realm of sugarcane cultivation, specifically focusing on the detection and management of Top Borer disease. Sugarcane plant diseases are a large scientific topic of study that focuses on the disease's biological features. In conventional practice, disease detection, recognition, and treatment of ailments in sugarcane are mostly done manually. There will be no difficult instances and less time spent executing these tasks manually thanks to the recent development of automated solutions for clients. CNN is a type of neural network that uses DL techniques based on Artificial Neural Network (ANN). DL has gained popularity in the field of agriculture because of its performance and accuracy, notably in the diagnosis of plant diseases. CNNs are very capable of controlling complicated processes and identifying patterns in pictures. Subsequently a Graphical User Interface (GUI) is designed for user-friendly detection of sugarcane topborer diseases. optimizing resource utilization, and promoting sustainable agricultural practices in the face of evolving challenges. Disease control is a difficult endeavor. Colour dots or streaks appear on the plants' leaves, which are disease symptoms. . These disorders are usually identified by hands and naked eyes. Image processing can be used to detect a variety of diseases automatically.

## 2. LITERATURE SURVEY

Crop diseases mentioned by Park et al. [1] are the most important factor because they reduce crop productivity by 20-30% when they infect a crop. Agricultural diseases have a significant impact on crop productivity. When a farmer sends a leaf image taken with a smartphone to an analysis engine system, the process for diagnosing and predicting diseases is examined. When the condition is doubtful, farmers have to rely on professional judgment or personal experiences. The paper discusses the existing literature in the field of sugarcane disease recognition using deep learning technique. However, the paper acknowledges the need for this study due to the rapidly expanding classes of diseases and farmers' insufficient knowledge of disease identification and recognition. This suggests that previous research may have been limited in addressing these challenges. Additionally, the paper highlights the importance of automating the disease detection process, indicating that previous research may have been limited in providing efficient and automated solutions for sugarcane disease recognition. They developed a system for diagnosing the diagnosing the condition that included two convolutional and three fully connected networks. When running on a central processing unit (CPU), the model has an accuracy of 89.7%. Plant diseases studied by Danda wate et al. [2] Deep learning algorithms are implemented to create models that can classify sugarcane diseases using 16,800 images of training data, 4,800 images for validation tasks, and 2400 images for testing. Results show that the InceptionV4 algorithm outperforms other models in classifying sugarcane leaf diseases at 99.61 accuracy. Different models such as VGG16, AlexNet achieve high accuracies of 97.88%, 98.23%, and 98.24%, respectively. The study suggests that deep learning models can be effective in classification problems and provides evidence for their performance in identifying and detecting sugarcane diseases. The proposed approach achieves an AUC of 90.2% using VGG-16 as the feature extractor and SVM as the classifier. Militante et al. [3] studied the trained model that was 96.5% accurate. They identified and detected 32 different plant species and diseases using a CNN. The four key components of CNN are convolution layers, pooling layers and activation functions These element work together to enable feature extraction, dimension reduction ,and classification in image data. Suryawati et al. [4] studied that the outbreaks of plant diseases can pose a serious threat to the safety of our food supply. With ML-based early illness detection, such a tragedy could be avoided. DL, a relatively new ML method, is already widely used for tasks requiring object recognition. According to the findings of the studies, a CNN with a deeper architecture performs this function better. Militante et al. [5] analyzed that the sugarcane disease is a threat to the sugarcane industry because it destroys infected crops, reduces cultivation, and costs farmers money. Viedienieiev and Piskunova [21] have worked on the use of ML to forecast the price of agricultural products (barley crop) with special reference to Ukraine. They used traditional forecasting methods such as linear regression and DL methods such as direct-recursive hybrid CNNs. The present study, considering the effect of disease detection, carried out by the authors can be combined with agricultural productivity enhancement and price forecasting using AI tools and techniques, thereby aiding the farmers in effective decision making. Here we basically focusing on sugarcane topborer disease. Various researchers have attempted to improve the crop productivity using tools and techniques of AI. For maize crop, Prabavathi and Chelliah [20] used ML algorithms to predict soil fertility, crop selection and yield rate. The crop prediction performance analysis was seen to be high using decision tree method. Viedienieiev and Piskunova [21] have worked on the use of ML to forecast the price of agricultural products (barley crop) with special reference to Ukraine. They used traditional forecasting methods such as linear regression and DL methods such as direct-recursive hybrid CNNs. Results indicated that traditional forecasting methods are more effective (require less time) and require less resources as well. In Ukraine, the use of neural

The present study, considering the effect of disease detection, carried out by the authors can be combined with agricultural productivity enhancement and price forecasting using AI tools and techniques, thereby aiding the farmers in effective decision making. CNNs are observed to be a powerful tool to deal with plant disease detection but building the dataset for robust tool is the challenging one. DL is employed throughout the technology solution to obtain high accuracy in sugarcane disease based on previous sugarcane disease prediction. The project's main purpose is to predict sugarcane disease, which will be incredibly valuable to farmers when planning sugarcane sales. To predict sugarcane disease can be extremely useful to farmers to identify and control the disease in order to increase the quality of the crop and its yield. Implementation of a DL based CNN algorithm gives better prediction of sugarcane disease. This work aims to predict sugarcane disease based on CNN algorithm.

## 3. PROPOSED METHODOLOGY

**Data Collection: Collect a diverse dataset of** labeled images featuring healthy sugarcane plants and various diseases. Ensure that the dataset covers different stages and severities of the diseases.

**Data Preprocessing**: Preprocess the images by resizing, normalizing, and augmenting them to enhance the model's ability to generalize. Data augmentation techniques include rotation, flipping, and changes in brightness and contrast.

**Labeling**: Annotate the images with corresponding labels indicating whether the sugarcane plants are healthy or affected by a specific disease. Ensure accurate and consistent labeling for effective training.

**Model Architecture**: Choose or design a CNN architecture suitable for image classification. Consider well-known architectures like VGG, ResNet, or design a custom architecture based on the complexity of the dataset.

**Model Training:** Split the dataset into training, validation, and test sets. Train the CNN using the training set, adjusting weights through backpropagation to minimize classification errors. Validate the model on a separate validation set to prevent overfitting.

**Hyperparameter Tuning:** Fine-tune hyperparameters such as learning rate, batch size, and dropout rate to optimize the model's performance. Experiment with different configurations to achieve the best results.

### Deployment

Integrate the trained CNN model into a system for sugarcane disease detection. This system may include:

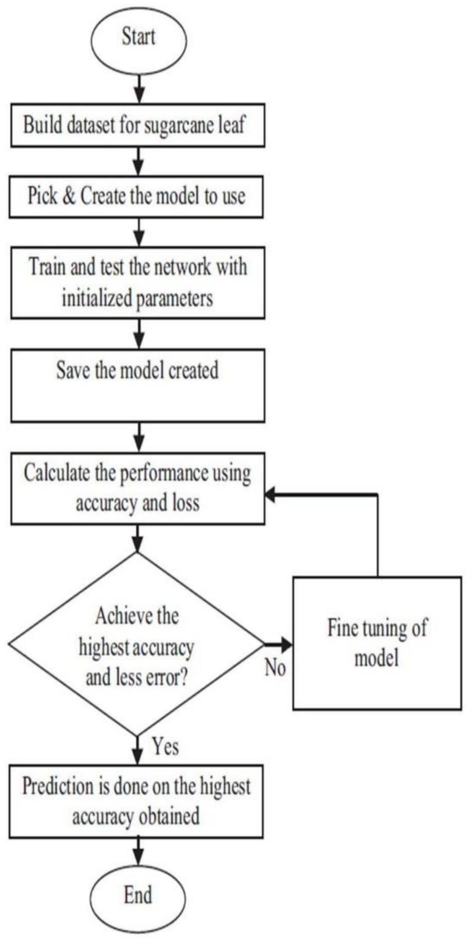
- **Image Input Module**: Accepts images of sugarcane plants.
- **Preprocessing Module**: Normalizes and preprocesses the input images.
- **CNN Model**: Processes the preprocessed images for disease classification.
- **Output Module**: Provides the classification result (healthy or diseased) along with the probability or confidences.
- **Activation Function** (e.g., ReLU):Introduces non-linearity after the convolution to capture complex patterns.
- **Repeat Convolutional + Activation + Pooling layer** - Stack multiple layers for hierarchical feature extraction.
- **Fully Connected (Dense) Layer** - Neural network layer for further feature learning.

- **Dropout Layer (optional)** - Reduces overfitting by randomly dropping a fraction of neurons during training.

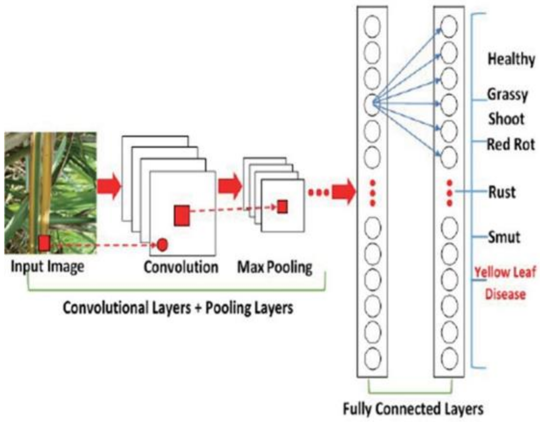
- **Monitoring and Updates** - Regularly monitor the model's performance and update as needed based on new data or changes in the sugarcane disease landscape.

- The system's output provided as a result. The user is logged out.

The collected dataset is verified from the experts with the proper labeling and it is divided into several parts. All the training and testing dataset, wrong or correct data submitted, results and unpredicted values are considered as objects under one set, where the input and desired output are the subset of the system.




Flow Chart for Disease Prediction **fig1.1**




**ALGORITHM:** A1: Sugarcane leaf data prediction

2. A2: Training data

3. R1: Resultant output provided by the system

4. A3: Wrong or incorrect data submitted.

5. R2: Unpredicted value Several people can get one or more outcomes.

Set Theory:

S = {s, e, X, Y, ϕ} where,

s = Beginning of the programmer

1. Input data

2. Data Extraction.

3. Statistical Feature Analysis

4. Classification

5. Training

6. Final Result

e = Programmer End.

1. The system’s output provided as a result.

2. The user is logged out.

X = programmer input, and input must be an image.

Y = programmer output.

Predicted sugarcane disease

X, Y belongs to U Suppose U denotes the Set of Systems.

U= {Client, I, TD1, TD2, C, A, D, R}

Space complexity: The presentation and visualization of revealed patterns affects the space complexity. The space complexity increases as more data is stored. It is also defined as the space required for getting results from the classifier when input is given. In this research the space complexity is 83 kilo bytes.

Time complexity: Let n is the number of patterns that exists in the database. When n is greater than one, information retrieval can take a long time. So, for this algorithm, O(n) represents the time complexity.

$\phi$ = Failures and success conditions.

Failures:

1. Large database leads to delay to retrieve information.

2. Failure of Hardware.

3. Failure of Software.

Success:

1. User obtains results fast and appropriately.

2. Find the necessary data by searching the datasets.

**DATASET**: A database, such as a picture, has been used as the input to the system. Figure 4 shows the architecture of the proposed system for identification of the disease. Total 904 pictures are used in this research work, out of which 624 pictures (i.e., 66% of total pictures) are used for the training purpose and 420 pictures are used for the testing purpose. Thus, total pictures in the dataset = 904, pictures per class = 204, total pictures for training purpose = 406, pictures per class for training purpose = 201 to 202, total pictures for testing purpose = 374, pictures per class for testing purpose = 63 to 64. A balanced dataset (it means the number of pictures for each class is approximately same) is used. The dataset is already labeled and verified by the experts. There are many classes/diseases related to sugarcane. The labeled dataset verified by experts was available only for 4 classes/diseases hence in this study, only 4 classes/diseases have been used. The verification of the classes was already done by the concerned experts from the domain. A database is a collection of organized structured data that has been organized logically and has been kept digitally on a computer system. In the majority of the cases, a Database Management System (DBMS) is in control of the database. This data, saved in a single or multiple files, becomes easily accessible, controllable, and organizable. The division of data in these files can be made into records and fields which contains information about feature or attribute of the database. Tables are used to arrange records that convey information about how fields relate to one another. With the help of keywords and sorting options, users quickly find, recognize and choose fields from various records to produce reports on specific data.

**Implementation:** The first processing of data in order to prepare it for secondary or primary processing is known as preprocessing. Preprocessing methods include obtaining data from a bigger collection, filtering it for various reasons, and merging subsets of data. It is difficult to work on raw data hence we require to convert it into usable data. This conversion process is known as data preparation. Assurance of good quality data is important while using ML.

**Feature Extraction**: From scaled images, the convolutional layers extract features, then further to lower the dimension of the recovered feature, a rectified nonlinear activation function is applied with the help of different types of pooling arrangements (max pooling and average pooling). This combination works together as a filter to create a feature. The features are extracted from the pictures which consist of color, entropy of the texture, and spots on the leaf. Every feature has the same weight. It means features are balanced. Fully connected layers are used for classification, while convolutional and pooling layers are used for feature extraction. This layer is responsible for identifying sugarcane images and assessing whether they are diseased or not.

**Convolutional Neural Network (CNN):**

Neural networks are a group of pattern-recognition algorithms that, in some ways, take their cues from the human brain in various aspects. They comprehend sensory information provided as input by employing machine perception to categories or cluster raw data. Whether it is photos, sound, texts, or time series, it is necessary to obtain the numerical output in the form of recognizable patterns that is recorded in vectors by carrying out the translation of entire real-world input. Neural networks help with data classification and clustering. In addition to the data you keep and administer, they act as an additional layer of grouping and categorizing. They assist in the unlabeled data grouping based on similarities between the inputs when they have a labelled dataset on which to train. Deep neural networks are thought as components of bigger ML systems that include algorithms for reinforcement learning, classification, and regression; they can also extract characteristics used by algorithms of clustering and classification. Taking input images, assigning learnable weights and biases to different objects in images, and differentiating them, all this is performed by a deep learning system called CNN. Pre-processing time for a ConvNet is significantly lower than for other classification techniques. While simple approaches necessitate hand-engineering of filters, adequate training is required for ConvNets to learn filters/characteristics. human brain. An only stimulus within the receptive field, a small fraction of the visual field, could get responded by individual neuron. Using fully connected layers to learn high-level nonlinear combinations of the information represented by the outputs of convolutional layers is a (usually) cheap method. In this section, fully connected layer learns non-linear function. Layers of CNN architecture:

1. Convolution layer.
2. Rectified Linear Unit (ReLU) layer (Rectifier activation function)
3. Pooling layer.
4. Fully connected layer

**Convolution Layer - the Kernel**

To get a 3x3x1 scaled down feature, scale a 5x5x1 image with a 3x3x1 kernel. Clear operations on the right with positive step values until full width parsed. The method then uses the same step values to go to the beginning of the image (left) and repeats until the entire image has been explored. An example of a CNN architecture is shown in Figure 5. Classes shown in Figure 5 are differentiated on the basis of diseases of sugarcane in which class 1, class 2, class 3, and class 4 are assigned for presence of disease such as wilt, black rot, grassy shoot, and smut respectively and class 5 is assigned for healthy plant image (not affected by any disease).

**3.5. Pooling Layer**

A reduction in the spatial length of convolution layer is performed by pooling layer, like the Convolutional Layer. This is done to reduce the amount of power that computer needed to operate on the data by reducing dimensionality. It is also useful to derive rotational and positional invariant dominant functions, allowing the model to be successfully educated.

**3.6. Classification - Fully Connected Layer (FC Layer)**

Addition of a Fully Connected layer is economical to learn non-linear combinations of high-level functions. A nonlinear feature is learnt by fully connected layer. As pictures are taken directly from the farm with different cameras, so algorithm is designed in such a way that irrespective of the orientation/field of view/image resolution/angle of pictures, the developed algorithm can easily classify the disease with good accuracy. Figure 6 provides a glimpse of the stages to be followed while working with web-based application. The stages are: access application, signup, login, understand the application, upload image, and get result with remedial suggestion.

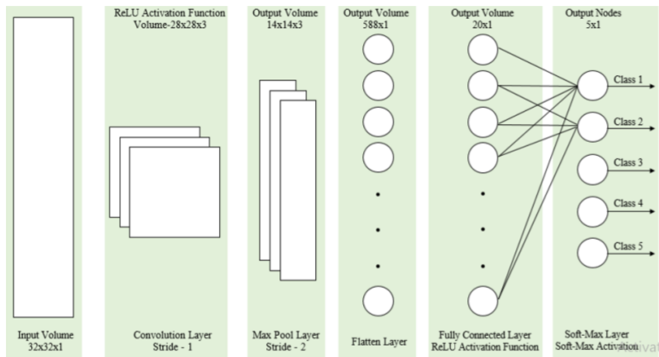



**fig :3** CNN Architecture

1. Future Scope : Improved Model Architectures:

- Ongoing research in deep learning may lead to the development of more efficient and accurate CNN architectures specifically tailored for sugarcane disease detection. These architectures might be optimized for resource-constrained environments, enabling deployment in various agricultural settings.

2. Transfer Learning and Pre-training:

- Continued exploration of transfer learning and pre-training on large-scale datasets could enhance the generalization ability of CNN models for sugarcane disease detection. Leveraging knowledge from related domains and transferring it to sugarcane disease detection tasks may become more common.

3. Ensemble Models:

- Combining multiple CNN models into ensemble systems might become a standard practice. Ensemble models can leverage diverse architectures and improve overall accuracy, robustness, and the ability to handle variations in environmental conditions.

4. Integration with Multi-Sensor Data:

- Future systems may integrate information from various sensors beyond visual data. Combining data from sources such as hyperspectral imaging, drone-based sensors, and IoT devices could provide a more comprehensive understanding of sugarcane health, enabling early detection and precise disease identification.

5. Explainable AI (XAI):

- As AI systems become more integral to agriculture, the demand for explainable AI models will likely increase. Researchers may focus on developing CNN models that provide interpretable results, making it easier for farmers to understand and trust the system's disease detection decisions.

6. Edge Computing and Real-time Processing:

- Advancements in edge computing capabilities may allow CNN models to be deployed directly on edge devices such as drones, cameras, or smartphones. Real-time processing at the edge can provide instant feedback to farmers, facilitating timely interventions.

7. Blockchain and Data Security:

- Incorporating blockchain technology for secure and transparent data sharing may become crucial, especially in collaborative agricultural environments. This could help in building trust among stakeholders and ensuring the integrity of the data used for training and inference.

8. Global Collaboration and Data Sharing:

- Collaborative efforts among researchers, agricultural organizations, and technology companies may lead to the creation of large, diverse datasets for training robust models. Global data sharing initiatives could accelerate the development of effective CNN models for sugarcane disease detection.

9. Mobile and Web Applications:

- The development of user-friendly mobile and web applications may increase, allowing farmers to easily interact with and benefit from sugarcane disease detection systems. These applications could provide insights, recommendations, and alerts directly to the end-users.

10. Automated Intervention Systems:

- Integration with automated intervention systems, such as robotic or drone-based application of treatments, may become more common. These systems can be triggered based on the CNN model's disease detection results, providing a closed-loop solution for crop management.

11. Adaptation to Climate Change:

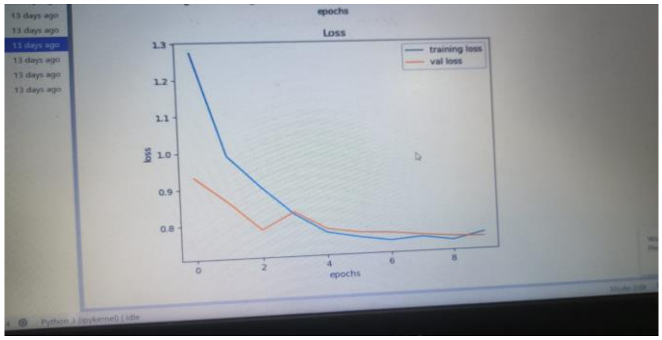
- CNN models for sugarcane disease detection may evolve to consider the impacts of climate change. Models could be trained to recognize disease patterns influenced by changing climate conditions, enabling more adaptive and resilient agricultural practices.

12. Continued Research on Novel Diseases:

- Research may expand to cover the detection of novel diseases affecting sugarcane crops. CNN models could be adapted to identify emerging threats, contributing to proactive disease management strategies.

The future of sugarcane disease detection using CNNs is likely to be shaped by ongoing advancements in deep learning, sensor technologies, and the increasing integration of AI in precision agriculture. Collaboration among researchers, practitioners, and technology developers will play a crucial role in realizing the full potential of these innovations.

## RESULTS




## CONCLUSION

1**. Precision and Accuracy:**

- CNNs demonstrate high precision and accuracy in identifying sugarcane diseases based on visual symptoms. The ability to learn intricate patterns and features in images contributes to reliable detection, aiding farmers in making informed decisions.

2. **Early Disease Detection:**

- The real-time and early detection capabilities of CNN models empower farmers to identify potential diseases in sugarcane crops at their incipient stages. Timely intervention is crucial for effective disease management and crop protection.

3. **Efficient Resource Utilization:**

- By leveraging CNNs, farmers can optimize resource utilization, applying treatments only where necessary. This targeted approach minimizes the use of pesticides and resources, reducing costs and environmental impact.

4. **Adaptability to Environmental Variability:**

- CNNs can adapt to variations in environmental conditions, making them robust tools for sugarcane disease detection across diverse climates and geographical regions. This adaptability enhances the applicability of CNN-based solutions in global agriculture.

5. **Integration with Modern Technologies:**

- The integration of CNNs with other modern technologies, such as remote sensing, IoT devices, and mobile applications, creates comprehensive systems for sugarcane disease monitoring. This holistic approach facilitates seamless data collection, processing, and dissemination of actionable insights.

6. **User-Friendly Applications:**

- The development of user-friendly applications, equipped with CNN models, empowers farmers with easy-to-use tools for disease detection. Visual interfaces and real-time alerts enhance accessibility and adoption by agricultural practitioners.

7. **Potential for Continuous Improvement:**

- The dynamic nature of CNN models allows for continuous improvement through iterative training and adaptation to new data. This adaptability ensures that the models remain effective in the face of evolving disease patterns and environmental changes.

8. **Contribution to Sustainable Agriculture:**

- CNN-based sugarcane disease detection contributes to sustainable agriculture practices by promoting efficient resource management, reducing the environmental impact of pesticide use, and optimizing crop health.

9. **Challenges and Considerations:**

- It is important to acknowledge challenges such as the need for large and diverse datasets, model interpretability, and the potential impact of imbalanced data. Continuous research and collaboration are essential to address these challenges and enhance the robustness of CNN m

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