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IDENTIFICATION OF SUGARCANE DISEASES USING DEEP LEARNING-SURVEY

Mr. Pratik D. Palkar*[1], Dr. Geetika Narang*[2], Prof. Rutika Shaha*[3], Prof. Rupali Maske*[4], Prof. Barkha Shahji*[5], Prof. Jayashri D. Palkar*[6]

*[1,2,3,4,5,6]Computer Engineering, Trinity College Of Engineering & Research, Pune, India.

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ABSTRACT

Sugarcane is a major crop worldwide and the main source of both sugar and ethanol. India's economy is mostly based on agriculture, which is the country's main source of income. Sugarcane is widely farmed in several Indian states, including Bihar, Karnataka, Tamil Nadu, Uttar Pradesh, Maharashtra, and many more, because it is a crop that grows again. The proliferation of diseases that infect sugarcane, forcing farmers to eradicate disease-ridden areas and costing small-scale farmers money if the infections are not treated and detected early, is one issue specifically impacting the sugar business. In agricultural settings, viruses and bacteria are secondary sources of plant infection, while natural disasters like storms and floods are the primary sources of damage to crops. The decline in quality might also be attributed to viral illnesses. Disease control is crucial for maintaining crop quality. When specialized agricultural specialists assist farmers with vast farming experience, they can usually diagnose ailments in crops. Occasionally, variations in weather might make it difficult to diagnose certain illnesses. It restricts the ability to diagnose problems of sugarcane. In order to address this problem, we suggested machine learning via computer vision using deep learning approaches in this study. This work trained and evaluated a deep learning model with 13,842 sugarcane photo datasets that showed both disease-infected and healthy leaves, with an accuracy of 95%. The trained model achieved this by recognizing and classifying sugarcane pictures into groups that represented healthy, sick, or diseased sugarcane leaves. As a result, this study provides a deep learning algorithm-based approach for classifying and diagnosing sugarcane diseases to support farmers.

Keywords: Convolutional Neural Network (CNN), Classification Of Images, Deep Learning.

I. INTRODUCTION

A major crop in the globe, sugarcane is essential to the production of sugar. On the other hand, there are some challenges associated with sugarcane production, such as the impact of diseases, which can significantly affect crop output and quality. Most often, infections caused by bacteria, viruses, and fungi are the culprits of sugarcane diseases. Below is a summary of some of the most common illnesses that affect sugarcane:

The fungus Colletotrichum falcatum is the cause of red rot (Colletotrichum falcatum). Red internode staining, withering, and general deterioration are among the symptoms. Impact: The reduced sugar content and overall yield have a significant economic impact. Smut is caused by the fungus Sporisorium scitamineum (Sporisorium

scitamineum).One of the signs is the development of black whip-like structures, or inflorescences. A decrease in the amount of millable canes has an effect on the amount of sugar produced. The causative agent of ratoon stunting illness is Leifsonia xyli subsp. xyli, a bacterium. The symptoms include reduced sugar content, chlorosis in the leaves, and slowed growth. The ability of sugarcane plants to regenerate, or ratoon, after the initial harvest is impacted by certain events. Pokkah Boeng (Ralstonia solanacearum) is caused by the bacteria Ralstonia solanacearum. The symptoms include vascular discoloration, yellowing, and wilting. Effect occurs, changing the sucrose concentration and reducing cane yield. The culprit is the bacteria Xanthomonas albilineans, which causes leaf scaling. Leaf dryness and longitudinal white streaks on the leaves are symptoms.Impact diminishes photosynthetic capacity, causing output to decline. Infections, dietary anomalies, and environmental factors interact intricately to induce yellow leaf syndrome. Yellowing of the leaves and reduced growth are among the symptoms. Plant health and productivity are impacted by impact. Orange rust is brought on by a fungus called

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Puccinia kuehnii. The symptoms are orange pustules on the leaves. Impact happens as a result of reduced photosynthesis, which affects sugar content and yield [1].

Figure 1: Leaf yellowing of sugarcane crop [4].

An awareness of sugarcane illnesses and effective management of them are prerequisites for sustainable sugarcane production. Implementing integrated pest control approaches, early problem identification, and continuous research are critical to reducing the impact of these diseases on sugarcane crops. In some studies, machine learning is used as a cutting-edge method for classifying and detecting plant diseases. Traditional machine learning techniques [2] frequently use algorithms like SVM, SIFT [3], and others. This approach requires more intricate computations for online applications. As such, applying these methods can only yield positive results. To boost the efficiency and accuracy of feature extraction, complex tools such as plant genomes, infrared spectra, and electromagnetic radiation are required; however, small-scale farmers cannot afford to use these technologies to extract characteristics of plant diseases.

Deep learning uses an artificial neural network architecture and usually incorporates numerous layers for processing, in contrast to normal neural network topologies. Deep learning has transformed the picture identification, image classification, acoustics, and other sectors that require large amounts of data to process. The application of deep learning to the diagnosis of plant diseases has created new opportunities for professional analysis and judgment. In the current study, the researchers' primary deep learning method of choice is Convolutional Neural Networks (CNNs).CNN is one of the most widely used methods for presenting complex concepts since it can process large amounts of data and identify patterns in it. CNN can recognize plants just by looking at images of their leaves. For this investigation, 13,842 images of sugarcane will be used as training data. The data includes seven classes: one healthy class and six types of sugarcane leaf illnesses.

The essay's remaining sections are arranged as follows: In the following section, we discuss the crisis response design process in more detail. Methods for Sugarcane Disease from Picture of Higher Resolution Images are included in Section 2. In division 3, we provide a summary of the design and development of this specific investigation. Section 4 offers the structure and different strategies. This article's section 5 provides explanations of the research experiment results, and section 6 concludes with those findings.

II. LITERATURE SURVEY

Crop diseases have the biggest impact; when they infect a crop, they reduce agricultural output by 20–30% (Park et al., 1). Agricultural diseases have a major impact on crop productivity. In unclear situations, farmers must rely on professional judgment or their own experiences. A farmer can use an analysis machine system to identify and anticipate illnesses by uploading a smartphone snapshot of a leaf. They developed a diagnostic system consisting of two convolutional networks and three fully linked networks. When running on a central processing unit (CPU), the model's accuracy is 89.7%. Plant diseases are the primary cause of the reduction in agricultural output, both in terms of quantity and quality, according to studies by Dandawate et al. [2].Farmers face difficulties in diagnosing and treating plant diseases. In the end, the test findings show that this system can categorize leaves with an average accuracy of 93.79%.

Militante et al.'s study [3] looked at the trained model's 96.5% accuracy rate. They were able to recognize and diagnose illnesses as well as 32 different plant types using a CNN. Using the trained model, real-time photographs were assessed for the diagnosis and detection of plant diseases. Their recommended method can help farmers diagnose and categorize plant diseases with a 96.5% accuracy rate. Hu et al.'s investigation [4] indicates that illnesses of tea leaves may be promptly and precisely recognized, which helps with control and prevention. The results of the experiments demonstrate that the proposed method performs better than conventional DL strategies and standard Machine Learning (ML) techniques, with an average identification accuracy of 92.5%. The enhanced model requires fewer iterations to attain convergence and has fewer parameters than the network models of AlexNet DL and the Visual Geometry Group-16 (VGG16). According to the study results, the proposed model has minimal parameters, high identification accuracy, and fast rate of identification. Suryawati et al.'s research [5] indicates that outbreaks of plant diseases can pose a serious threat to the safety of our food supply. A calamity like this might be avoided with early machine learning-based illness diagnosis. Deep learning (DL), a relatively new machine learning technology, is already widely used for tasks requiring object identification. The study's findings demonstrate that a CNN with a deeper architecture performs this task better.

Using a subset of the Plant Village dataset, particularly the tomato dataset, they investigate several deep CNNs, including VGGNet, AlexNet, GoogleNet, and a simple two-layer CNN as a baseline for tomato plant disease recognition tasks. The sugarcane disease is a problem for the industry since it harms crops, reduces cultivation, and costs farmers money, according to Militante et al.'s investigation [6]. Machine learning technology can help prevent these losses by detecting illnesses early. For this reason, deep learning is an intriguing approach to machine learning on this problem. They classified and identified sugarcane diseases using three different DL models. The LeNet, StridedNet, and VGGNet models are compared inside the research architecture. It also determines which model works best for recognizing and classifying diseases unique to sugarcane. Of the three models, StridedNet had the lowest accuracy rate in diagnosing sugarcane infections, while VGGNet has the greatest. Huang et al. [7] investigated the precision of the spectro-optical Photochemical Reflectance Index (PRI) in quantifying the wheat yellow rust Disease Index (DI) to ascertain how well the PRI may be applied to hyperspectral imaging for disease diagnosis. Wheat plants with varied degrees of yellow rust infection had their growth observed five times over the course of two seasons in order to determine the canopy reflectance spectrum and DI. During the second season, aerial photographs of the field site were also captured using hyperspectral imaging.Based on these findings, winter wheat fields can be equipped with an image sensor that can be utilized from space or the air to detect yellow rus. Gradient-based strategies are employed to minimize a performance metric and enable multimodal system training on a global scale. In addition, a bank check is read via a graph transformer network. It combines CNN character recognizers with international training approaches to deliver unparalleled accuracy on commercial and private inspections. Millions of checks are read daily by the same gadget in the commercial sector. CNNs have been shown to be able to replace manual feature extractors. It has been demonstrated that GTNs eliminate the requirement for manually created heuristics, labor-intensive labeling, and human parameter tweaking for document recognition systems. In the right meteorological conditions, a virus called Grapevine Leafroll Disease (GLD) can quickly spread throughout vineyards and reduce grape yield by almost 60%, according to Hou et al. [9]. Especially in the early stages of sickness, accurate diagnosis and unbiased evaluation of GLD distribution are essential to halting the development of GLD infection. In order to effectively cure the illness, this study used the Ant Colony Clustering Algorithm (ACCA) to identify GLD spectrum abnormalities on four GLD-infected vineyards. Three stages of GLD were identified based on the extent of infection: GLD1, GLD2, and GLD3. Tea Leaf Blight (TLB), a prevalent disease on tea plants, has been found by Hu et al. [11] to have a negative impact on tea yield and quality. By precisely measuring the degree of tea leaf bulging, tea growers can calculate the appropriate dosage of insecticide. This study proposes a four-step process to segment disease spots, segment sick leaves, segment area fit infected leaves, and estimate disease severity in natural scene images for TLB. To determine the severity of the sickness, the metric learning model is fed TLB leaf texture data, color features, and the indication of initial disease severity (IDS).

The experiment's outcomes shown that, in comparison to conventional CNN approaches and conventional ML, the suggested strategy has a greater estimate accuracy and is more resistant to rotten and blocked TLB leaves. The scientists' ongoing research on the effects of disease detection can be combined with AI techniques and tools to increase agricultural productivity and forecast pricing, assisting farmers in making better decisions. Plant disease diagnosis is recognized to benefit greatly from CNNs; nevertheless, building a robust dataset for the

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technique is a challenging task. In order to anticipate sugarcane diseases with high accuracy using historical data, DL is applied throughout the technological solution. Predicting sugarcane disease is the main objective of the study, which will be very beneficial to farmers in planning sugarcane sales.By using predictive disease prediction to detect and control sugarcane disease, farmers may increase the amount and quality of their crop. Better sugarcane disease prediction is provided by a CNN system based on DL. This research aims to forecast sugarcane disease using the CNN algorithm.

III. METHODS FOR OF SUGARCANE DISEASE FROM PICTURE OF MORE RESOLUTION IMAGES

The two primary methods of identifying sugarcane disease are the utilization of the sugarcane area and the sugarcane disease itself. Applications for identifying sugarcane diseases usually use higher-resolution, high-quality pictures. Thanks to the use of cameras and NIR illumination, higher-resolution pictures of sugarcane disease may be captured quickly and included into the detection system. This could vary based on the implementation situation. A higher resolution image of the sugarcane disease area is obtained, as shown in Figure 1a, from which Figure 1b, the sugarcane disease area, is identified. Generally speaking, recognition requires an expensive photo taken with a higher resolution camera. Furthermore, there is a method (Figure 2) for collecting only the sugarcane illness by using a zoom capability on a camera with a tiny field of vision. Sugarcane disease from that image focuses on accurate sugarcane disease segmentation because the image already has numerous distinguishing features. The methods of recognition are then selected according to the result. The next paragraph provides an introduction to the typical image of higher resolution image-based sugarcane disease recognition investigations. Only can be bought and used immediately. Generally speaking, recognition requires an expensive image from a higher quality camera. Furthermore, a method exists for acquiring solely the sugarcane disease region.

Figure 2: A sample of a database that contains picture of the sugarcane disease.

Figure 3: A sample of a database that contains picture of the sugarcane disease.

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Figure 1 uses a zoom capability and a camera with a narrow field of view. The precision with which the sugarcane disease features are extracted determines the efficacy of sugarcane disease detection when use the traditional photo processing technique.

Performance is evaluated using the error equal rate (EER), a widely used biometrics statistic. When genuine recognition is performed and the false acceptance rate (FAR) and false rejection rate (FRR) are equal, the EER shows the error rate at that point. The probability that a user will be incorrectly denied as someone else is known as the FRR, while the probability that a topic will be accepted incorrectly is known as the FAR. Three categories can be used to group the study on sugarcane disease detection in the context of greater resolution: expert systems, computer vision, and image analysis.

A. Image Processing Technique

First, image processing with sugarcane disease segmentation. Afterwards, the peak side-lobe ratio (PSLR), a signal-based performance evaluation, is used in the last recognition method. To do this, the rubber-sheet image of the sugarcane illness is transformed into a frequency signal area (FFT) using the quick Fourier transform. After that, the proposed method matches templates to identify objects, using the PSLR value as a similarity measure for the enrolled and grateful photographs. The suggested method uses a morphological filter to identify the sugarcane disease region in order to block pupil-reflected light. The sugarcane disease area is located by first locating its vertical and horizontal preliminary directions using a circle template.Subsequently, the area affected by sugarcane disease is identified using image-enhancing methods such as the Hough transform, the Gaussian filter, the smart edge sensor, and histogram equalization. The refine-connect-extend smooth (R-C-E-S) method is then used to identify the area around the eyelid, and an eye mask is created to protect the eye. Compared to sugarcane disease gratitude based on discrete wavelet transform (DWT). The performances are better than what the DWT offered. An technique for dynamic radius matching for sugarcane disease gratitude. The size of the sugarcane disease area may vary as a result of the pupil. The sugarcane disease area grows and the pupil area shrinks in overly bright lighting, and vice versa. An undesirable outcome is that the recognition performance could deteriorate if a particular degree of input image quality is not assured.Another disadvantage of the recognition method is its complicated implementation strategy. When unexpected images or low-resolution photos are used in such a system, the recognition performance may deteriorate significantly, requiring the use of a suitable technique.

B. Using Machine Learning to Learn

Given the aforementioned shortcomings of image processing techniques, machine learning algorithms have been introduced. Two tools are used: an artificial neural network (ANN) and a support vector machine (SVM). First off, image preparation follows standard image processing protocols most of the time. The 1D log-Gabor wavelet transform is used to eliminate the sugarcane disease code after the sugarcane disease region has been segmented using the Hough transformation and canny edge detector techniques. To recognize sugarcane illness, the acquired sugarcane disease code is fed into an artificial neural network (ANN) and a support vector machine (SVM)-based classifier.

C. Method of Deep Learning

Finer control over the recognition process is made possible by machine learning technologies, and training frequently yields a high recognition rate. A photo must be of an acceptable quality or better in order to be adequately preprocessed and turned into a rubber-sheet model, which is a distinctive feature of sugarcane disease recognition approaches. Put another way, performance can be affected if a low-resolution image is entered.

The low capacity for gratitude for photos taken in unfamiliar locations compared to other settings is another problem. There has been deep learning research on sugarcane disease thankfulness due to the limitations of machine learning techniques. Without changing the sugarcane illness image further, principal component analysis (PCA) is used to reduce the dimensions of the attributes obtained by the VGG-16 model. The multiclass SVM is then used to determine thankfulness for the sugarcane disease. Various methods of deep learning sugarcane disease recognition are available that extract features and carry out identification by constructing a

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rubber-sheet model with sufficient pre-processing or by prioritizing self-trained sorting skills and the deep learning model without segmentation. A deep learning model can show strong recognition performance over a wider range of image alterations if it is appropriate in this case. On the other hand, the masses of the model trained on higher-resolution photos might be approximated incorrectly if a low-resolution image is provided.

Table 1: Comparative Literature

Ref.	Approach	Infected Disease Plant	Database	Performance
[35]	CNN model of 16 layers	Tea Plant	Unakoti district, tripura	Accuracy 96.56 %
[36]	CNN model of 4 layers	Tomato Plant	Plant Village dataset	Accuracy 98.19 %
[37]	CNN model of 15 layers	Rice Plant	on-field images	Accuracy 99.66 %
[38]	SVM Classifier	All types of Plant	Plant Village dataset	Accuracy 91.8 %
[39]	KNN model	Sugarcane Plant	On-field images	Accuracy 95.8 %
[43]	CNN model of 4 layers	Sugarcane Plant	On-field images	Accuracy 98.69 %
[45]	QBPSO-DTL approach	Sugarcane Plant	On-field images	Accuracy 98.69 %
[40]	Convolutional Neural Network-Based VGG16 Model	Multi-Crop Leaf Disease	On-field images	Accuracy 95.71 %
[41]	Adaptive K-mean clustering	Sugarcane Plant	On-field images	Accuracy 95 %

IV. RESEARCH PROCEDURE

By teaching a model to identify patterns and traits in images of sugarcane plants that correlate to different diseases, deep learning is a method for diagnosing diseases of the crop. Here is a general guide to assist you in doing this task:

1. Data collection: Assembles a diverse photo gallery of sugarcane that features both healthy and differently injured plants. Select the type of ailment that each image relates to. A manually collected picture dataset of sugarcane leaf disease. Usually, it is separated into five groups. Rust, Yellow, Redrot, Mosaic, and Healthful. The dataset was gathered using smartphones that were configured differently in order to maintain variation. This database was assembled in the state of Maharashtra, India. The photos are not all the same size because they were taken using various cameras. All images are in RGB format.
2. Data preprocessing: Resize photos to a consistent scale before feeding them into the model. Normalizing pixel values to a traditional range, such [0, 1], is necessary. Use operations like flipping, rotating, and zooming to bolster the dataset in order to increase the model's durability.

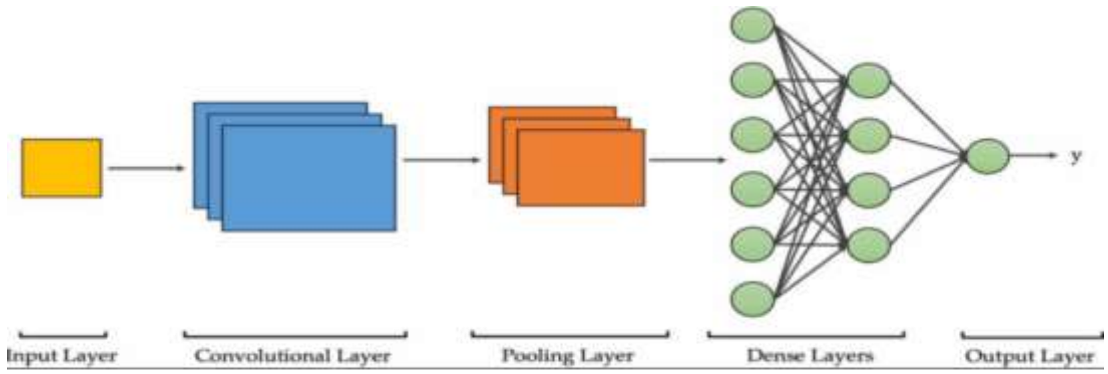

Figure 4: Architecture of Convolutional Neural Networks (CNNs)

3. Model selection: Pick a suitable deep learning architecture for picture classification. Convolutional neural networks, or CNNs, are widely used for this. One alternative is to use pre-trained models like VGG, ResNet, or EfficientNet.
4. Transfer of Learning: Adjust the preferred pre-trained model using the sugarcane dataset. This facilitates the application of the insights the model gained from a large dataset (like ImageNet) to your specific problem.
5. Training the Model: Separate the training, validation, and test sets from your dataset. Train the model with the training set, and then use the validation set to confirm its accuracy. Adjust hyperparameters like learning rate, batch size, and epochs to optimize performance.
6. Evaluation: To determine how effectively your model generalizes to new, untested data, use the test set. Use metrics like F1-score, recall, accuracy, and precision to gauge performance.
7. Deployment: Use the model in real-world scenarios once you're satisfied with its functionality. Consider developing an easy-to-use user interface or adding the model to an existing system.-existing system or creating an intuitive user interface.
8. Continuous Improvement: Monitor the model's output over time and update it with new data to ensure that it keeps functioning even if the circumstances surrounding sugarcane diseases change. Try out different architectures and combinations of hyperparameters to see which suits your specific problem the best. Try implementing Explainable AI concepts to understand how the model is making decisions, particularly in important domains like agriculture. Projects involving deep learning usually use Python. Two well-liked deep learning frameworks are PyTorch and Tensor Flow. Libraries like Keras provide high-level abstractions for setting up and training neural networks.Ensure that a balanced dataset has representation for every ailment class. It could be necessary to address inequality if the model is to prevent the dominant class from being favored. Acknowledge the possibility of biases in the dataset and model predictions. The development and quality of sugarcane plants are enhanced by the automated diagnosis and early identification of diseases, both of which are made possible by computational techniques. Using image processing techniques such pre-processing, ROI extraction, features extraction, and classification, the diseases in sugarcane plants were categorized.

V. TECHNIQUES AND FRAMEWORK

This section presents the architecture and development of the proposed deep learning-based Recognition of Sugarcane Diseases.

1. **Getting pictures of diseases related to sugarcane:** Each image related to this sugarcane disease was obtained from a dataset. The collected dataset is divided into numerous pieces, each of which is verified by experts and labeled appropriately. Every dataset used for testing and training, both accurate and erroneous.
2. **Adaptive Window Filtering:** This technique is used in computer vision and image processing to enhance or filter images to eliminate noise by applying a filter with various parameters depending on the characteristics of the image [28]. Adaptive window filtering is used to change the filter properties based on the image's local content. This could improve the image quality.
3. **Image Segmentation:** In computer vision and image processing, segmenting an image is a fundamental task that entails breaking a picture into discrete and meaningful sections. Shared visual characteristics, including color, texture, intensity, or other elements, frequently define these parts. This method finds the damaged areas in the sugarcane image by using the preprocessed photo as input during the image segmentation phase.

Convolutional neural networks (CNNs) are a subclass of deep neural networks that are used to process structured grid data, including images and videos. Many computer vision applications, including segmentation, object detection, and picture categorization, now depend heavily on CNNs. CNNs use convolutional layers with kernels or filters to scan the input data. These filters work by swiping over the input, multiplying each element individually before aggregating the result to create feature maps. Convolution facilitates the learning of feature spatial hierarchies by the network. By using pooling layers (such as max pooling), feature maps are down

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sampled, reducing their spatial dimensions. This helps reduce processing complexity and manage overfitting. Pooling allows the most important information to remain intact while discarding less relevant bits. Rectified Linear Unit, or ReLU, is a common activation function in CNNs that gives the model non-linearity so that it may learn from complex input. CNNs usually consist of several convolutional and pooling layers followed by one or more fully linked layers. Based on the obtained attributes, these layers make global forecasts. Before completely linked layers, the 2D output of the convolutional and pooling layers is flattened into a 1D vector. CNNs learn parameters (weights and biases) during training by using optimization techniques like stochastic gradient descent (SGD) and back propagation. A loss function measuring the difference between expected and actual outputs needs to be minimized in order for the system to learn. CNNs usually employ pre-trained models using large datasets such as Image Net. Transfer learning is the process of using knowledge from one activity to improve performance on a related task using a smaller dataset. CNNs can be enhanced to perform additional functions, such as localization and object recognition. This requires the ability to predict bounding boxes and class labels for objects in a picture. Batch normalization can reduce internal covariate shift and expedite training by normalizing the input of each layer. A regularization procedure known as dropout ignores random neurons during training to prevent overfitting. Data augmentation involves randomly varying the training set, such as flipping, rotating, and zooming, in order to increase model resilience. Data augmentation involves randomly varying the training set, such as flipping, rotating, and zooming, in order to increase model resilience. CNNs are widely used in a wide range of applications, such as photo categorization, medical image analysis, autonomous driving, and facial recognition.

CNNs are a standard in computer vision due to their remarkable ability to extract useful properties from images and manage spatial hierarchies. Their innate ability to learn hierarchical representations has been linked to their effectiveness in a range of visual activities.

4. A Feature Extraction Method Employing the ReLU

When using the Rectified Linear Unit (ReLU) activation function in neural networks, especially Convolutional Neural Networks (CNNs), the focus is often on how this activation function adds to the non-linearity of the model. ReLU is popular because of its simplicity of use and ability to accelerate convergence during training.

5. **Classification:** Fully connected layers are utilized for classification, whereas convolutional and pooling layers are employed for feature extraction. The sugarcane leaves are categorized in this layer based on whether or not they are infected.

A method called "data augmentation" makes it possible to artificially increase the size of a dataset by applying various modifications to the existing data. This improves the generalization and durability of machine learning models, especially for tasks like picture classification where the model has to recognize objects under different conditions.

VI. CONCLUSION

In this study, deep learning was utilized to classify and identify healthy versus diseased sugarcane leaves. A simple convolutional neural network was used by the architecture to classify the sugarcane leaf. In this study, we compared research that used CNN algorithms to address problems that occur when low-resolution images are used for recognition with approaches that use higher-resolution images to treat sugarcane and retinal diseases. We also examined the problems with each study and examined each in detail. Major challenges to the implementation of sugarcane disease systems include the extraction of distinctive characteristics from the sugarcane disease data to distinguish individuals and the dependable extraction of the sugarcane disease area segmentation. Deep learning-based super resolution (SR) approaches have been thoroughly studied recently and can achieve comparable performance to higher resolution imaging systems when used in situations where low resolution images are captured. This can increase the level of security in settings with mobile devices that are frequently used in everyday life and make the establishment of a sugarcane disease system easier when done in a secure setting. as a consequence of these studies.

To guarantee system reliability in these applications, algorithms that are resistant to occlusion, camera variety, and subject position should be investigated. Furthermore, a small-sized method ought to be looked upon for usage in embedded systems with little processing power.

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