Identification of Sugarcane Foliar Diseases: Methods and Datasets

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Abstract*: Agriculture is the major part of the Indian economy as it provides key support to social and economic development of the country. Sugarcane is the leading cash crop in various states of India which has larger share in the net agriculture produce. Recently, researches have highlighted the impact of different disease on various plants. Estimated loss is much severe for the sugarcane crop via foliar diseases. Foliar diseases like rust, eye spot, mosaic and banded chlorosis may hamper the overall productivity of sugarcane and sugar recovery rate (RR). Early prediction of these diseases may limit the losses in terms of produce net benefits. This paper addresses the concerns, types of the foliar disease and researches undertaken to overcome the problems related to the diseases. Morphological characters of these diseases may help in identifying the representative features and to use them for the optimum classification. Currently the use of deep neural networks (DNN) is encouraged for the classification. DNN demands the huge and accurate databases. Intuitively the use and important methods used in database creation for disease diagnostic system (DDS) has been highlighted in the paper. Modifications made to the Convolutional Neural Network architecture have suggested the improved performance in terms of recognition accuracy (RA) and lesser recognition time.

Keywords*: Sugarcane, Deep Neural Network (DNN), Recovery rate (RR), recognition accuracy (RA), Video Signal Processing, Disease Diagnostic System (DDS).

I. INTRODUCTION

More than 50 percent of the workforce in India is engaged in agriculture and it contributes to around 17-18 percentage of the GDP [1]. Sugarcane industry is the second largest agriculture based industry and it also contribute to the overall socio-economic development of the country like India. It is evident that the production of sugar has been increased over the last decades and the recovery rate has also shown the significant improvement. The sugar factories are modernizing the sugarcane cultivation practices which benefit the cane growing farmer fraternity across the India. Sugarcane crop has played vital role in socio-economic development of the various states in India [1]. Sugarcane (Saccharum officinarum L.) is leading cash crop in various

states of India. The facilities provided for the cane grower includes credit fertilizers, disease free seeds, harvesting units, transportation facilities and institutes like Vasantdada Sugar Institute (VSI)) etc. The productivity of sugarcane is worst affected by the diseases. In the state of Maharashtra only, around 30 diseases caused by various pathogen and its agents are affecting various sugarcane varieties viz. Co 86032, CoC 671, Co 94012, Co 8014, Co 740, Co 7219, Co 7527, Co 419 and Co 8021. Various plant pathology sections were formed by the Government of Maharashtra (GoM) to solve the problem raised due to the diseases, conducting the surveys for finding their causes, and production of disease free seeds etc. Sugarcane foliage diseases like rust, eye spot disease, mosaic and banded chlorosis are the major categories of the disease affecting crop production. It has been strongly argued that the production crop severely decreases once it has been affected by disease. It has created the urgency to find a mechanism which could forecast the diseases in early stages of the crop lifespan. This paper is organized into different sections as follows. Section II gives the literature review of related work. Section III gives the detailed information about the databases used in different experimentations. Section IV, deals with architectural variants of CNN. Section V concludes the paper.

II. LITERATURE REVIEW

Due to climate change and unexpected weather conditions foliage diseases are more prevalent in the sugarcane crop. Major districts in south Maharashtra including Kolhapur, Sangali and Satara are more prone to this disease in recent years. The variety CoM 0265 is found to be more affected by foliage damage. It is predicted that in coming years influence of disease may span pan Maharashtra and nearby states [2]. Attempts were made to thoroughly understand the cause and effects of foliage diseases on sugarcane produce. It was argued that early detection and estimation could be the way to reduce severity and save the crop yield to better extent. The combination of gray level co-occurrence matrix (GLCM) as a feature and support vector machines as classifier for spot disease shows the accuracy and error severity estimation about 80% and 5.73,respectively[3]. Fuzzy C-means clustering and rough set were employed to detect the insect pest of sugarcane cotton aphis. Segmentation rate and accuracy was significant in the work carried [4].The combination of color feature extraction and texture could be used to identify the rust disease in sugarcane leaf. The multi class support vector machines trained with features extracted from images has shown around 98.5% classification accuracy with polynomial kernel [5].

Sugar recovery rate (RR) is the amount of crystal sugar produced per metric ton sugarcane crushed. RR severely gets hampered when the sugarcane is infected with diseases [6].

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The response shown to the different wavelengths was key point of research in multi spectral imaging. Aerial imaging made it possible to determine the exact percentage of the crop prone to the disease and estimates were made regarding the net produce from the sugarcane field. Spectral information provided the base for classification of disease prone and healthy areas using kappa statistics, another solid approach of estimating the values and number. It strongly highlighted the importance of spectral imaging combined with suitable technique of classification [7]. Data mining techniques including namely decision tree model and random forest method for sugarcane yield prediction in Indian scenario was proposed in [8].Another interesting approach to detect mulberry leaf diseases by using red edge point gave significant improvements in the estimation of diseases on the mulberry leaves. But the work was lacking in terms of data points considered for the analysis. However use of multispectral imaging approach was worth noting in the research carried by authors in [9].Artificial neural networks were used to predict the sugarcane yield by few people in the last decade.

Weka tools with multilayer perceptron and simple k means clustering has been proposed for the leaf disease identification. However no state of the art system is available for the quick identification of the disease in real time situation [10]. Like sugarcane other plants are relevantly prone to the various fungal and bacterial dis-eases. A DDS for citrus plant based on convolutional neural network (CNN) has shown significant performance. The system also focused on the service provision to the farmers via smart mobile system and relevant architecture.

It employed densely connected convolutional network, a sophisticated variant of CNN to give satisfactory results to the users. It has highlighted the recognition accuracy up to 88 percent with less time. A detailed study of verticullium wilt disease which is soil borne multi symptomatic for strawberry plant has been given in the article. Early prediction of the same and use of attention mechanism for the feature extraction with optimized network has been proposed in the work of [11]. Images for the database were collected using smart phone with manual annotation. A dataset containing 3531 images collected manually from growing greenhouse. In data augmentation, images were rotated by certain angles to increase the size of dataset. It helped to avoid over fitting of the system. Multi-task learning is adapted to introduce a new disease detection task, which judges whether the plant has verticillium wilt from the detected young leaves and petioles. This task achieves an accuracy of 99.85 percent on the collected dataset. It addresses the use of faster R-CNN with the disease detection network (DDN) [12]. Similar attempts were made for the Mango plants with multilayer convolutional neural network (MCNN). It worked with dataset original size of 1070 followed by data augmentation. The results envisaged higher classification accuracy of the proposed MCNN compared to the other approaches [13].

Few other technocrats worked on apple disease with approach oriented around strong correlation and genetic algorithm based feature selection. The core idea was to use machine learning (ML) approaches for the efficient classification of the apple diseases [14]. Similarly improved convolutional neural network was employed for real time detection of apple leaf diseases. System was significant and used variants of convolutional network [15]. Similar knowledge based methods for crop disease detection is thoroughly mentioned in [16].

The recent advancements in the field of machine learning, deep learning and artificial intelligence could play a significant role in predicting the leaf diseases at early stages by implementing suitable image processing algorithms. The modifications to earlier said deep learning architectures could also play a vital role in making task efficient and optimum. The problems associated in the deep learning architecture are mainly related to the less availability of the database which could be addressed by implementing thorough exercise at the time of collection process. The problems of over fitting and under fitting may easily be addressed by paying more attention to the database size. Recent trend in deep learning could be much close to the farmers of India, if a system like this could be handed over to them in precise and simpler manner via platforms like mobile. They could easily identify the diseases by their own and could get diagnostic instructions and access of facility centers more easily.

III. DATABASES

For accurate result estimation and analysis state-of-the-art database is needed, which can be done by means of survey. The table gives the list of databases used for the different experimentation and its results expectations.

Fig. 1.Helathy sugarcane leaf

The experimenation to be performed are totally dependent on the quality of the dataset used. Table 1 show the comaprative study of the different databases used in the experimenatation. The selection of the imaging mechanism has influenting impact over the system. High resolution and color details are the criterias which must be considered for the application.

The imaging environment should simulate the real time conditions as system has to be checked on the images taken in the relevant environment. The background of the images taken must be uniform in order to avoid the spurios effect involved. The figure 1 shows the image of healthy sugarcane leaf, it shows no sign of any disease on it. The severity of disease can be seen in the figure 2, 3 and 4. Figure 2 shows the sugarcane leaf affected with rust disease. Figure 3 and 4 shows the leaves affetcted by mosaic and eye spot disease, respectively. Each disease shows distinct visual patterns of the sugarcane leaves. These unique visual patterns could be helpful in identication and classfication of these diseases by using suitable techniques.

Table 1. Plant Disease Detection Methodologies: A Comparison

Plant	Database	Research Method	Research Gap
Strawberry [12]	• Tool used: Smart Phone • Manual annotation • Own created: 3531 Images 789 healthy samples 2742 disease samples • Data augmentation by rotating images with different angles	• Adaption of multitask learning • Accuracy: 99.85% • Use of Faster R-CNN • Novel attention mechanism	• Comparative analysis is missing • Use of modified network is missing
Mango [13]	• Combination of Real time mango leaves dataset and Plant village dataset • 1070 self-acquired and 1130 from plant village • Four classes were used for classification	• detection of fungal disease (Anthracnose disease • Multilayer CNN • Satisfactory result 87.65% accuracy	• Comparative analysis is missing • More versatile databases could be employed for the work • The usage of the said network over other economically important plant is missing
Citrus [11]	• Collected through network and local material • Annotation by experts • Total 6 type of disease studied • Data Augmentation by H-flip, V-flip, Increase brightness, increase contrast etc. • Dataset splitting (6:2:2) Train: Test: validate	• Use of mobile services computing in agri • Developed an intelligent diagnosis system • bridge the gap between citrus growers and plant diagnostic experts • simplified densely connected convolutional networks (DenseNet). • The system is realized using the WeChat applet in the mobile device • recognition accuracy of citrus diseases exceeds 88% • Reduced time with DenseNet	• No comments about the feature extracted by CNN • Proper dataset is needed • Data augmentation is missing • architectural details of the network subunits are missing
Apple [14]	• Nearly 1800 images • Canon EOS 100D • Around 316 supplemental images from Internet • 511 from ImageNet (an open source database) were acquired for diversity of samples.	Three approaches discussed • Image processing • Machine Learning • Deep Learning • Improved architecture by omitting landmark loss of three cascaded networks for fruit detection task	• Sufficient database is missing • Variety in database is limited • If there is great gap between test set and training set the detector may miss some objects
Apple [15]	• Apple leaf disease dataset (ALDD) • data augmentation and image annotation techniques were used	• Disease detection model that uses deep CNN is proposed • GoogLeNet inception structure and rainbow concatenation • detection performance of 78.80% high detection speed 23.13 fps (frames per second)	• No Communication to the farmers • Manual annotation

Fig. 2.Rust affected sugarcane leaf

Fig. 3. Mosaic affected sugarcane leaf

Fig. 4. Eye spot affected sugarcane leaf

IV. METHODOLOGY: DEEP NEURAL NETWORKS

With advent of highly dense architecture of the neural networks, the image classification and recognition has become much trivial. However the proper addressing of the issues related to the architecture is crucial. The use of deep neural network demands huge database. Need of large database could be solved by employing data augmentation. Different data augmentation techniques are mentioned in the table 1. Deep learning is at upper hand in automatic feature extraction unlikely machine learning techniques which need decisive method to extract features from the set of images. The task of disease classification can be easily handled with opulent database and need no external intervention in the process.

In [12] multitask learning was achieved by using attention mechanism as novel method for feature extraction. It creatively used ResNet-50 as the backbone network with support of GPU facility for the training.

A real time and low cost disease monitoring system is proposed for classification of mango leaves into healthy and unhealthy categories. Accuracy of around 97.13% achieved in the experimentation which is quite high compared to the other methods proposed in [13]. In [14] state of the art database could have used and as a result significant classification accuracy in not seen. There seems to have confusion over few disease characteristics. Use of web services in the disease recognition appears to be costly initially for the third party observer. Use of deep learning for identification of the diseases has been challenging initially but construction of dense network helped to raise identification accuracy to significant level later. Use of We chat applet is special point to ponder. A common mobile applet could be effectively tuned into task of disease recognition. It highlights the use of such services in many such applications in future. Use of information circulation to the farmer is unique approach proposed in the paper.

Standalone systems may sometime fail to speed up the task of classification. Recognition accuracy was improved in [15] and GPU helped to complete task in lesser time. Two improved deep convolutional neural networks models, GoogLeNet and Cifar10, can achieve high identification accuracy, 98.9% and 98.8%.

A detection model VGGNet is modified by changing parameters to obtain new network VGG-INCEP. It was developed by introducing GoogLeNet inception module to improve the detection performance for multi scale disease spots. Next rainbow concatenation in R-SSD is integrated. Pooling and de convolution are utilized simultaneously to integrate the context and fuse features of the feature pyramid at the backbone of the SSD for highest small disease object detection in [16].

Few researchers have explored various machine learning (ML) algorithms for the classification of the plants. Later these methods also have been used for the plant disease identification and recognition. However the use of ML algorithms demands proper understanding the morphological aspects of the disease. The careful observations and understanding of the disease characteristics becomes crucial while applying the ML algorithm for plant disease detection task. In order to avoid these complications the neural networks and its variants are favorite choice of the researchers in recent times. Internet of things (IoT) with ambience sensing and image analysis has also opened new opportunities to the researchers to forecast the plant physiological behavior. Table 2. gives the insight to the various technologies related to the deep neural network and its variants.

TABLE 2. USE OF DEEP NEURAL NETWORK VARIANTS FOR VARIOUS PLANTS

Author	Plant	Method	Accuracy
Eftekhar Hossain [17] Md. Farhad Hossain	Arkansas	Color features with K-nearest neighbor (kNN)	97.30%
Dongyan ZHANG [18] Daoyong WANG	Wheat	Color features(HSI/HSV) Texture (Local Binary pattern (LBP)) Support vector machines (SVM)	92.70%
Monirul Islam Pavel et.al [19]	Cucumber tomato egg plant	Features: Homogenity, contrast Classification: Multiclass SVM	97.33%
Kesava Prasad S.A et.al [20]	Any affected plant	Convolutional Neutal Network (CNN) Darknet	81.33%
R Amog Shettyn et.al [21]	Plant Village (Mixed plants)	Base model with L2 regularization	98.73%
Alexandre P. Marcos et.al [22]	Coffee	CNN	82.33%
Mohammed Brahimi et.al [23]	Plant Village (Mixed plants)	Teacher student architecture VGG16	90.70%
S.Santhana Hari et.al [24]	Maize, grape, apple,tomato	Plant disease detection neural network (PDDNN)	97.50%
Sijiang Huang et.al[25]	Tomato	2 head network (variant of CNN)	98.07%
Md. Rasel Howlader et.al [26]	Guava	Deep CNN	98.74%

TABLE 3: CLASSIFICATION ACCURACY

Methods	Classification accuracy
ResNet50[11]	85.39%
DenseNet201[11]	86.53%
InceptionResNetV2[11]	80.55%
Simplify DenseNet 201[11]	86.53%
Inception V3[11]	86.53%
Proposed	83.30%

It is obvious enough to understand that deep neural network for the disease diagnosis system is giving optimum performance in controlled environment.

In the research work ResNet50 [11] for the sugarcane disease database is considered. The classification accuracy (CA) has been slightly decreased as compared to the methods mentioned. It may be due to the lack of standard practices followed during the image capturing and lack of suitable of data augmentation techniques. It has created the urgency to pay careful attention to these practices. Table 3 shows the comparison of methods used for citrus mentioned in [11] and the methodology we employed for sugarcane diseases. Results are shown with little deviation from the mentioned in [11]; however range of the result is nearer to the results obtained.

V. CONCLUSION

Plant disease detection is promising innovation which empowers farmers incredibly to forecast the diseases in advance. It helps farmers to seize the losses and improve the quality of overall production. Large quantum of the Indian farmers those who are still unfamiliar to the technological advances could benefit mostly out of this technology.

Use of video signal as input helps the system to predict the dynamic physiological behavior of the plant species. The abundant datasets used in the research work form literature assures the authenticity of the work. Identifying the plant diseases at early stage minimizes the overall risk of the farmers.

Databases with proportionate variety and good sample space are key requirement for the good performance of the system. Noise removal at the time of capturing images must be dealt in precise way to avoid degradation in the performance. Minimum 2000 images must be database size, which can further be increased by augmentation methods to avoid over fitting.

DNN provides the good choice for identification of the diseases. The challenge of ample dataset for the DNN could be overcome by the suitable data augmentation techniques suggested in the paper. Architectural modifications made to the DNN could help significantly to enhance the classification accuracy (CA) and the performance of the system. The CA observed is slightly less than that citrus plant; however proper handling of dataset and different network tuning strategies may improve the results.

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