



Research Article

Disease detection in sugarcane crop using deep learning

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ABSTRACT

Sugarcane is a special crop that developed from a wild grass species to a major crop utilized for food and energy as a result of human activities. Due to its substantial contribution to the national finances and employment of more than a million people, mostly in the production of sugar and renewable bioenergy, it is a major crop that requires careful monitoring. Crop losses for farmers, both in terms of quantity and quality is caused by diseases in crop. In order to increase agricultural output and performance, scientists are now focused on early disease detection and identification. Additionally, agriculture makes substantial use of artificial intelligence. This study attempts to classify diseases in sugarcane using transfer learning and deep learning algorithms. In this context, first a detailed review on the recent contribution in sugarcane disease detection is discussed. Then, using leaf images as data, deep learning techniques are implemented utilizing transfer learning to build models that can identify sugarcane diseases. Metrics like confusion matrix, accuracy, precision, recall, and f1-score are used to evaluate the performance of various deep learning models. Different deep learning models such as Convolutional Neural Network (CNN), Visual Geometry Group 16(VGG16), Visual Geometry Group 19 (VGG19), Alex Krizhevsky's Network (AlexNet), Inception convolutional neural network Version 3 (Inception V3) and Densely Connected Convolutional Network with 201 layers (DenseNet201) were trained and results show that DenseNet201 outperforms compared to others with 94.14 % accuracy. This study not only shows how transfer learning can improve sugarcane disease classification, but it also verifies that deep learning models can function well in classification-related tasks.

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INTRODUCTION

Agriculture is one of the largest growing sector in Indian economy. It is one of the primary source of income for around two-third of population in India. Sugar cane is

one of India's primary agricultural products [1]. Biofuel can be produced from sugarcane byproducts like straw and cane fibers. Moving from conventional fuels to biofuels has many financial advantages that can help society financially and lessen the need to dispose of biomass in the future

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[2]. Lots of sugarcane products contain molasses, rum and fibers, which are used to feed animals [3]. Different factors that cause diseases in crop are varying temperature, composition of soil, an unfavorable pH level and changing climatic conditions. Plant diseases can be defined as unusual variations caused by any one or more biotic or abiotic factors that affects the normal growth of a crop. Generally, crop diseases can be classified as either infectious or non-infectious. Infections with bacteria, fungi, and viruses result in

infectious illnesses. Negative environmental variables are the origin of non-infectious diseases, that cause damage to crop [4]. Worldwide crop output is hampered by sugarcane diseases, and no nation is immune to the damaging effects of plant infections and pests. Worldwide reports of more than 125 sugarcane diseases attributed to bacteria, viruses, nematodes, phytoplasma, and fungus have been received [5]. The symptoms of some of the important diseases affecting sugarcane plants are included in Table 1 [6-9].

Table 1. Indicators of major diseases in sugarcane

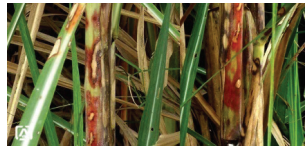
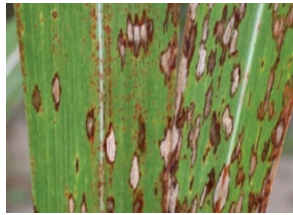
Sr no	Sugarcane Disease name	Symptoms	Causes for Disease	Image of Diseases
1	Red rot	The infected leaf undergoes colour change from time to time. As time passes the stalks becomes hollow. [6].	Rain, Air and humid weather. Fungus named Colletotrichum Falcatum causes red rot disease	
2	Wilt	The crown leaves shrink and become yellow in infected plants.[7]	High Temperature, low humidity, soil moisture. Cephalosporium sacchari infection causes Wilt disease	
3	Grassy shoot	Crowded bunch of tillers having narrow leaves are formed due to proliferation of vegetation buds from the base of the cane.	The diseases are caused by a phyto-plasma bacteria.	
4	Smut	Production of whiplike structure from the growing point of the canes.[8]	Hot and dry weather. Ustilago scitaminea is the fungus that causes Smut illness	
5	Red striped disease	Dark red stripes appear either all over the blade or in the middle. [9]	wet and hydrated circumstances. The bacteria Xanthomonas Albilineans is the cause of red striped disease	
6	Mosaic disease	Leaves that are kept away from sunlight appear chlorotic and creates a mosaic pattern	It is spread by a cutting knife and contaminated seed.	
7	Pokkah Boeng	Leaf blades or base of the young leaves suffers from chlorotic condition	Humid, cloudy weather and drizzling rains	

Table 1. Indicators of major diseases in sugarcane (continued)

Sr no	Sugarcane Disease name	Symptoms	Causes for Disease	Image of Diseases
8	yellow leaf disease	Middle region of the leaf turns yellow in colour	dry conditions	
9	RUST	small yellowish and reddish spots appear on both sides of leaf.	Warm weather with high humidity	
10	Leaf scald disease	«pencil lines» of white and yellow border appears on the leaf.	drought, waterlogging, and low temperature	
11	Eye Spot Helminthosporium	The wet patch appears on the leaves, grows longer over time, and eventually takes the form of an «eye» with a reddish-brown centre encircled by straw-coloured tissues.	Moist and humid conditions	

In the traditional method, farmers manually search their crops for visible signs of crop disease, consulting plant pathologists or crop disease experts for further guidance. Moreover, it involves laborious, drawn-out, and frequently challenging procedures of microscopy, pathogen culture isolation, and visual symptomatology observation in diagnosing crop disease. Therefore, precise disease detection and classification are necessary to assist farmers in farming. Artificial intelligence methods can be used to develop more robust system to identify agricultural diseases. These tools are quicker than previous approaches and may not require very complex or advanced procedures [9]. Recent studies showed that models using Machine learning algorithm like SVM are less accurate at predicting and detecting disease. Also, model is trained for small to medium number of images considering a smaller number of diseases. In this case, deep learning and transfer learning can improve the efficiency and accuracy of sugarcane disease detection. For the purpose of predicting dynamic time-series responses, another model based on deep learning neural networks has been developed in MATLAB. [10]. A novel method to enhance the deep learning model's performance has

been put forth that uses fuzzy edge detection to maintain the edge pixels and fuzzy filtering to modify the filtered image pixels in order to produce a denoised image [11]. Researchers are always ready to search for new and inexpensive ways to solve the problem of diseases in crop [7, 8]. Different horizons of logic such as Fuzzy logic, neutrosophic logic and bitopological spaces can be combined that have a huge potential in various applications that can handle uncertain or imprecise image data [12]. This is because the early disease detection in crop allows farmers and other stakeholders enough time to minimize the risk of a disease outbreak and yield losses. Additionally, comparisons between deep learning and other widely used methods are made with regard to variations in classification or regression performance, and the results show that deep learning offers high accuracy, outperforming other well used image processing methods. [13]. A multi-layer perceptron (MP) based on a deep learning (DL) model is used to detect and classify images infected with Sugarcane Red Rot (SRR). [14]. In addition, green fuel, ethanol can be produced from surplus sugarcane by sugar factories and used with gasoline to reduce foreign exchange costs associated with the import

of crude oil. The government has set a goal to blend 10% fuel-grade ethanol with gasoline by 2022 and 20% by 2025. To improve the quality and yield of sugarcane is the need of an hour. Hence, research and development in the field of sugarcane will help to address issues like low yield and poor quality. This study uses 6748 photos and 11 class categories to classify diseases in sugarcane using deep learning techniques and transfer learning.

Literature Review

Deep learning approaches have showed considerable potential in the field of crop disease identification. These methods are useful for identifying diseases in crop since they automatically recognize and extract features from plant images using multilayer neural networks or deep neural networks. Convolution neural networks (CNNs), recurrent neural networks (RNNs), and ensemble learning are a few instances of these methods. While CNNs are more popular for image-based tasks, Recurrent Neural Networks (RNNs) are useful for sequential data RNNs can be used to time-series data, such as the evolution of disease symptoms over time, in the context of plant disease detection. Ensemble predictions from various models (ensemble learning) can improve disease detection systems overall robustness and performance. A sugarcane disease prediction model has previously been constructed using different types of machine learning and deep learning models, each with a distinct purpose.

[15] used a convolution neural network (CNN) to identify illnesses in sugarcane crops. Six distinct forms of sugarcane leaf disease are included in the data, which was manually recorded with the aid of a camera. Patterns that develop on the leaves are used to identify and categorize diseases in sugarcane, with an accuracy of 95%. Different models may use the training set in the future to improve performance. Additionally, the model's performance can be improved by utilizing various learning rates and optimizers.

CNN and deep learning architectures are used to detect diseases [16]. "Cercospora Leaf spot, Helminthosporium Leaf spot, rust, Red rot, and Yellow Leaf disease" are the five sugarcane diseases that are taken into consideration. The images were personally gathered from several Karnataka farms. Using two different object-detection algorithms, "YOLO and Faster-RCNN," the infected areas in the sick leaf image were correctly recognized with an average precision score of 58.13%. CNNs have been shown to be incredibly reliable at spotting patterns in images. Images captured under both controlled and uncontrolled circumstances were used to evaluate the model. Larger datasets in the future may further enhance the outcomes.

For the purpose of detecting sugarcane disease, a unique deep learning system is developed [17]. Three distinct scenarios are presented in the paper, each utilizing a different feature extractor: "Inception V3, VGG-19, and VGG-16." Images from Makwana Sugar Mill Pvt. Ltd.'s fields were manually gathered for the data set. Data analysis

and visualization were done using Orange software. The collected features are then fed into different classifiers such as "SVM, KNN, Neural Network, Logistic regression, Ada boost, SGD, and Naïve Bayes" in each of the three cases. Out of all, the SVM classifier and pre-trained Deep Learning model VGG-16 produced an AUC of 90.2%. This model may be expanded in the future to include diseases in humans, animals, and plants

Sugarcane diseases are classified using the CNN model [18]. The data collection included large number of photos of sugar cane leaves from Agarian University and the field of Bangalore in various states of distress. Also, five different sugarcane disease considered are "Cercospora Leaf spot, Helminthosporium Leaf, Rust, Red rot and yellow leaf disease." The identification of illnesses in sugarcane was done with high precision and accuracy of 93.2% using the proposed design.

Sugarcane disease is identified using a Deep Convolution Neural Network model [19]. The dataset is manually captured through different modes of camera. Different sugarcane disease considered are Eye Spot, Yellow leaf, red rot and Rust. "Faster Region-based Convolutional Neural Network" is used in conjunction with YOLOV5 to locate infected areas in sick leaves. The user interface for taking images and immediately recognizing illness is also served by an Android application. Real-time captured images from android application serves as front end whereas detection of disease is done by Machine learning algorithm which serves as back end. Faster RCNN shows higher performance than YOLOV5.

A CNN model is used for detection of disease in sugarcane leaf [20]. It consists of large image datasets divided into seven different classes which are acquired manually. K-means model is compared with CNN and CNN showed more promising result. Along with disease detection it also recommends suitable pesticide. It uses Tkinter framework to construct this application.

A model which is combination of vision transformer model and CNN model is used for detection of disease in sugarcane leaf [21]. Four different sugarcane disease considered are mosaic, yellow leaf, rust and red rot. Vision Transformers (ViT) is a model first revealed in 2021. The ViTs are different than CNN because they process input image on a single scale. Three model are trained DenseNet121, ViT and ViT+CNN combination for disease detection, out of which ViT showed promising results and achieved accuracy of 92.85%. The researcher has provided a new way of implementing Vision transformer in detecting disease in sugarcane plant. In future the model can be evaluated in comparison with other existing models for performance and the study can also be extended on humans and animals.

A web-based application for detecting sugarcane disease is developed [22]. Three sugarcane diseases—Black Rot, Grassy Shoot, and Smut—are classified using the CNN model. The accuracy attained is 98.69%, and the dataset is

balanced in terms of agroclimatic area, diverse light impacts, and different times of day and year. In future the model can be combined with productivity enhancement and price forecasting with AI tools. Also, the model can be fine-tuned with the help of feedback taken from the user.

The use of Dense Net201 in conjunction with SVM were used to identify red rot and red rust diseases in sugarcane leaves [23]. The data set includes photos that were taken when visited sugarcane crop fields in Pune's Loni Kalbhor area. Red rust and red rot are detected with an accuracy of 98% using the CNN-based DL model. It is possible to expand the model to forecast additional sugarcane disease classes.

An Ensemble learning (EnC-SVMWEL) method for detecting disease in sugarcane leaves is developed [24]. The dataset consists of manually captured images along with photos captured from different fields of Bangalore. Different disease considered are "Yellow leaf disease, Rust, Helminthosporium leaf spot, Red rot and Cercospora leaf spot." After image preprocessing DenseNet201 issued for feature extraction. In the end, the model trained and then classified the retrieved image features. The detection accuracy recorded is high compared to other existing methods like CNN, VGG, and SVM. New method is explored by using "CNN with Ensemble SVM" for detection of disease with accuracy of 97.45% but this increases the training time. The model can be expanded to include other leaf diseases in the future, and "fusion-based extraction techniques" can be used to boost performance.

Different DL model such as Inception V4, VGG16, ResnetV2-152 and AlexNet were implemented to classify Sugarcane Leaf disease [25]. The algorithms used 16,800 images for training (70%), 4800 images for validation (20%) and 2400 images for testing (10%). The images were collected from farms of sugarcane located in Philippines. Different sugarcane leaf disease considered are "Cercospora Leaf spot, helminthosporium leaf, rust, red dot and yellow leaf disease." According to the results the Inception V4 algorithm out performs other models in classification. More data sets can be used in future work to improve performance. It is also possible to collect valuable data in real-world situations.

A "quantum behaved particle swarm optimization learning (QBPSO-DTL)" model is developed for detection and classification of diseases in sugarcane leaves with high accuracy [26]. The data used is self-collected for classification. The leaf's affected area is detected using the segmentation method along with Squeeze Net model for feature extractor. Further, classification is done using deep stacked autoencoder (DASE) model. After performing QBPSO-based hyper parameter tuning the model has achieved accuracy of 97.5%. It has helped to reduce validation loss but the accuracy is reduced. Segmentation techniques may be employed in the future to increase classification and detection accuracy.

A deep learning approach is used with Adam optimizer and transfer learning for disease detection in sugarcane [27]. The data contains self-collected images of healthy and unhealthy sugarcane leaves. Different sugarcane disease considered are Red Rust, Red Rot and Bacterial Blight. The proposed transfer learning model utilizes pre-trained deep learning models like "AlexNet, VGG 16, VGG19, Dense Net, Mobile Net, Efficient Net, ReseNet50 and ResNet101." By using a pre-trained model and the transfer learning technique, more accuracy has been achieved with less training data. With ResNet101 outperforming other models, the suggested model achieved great accuracy. Furthermore, improving the training process and reducing the loss have been made possible by the Adam optimizer. In order to improve performance, the model may eventually incorporate more sugarcane diseases and be coupled with other agricultural systems.

The performance of disease classification models can be enhanced by the deep learning technique due to technological advancements.

MATERIALS AND METHODS

Farmers can improve crop quality and quantity and avoid long-term financial and other losses by developing a model that can identify disease early. Additionally, it will benefit the sugar industry by helping it to produce more sugarcane products of higher quality and quantity. This system uses deep learning to predict sugarcane disease using transfer learning. It will use deep learning algorithms to automatically detect the type of disease by identifying pertinent features and patterns from images of infected sugarcane leaves. The system uses concept like CNN and transfer learning.

Convolutional Neural Networks (better known as CNNs) are algorithms used in Deep Learning that assign weights and biases that can be learned, and are able to distinguish between different objects and aspects of an input image. Nowadays, computer vision researchers are fond of using CNNs, which carry out various processing layers over a number of stages of execution. The elements of a CNN model are shown in Figure 1 that consists of an input image, convolutional layers, pooling layers, fully-connected layers, activation functions and an output. CNN's can be used for detection of disease in plants. It includes convolution and Max Pooling layers. These layers automatically extract features from input images and represent them hierarchically. CNNs are good at learning spatial hierarchies and patterns in images, making them well-suited for identifying visual indicators of plant diseases. In a standard ConvNet design, the output layer also known as a fully connected layer is the final processing layer. The convolution process includes the shifting, multiplying, and summing processes. Improved performance with limited labelled data can be achieved by adapting models that were pre-trained on image datasets like "ImageNet" which is large in size.

Because it applies a previously trained model to a new problem, the transfer learning technique is quite popular these days. In this technique, knowledge gained by a machine from the previous task is used to improve generalization in another task. The general idea is instead of starting the learning process from scratch, it can be started with already learned patterns from related task. Some of the commonly used transfer learning models are Inception, VGG family, Xception, ResNet etc. The block diagram for disease detection using the transfer learning technique is shown in Figure 2.

Figure 3 shows how the system operates. The workflow begins with the collection of image data. The sugarcane image dataset was collected from the freely available Mendeley library. The data is pre-processed using image augmentation and data normalization to ensure it is in a format suitable for training. Also, for noise reduction, regularization technique such as dropout, batch normalization is used to help reduce internal noise. Dropout randomly drops out neurons during training which also reduces

overfitting and increase robustness to noise and other forms of variability. Batch normalization normalizes the input to each layer of the network. Adding dropout and batch normalization layers helps in reduction of noise. By fine-tuning a previously trained model, transfer learning also aids in noise reduction. The collected data after being pre-processed will be split in training and testing set. The data gets loaded in Deep Learning model such as CNN, where model can predict disease by using learning. The transfer learning (TL) method is the simplest way to put the deep neural network into practice. Different deep learning models such as VGG16, VGG19, AlexNet, Inception V3 and DenseNet201 are trained using transfer learning and the performance is evaluated using various metrics.

Dataset

The collection, which includes 6748 images with high resolution taken with high-quality cameras, is a useful tool for researching both healthy and diseased sugarcane leaves. The dataset was gathered from Mendeley, a publicly accessible repository [28]. The images are 768 x 1024

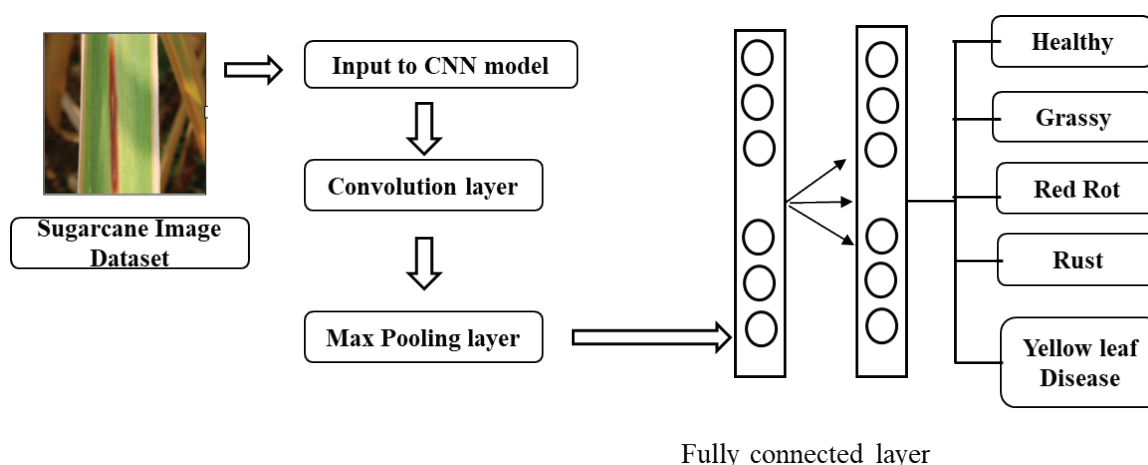


Figure 1. CNN model for disease detection.

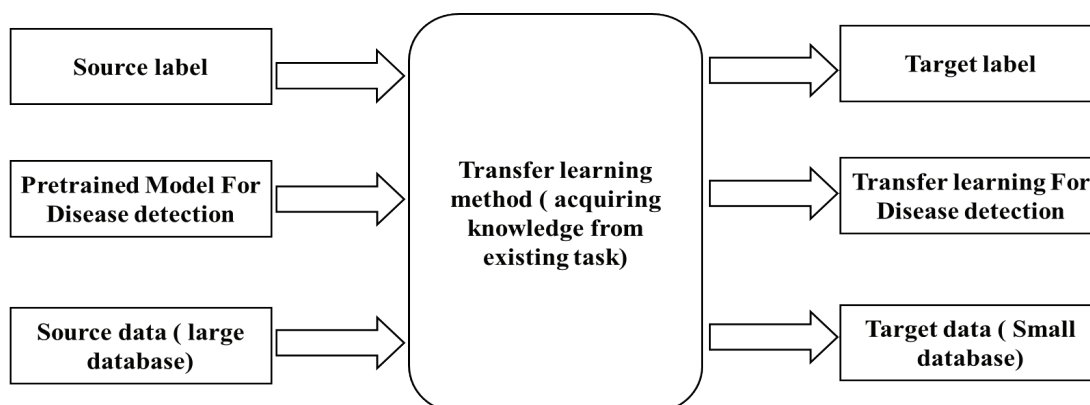


Figure 2. Transfer learning model for disease detection.

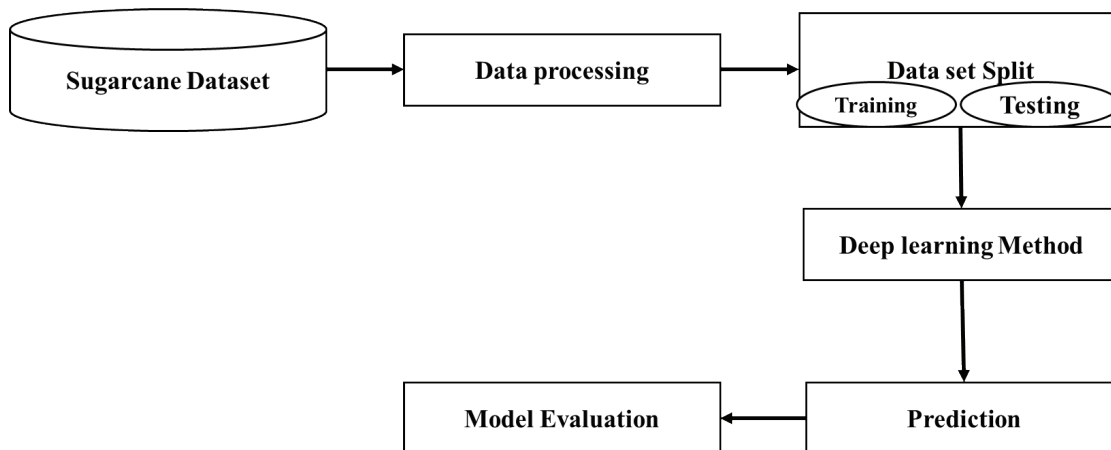


Figure 3. Block diagram of System.

pixels in size and are saved in JPEG format. The resolution of the images is 72 dots per inch (dpi). Table 2 presents the image data set of the study. It helps in efficient detection and classification of sugarcane diseases. The dataset consists of a wide range of sugarcane leaf states with 11 categories, including nine diseases, a category for healthy leaves, and a category for dried leaves. The dataset on sugarcane leaf disease was collected from the farm of Kendur hamlet, Taluka-Shirur, District-Pune, Maharashtra, India. The images were also reviewed by experts to confirm the disease categories they represented. Following a pre-processing stage, the final photos were scaled, renamed, and organized into folders that matched the various disease classifications.

Image data generators are a crucial tool in deep learning for efficiently generating and preprocessing image data. It is a function or class that generates image data randomly during training and testing.

Hyperparameter Settings

Hyper-parameter settings were implemented in the various deep learning algorithms in this work. These configurations may enhance the algorithm's performance. However, experiments need to be done to evaluate the performance and make necessary modifications. The batch size, image size, dataset split, classes, epochs, optimizer and learning rate used for testing are shown in Table 3.

Callbacks are also used in training to adapt the learning rate dynamically according to the validation loss. This helps to prevent overshoot and improves the model's overall performance and stability.

Model Training

In this study, the model was trained using the Keras and Tensorflow frameworks. The images were saved to a cloud database for convenience. In this study, Google Colaboratory was used for the implementation of the model

Table 2. Distribution of images into different classes

Sr No	Class	Count	Training	Testing
1	Banded Chlorosis	471	376	95
2	Brown Spot	1722	1377	345
3	Brown Rust	314	251	63
4	Dried Leaves	343	276	69
5	Grassy shoot	346	276	70
6	Healthy Leaves	430	344	86
7	Pokkah Boeng	297	237	60
8	Sett Rot	652	521	131
9	Viral Disease	663	530	133
10	Yellow Leaf	1194	955	239
11	Smut	316	252	64
	Total	6748	5395	1355

Table 3. Hyper-parameter settings

Parameter	Details
Batch size	32
Image size	224x224
train: test	80:20
Classes	11
Epochs	15
Optimizer	Adam
Learning rate	0.001

and testing tasks. Table 4 shows the hardware and software used in the experiment.

Evaluation

Here, we briefly review the various evaluation metrics used to assess the performance of methods developed for crop disease detection in sugarcane. Assessing the effectiveness of a detection system or model in precisely identifying the presence of diseases is part of evaluating disease detection in sugarcane crops. The evaluation metrics utilized in this situation are displayed in Table 5.

RESULTS AND DISCUSSION

In order to categorize sugarcane leaf disease, this study used transfer learning in conjunction with model training and testing of six deep learning algorithms. Banded Chlorosis, Brown Spot, Brown Rust, Dried Leaves, Grassy Shoots, Healthy Leaves, Pokkah Boeng, Sett Rot, Viral Disease, Yellow Leaf, and Smut are the eleven classifications which make up the sugarcane disease system. Depending on the condition, the test image will be categorized into any one class, producing true positives. According to the results, DenseNet201 outperforms other models with 94.14% accuracy because of its dense connections. A confusion matrix, which offers a thorough analysis of how well the model predicts each class, is a performance measuring tool for

classification models. The confusion matrix of various deep learning models is shown in Figure 4. The precision, recall, and F1-score of several models are shown in Table 6. The training and validation accuracy of various algorithms used to identify diseases in sugarcane crops is shown in Table 7. As shown in Tables 6 and 7, the findings demonstrate that the optimizers employed greatly enhance the sugar classification model's performance.

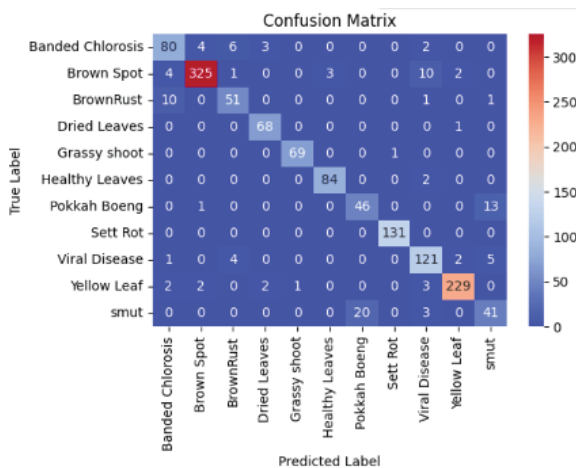
The results demonstrate that the deep learning models greatly enhance the sugar classification models' performance. Additionally, the optimization methods offer dependable performance. Also, deep learning algorithms using transfer learning like VGG16, VGG19, Inception V3, AlexNet, DenseNet201 shows high accuracy in detecting disease in sugarcane crop out of which DenseNet201 outperformed due to its dense connectivity, improved feature extraction & regularization. It has been observed that two classes namely Pokkah Boeng and Smut generated maximum False Positives. Plant diseases are complex, diverse, and variable, making it challenging to create a large-scale, high-quality dataset. However, scientific developments in fields like computer science, telecommunications, artificial intelligence, and even the social sciences have produced a multitude of tools that, when thoroughly investigated and integrated into expert systems, can be extremely useful. The performance indicators of our model in comparison to current methods for sugarcane disease diagnosis are presented in Table 8 [29-40]. According to research in related work, models that use machine learning algorithms

Table 5. Evaluation parameter

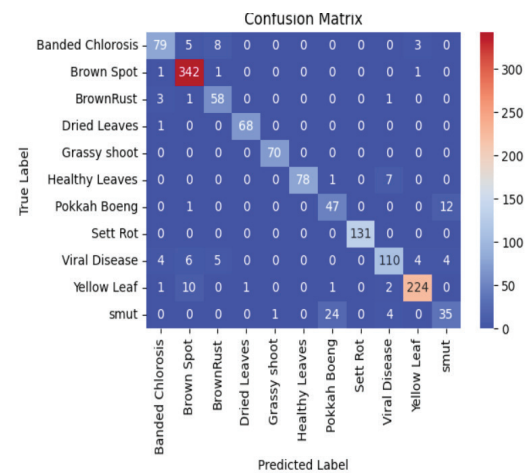
Evaluation Parameter	Formula
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$
Precision	$TP / (TP + FP)$
Recall (Sensitivity)	$TP / (TP + FN)$
F1 Score	$2 * (Precision * Recall) / (Precision + Recall)$

Table 4. Hardware and software requirement

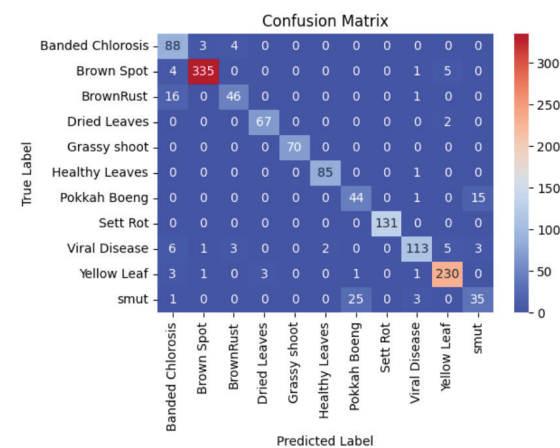
Hardware	
Graphics Processing Unit (GPU)	High-performance NVIDIA GPU
Central Processing Unit (CPU)	Multi-core CPU with high clock speeds
Software	
Deep Learning Framework	TensorFlow, PyTorch, or Keras
GPU Acceleration Libraries	CUDA, cuDNN (for NVIDIA GPUs)
Python and Libraries	Python, NumPy, Pandas, Matplotlib
Data Processing Tools	OpenCV, scikit-learn (for data preprocessing and feature engineering)
Development Environment	Jupyter Notebook, Google Cola, PyCharm



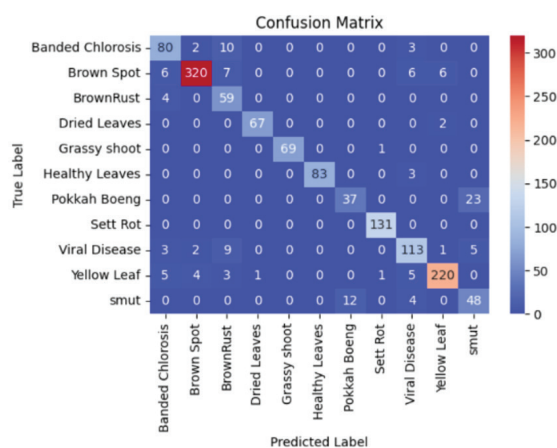
(a)



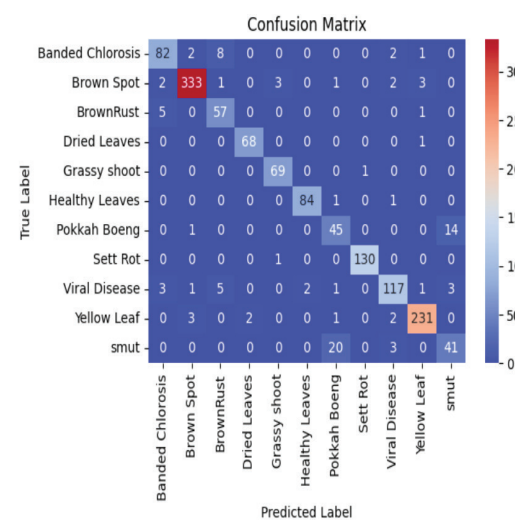
(b)



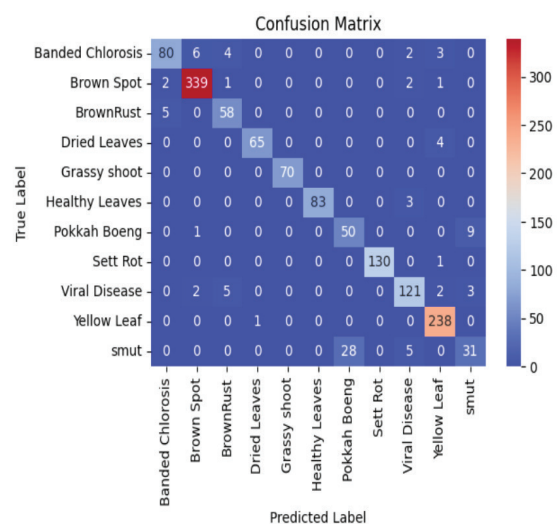
(c)



(d)



(e)



(f)

Figure 4. Confusion matrix (a) CNN (b) VGG16 (c) VGG19 (d) Inception V3 (e) Alexnet (f) DenseNet201.

Table 6. Comparison of disease classification in different models

Model	Class	Precision	Recall	F1-Score
CNN	Banded Chlorosis	0.82	0.84	0.83
	Brown Spot	0.98	0.94	0.96
	Brown Rust	0.82	0.81	0.82
	Dried Leaves	0.93	0.99	0.96
	Grassy shoot	0.99	0.99	0.99
	Healthy Leaves	0.97	0.98	0.97
	Pokkah Boeng	0.70	0.77	0.73
	Sett Rot	0.99	1.00	1.00
	Viral Disease	0.85	0.91	0.88
	Yellow Leaf	0.98	0.96	0.97
	Smut	0.68	0.64	0.66
VGG16	Banded Chlorosis	0.89	0.79	0.84
	Brown Spot	0.97	0.98	0.98
	Brown Rust	0.86	0.81	0.94
	Dried Leaves	0.86	0.99	0.96
	Grassy shoot	0.93	1.00	0.99
	Healthy Leaves	0.99	0.98	0.99
	Pokkah Boeng	1.00	0.60	0.75
	Sett Rot	1.00	1.00	1.00
	Viral Disease	0.85	0.92	0.89
	Yellow Leaf	0.98	0.95	0.96
	Smut	0.67	0.95	0.79
VGG19	Banded Chlorosis	0.82	0.84	0.83
	Brown Spot	0.98	0.93	0.95
	Brown Rust	0.67	0.94	0.78
	Dried Leaves	0.99	0.97	0.98
	Grassy shoot	1.00	0.99	0.99
	Healthy Leaves	1.00	0.97	0.98
	Pokkah Boeng	0.76	0.62	0.68
	Sett Rot	0.98	1.00	0.99
	Viral Disease	0.84	0.85	0.85
	Yellow Leaf	0.96	0.92	0.94
	Smut	0.63	0.75	0.69
InceptionV3	Banded Chlorosis	0.75	0.93	0.83
	Brown Spot	0.99	0.97	0.98
	Brown Rust	0.87	0.73	0.79
	Dried Leaves	0.96	0.97	0.96
	Grassy shoot	1.00	1.00	1.00
	Healthy Leaves	0.98	0.99	0.98
	Pokkah Boeng	0.63	0.73	0.68
	Sett Rot	1.00	1.00	1.00
	Viral Disease	0.93	0.85	0.89
	Yellow Leaf	0.95	0.96	0.96
	Smut	0.66	0.55	0.60

Table 6. Comparison of disease classification in different models (continued)

Model	Class	Precision	Recall	F1-Score
Alexnet	Banded Chlorosis	0.89	0.86	0.88
	Brown Spot	0.98	0.97	0.97
	Brown Rust	0.80	0.90	0.97
	Dried Leaves	0.97	0.99	0.98
	Grassy shoot	0.95	0.99	0.97
	Healthy Leaves	0.98	0.98	0.98
	Pokkah Boeng	0.65	0.75	0.70
	Sett Rot	0.99	0.99	0.99
	Viral Disease	0.92	0.88	0.90
	Yellow Leaf	0.97	0.97	0.97
	Smut	0.71	0.64	0.67
DenseNet201	Banded Chlorosis	0.92	0.84	0.88
	Brown Spot	0.97	0.98	0.98
	Brown Rust	0.85	0.92	0.89
	Dried Leaves	0.98	0.94	0.96
	Grassy shoot	1.00	1.00	1.00
	Healthy Leaves	1.00	0.97	0.98
	Pokkah Boeng	0.64	0.83	0.72
	Sett Rot	1.00	0.99	1.00
	Viral Disease	0.91	0.91	0.91
	Yellow Leaf	0.96	1.00	0.98
	Smut	0.72	0.48	0.58

Table 7. Performance analysis

Sr no	Model	Accuracy	Validation Accuracy
1	CNN	92.98%	91.88%
2	VGG16	93.92%	93.36%
3	VGG19	91.76%	90.55%
4	Inception V3	94.00%	91.81%
5	AlexNet	92.15%	92.77%
6	DenseNet201	94.14%	93.36%

Table 8. Performance analysis of related work

Sr no.	Author	Dataset	Method used	Evaluation metric and their results
1	(Ratnasari et al. 2014` [29])	Real data of 30 images of infected sugarcane leaves were collected from fields .	SVM	Accuracy 80%
2	(Renugambal 2015 [30])	100 photos of five sugarcane leaf diseases	Linear and nonlinear SVMs & ANN	Accuracy 91% 94% 85%
3	(Hasan et al. 2015 [31])	Photo Gallery	Expert System CaneDES	Average Confidence Factor 58.33%

Table 8. Performance analysis of related work (continued)

Sr no.	Author	Dataset	Method used	Evaluation metric and their results
4	(Goel et al. 2018 [32])	5359752 images of a single leaf disease from ipmimages.org	SVM K means algorithm	Accuracy K=11 gave best accuracy
5	(Militante et al. 2019 [15])	13,842 sugarcane images of healthy and unhealthy leaves	CNN	Accuracy 95%
6	(Padilla et al. 2019 [33])	9 images of sugarcane leaves.	SVM	Accuracy 86.66%
7	(Alauddin et al. 2019 [34])	List of question along with symptoms table addressed to Sugar cane farmers and research center in Pasuruan city.	ELM ELM+PSO	ELM alone only achieved 71.92% classification accuracy, ELM and PSO together, were able to identify sugarcane diseases with 79.92% accuracy.
8	(Srivastava et al. 2020 [17])	Total 240 sugarcane leaves out of which 120 are sick leaves	Inception V3 , VGG-16 ,VGG-19 are used for feature extraction and SVM, SGD, ANN ,naïve Bayes, KNN ,logistic regression are used for classification VGG-16 as feature extractor and SVM classifier gives the highest performance	AUC 90.2%
9	(Shadab et al. 2021 [16])	2940 images of healthy and unhealthy sugarcane leaves.	VGG-19 ResNet-34 ResNet-50 YOLO Faster-RCNN	Accuracy 92% 92.4% 93.2% Mean average Precision score 58.13%
10	(Kumar et al. 2021 [18])	dataset consist of 2940 images of sugarcane leaves	Quicker Region-Based CNN	Accuracy 93.2%
11	(Rajesh et al. 2021 [35])	dataset is considered of previous years restricted to Maharashtra.	Naïve Bayes KNN RF SVM	Accuracy 61.21% 83.645 82.42% 83.64%
12	(Murugeswari et al. 2022 [19])	1500 images showing both healthy and diseased sugarcane leaves	YOLOV5 Faster RCNN	Faster RCNN shows higher performance than YOLOV5.
13	(Prithvi et al. 2022 [20])	13842 manually collected images of sugarcane leaves	K means CNN	CNN showed more promising result
14	(Atheeswaran et al. 2023 [36])	400 images of sugarcane leaves	MDC(Multi-Domain Connectome) KNN SVM CBR(Case Based Reasoning) ANFIS(Adaptive Neuro Fuzzy Inference System)	Accuracy 82% 85% 88% 93% 97%
15	(Selvakumar et al. 2023 [37])	240 images of diseased and Non-diseased sugarcane leaves	MFO-CNN gives higher average accuracy than another existing model VGG16 ,VGG 19 and Inception IV3.	Average Accuracy 12.8% 11.7% 16.4%

Table 8. Performance analysis of related work (continued)

Sr no.	Author	Dataset	Method used	Evaluation metric and their results
16	(Simoes et al. 2023 [38])	3508 images of sugarcane leaves infected with rust disease	KNN RF Radial SVM	Accuracy 89% 90% 90%
17	(Ogrekci S et al. 2023 [21])	2521 images of healthy and infected sugarcane leaves	DenseNet121 Vision Transformers(ViT) ViT + CNN	Accuracy 91.98% 92.85% 88.28%
18	(Daphal and Koli 2023 [39])	2569 images showing both healthy and infected sugarcane leaves	MobileNet-V2 Ensemble model	Accuracy 84% 86.53%
19	(Sarode et al. 2023 [27])	Self-collected images showing both healthy and diseased sugarcane leaves from the fields.	ResNet101	It outperformed other models giving high accuracy.
20	(Bagchi et al. 2024 [40])	2522 images of healthy and unhealthy sugarcane leaves	Hybrid Model cspdarknet53+proposed model cspresnet50+VGG16 inception_v3+proposed model	Accuracy 96.8% 87.7% 86.3%
21	Proposed work	6748 high resolution images of healthy and unhealthy leaves	CNN VGG16 VGG19 Inception V3 AlexNet DenseNet201	Accuracy 92.98% 93.92% 91.76% 94.00% 92.15% 94.14%

like SVM, KNN are less accurate in identifying and predicting diseases. Furthermore, smaller images are used to train the algorithm, accounting for fewer diseases. In this instance, deep learning and transfer learning can be combined to improve the precision and effectiveness of sugarcane disease diagnosis. Additionally, hybrid and ensemble approaches can increase forecast accuracy and robustness.

Limitations of the Work

However, there are some shortcomings in this study. First, just a small number of data sets were used in this investigation. More sugarcane disease variants and environmental factors could be added to the dataset, increasing its size and diversity. Although our model does well on the provided dataset, more validation is needed to determine how well it works in real-world scenarios, such as when environmental changes impact disease diagnosis. Deployment in resource-constrained contexts, like mobile or edge devices, may be limited by high resource requirements. Last but not least, farmers and agricultural specialists find it difficult to interpret forecasts because deep learning algorithms operate as “black boxes.”

CONCLUSION

One of the most-wide field that has been benefited from many advancements in technology is Agriculture. In Sugarcane industry mostly utilized product is Sugarcane. Crop quality and yield are highly affected due to disease contaminated agricultural products. Inadequate disease management practices have an adverse effect on sugarcane productivity. Farmers have to pay lots of money to treat diseases that affect the sugarcane crop as a result of inadequate disease control. Consequently, advancement in computation techniques can help in detecting disease in sugarcane plants. Deep learning tools is popularly used for crop health monitoring and precision agriculture [40]. Since Sugarcane is a recurrent crop, it is necessary to maintain the quality of crop and control the diseases [41]. This study's primary goal is to examine how well deep learning algorithms and transfer learning work together to identify disease in sugarcane leaves. In order to classify sugarcane leaf disease in eleven distinct classes, this study used transfer learning in conjunction with model training and testing of six deep learning algorithms. Results show that out of all six DL models, CNN (92.98%), VGG16

(93.92%), VGG19 (91.76%), InceptionV3 (94.00%), AlexNet (92.15%), DenseNet201 outperforms with 94.14% accuracy. In this study, a deep learning approach is proposed for farmers to identify and classify sugarcane disease. This method is not only aimed at increasing the crop yield but also at reducing the use of chemical treatments, thereby promoting a more sustainable agricultural practice. The newest technology allows farmers to identify problems early and address them in a targeted way, leading to healthier crops and improved economic outcomes. Additionally, it validates the effectiveness of deep learning-based models utilizing transfer learning in sugarcane leaf disease classification tasks.

Future Scope

Our research concentrated on classification of sugarcane leaves in 11 different categories, still there is much opportunity for researcher to expand the dataset to include images from multiple geographical locations and different growth stages of sugarcane in future. Also, lightweight models can be developed to facilitate real-time disease detection on mobile and IoT-based platforms. However, integrating additional techniques, such as multi-modal data, explainable AI(XAI) or domain-specific rule-based systems could enhance interpretability and provide a more comprehensive diagnosis of disease in future work. Besides the correct estimation of parameters, artificial neural networks (ANNs) may be used to predict the changes in plant color and bioactivity under different situations [42, 43]. Also, working with subject matter experts such as agronomists and plant pathologists can provide insightful information and improve the system's accuracy and efficiency. The present work can be extended to other crops beyond sugarcane to diagnose the impact of the disease and can also focus on rare diseases, which often require specialized knowledge and expertise. Nowadays advanced techniques like hybrid and ensemble method are popular and researchers can explore them to develop more accurate and robust disease detection models, opening up opportunities for future deep learning. Also, an accurate, rapid and responsive system such as web app, mobile app can be deployed for interaction with the end user (farmer) and depending on the feedback model can be improved in future.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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