Detection and Classification of Diseases in Coffee Plant using CNN-XGBoost composite model

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***Abstract*—Diseases in plants have always been a major concern for the agriculture community. Due to the absence of competent ways for detection, they suffer from loss of crop yield every year. This particular subset of ML, deep learning (DL) seemed to have shown much better performance in terms of accuracy. In this paper, we use the deep CNN architecture, InceptionNet and transfer learning for the detection and classification of plant diseases. Due to insufficient data availability, we have used DCGAN along with other traditional data augmentation techniques, to increase our dataset. This paper uses a InceptionNet-XGBoost composite model for classification. The said model is also compared against other deep CNN models, and seen to perform better. Moreover, the validity of XGBoost as the most suitable classifier is also shown. The composite model proposed has attained an accuracy of 98.32%. We have also precision, recall and F1 Score as other performance metrics for the comparison of the model.**

***Index Terms*—detection, deep learning, CNN, augmentation, DCGAN, classifier, XGBoost, accuracy, performance**

I. INTRODUCTION

THE coffee cultivation in India is mostly centralized around the southern states of Karnataka, Kerala and Tamil Nadu. In past years, certain parts of Andhra Pradesh and Orissa in eastern coast and a third region comprising the states of Assam, Manipur, Meghalaya, Mizoram, Tripura, Nagaland and Arunachal Pradesh of North eastern India. Most of the Indian coffee is exported, so it is an important source of revenue for the country. India ranks among one of the largest producers of coffee in the world, with a contribution of 3.5% of the world's production. Farmers in remote areas often pursue help from agro-advisory systems by explaining obvious symptoms over the phone. In that scenario, data may be misinterpreted. In addition, as specialists are not available in vast quantities, the processing period can be considerable. The other approach is to manually submit to the specialist a specimen that is both time-consuming and costly [1]. Farmers typically diagnose diseases without the use of technology, and it is impossible to measure the severity of symptoms [2]. In financial terms, the cumulative losses caused by plant pests and diseases and intricately carved processing processes are valued at millions of dollars [3].

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II. LITERATURE SURVEY

Coffee plants are mostly affected by diseases like; Cercospora, Leaf miner, Phoma and Leaf Rust. The symptoms are identifiable externally, but having done explicitly by experts is a resource exhaustive process [4]. CNN has proved itself to be in terms of feature extraction because it can decrease the intricacy of network topology and the number of parameters through localised feature map, shared weights, and pooling operations. Montalbo et al [5], performed their study on classifying diseases on Borako leaves using VGG-16 architecture. but as it seems that the leaves were isolated manually and used as a dataset and no segmentation technique was mentioned. It cannot completely comprehend the extracted features. As a result, a potential avenue for offering novel solutions to the picture categorization problem has been established. Driven by the foregoing facts [6-8], this study investigates the integration of the CNN model and the XGBoost method, both of which have demonstrated good performance in image classification problems. Findings by Chlebus et al [9] suggests that XGBoost was most successful in discriminating between the classes in the validation phase and due to the use of multithreading, XGboost has always been shown to be superior in terms of execution speed than its peers Santhanam et al [10] However, deep networks are extremely vulnerable to overfitting. Augmentation of data helps to maximise the scale of the dataset. To solve this problem, a new concept of Generative Adversarial Network developed by GoodFellow et al [11] was used. More specifically, DCGAN is used to neutralize the shortcomings in real dataset, by generating real like images which makes the dataset more informative and diverse. This paper studies the performance of various CNN based deep learning models for coffee plant disease detection and classification with DCGAN based data augmentation technique [12-14] to the traditional augmentation and manual collection of data. The contribution of this technique is studied by the classification performance using transfer learning. For the purpose of transfer learning, InceptionNet, ResNet, VGG19 are selected as feature extractor and the last fully connected layers are swapped with the XGBoost classifier for desired results. The results are compared by coupling CNN with classifiers like gradient boosting, decision tree and gaussian naive bayes, for authentication.

III. Dataset Preparation

A wide range of photographs of coffee leaves for disease identification are included in the pre-processed dataset [15]. The dataset is categorized in two parts: (a) Leaf; contains the 1747 complete leaf images of 5 classes: Cercospora, Leaf miner, Phoma, Healthy and Leaf Rust and (b) Symptom; contains the 2147 cropped images of leaves of same 5 classes. The dataset is also unbalanced, which might incur some bias. To deal with this we are using DCGAN for data augmentation along with other traditional augmentation techniques. From each class, 80% of the data is used as a training set and 20% is used for validation [16]. With the augmentation, we expand the dataset to 1000 images per class. This will make the dataset both balanced as well as robust. The images generated (denoted by red) replicate a similar distribution pattern like the real images (denoted by orange) and that is evident by the intersection between their regions of distribution. This is verified based on the work of Wu et al[16] by generating t-SNE plots for all 5 classes, as shown below.

IV. Model Development

A. CNN

Convolutional Neural Networks (CNN) have completely dominated the machine vision space in recent years [17]. Transfer learning is the enhancement of learning by transferring knowledge from a specific task that has already been learned into a new task. It helps in improving the baseline performance and reduces the time for model development. Pre-trained model approach of transfer learning is used and models chosen for comparison are VGG19, InceptionNet and ResNet.

B. Extreme Gradient Boosting

Gradient Boosting is a machine learning algorithm that can be used to solve problems in classification and regression. XGBoost is an improvement over traditional gradient boosting in a way that the mechanism of combining weak learners does not happen one after the other, as it does in gradient boosting, instead it enhances the speed and efficiency of cpu by thoroughly examining its cores by using a multi-threaded approach. It utilizes a loss function that optimizes the following term:

$$Z(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(y_i, y_i)$$

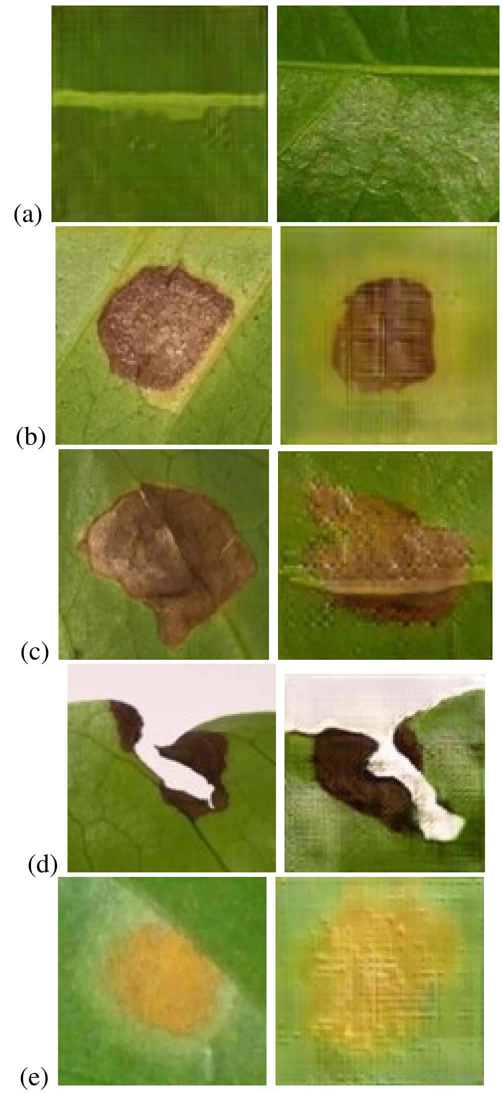

Fig. 1. Real vs Fake image
a) healthy b) cercospora c) miner
d) phoma e) leaf rust

where,

$$\Omega(f_k) = gT + 1/2l||w||^2$$

The greedy approach adopted by the algorithm when making a splitting decision is:

$$Z_s = 1/2[[(\sum_{i\in I_L} g_i)^2/\sum_{i\in I_L} h_i + \lambda] + [(\sum_{i\in I_R} g_i)^2/\sum_{i\in I_R} h_i + \lambda] +$$

$$[(\sum_{i\in I} g_i)^2/\sum_{i\in I} h_i + \lambda]] - \gamma(1)$$

The sole idea of using a composite model is to combine the best from both worlds. CNN networks are excellent in feature extraction as they use the adjacent pixel information to effectively down-sample the image first by convolution, and learn the complex features. The last fully connected layers of CNN model are replaced by the XGBoost classifier. The CNN mode is trained until the error is minimized. The output thus generated are considered as features and are fed as input

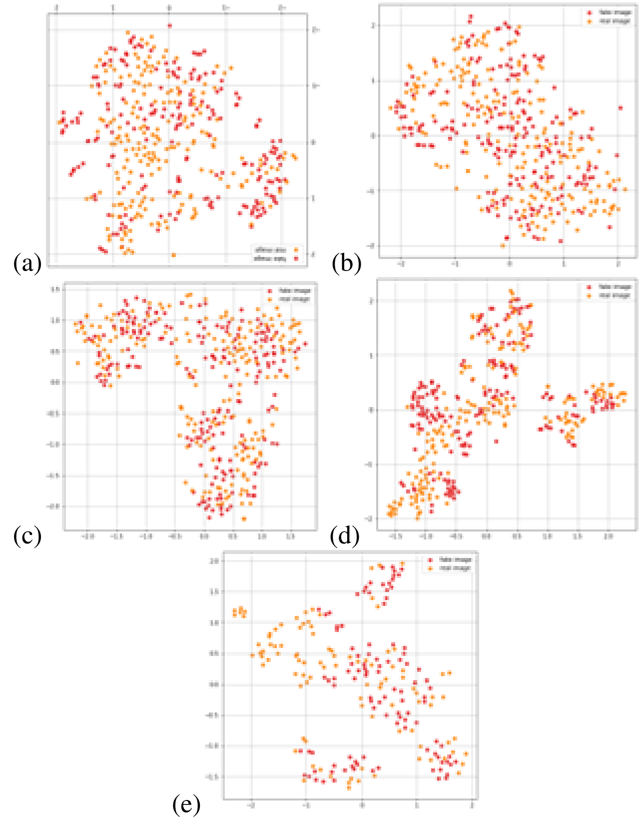

Fig. 2. Distribution of Real Image and Fake Image depicting there closely related features a) healthy b) cercospora c) miner d) phoma e) leaf rust

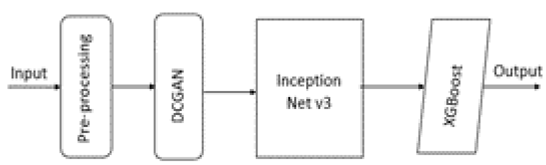

Fig. 3. Inception + XGBoost model for classification

to XGBoost, for classification., which consistently achieves higher performance and reduces overfitting.

V. Results and Discussion

A. DCGAN augmentation

Here, the model of interest is Inceptionv3, as it outperformed the rest of its peers with 96% accuracy, when they were made to perform classification on the augmented dataset, on their own, using FC-layers.

B. CNN's FC-layer vs XGBoost performance

In order to support our claims, we used InceptionNet v3 as our base CNN model and combined it with XGBoost, and compared its performance against traditional CNN models with FC layers for pairing up the CNN model with Gradient Boosting, GNB and Decision Tree classifier as well. The comparison was evaluated in terms of precision, recall and

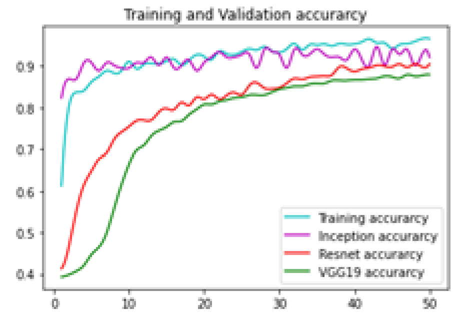

Fig. 4. Accuracy curves show Inceptionv3 outperforming VGG19 and ResNet for the augmented dataset built earlier

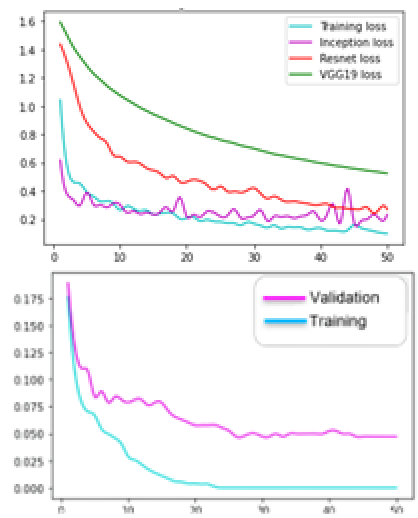

Fig. 5. Loss curves showing the Inceptionv3+XGB outperforming solo deep CNN models

F1-score, and XGBoost was found to outperform its peers. The results are shown as follow classification. Fig, shows that the error rate for the CNN models were much higher. The least among them was that of Inceptionv3 with a value of 0.2673. The hybrid model on the other hand minimized the error by almost 2%, to 0.0556, on testing data.

C. CNN XGB performance over its peers

Moreover, the performance of XGBoost as best suited classifier is concluded after pairing up the CNN model with Gradient Boosting, GNB and Decision Tree classifier as well. The comparison was evaluated in terms of precision, recall and F1-score, and XGBoost was found to outperform its peers. The results are shown as follows.

D. Validity of the proposed model

The uncalled events of false positive or false negative are avoided by the high precision and recall value for the XGB hybrid. The gaussian naive bayes, seems to deal with the increasing number of FN, which is seen by the low recall value. Decision trees and gradient boosting seem to work satisfactorily, but still inferior to the XGB hybrid. The enhanced accuracy may be explained by the use of feature selection

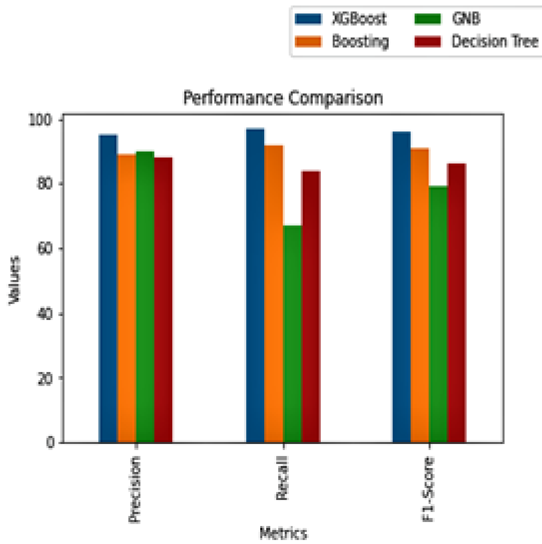

Fig. 6. Precision, Recall and F1-Score plots after combining Inceptionv3 with XGBoost, Gradient Boosting, GNB and Decision Tree classifier.

TABLE I
TABULATED FORM OF PERFORMANCE COMPARISON (*APPROACH USED IN THIS PROJECT).

Architecture	Accuracy
Expert System based on Fuzzy Logic [18]	85%
RBF (Radial Basis Function) + SOM (Self Organizing Map) [19]	90.07%
MLP with FCM (Fuzzy C-Means) segmentation technique [20]	94.54%
Data Augmentation + CNN [21]	95%
CNN (Inception v3) with data augmentation [22]	07.61%
DCGAN + Inceptionv3 + XGBoost [*]	98.37%

by CNN, which gives a subset of the most discriminating characteristics, as well as the extensive set of texture and colour information, thus proving itself as an efficient feature extractor, followed by fast paced XGBoost for classification.

VI. CONCLUSION

This study provides a unique image classification approach utilizing CNN-XGBoost model in order to improve the classification performance of the existing CNN framework as an efficient feature extractor to automatically acquire subset of colour, features etc. from input and merging it to XGBoost, as a recognition system in the upper layers of the network to obtain the desired results. Tests were conducted on the RoCoLe coffee leaf dataset to assess performance and the findings show that this applied technique outperform its standalone CNN peers as well as other existing classifiers when use together as hybrid like XGB, thereby, proving the efficacy and validity of the proposed technique in image classification.

FUTURE SCOPE

The system currently will only be able to categorize data that are visually distinctive and available in the training dataset, as its only constraint. Moreover, this work could be further extended into developing a system which is able to extract higher quality features from the input image, and by changing the optimization strategies to speed up the convergence of the cost function in order to improve the classification result and training effect.

REFERENCES

[1] Aditya Parikh et al. Disease detection and severity estimation in cotton plant from unconstrained images”. In: 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA). IEEE. 2016, pp. 594-601.

[2] J. MS Mustafa et al. Development of automated hybrid intelligent system for herbs plant classification and early herbs plant disease detection”. In: Neural Computing and Applications 32.15 (2020), pp. 11419-11441.

[3] Kiran R Gavhale, Ujwalla Gawande, and Kamal O Hajari. Unhealthy region of citrus leaf detection using image processing techniques”. In: International Conference for Convergence for Technology-2014. IEEE. 2014, pp. 1-6.

[4] Filippos Konidaris et al. Adversarial Networks as an Advanced Data Augmentation Technique for MRI Data.” In: VISIGRAPP (5: VISAPP). 2019, pp. 48-59.

[5] R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[6] Francis Jsmar P Montalbo and Alexander A Hernandez. Optimized Classification Model for Coffea Liberica Disease using Deep Convolutional Neural Networks”. In: 2020 16th IEEE International Colloquium on Signal Processing Its Applications (CSPA). IEEE. 2020, pp. 213-218.

[7] Florian Schro, Dmitry Kalenichenko, and James Philbin. “Facenet: A unified embedding for face recognition and clustering”. In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2015, pp. 815-823.

[8] Sharada P Mohanty, David P Hughes, and Marcel Salathe. “Using deep learning for image-based plant disease detection”. In: Frontiers in plant science 7 (2016), p. 1419.

[9] Kiran R Gavhale, Ujwalla Gawande, and Kamal O Hajari. “Unhealthy region of citrus leaf detection using image processing techniques”. In: International Conference for Convergence for Technology-2014. IEEE. 2014, pp. 1-6.

[10] S Ramraj et al. “Experimenting XGBoost algorithm for prediction and classification of different datasets”. In: International Journal of Control Theory and Applications 9 (2016), pp. 651-662.

[11] Ian J Goodfellow et al. “Generative adversarial networks”. In: arXiv preprint arXiv:1406.2661(2014).

[12] Clement Douarre et al. “Novel data augmentation strategies to boost supervised segmentation of plant disease”. In: Computers and electronics in agriculture 165 (2019), p. 104967.

[13] David Liu and Nathan Hu. “GAN-Based Image Data Augmentation”. In: (2020).

[14] Connor Shorten and Taghi M Khoshgoftaar. “A survey on image data augmentation for deep learning”. In: Journal of Big Data 6.1 (2019), pp. 1-48.

[15] Ventura A Krohling R Esgario J. BRACOL - A Brazilian Arabica Coee Leaf images dataset to identification and quantification of coffee diseases and pests. http://https: //data.mendeley.com/datasets/yy2k5y8mxg/1. May 2019.

[16] QiufengWu, Yiping Chen, and Jun Meng. “DCGAN-based data augmentation for tomato leaf disease identification”. In: IEEE Access 8 (2020), pp. 98716-98728.

[17] Mahbub Hussain, Jordan J Bird, and Diego R Faria. “A study on cnn transfer learning for image classification”. In: UK Workshop on computational Intelligence. Springer. 2018, pp. 191-202.

[18] Suhartono, Derwin Aditya, Wahyu Lestari, Miranty Yasin, Muhammad. (2013). Expert System in Detecting Coffee Plant Diseases. International Journal of Electrical Energy. 156-162. 10.12720/ijoee.1.3.156-162

[19] Mengistu, A. D., Alemayehu, D. M. Mengistu, S. G. 2016. “Ethiopian Coffee Plant Diseases Recognition Based on Imaging and Machine Learning Techniques”. International Journal of Database Theory and Application, 9, 79-88.

[20] Mengistu A. D., ”The Effects of Segmentation Techniques in Digital Image Based Identification of Ethiopian Coffee Variety,” TELKOMNIKA Telecommunication Computing Electronics and Control, Vol. 16, No. 2, pp. 713-721, 2018.

[21] Marcos, a. P., rodovalho, n. L. S., backes, a. R. (2019). Coffee leaf rust detection using convolutional neural network. 2019. Xv workshop de visão computacional (wvc). Doi:10.1109/wvc.2019.887693

[22] Kumar M., Gupta P., Madhav P. (2020). Disease detection in coffee plants using convolutional neural network, in 2020 5th International Conference on Communication and Electronics Systems (ICCES) (Coimbatore: IEEE), 755–760. 10.1109/ICCES48766.2020.9138000.