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SUGAR CANE LEAF DISEASE CLASSIFICATION AND IDENTIFICATION USING DEEP MACHINE LEARNING ALGORITHMS

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ABSTRACT

The identification of crop diseases is one of the major concerns that the agricultural industry has to deal with. The detection and classification of leaves is essential in agriculture, forestry, rural medicine, and other commercial applications, among other things. The diagnosis of sugar cane plant leaf disease is required for automatic weed identification in precision agriculture. This paper discusses a novel approach to the development of a plant disease recognition model that is based on sugar cane leaf image classification and employs deep convolutional networks to recognise disease in sugar cane plants. The method used for identification and automatic recognition investigates the possibility of using k-NN and SVM in pre-training with ANN, followed by CNN-based approaches for recognition.

Keywords: *KNN, SVM, Leaf Disease, Calssificaiton, ML*

1. INTRODUCTION

Earlier those diseases were of minor importance but it has become matter of concern as it is sporadic rapidly in sugarcane growing area heavily monoculture of single variety and due to lack of effective technologies. But now a day's many techniques are applied this sector to predict or detect crops diseases. Some of the techniques are Image Processing, Machine Learning, Deep convolutional Neural Network (DCNN), Support Vector Machine (SVM), Public Neural Network (PNN) [1]. Many researchers are publishing their paper to follow those techniques. Many scientists have already achieved a significant improvement in all those techniques. In this research I apply Deep Convolutional Neural Network (CNN) which is the advanced method of machine learning. The Sugarcane industry within the Bangladeshis contributes high profits to the economy. It is one of the biggest crops cultivated in several provinces round the country [2]. This crop provides 3 major products: sugar, bioethanol, and power. At present, sugarcane is cultivated in regarding a hundred countries.

The cane industry produces approximately 5.5 million tonnes of cane per year. It is considered to be one of the most important money plants in the country. A sugarcane plant has stalks that are prominently jointed and bear two ranks of sword-shaped but gracefully arching leaves on each of their stalks. Some varieties may also have stalks that are between 5 and 7 metres in length. Sugarcane grows to its full potential in a tropical climate with rich, moist soil, bright sunlight, and warm temperatures

[3]. Among the best soils for sugarcane cultivation are clay-loam soils that contain a small amount of sand and silt and are rich in organic matter. Bangladesh's modern sugar manufacturing accounts for only about 5% of the country's total sugar consumption. Jiggery production, which is primarily based on sugarcane, accounts for approximately 20% of total demand, with the remaining 75% of total demand being met by imports. The primary reasons for the decrease in sugar production at the company include a decrease in the supply of sugarcane in the factories, which is due to the fact that the majority of the sugar is affected by one-of-a-kind diseases, and a decrease in the number of employees.

Diseases Sugarcane is susceptible to a number of diseases at various stages of its growth. All of these diseases are the most common in Bangladesh, and they are preventing the country from cultivating more sugarcane. Sugarcane crops are being destroyed at a rate of 30 to 40% per year because of this practise. So, in order to alleviate sugarcane diseases, we can employ some techniques that will produce a more favourable outcome. In this work, A popular technology at the moment is the use of machine learning to classify and detect plant diseases, and this is becoming increasingly common [4]. In order to use this method, more complex calculations must be performed, which can be time-consuming when using online applications. The performance of these methods, as a result, may only produce a satisfactory result in some instances.

Compared to the traditional architecture of the neural networks, profound learning uses artificial neural network architecture which usually has many layers of information processing and is more sophisticated than regular neural network topologies. Deep learning has resulted in considerable increases in performance in the domains such as picture identification, image classification, acoustics and other sectors requiring extensive data processing. A profound learning for the detection of plant disease has prepared the road for the analysis and decision-making of professionals in the field [5]. The primary deep learning method in this study has been the Convolutionary Neural Networks (CNNs), which accounted for most of the findings. CNN technology is utilised as one of the most common approaches for demonstrating and relying on a big quantity of data, for pattern recognition applications.

Once the system has detected the image, we place some images for training and testing purposes, and then demonstrate the accuracy of the image result once it has been detected by system. A trend toward escapade in deep learning methodology for disease recognition is being observed as deep learning techniques advance and are applied in more and more applications in the following years [6]. There are several components to a CNN model depicted in Figure 1. These components include an input image, convolutional layer(s), pooling layer(s), fully connected layer(s), activation function(s), and an output. The components of a CNN model are depicted in Figure 1.

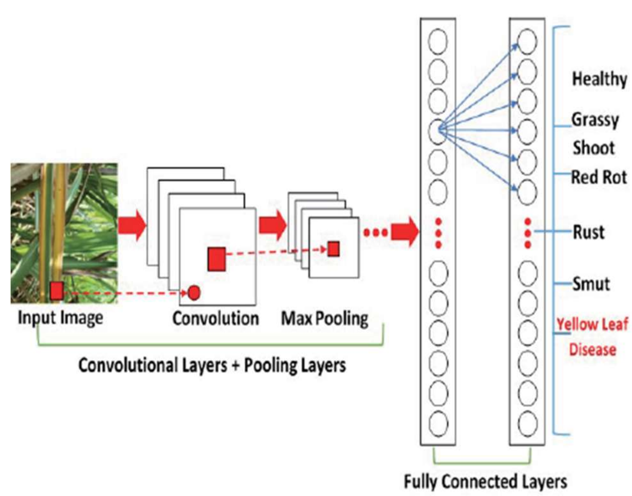

Fig. 1: Architecture For CNN

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2. RELATED WORK

In the collection of disease images, four classes of diseases have been selected, with each class containing images of a different type of disease. Those all-class images are also assigned to a class, one of which is train data and the other which is testing data, and so on [7]. All of the photographs were taken with a mobile phone on sugarcane land. When collecting images, make an effort to find images of high quality. The majority of the images are not disordered; some images are also in good health. Red rot, sugarcane borer, rust, and wilt are the diseases that affect sugarcane.

Red Rot

Fig 2: Image For Red Rot Sugar Cane Disease

Sugarcane Borer

Fig 3: Image For Sugarcane Borer Disease

Rust

Fig 4: Image For Rust Sugar Cane Disease

Wilt

Fig 5: Image For Wilt Sugar Cane Disease

a. Classification

Deep learning was effectively used in a number of applications such as the detection and classification of crop varieties, plant identification and classification, picture grading of fruits and vegetables, and image classification. A rise in popularity has also been seen in photographs taken with mobile cameras, as well as photographs taken with any camera device mounted on a robot. Convolutional Neural Networks, also known as CNNs, are becoming increasingly popular among computer vision researchers, particularly in the field of computer vision, due to their ability to execute different layers of processing through multiple stages of execution. Because of this, CNNs are becoming increasingly popular among computer vision researchers, particularly in the field of computer

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vision [8]. Using an architecture of convolutional neural networks to illustrate the process, Figure 6 depicts several stages in the prediction of plant disease at various stages in the process. Using an architecture of convolutional neural networks, the figure 6 depicts several stages in the prediction of plant disease. It is proposed that the proposed work include a detailed description of how the model will be put into practise.

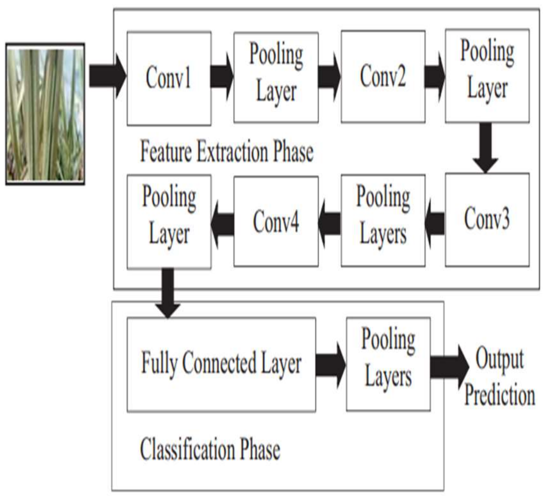

Fig. 6: Disease Prediction Using CNN Architecture

b. Detection process

In order to determine how well two cutting-edge detection networks, YOLOv3 and Faster-RCNN, perform when it comes to identifying infected regions in images, they will be tested and evaluated in this experiment. Models such as R-CNN and Fast R-CNN have been developed in the past, but the aforementioned models are significantly more rapid than those that came before them. When it came to finding the regions on which CNN will be passed separately for classifying the label, it used a more time-consuming method known as selective search, which was significantly more time-consuming than the previous method [9]. In order to generate a small number of thousand regions of interest, each one was generated and passed separately to the network for further classification and analysis. This method was created with the intention of being unsuitable for real-time inference. In the case of Faster-RCNN, a region proposal network (RPN) is used to predict region proposals on a convolutional feature map after the image has been passed through a CNN, as opposed to a CNN alone.

We trained the complete model on ImageNet dataset, starting with pretrained block weights in the two models and on from there, to assess the realisation of both architectures in our dataset. The quicker R-CNN was trained and evaluated using images with the same resolution at a resolution of 600x1000 pixels across 15 epochs. It was trained on images with a resolution of 416x416 for 6000 iterations before being tested on images with resolutions of 416x416 and 608x608 for a total of 6000 iterations on 416x416 and 608x608 images.

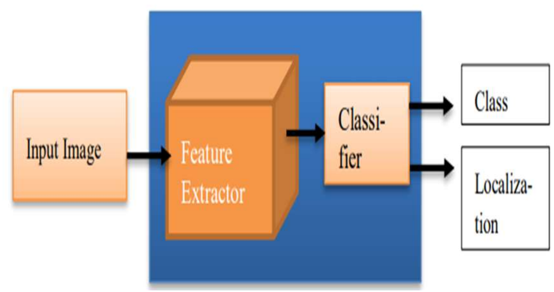

Fig. 7. Pictorial Representation Of Detection Process.

3. LIMITATIONS OF THE EXISTING WORK

In organic farming, crop protection is a tricky subject. It demands a thorough understanding of the crops being farmed, as well as any pests, illnesses, or weeds present. Based on particular convolutional neural network designs, our system created specialised deep learning models for identifying plant illnesses using leaf pictures of healthy or diseased plants. Our detector combined photos from a variety of sources with photos collected on-site by various camera systems. The algorithms used in this paper and their Limitations; advantages are listed in the below table.

PROBLEM STATEMENT

This paper addresses the critical need for automated Sugar Cane Leaf Disease Classification and Identification using Deep

Machine Learning Algorithms. Sugar cane crop health directly impacts yield and quality, and the project's main objectives include collecting and preprocessing a diverse dataset of sugar cane leaf images, selecting appropriate deep learning models like Convolutional Neural Networks (CNNs), implementing feature extraction and pattern recognition techniques, rigorous training and validation, and the development of a user-friendly interface for instant disease diagnosis. Performance evaluation metrics will be used to continually improve the model, ensuring scalability to accommodate a growing user base, ultimately aiding sugar cane farmers and agricultural experts in prompt disease detection and crop management for enhanced yield and sustainability.

Sno	**Method**	**Limitations/Demerits**	**Merits**
1	**KNN**	• The quality of the data determines its accuracy. • The prediction stage may take a long time if there is a lot of data. • Aware of the data's size and irrelevant characteristics. • Requires a large amount of memory due to the fact that all of the training data must be saved. • Because it stores all of the training, it can be computationally expensive.	Calculation time is limited. To decipher a straightforward algorithm. It has a wide range of applications, including regression and classification. There's no need to compare to more supervised learning models because of the high precision.
2	**SVM**	For big data sets, the SVM algorithm is ineffective. When the data set contains more noise, such as overlapping target classes, SVM does not perform well. The SVM will underperform if the number of features for each data point exceeds the number of training data samples.	SVM performs reasonably effectively when there is a clear separation between classes. SVM is stronger in high-dimensional spaces. SVM becomes effective when the number of dimensions exceeds the number of samples. The SVM algorithm was created with memory conservation in mind.
3	**ANN**	Operation of the Network That Isn't Clearly Explained System Requirements Make sure the network's structure is correct. The difficulty of informing the network about the situation The network's lifespan is unknown.	ANNs have several major advantages that make them ideal for a variety of issues and scenarios: ANNs can learn and represent non-linear and complicated interactions because many of the relationships between inputs and outputs in real life are both non-linear and intricate.
4	**CNN**	The position and orientation of an object are not	CNN has a significant advantage

		encoded by CNN. A convolutional layer is the most important part of a CNN. Inability to be spatially invariant when dealing with incoming data. A single scalar is produced by artificial neurons. What's the best way to cope with CNN?	over its predecessors in that it can detect crucial characteristics without the requirement for human interaction. It can learn distinctive features for each class on its own given a sufficient number of images of cats and dogs. Furthermore, CNN is a computationally efficient algorithm.

Method	Normal Accuracy prediction	Training parameters	Accuracy prediction by cross validation
KNN	75	K=13	75.02
SVM	93	Rbf Kernel	93
ANN	61	5-15 Neurons	26
CNN	88	0-288	87

4. METHODOLOGY

Figure 8 illustrates a process diagram based on experimental design that shows if the sugarcane plant is infected or not with leaf pictures from the disease [10].

A. Image Dataset Acquisition

Images of sugarcane leaves are captured manually with a camera and then enhanced and segmented using computer software. In order to differentiate between diseased and healthy images of sugarcane leaves, each image is saved in its own folder with a label indicating which class it belongs to. 3295 images were collected and organised into seven different categories in the image dataset that was acquired. Each image is saved in the uncompressed JPG or PNG format, and it is coloured using the RGB colour space as a base colour.

B. Pre-processing of Images

Pre-processed images include images that have been reduced in size, images that have been cropped, and images that have been enhanced. For the purposes of this study, we have used coloured images that have been resized to a resolution of 96x96 pixels in order to be processed further.

C. Feature Extraction

The convolutionary layers extract characteristics from scaled images. The nonlinear activation function Rectified (ReLU) is applied after convolution with the purposes of reducing the size of features extracted, using various methods of packing such as maximum pooling and average pooling. When the convolution and pooling layers are combined, the result will be a filter that generates features for analysis.

D. Classification

Classification is accomplished through the use of fully connected layers, and feature extraction is accomplished through the use of convolutional and pooling layers.

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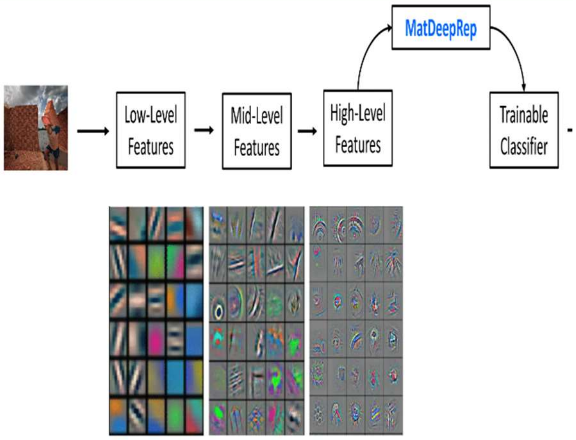

Figure-7.1 Classification

This layer is responsible for classifying the sugarcane leaves and determining whether or not they are infected with the disease.

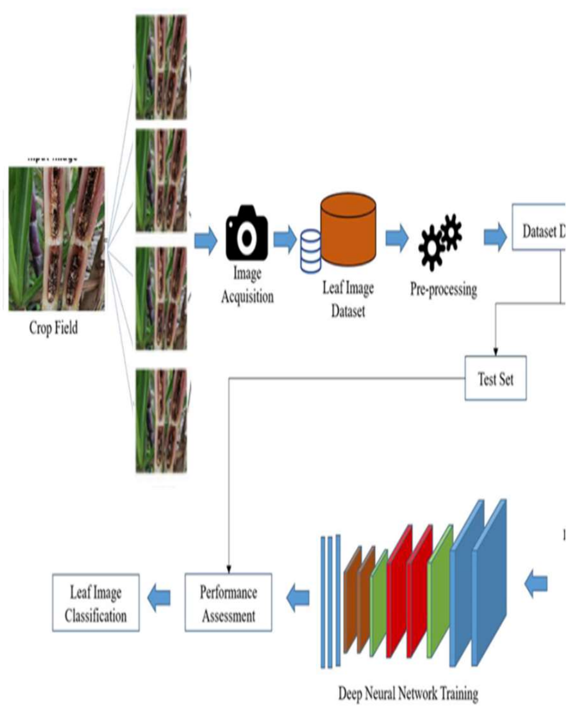

Fig 8: Working Of The Classification Of The Sugarcane Leaf Disease

The entire procedure of creating a replica for plant disease identification through the use of deep CNN is described in detail right here in this document. The entire system is divided into a few critical steps, starting with the recruitment of images for the classification system and progressing to the application of deep neural networks. Figure 9 depicts an experimental design based on a workflow diagram that, through the use of images, indicates whether or not the sugarcane plant has been infected with the disease, as well as the results of the experiment [11]. Figure 9 Experimental design based on a workflow diagram.

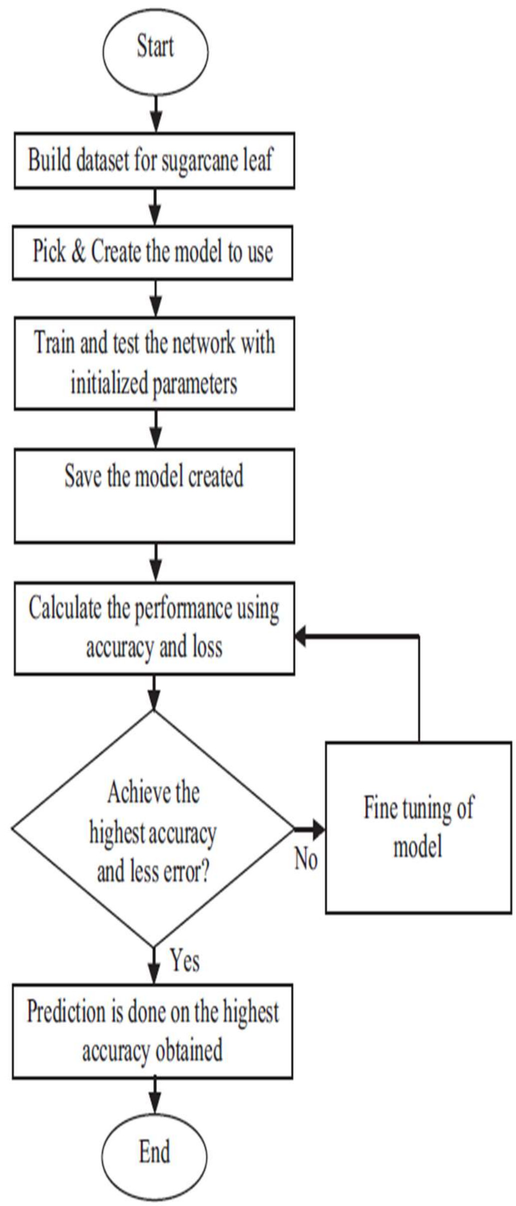

Fig. 9: Prediction Model Flow Chart

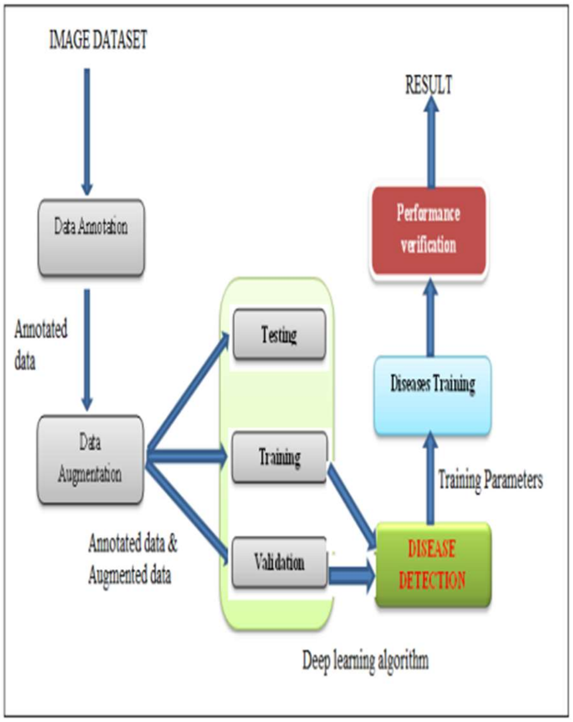

Fig 10: Working Of Deep Learning Algorithm

Data Set

The dataset contains 3295 images of sugarcane leaves, which are divided into six different categories by their shape and size (consisting of 4 diseases and 1 healthy). It is these diseases that have caused the most serious damage to Indian crops over recent years that are listed here [12]. All of the photographs were taken in a natural setting with a wide range of variations in light and composition.

These images were taken from a range of cultivation areas, including those at Mandya Bangalore's Agricultural Science University and farms owned by farmers in the vicinity. Everything in a range of ways, orientations and backdrops was shot using telephone cameras and thus represents the vast majority of changes that can appear in real world images. The sample collection was assisted by a group of pathologists who are well knowledgeable in their profession. We manually annotated the dataset for tracing the sick spots on the leaves (object detection) that match four different diseases [13]. The majority of the photos in the data set have several diseased spots and they have various patterns. The different parks in accordance with their geographical position were noted individually for all these places. Table 1 offers further information on each category, which illustrates also how the photographs have been sorted into distinct categories. Figure 11 shows the classes utilised for classification and detection and their relative distributions and distributions.

Table 1: The Distribution Of The Images Into Different Classes

S. No	Classes	Count
1	Red Rot	545
2	Rust	832
3	Sugarcane Borer	570
4	Wilt	420
5	Healthy	928

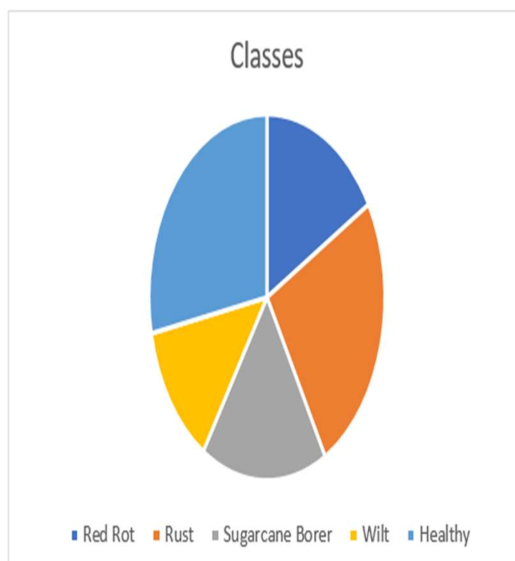

Figure 11: The Distribution Of The Images Into Different Classes

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The test is a critical component of this research in order to achieve higher overall performance. We have already trained the data set using a convolutional network process, and the information about the training is available to us at this point [14]. Figure 12 shows how to select a train image as input, after which the image is sent to exhaustive search, which aids in the images enumerating all possible tasks, and then it is sent to CNN for the purpose of producing an output image [15]. The output image is checked by the SoftMax classifier before being used. When we talk about SoftMax classifier, we are talking about a loss function, which in the context of Machine Learning and Deep Learning tells us to quantify how good or bad a given classification term is at precisely classifying data points in our data set.

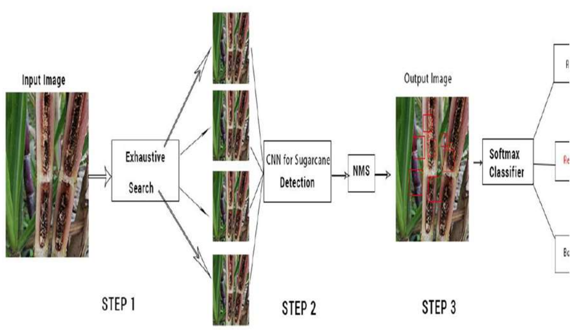
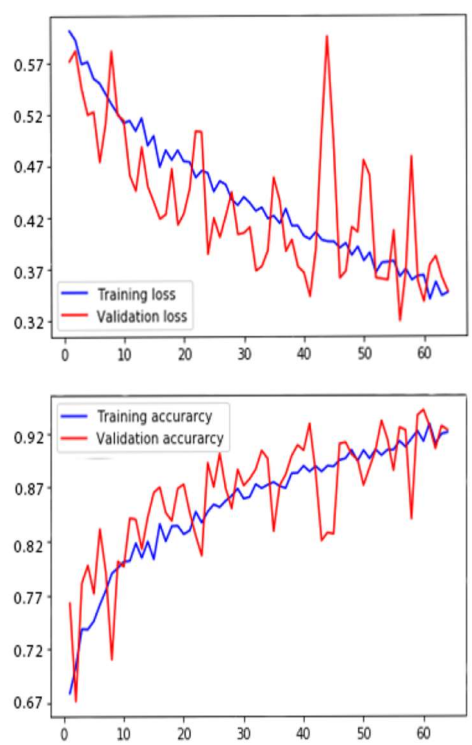


Fig 12: Overall Testing Process

5. RESULTS

The overall process graph is depicted in the preceding figure 13, which is shown in the preceding paragraph. For the purposes of this chapter, we will set up all of the images with various classes in an experimental manner. After that, the images are rotated to a 25-degree angle for enhancement, after which they are flipped and shifted horizontally and vertically to achieve the desired effect. When the batch size is set to 10, the model train will run for a total of 60 iterations. In the end, the Deep Convolutional Neural Network with Confusion Matrix brings everything together and provides the final result. It is possible to calculate the accuracy and error rate of a calculation by using a confusion matrix. Table 1 of the confusion matrix is shown in the preceding image. Figure 13 shows that the training accuracy is very close to the validation accuracy, which is a good thing. Because of this method's use, we can say that training accuracy has been improved. Sixty-two epochs were used in the development of the training model, resulting in accuracy rates as high as 88 percent. The outcome was described as more favourable by the authors of the paper. Any solution that has an accuracy lower than 60% cannot be considered satisfactory. Figurine 13 illustrates the recognition of plots of train and test accuracy when testing random images of sugarcane plant diseases. Figurine 13 depicts the recognition of plots of train and test accuracy when testing random images of sugarcane plant diseases in addition, we can see the graphs of training loss and validation loss, which show that the training loss is decreasing slowly with each passing day as time progresses. In the example above, the training loss and validation loss are shown, and they are obtained after 60 epochs. It's simple to calculate the error rate from accuracy after you've finished the process, and an error rate of 8 percent indicates a more favourable outcome. Finally, we can state that the Convolutional Neural Network produces a better result and greater accuracy throughout the process.



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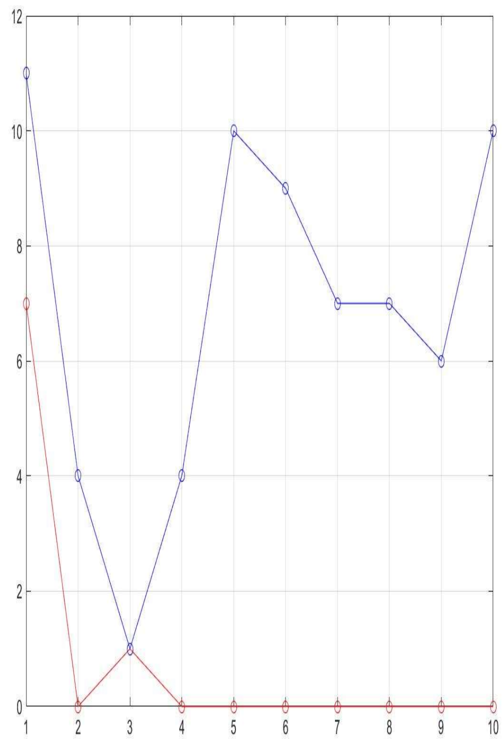

Figure 13: Training Accuracy, Validation Accuracy And Training Loss, Valadon Loss.

Accuracy = (TP+TN)/Actual No. of samples

Accuracy = (397+2504)/3295

Accuracy = 88%

Error rate= 100-88 = 12%

Table 2: Confusion Matrix

Sugarcane Diseases		Predicted class	
		Healthy	Infected
Actual Class	Healthy	397 (TN)	252 (FP)
	Infected	140 (FN)	2504 (TP)

Table-3 Confusion Matrix

1.676063	2082.261	0.82389	0.802512	66.66038	0.133703	0.716318	3.854602	0.82389	0.01064
3.592954	1192.334	0.661826	0.960488	73.85498	0.033489	0.433486	5.8215	0.661826	0.002665
1.513194	1683.856	0.715529	0.750515	56.95801	0.077869	0.705022	4.779018	0.715529	0.006197
1.605346	327.0322	0.829384	0.782287	25.85441	0.240615	0.724815	2.86035	0.829384	0.019147
1.388651	1342.31	0.449807	0.693846	48.71672	0.032243	0.661597	6.729246	0.449807	0.002566
1.606708	1204.9	0.475088	0.782707	151.4006	0.020066	0.514337	7.030892	0.475088	0.001597
1.79	970.	0.67	0.82	47.0	0.14	0.63	3.33	0.67	0.01

0475	6919	8112	9497	4137	8754	7371	1176	8112	1837
2.249791	5471.176	0.875213	0.895786	125.1891	0.381658	0.643822	2.266549	0.875213	0.030371
3.843421	3218.747	0.684199	0.965559	125.504	0.072707	0.444922	4.11351	0.684199	0.005786
4.686122	1171.544	0.808542	0.976966	83.60673	0.14657	0.432691	2.926188	0.808542	0.011664
6.629932	1073.163	0.971066	0.98856	95.1793	0.354079	0.376264	1.726159	0.971066	0.028177
1.519388	16031.45	0.871048	0.752878	176.1067	0.12317	0.767078	4.14105	0.871048	0.009802
12.50858	271.2538	0.92528	0.996799	65.72748	0.154222	0.256188	1.897722	0.92528	0.012273

3.954238	850.48	0.745016	0.967494	65.43626	0.111439	0.425226	3.194014	0.745016	0.008868
2.514137	5591.978	0.928784	0.917494	133.7927	0.138341	0.601828	3.636777	0.928784	0.011009
2.133038	3403.127	0.489085	0.883296	96.13764	0.090809	0.496847	3.526471	0.489085	0.007226
1.189081	9440.067	0.34131	0.541057	119.5496	0.028601	0.554886	5.599012	0.34131	0.002276
1.425632	3125.63	0.34607	0.712726	75.32301	0.026401	0.542781	6.168062	0.34607	0.002101
8.366251	251.3671	0.685686	0.992831	51.74575	0.122517	0.303125	2.430181	0.685686	0.00975
1.6259	6082.5	0.419	0.7885	112.21	0.0314	0.4831	5.304	0.419	0.0024

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55	78	37	09	56		68	05	37	99
1.026846	22201	1	0.227165	170.3703	0.829604	0.964347	1.685125	1	0.066018
1.020038	45132.62	0.91698	0.197239	242.1077	0.126786	0.945436	4.212141	0.91698	0.010089
1.340449	24188.16	0.743732	0.665925	203.1803	0.068171	0.806315	5.556544	0.743732	0.005425
3.359216	6513.126	0.967969	0.954663	166.9048	0.216585	0.532257	2.768766	0.967969	0.017235
1.55058	7277.923	0.395313	0.76425	119.8687	0.020661	0.511603	6.797692	0.395313	0.001644

6. CONCLUSION

This paper has been thoroughly trained in whether sugarcane leaves and steam are diseased or healthy by the Convolutional Neural Network (DCNN). The structure utilised to categorise the sugar cane leaf using a simple convolutionary neural community with 6 unique instructions, the accuracy achieved is 88% and the error rate of 12%. In order to efficiently detect and classify photographs of sugar cane into good and ill class, the trained model has made its intention mainly through leaves and steam samples. In future, a mobile application has been implemented on the basis of our search to detect the sugar cane leaves and stems disorder and to provide records of this disease. Artificial neural community (ANN) that we are able to easily detect plant damage items provided on Android phones. The Future work of this paper is to implement the system with below mentioned algorithms Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD),

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