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Investigating Efficiency of Machine Learning Algorithm Over Crop Stress Dataset

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Abstract : Many people in India depend on agriculture for daily livelihood. But farmers suffer a lot of problems during cultivation of crops. One of the main problems is crop stress. Crop stress destroys the crop productivity and yield. Early detection of crop stress will be very helpful for the farmers. Machine learning and deep learning can contribute a lot in this arena. This project attempts to find performance of machine learning algorithms over crop stress data sets. The system collects data as images. These are images of stressed grape crops and collected in an image dataset. Different machine learning's deep learning techniques are used for classification. This paper makes an attempt to find efficiency of different classification models over crop stress image dataset. Classification models like LSTM, CNN and SIFT with LSTM are developed and respective results are compared with each other on crop dataset. The results are analyzed and the best suitable model is identified according to the accuracy.

I. INTRODUCTION

Crop stress decreases the total yield and thus causes a huge decline in total production. This project takes an attempt to compare different machine learning classification models which can contribute to understand the best suitable model to crop dataset for stress diagnosis.

1.1 Introduction to Crop Stress

Crop stress is something that affects the yield of plants. The two types of stress occurring in plants are abiotic and biotic stress. Examples of abiotic stress are flood, salinity, drought, etc. Biotic stress includes attack by some pathogens like fungi, bacteria, etc. Grapes are a type of fruit that grow in clusters and can be black, dark blue, yellow, green, orange, and pink. It is one of the most economically important food crops. In most of the regions where grapes are cultivated they suffer a lot of crop stresses. A grape is a type of fruit which has a great economic importance. The stresses that this project deals with are bacterial blight, Boron deficiency, Chemical injury, drought, Fungal blast, Iron deficiency, Nitrogen deficiency, Normal, Phosphorus deficiency, Potassium deficiency, Submergence and Zinc deficiency.

1.2 Machine Learning

Major part of artificial intelligence is machine learning and deep learning. Machine learning is the science of persuading computers to behave in accordance with algorithms that have been devised and implemented. Machine learning, according to many experts, is the best technique to get closer to human level AI. Machine learning (ML) is a subfield of AI concentrating computational strategies that can improve execution on some assignments by learning. The point of machine learning exploration might be intellectual, specialized or theoretical. Subjective points look to show human learning in some dimension. Hypothetical examination considers, for instance, qualities of learning strategies, for example, their degree and confinements. Like AI, machine learning is an intrinsically interdisciplinary record.

1.3 Problem Statement

This work is an attempt to find efficiency of different classification models over crop stress image dataset. Image dataset has been used which contains images of stressed crops. Machine learning's deep learning techniques are used for development of classification or prediction models. Classification models like LSTM, CNN and LSTM with SIFT are developed and respective results are compared with each other on crop dataset.

II. LITERATURE SURVEY

Many sectors are applying machine learning models to address a variety of use cases. Below are just a few of the many applications of machine learning in the real world.

Basavaraj S.Anami, Naveen N.Malvade, Surendra Palaiah [1] proposed a deep convolutional neural network (DCNN) framework for automatic recognition and classification of paddy crop stresses. This system finds application in developing decision support systems and mobile applications. Using the on field pictures the paddy crop stresses are classified and recognized by applying deep learning techniques. The approach given is applicable to eleven classes of biotic and abiotic stresses from five- different paddy crop varieties.

Lus Santos, Filipe N.Santos, Paulo Moura Oliveira, Pranjali Shinde [2] performed a survey of different deep learning techniques applied to various agricultural problems such as disease detection and identification. This paper presented a review of deep learning based research in agricultural domains. It examined the agricultural area and described the problems faced by them.

They also listed technical details such as DL architecture and model, described the data source, reported the overall accuracy of each work compared to alternative methods and verified the employed hardware and possible real-time application.

Chege Kirongo, Kelvin Omieno, Makau Mutua, Vitalis Ogemah [3] proposed and investigated the application of deep neural networks to detect pests and diseases. This paper focused on detection of multiple plant diseases in different conditions. In this paper tomato image datasets are captured and used to predict detection accuracy of plant stress. A selected category of activation functions was implemented with neural networks. The results indicate that the SoftMax and ADAM optimizer performs better resulting in higher accuracy levels.

Aditi, Mayank Kumar Nagda, Poovammal E [6] proposed a model which is a deep neural network consisting of LSTM and CNN that helps in improving the accuracy of image classification tasks. This model is proposed on the basis of artificial neural networks like recurrent and convolutional neural networks. In this work, they proposed a novel LSTM-CNN hybrid model for improving the accuracy of the image classification task.

A.Kavitha [11] proposed a paper in which how deep learning is implemented in smart agriculture. This paper also tells us the applications of deep learning, machine learning, ioT, etc. They are very helpful in agriculture to minimize manpower. These technologies are used by farmers to attain high crop yield, production, etc.

Different machine learning and deep learning methods are used in the literature for prediction and classification. Various papers use deep neural networks for classification purposes. In most of the literature convolutional neural networks are used for crop disease classification. While reviewing different literature it is found that no work is carried out to perform SIFT with LSTM as well as comparison of machine learning algorithms on Crop Image Data set is missing.

III. PROPOSED SYSTEM

Existing system works on the basis of image processing technique. It Uses Open CV2 which does not provide accurate image prediction. OpenCV is a cross-platform library using which we can develop real-time computer vision applications. It mainly focuses on image processing, video capture and analysis including features like face detection and object detection.

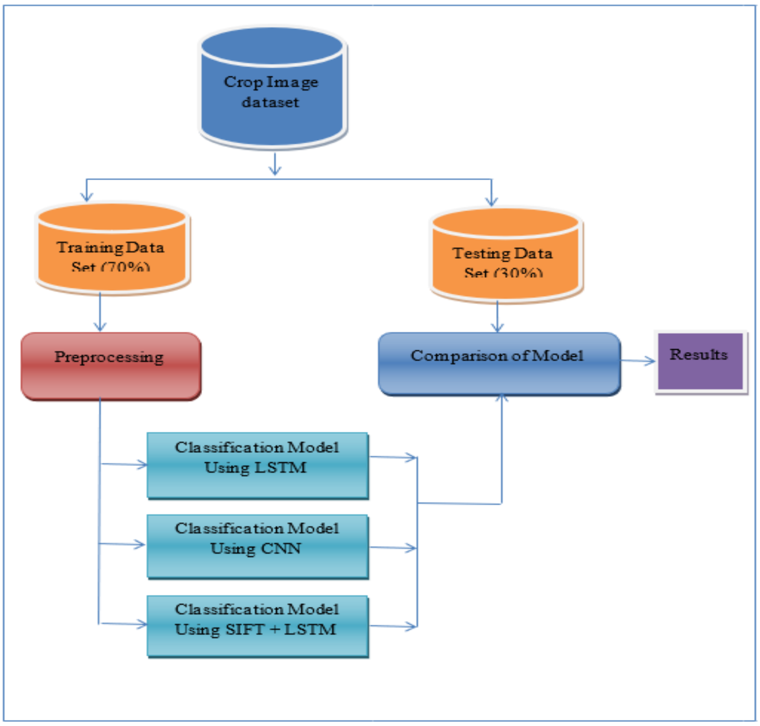


Fig 3.1 Architecture of proposed system

Above figure 3.1 is the architecture of the proposed system is mainly divided into two sub parts. First is the training part and second is the testing part.

Image Dataset: The experiments were carried out by considering the datasets from MNIST. There are certain functions used for downloading and reading MNIST data.. A total of 12 different classes of stress types of grape plant are taken. All these 12 stresses are stored in 12 different repositories. The stresses included in this dataset are Bacterial blight, Boron deficiency, Chemical injury, drought, Fungal blast, Iron deficiency, Nitrogen deficiency, Normal, Phosphorus deficiency, Potassium deficiency, Submergence and Zinc deficiency. For one stress there are 200 images. That is there are 200 images for bacterial blight, 200 images for boron deficiency, etc. So a total of 2400 images are there in this dataset. 70% of images are given for training and 30% of images are given for testing.

Preprocessing: This is the stage in which formatting of images is done. It helps to boost the contrast level of input. The chosen images can be reshaped and limited as it can be sampled in an effective manner. It is utilized to improvise the visibility of an affected region in an image when compared with the actual image. The formatted image will be used by the system model for training. It improves the quality of the image In preprocessing distortions are avoided and some features are enhanced. Improvement of image data is the main aim of image preprocessing. The crop image from the dataset has been sent for image preprocessing. After preprocessing of images there will be training and testing of the same images.

Classification model using LSTM: Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. It can not only process single data points (such as images), but also entire sequences of data (such as speech or video). The network should be trained for a fixed number of epochs to the training dataset. For training the model for a fixed number of epochs (iterations on a dataset), we need to define the batch size and the maximum epochs. It takes x as the input data which is the crop image. Before applying LSTM, features have to be extracted from the crop image. In order to perform operations on crop images it should be converted first. That is the crop image should be converted into pixels. Here the dimension of the image is specified as 28*28=784 px. The number of features is the same as the number of pixels. So the number of features will be 784. The first step is to define the network. The first layer must define the number of inputs to expect. The architecture consists of an input layer that is directly connected to the output layer and is good at classification.Every neuron in the network entireties up the information and applying the enactment capacity to the summed information lastly gives the yield that may be spread to the following layer. Thus there are three hidden layers in our system. Then we define the layers structure for all three hidden layers.

Classification model using CNN: Firstly the input crop image is resized and feed as an input to the convolutional layer. In this project the input is 28x28 px. After that there will be the process of extracting valuable features from the image. The input layer is followed by a convolutional layer. This layer has a small receptive field called filter or kernel and the dot product is executed. The result of the operation is a single output volume integer called feature map. Then slide the kernel through a stride over the succeeding accessible arena of the same input image and compute the dot products again. Finally the outcome is a feature map from the input. Once the feature maps are extracted, the next step is to move them to a ReLU layer and the generated output is a rectified feature map. Rectified feature map goes to the pooling layer to generate pooled features map. The pooling layer uses various filters to identify different parts of images like edges, corners, body and few symptoms. The next step in the process is called flattening. Flattening is used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as input to the fully connected layer to classify the image.

Classification model using SIFT with LSTM: SIFT is a technique used for detecting local features in an image. The different stages for SIFT are feature point detection, keypoint localization, Orientation assignment, generation of keypoint descriptors and keypoint matching. In feature point detection, the image is blurred using difference of gaussian blurring. Then the pixel is compared with 8 neighbours. If the intensity at this extrema is less than threshold value they are directly rejected in keypoint localization. Also we need features here not edges so using eigen values and their ratio edges are removed in this step. After this we will get the removal of low contrast keypoints and edge keypoints. Orientation is assigned to each key point as to where it is facing. This is best done by creation of orientation histogram. Next step is the generation of keypoint descriptors. Keypoint matching between two images is done by identifying the nearest neighbours. Further step involves ratio analysis between the closest and second closest one. After this the output of SIFT will be the same as the input to the LSTM and LSTM will work as described above.

Comparison of models

As it is decided and mentioned 30% of actual dataset which can be used as testing dataset. After training the dataset and generating the model, namely classification model using LSTM, classification model using CNN and classification model using SIFT with LSTM is generated. The same model will be deployed on testing datasets. The efficiency of this model is recorded through a confusion matrix. Using every model the results are displayed in the form of a graph.

IV. RESULT ANALYSIS

The proposed solution is implemented in Python. To provide good human computer interaction, a graphical user interface is designed. The system gives comparisons of different models and accuracy has been found out by plotting graphs and confusion matrices.

Test results for CNN model

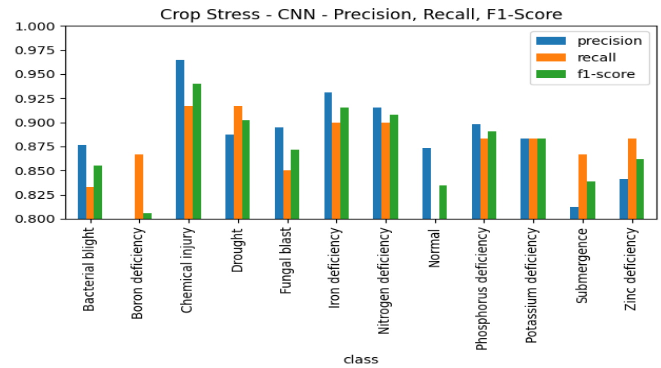


Fig:4.1 Precision, recall and f1 score for CNN

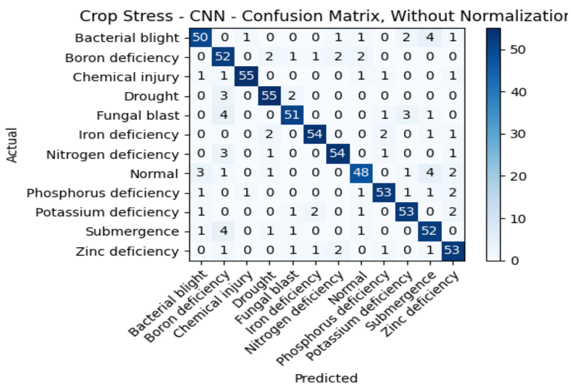


Fig:4.2 Confusion matrix for CNN

The above bar chart (fig:4.1) shows the graphical representation of the precision, recall and f1-score for CNN model. It performed well for chemical injury and did not perform satisfactorily while predicting normal and boron deficiency stress. Above figure 4.2 shows the confusion matrix for CNN model. Out of all chemical injury stress images the model predicted 55 images correctly as chemical injury stress. The model wrongly predicted 1 image as normal whereas those were actually chemical injury.

Test results for LSTM

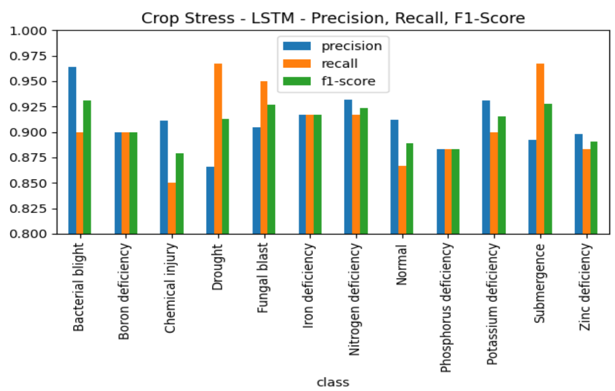


Fig 4.3: Precision, recall and f1 score for LSTM

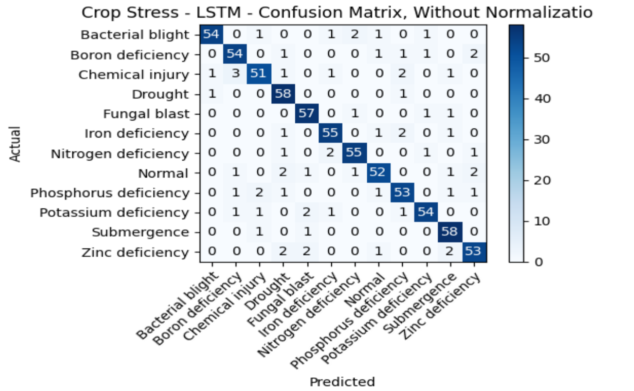
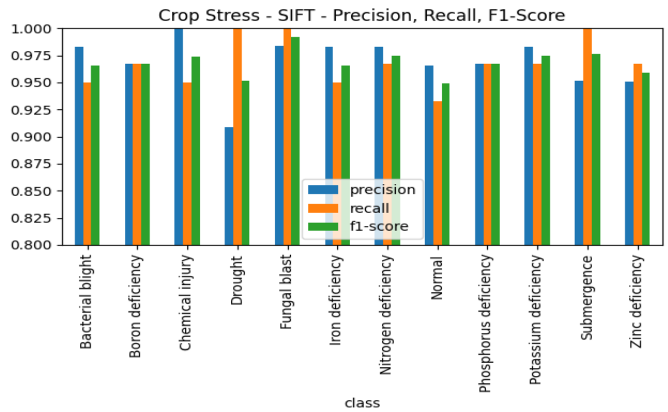


Fig 4.4: Confusion matrix for LSTM model

The above bar chart (fig:4.3) shows the graphical representation of the precision, recall and f1-score for the LSTM model. From this graph, it can be seen that the model performed well for bacterial blight and drought stress and did not perform satisfactorily while predicting chemical injury stress. Above figure 4.4 shows the confusion matrix for the LSTM model. Out of the drought stress images the model predicted 58 images correctly as drought stress. The model wrongly predicted 1 image as phosphorus deficiency whereas those were actually drought.

Test results for SIFT with LSTM



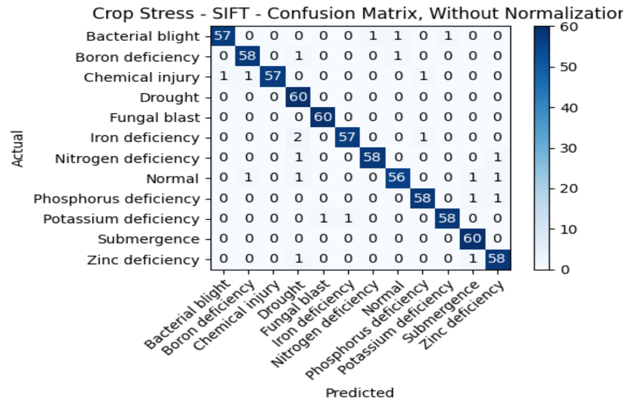
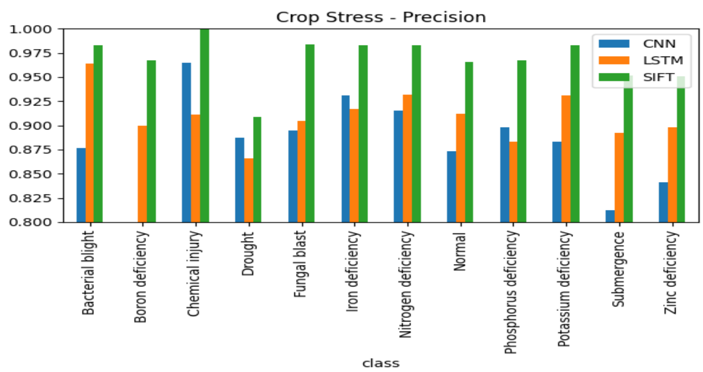


Fig 4.5: Precision,recall and f1 score of SIFT with LSTM

Fig 4.6: Confusion matrix for SIFT with LSTM

The above bar chart (fig:4.5) shows the graphical representation of the precision, recall and f1-score for the SIFT with LSTM model. From this graph, it can be seen that the model performed well for submergence and did not perform satisfactorily while predicting normal type. Above figure 4.6 shows the confusion matrix for the SIFT with LSTM model. For submergence stress images the model predicted 60 images correctly as submergence stress. The model does not predict submergence wrong in this model. For drought and fungal blast also the SIFT with LSTM doesn't give wrong predictions.



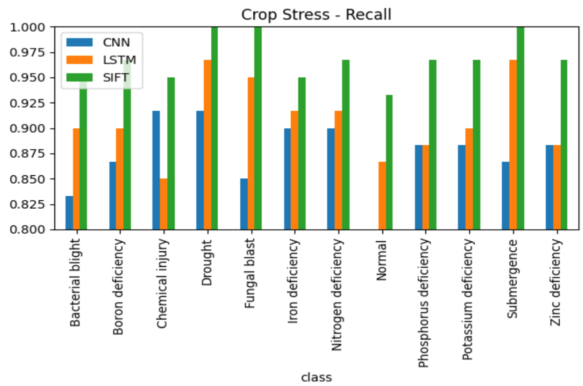


Fig 4.7: Precision of all models

Fig 4.8: Recall of all models

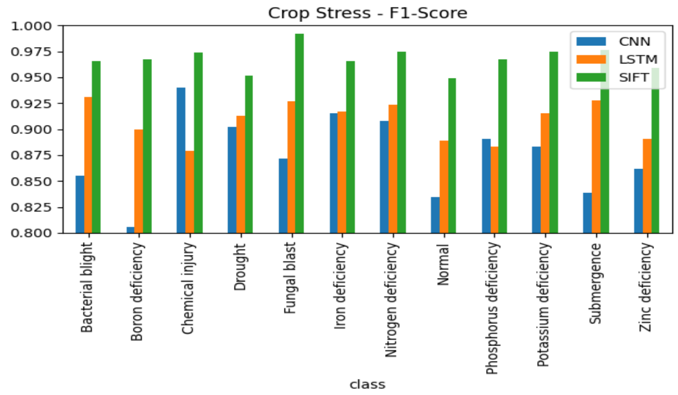


Fig 4.9: F1 score of all models

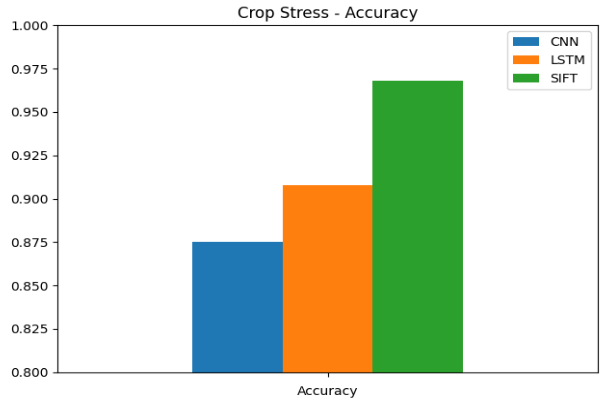


Fig 4.10: Accuracy of all models

The above bar graph illustrates the precision(fig:4.7), recall(fig:4.8) and f1 score(fig:4.9) values of CNN, LSTM and SIFT with LSTM for all 12 classes or crop stresses. From these figures it is evident that the SIFT with LSTM model gives the best results compared to the other two models. The above bar graph fig:4.10 shows the comparison of accuracy of all three models used in this project work. The accuracy of CNN is the lowest at 87.5%. The accuracy of the LSTM model is 90.80%. The accuracy of SIFT with LSTM is the highest at 96.80%.

V. CONCLUSION

The recognition and classification of various crop stress is a crucial process which improves the quality of the fruits and increases productivity. This project work has developed a set of intelligent Machine Learning and Deep Learning based models to identify the presence of stresses in grape plants. This work presented a crop stress image classification model by incorporating several processes. The proposed system compares different machine learning classification models. Among the compared models SIFT with LSTM gives better results with better accuracy. SIFT can generate large numbers of features from an image so it gives better results along with LSTM classification. Because the quantity of features in an image is very important for object recognition.

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