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Application of CNN and Deep Learning for Sugarcane Disease Detection: Perspectives from India

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Abstract:

Like other crops, sugarcane can get diseases that decrease the quality and quantity. For effective management of the farm of sugarcane, it is important to identify these diseases early stages. Infection and diseases can cause entire fields, which leads to significant financial losses for farmers. To help farmers and solve this problem, researchers are using Artificial Intelligence (AI) and its subfields Deep Learning (DL) and Machine Learning (ML) are used to examine agricultural data such as crop yield, and soil quality to prevent crop se damage. Farmers have to access real-time data and tools to handle this large amount of information and data. This paper specifically looks at using Convolutional Neural Networks (CNN) to detect sugarcane diseases, focusing on those diseases that are found in India majorly. This study addresses the rapid spread of new diseases and the limited ability of farmers to recognize them. By sorting sugarcane images, these images are categorized into healthy and diseased by the trained model, in disease detection accuracy of 98.73 is achieved by the trained model. A mobile-based application was also created to help farmers take pictures and detect diseases from provided data. Future research is suggested by the paper, by using feedback from users to improve the model and enhance the accuracy of the model for detecting diseases with productivity and price analysis to make decisions by farmers.

Keywords: India, Machine Learning (ML), Convolutional Neural Network (CNN), Sugarcane Diseases

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1.0 Introduction

Demanding situations due to sugarcane illnesses can impact farmers, resulting in sizeable financial and aid losses if these problems aren't diagnosed and resolved quickly. A decrease in sugarcane yield adversely affects both the satisfaction and amount of the crop whilst also hindering the effective use of vital sources such as water, fertilizers, and soil. Therefore, this reduces the market cost of the crop, making it less competitive and much less profitable. Historically, the identity of illnesses in sugarcane trusted professional visual inspections, a technique impractical for giant farming operations because of its time-consuming and work-extensive nature. Moreover, depending on guide observation often results in delays in intervention, permitting diseases to unfold unrestrained. This case highlights the pressing need for efficient, low-priced, particular disorder detection techniques.

Deep learning is a specialized department of device learning that uses artificial neural networks to manage large quantities of information and extract significant patterns. The one's networks include a couple of layers, with each layer remodelling input facts into increasingly precise representations. The period "deep" refers to the presence of many hidden layers inside the community, permitting it to model complicated relationships. Deep analysing models have a look at the aid of fixing their inner parameters, along with weights and biases, via schooling techniques like recognizer and optimization algorithms like gradient descent. in the assessment of conventional device reading, deep gaining knowledge minimizes the need for guide characteristic extraction through reading capabilities without delay from uncooked facts. It's far broadly applied in fields collectively with picture and speech popularity, herbal language processing, and self-sufficient systems. Popular architectures encompass convolutional neural networks (CNNs) for photo-related obligations and transformers for herbal language information. Deep gaining knowledge of success is predicated on big datasets and extensive computational energy, often leveraging GPUs or TPUs. At the same time because it has revolutionized AI, traumatic conditions like facts scarcity, high computational needs, and overfitting continue to be areas of energetic research and improvement.

Latest technological advancements have transformed agricultural methods, specifically through using artificial Intelligence (AI) and its branches like Deep getting to know (DL). Especially, Convolutional Neural Networks (CNNs) have been a robust aid for reading pixel, showcasing first-rate competencies in figuring out styles and irregularities in plant fitness. These networks excel at recognizing the sensitive visual signs of diseases, including spots, streaks, or discoloration resulting from fungi, microorganisms, or viruses. Through streamlining the detection system, CNNs lessen the want for guide labour, allowing for activated actions and lowering crop losses.

Sugarcane, an agricultural product of global monetary significance, is a key component in sugar production, biofuel production, and diverse industrial goods. In international locations such as India, wherein sugarcane performs a principal role in both agriculture and the economy, illnesses like crimson rot, smut, and leaf scald have historically brought about large decreases in yield. Timely identity and management of those sicknesses are vital no longer for retaining the viability of sugarcane cultivation but additionally for inspiring smallholder farmers, who rely on robust plants for his or her earnings. Set-off detection is also crucial for minimizing the reliance on chemical treatments, which enables lessening both ecological effects and production expenses.

This study makes use of the energy of Convolutional Neural Networks (CNNs) to create a sturdy, image-primarily based version for detecting sicknesses in sugarcane. With the aid of training this model on a labelled series of sugarcane photos, it is capable of as it should be distinguishing between healthful and diseased vegetation. The proposed answer features an easy-to-use cellular software that enables farmers to take and post pics of their plants for fast evaluation. This comfort guarantees that even those farmers with minimal technical skills can take advantage of state-of-the-art AI-pushed resources. Additionally, the research emphasizes the broader potential of incorporating such technology into the clever farming paradigm, where real-time facts can tell choices concerning pest control, water usage, and resource distribution.

Alongside handing over quick-term blessings, this study highlights the significance of ongoing enhancements to the model. Input from users can help first-rate-track the software, enhancing its precision and broadening its talents to include yield predictions, soil checks, and price forecasts. This application not only helps farmers detect diseases in real time but also provides farmers with tools by which they improve their productivity and quality of yield. By connecting advanced technology with practical solutions that can be easily used in the field

2.0 Literature Review:

The author presents a Dense Net-support vector machine (DNet-SVM: XAI) for disease prediction in sugarcane. This approach used Dense Net for feature extraction and integrates Local Interpretable Model- Agnostic Explanations (LIME) for enhanced interpretability. Automating disease detection aims to assist farmers in making informed pesticide decisions, ultimately improving crop yield [1,2]. For early detection of sugarcane diseases use of a Convolution Neural Network (CNN) is explored in this paper. The study describes the importance of timely disease identification to prevent financial losses for farmers and represents a balanced dataset of 580 images across four disease classes. The CNN model achieved an accuracy of 98.73%, and a mobile-based application was developed to facilitate real-time disease monitoring for farmers [3]. Sugarcane Leaf Dataset, which comprises 6,748 high-resolution images categorized into 11 classes, including nine disease types and healthy and dried leaves. This dataset provides the first open-access resource for sugarcane leaf diseases, enabling researchers to develop and validate machine learning algorithms for disease detection and classification. This dataset plays an important role contributes to enhancing agricultural practices and improving sugarcane production [4]. Improving the identification of sugarcane diseases using Convolutional Neural Networks (CNNs) optimized with the Environmental Adaptation Method (EAM). The study highlights a significant accuracy improvement of 89% in disease detection compared to other algorithms. While also discussing data collection, image enhancement, and augmentation techniques to increase model robustness. Future directions include integrating advanced imaging technologies to support proactive disease management in sugarcane farming [5]. The detection of white leaf disease (WLD) in sugarcane using unmanned aerial vehicles (UAVs) and deep learning techniques. The study employed various deep learning models, including YOLOv5, to analyse and detect diseases. UAV-acquired RGB images, achieving high-performance metrics with YOLOv5. Displays clarity and recall rates of 95% and 92%, respectively. This work provides a framework for holding UAV technology and AI for effective disease analysis in sugarcane agriculture [6]. A deep learning-based approach for detecting diseases in sugarcane leaves makes use of the Sugarcane Leaf Dataset and includes 6748 images across 11 disease classes. The study estimated various Efficient Net architectures, with EfficientNet-b6 achieving the highest accuracy of 93.39%, highlighting the potential of deep learning in enhancing disease diagnosis and management in agriculture. This work makes a point of the importance of automated solutions in improving efficiency and reducing crop losses in sugarcane production [7]. The paper explores the applications of artificial Intelligence (AI) in detecting plant ailments, emphasizing its transformative function in agriculture. It highlights strategies which includes photo processing, tool studying, and deep studying, together with convolutional neural networks (CNNs), to diagnose plant health problems efficiently and correctly. AI-powered strategies like drone-based imaging, IoT integration, and robotics are discussed for tracking crop health and automating agricultural methods. The have a take a look at underscores the significance of AI in enhancing yield and reducing resource usage at the equal time as advocating for sturdy datasets to enhance present generation. It concludes with a name for destiny research to deal with the demanding situations of developing population and agricultural goals [8]. The paper evaluations the software program of synthetic Intelligence (AI) and the internet of things (IoT) for crop sickness detection, emphasizing the significance of early identity to mitigate agricultural losses. It explores numerous techniques consisting of system mastering, deep studying, image processing, and hyperspectral imaging for computerized sickness popularity, comparing their benefits and barriers. The take a look at highlights IoT's function in an extended manner off monitoring and actual-time desire-making, addressing stressful conditions like dataset range and price-effective implementation. hints for enhancing those systems and capability studies commands are supplied, making this a treasured aid for advancing precision agriculture [9]. This work proposes a chatbot powered by the use of using AI and natural language processing (NLP) to help farmers pick out and control crop sicknesses. The chatbot allows farmers to have interaction via textual content or voice, even in some distance off areas with bad internet connectivity, and might diagnose sicknesses using images of affected flora. It offers custom designed advice on ailment severity and manipulate practices, which include cultural, chemical, and natural techniques. The chatbot's effectiveness is examined and validated to be correct and user-satisfactory, with the potential to lessen crop losses, enhance yield, and sell sustainable agricultural practices [10]. This takes a study offers a deep analysing-based really answer for actual-time insect detection in soybean plant life, aimed in the direction of improving early identity and minimizing crop harm. using transfer getting to know fashions like YoloV5, InceptionV3, and CNN, the solution achieves excessive accuracy (98.797979%) in insect identity. amongst those, YoloV5 is the fastest, running at fifty-three frames in line with 2nd, making it suitable for real-time use. The studies include a dataset of insect photos, pre-processing techniques, and the development of an Android app for smooth get entry to. The proposed answer enables lessen manual workload and gives inexperienced, accurate insect detection for farmers. This examine explores the use of AI, IoT, and tool studying (ML) for automatic plant disease detection, that specialize in tomato, chilli, potato, and cucumber plant life. It discusses the disturbing situations of conventional disease identity strategies and the benefits of AI in enhancing the rate and accuracy of detection. The have a take a look at outlines key steps inside the sickness prediction manner, which incorporates image acquisition, pre-processing, segmentation, and class. Several ML and deep getting to know (DL) models for plant ailment detection are reviewed, and destiny research commands are highlighted. The artwork hobbies to boom early detection and control of crop diseases, ultimately improving agricultural productivity.

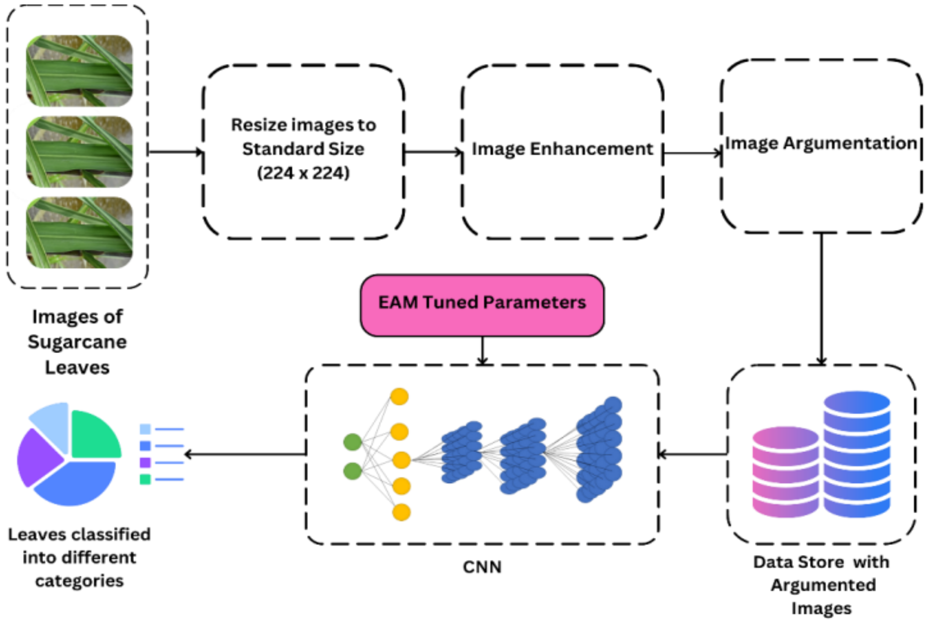

Fig.1. Proposed Research Methodology

3.0 Proposed Research Methodology for Sugarcane Disease Identification

The proposed method for identifying diseases in sugarcane using a Convolution Neural Network is shown in Figure 1. The first step involves using an image dataset for training and testing a Deep Learning Algorithm (CNN) model. The work details these processes in depth by Roshita Bhonsle et al. (2022) and includes images of different sugarcane diseases and their conditions: 175 healthy leaves, 174 with red rot, 73 affected by red rust, and 100 with bacterial blight. To achieve balanced representation, the dataset is modified according to the method described by Sharma et al. The images are organized into separate folders based on the disease type, with an additional folder for healthy leaves.

In the next phase, all images are with all images resized to a consistent dimension of 224 × 224 pixels. Various enhancement techniques can elevate the quality of images, such as sharpening, are applied to improve image quality. Each image is also labelled with a corresponding class number based on its folder.

3.1 Image Enhancement

Image Various enhancement techniques can boost or increase the quality of images for better analysis. These methods include:

Contrast Improvement: Enhances the contrast between light and dark regions.

Noise Reduction: Minimizes unwanted artifacts in the images.

Image Sharpening: Develop edges and details more distinct.

These enhancements help the CNN model extract important features from the images more effectively.

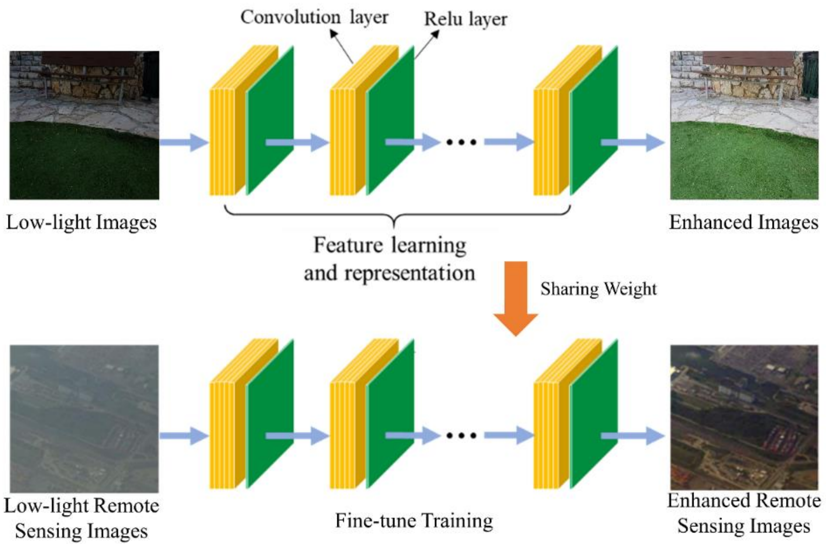

Fig.2. Image Enhancement

3.2 Data Augmentation

The dataset's size is expanded artificially by using the Data augmentation methods, creating greater varieties of images in the dataset. This method boosts the performance of the model by displaying it with a wide range of image variations. The data augmentation techniques include:

Rotation: Rotates images by any angle from 0 to 360 degrees.

Zoom: Adjusts the image size, either increasing or reducing it.

Width Shift: Moves the image left or right, fill up any empty spaces if available.

Height Shift: Moves the image up or down, similarly filling gaps.

Shear: Alters the image perspective, similar to rotation.

Horizontal Flip: Flips the image horizontally, creating a mirror effect.

To train the machine learning model these augmentation methods are very useful and effective, particularly in the other fields like computer vision tasks. By introducing different changes in orientation, size, and perspective, the model becomes more capable of dealing with various real-world situations.

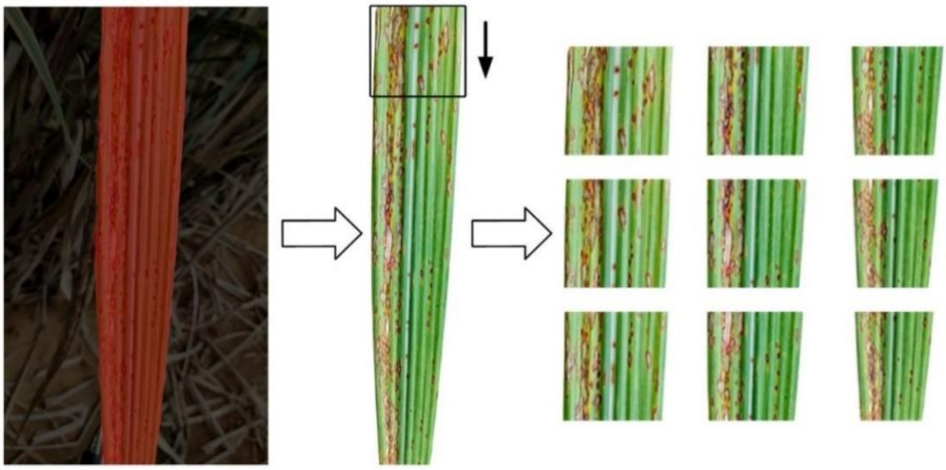

Fig.3. Data Augmentation

4.0 Convolutional Nerul Network(CNN)

Convolutional Neural Network (CNN) is a sophisticated algorithm innovative by the brain's ability to realize patterns. They process sensory information, such as images, sounds, texts, or time series data, to identify recognizable patterns. This transformation of raw data into numerical results allows CNNs to classify and group information effectively. When trained on labelled datasets, they can categorize unlabelled data based on similarities among the inputs. CNNs are a crucial part of bigger machine-learning systems, often working alongside algorithms for tasks like reinforcement learning, classification, and regression. They excel in extracting features that can be used in clustering and classification tasks.

Convolutional Neural Networks (CNNs) function by processing input images and utilizing adjustable weights and biases to recognize various objects present in those images. A key benefit of CNNs is their shorter preprocessing duration in comparison to conventional classification techniques, which typically necessitate manual filter creation. Instead, CNNs develop the ability to recognize filters during the development process. The structure of a CNN is designed to look like the visual cortex, where particular neurons are activated by distinct regions of the visual field.

4.1 CNN Architecture Layers

A CNN consists following layers:

i. **Convolution Layer:** This layer utilizes filters on the input images to extract features.

ii. **Rectified Linear Unit (ReLU) layer**: Introduces non-linearity through its activation function into the model.
iii. **Pooling Layer:** This layer diminishes the structural dimensions of the data, decreasing the evaluating load and helping the model learn important features regardless of their position.
iv. **Fully Connected Layer:** This layer learns complex, non-linear combinations of the features extracted in previous layers.

4.2 Convolution Layer and Kernel

In the convolution layer, a kernel (for example, a 3x3 filter) is used to analyse a larger image (like a 5x5 input). The kernel scans the image using defined step sizes, applying its operations to extract scaled-down features. A CNN architecture is shown in Figure 5, where distinct classes represent different sugarcane diseases, including lack of water, black spoil, grassy shoots, and muck, along with a class for healthy plants.

4.3 Pooling Layer

Following the convolution layer, the pooling layer helps to minimize the structural size of the data. This reduction helps lower the computational requirements and improves the model’s ability to learn functions that are invariant to rotation and position.

Classification - Fully Connected Layer

The fully connected layer learns complex non-linear relationships among high-level features. It is efficient and is essential to the model's overall performance.

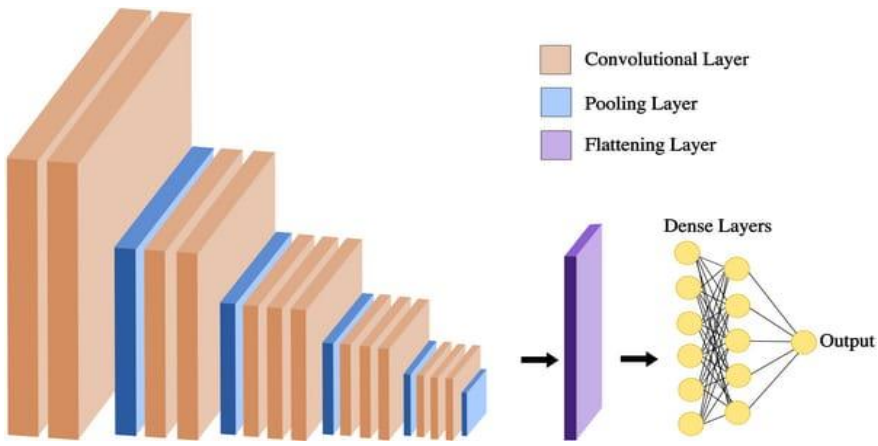

Fig.4. Convolution and Pooling

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To ensure robustness, the algorithm is designed to accurately classify disease regardless of factors like image orientation, area of view, resolution, or angle. **Figure 6** outlines the process for using the web-based application, which includes stages such as accessing the application, signing up, logging in, understanding the application, uploading an image, and receiving results with suggested remedies.

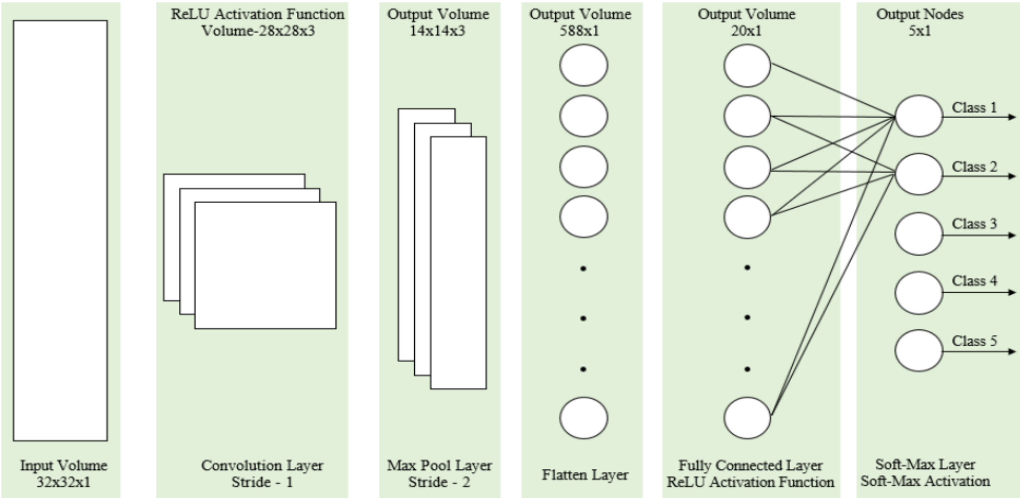


Fig.5. CNN Architecture

5.0 Diseases in Sugarcane

Table.1. Banded Chlorosis

Disease	Banded Chlorosis
Image	
Causative agent	a sudden drop in temperature
Symptom	symptoms are characterised by using mild inexperienced to white horizontal areas at the both leaf aspects. The discolored bands are seen close to the base of the older leaves and regularly near

	successively younger leaves. inside a area, signs and symptoms may be seen on extraordinary flowers at similar heights from the floor. useless spots and shredding are observed in the patches or bands of a few affected leaves. Shorter canes are normally free from this abnormality.
Prevention	Practice early planting

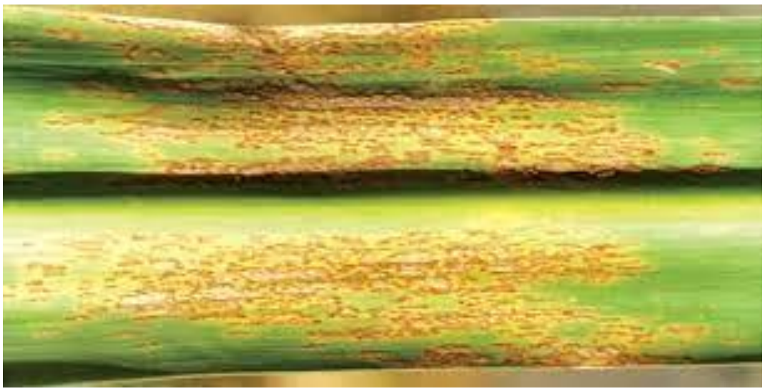
Table.2. Brown Spot

Disease	Brown Spot
Image	
Causative agent	Fungus-Cercospora longipes
Symptom	This disease causes red-brown oval-shaped lesions with a yellow halo on the leaf blade. The spots can be 3–15 mm in size.
Prevention	Apply Copper oxycholoride 0.2% or Mancozeb 0.3% to the leaves 2 to 3 times at an interval of 10 to 12 days

Table.3. Grassy shoot

Disease	Grassy Shoot
Image	
Causative agent	Mycoplasma like organisms
Symptom	Leaves become white or yellow, internodes shorten, leading to stunted growth and smaller leaves, with excessive shoot proliferation, resulting in a broom-like appearance.

Table.4. Brown Rust

Disease	Brown Rust
Image	
Causative agent	Fungus-Puccinia melanocephala

Symptom	Brown rust sign yellow leaf spot about 1-4 mm long. The spot is grown larger and turn into reddish-brown.
Prevention	Spray Tridemorph at 1.0 liter per hectare or Mancozeb at 2.0 kg per hectare. Use Dithane M-45 at 2 g per liter of water for one spraying. Apply triazole, strobilurin, or pyraclostrobin fungicide at 3 g per liter of water.

Table.5. Pokkah boeng

Disease	Pokkah boeng
Image	
Causative agent	Fungus- Fusarium
Symptom	It causes distortion and shortening of the plant's top and leaves, with the base of young leaves turning yellow. The rind of the stalk may also exhibit ladder-like cracks.
Prevention	Cultivate resistant varieties, remove canes with "top rot" or "knife cut" symptoms, spray with 0.1% carbendazim, 0.2% copper oxychloride, or 0.3% mancozeb every 15 days for two to three sprayings

Table.2. Sett rot

Disease	Sett Rot
Image	
Causative agent	Fungus- Colletotrichum falcatum
Symptom	Bud infection: Buds fail to germinate and turn brownish-black Sprouted settlings: Sprouted settlings die and turn orange-red Dead heart: Shoots with green leaves at the base and dead leaves in the whorl Discoloured stalks: Infected stalks turn orange to yellow and the leaves dry White spots: White spots or blotches develop in the pith of infected stalks
Prevention	Use resistant varieties: Plant varieties that are tolerant or resistant to red rot, such as Co 8021, Co 85019, Co 86010, and Co 86032

6.0 Advantages

6.1 Early Detection and Crop Protection:

By detecting sugarcane illnesses early, the method stops them from spreading and causing serious harm. Farmers can protect their crops and lower financial losses by acting sooner if infections are detected early. Stable productivity and healthier plants are guaranteed as a result.

6.2 High Detection Accuracy:

The system accurately detects sugarcane diseases with a remarkable 98.73% accuracy rate. It is a reliable tool for preserving crop health and guaranteeing higher yields because of its high precision, which provides farmers trust in its outcomes.

6.3 Easy-to-use Mobile App:

By snapping a picture of their crops, farmers may use the app to identify diseases. The app's user-friendly design removes the requirement for technical knowledge, making it useful and available for farmers with varying degrees of expertise.

6.4 Cost-effectiveness and Resource Optimisation:

The method saves time and money by eliminating the need for expert evaluations and manual inspections. By detecting problems early, it also reduces the need for needless chemical treatments and helps farmers make better use of resources like fertiliser and pesticides.

6.5 Environmental Sustainability:

The system encourages ecologically friendly farming methods by reducing the usage of chemical pesticides. This ensures a healthier ecology for upcoming farming operations by preserving the soil, water, and biodiversity.

7. Results & Discussion

The study's dataset is made up of pictures gathered from various farms using different cameras. The classifier has proven to be robust, providing accurate results even in daylight conditions. Since images are captured from multiple angles and orientations, the algorithm is designed to classify diseases effectively, regardless of the image's resolution or perspective.

Colour, texture entropy, and the existence of spots are important statistical characteristics that were taken from the pictures. Our findings indicate that factors such as lighting conditions, image orientation, resolution, and angle do not significantly impact the accuracy of the results. The algorithm performs well across varied plant densities and times of day.

8. Conclusion

This study reached a high accuracy of 98.69% by catching sugarcane diseases using a simple convolutional neural network with four different categories. Based on the leaf patterns, the algorithm was able to accept and verify sugarcane photos into groups that were healthy and unhealthy. Consequently, farmers can now recognize and categorize sugarcane diseases by utilizing machine vision and machine learning.

The primary objective of this project is to create a CNN that supports farmers via a mobile an application that is accessible from any device with an internet connection, including tablets, smartphones, and desktop computers. To identify plant diseases, this model helps to recognize real-time data. The system is user-friendly, allowing users to log in and easily upload images for analysis.

The model's ability to adjust to real-world usage via the mobile application will classify how effectively this strategy works. Future research could focus on improving the model based on user feedback, with an always-updated dataset being essential for magnifying its performance. This could be seen as a limitation of the current study and offers a chance for further research, highlighting the need for regular changes made to the data record throughout the operation of the web application.

9.0 Future Scope

9.1 Disease Detection Capabilities Extension:

The algorithm will eventually be trained to identify more sugarcane disease kinds and take weather and soil quality into account. This will increase its adaptability even further and efficient under various farming circumstances.

9.2 Integration with IoT for Real-Time Monitoring:

To deliver real-time information on crop health and environmental conditions, the system may integrate with IoT sensors. Farmers would be able to take swift action thanks to this real-time data, which would enhance their capacity to effectively manage crops.

9.3 Advanced Analytics for Market and Yield projections:

The system may be able to assist farmers in making better plans by including features for market trends and yield projections. They would be able to maximise planting, prudently distribute resources, and make well-informed decisions to increase their earnings as a result.

9.4 Enhancements to Localisation and Accessibility:

The system will be customised to handle multiple languages and include regional illness patterns. Farmers in various areas will be able to use it thanks to this customisation, which will promote widespread use and optimise its advantages.

9.5 Feedback-Based Continuous Improvement Mechanisms:

The system will be improved over time with input from farmers and agricultural specialists. The system will continue to be applicable and successfully satisfy farmers' needs by improving its accuracy and including new features.

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