

A Coffee Leaf Disease Detection via Deep Learning Algorithms

Praveen M Bidarakundi

Research Scholar, School of Computing and Information
Technology,

REVA University, Bangalore,
Karnataka 560064 India
praveenbidar.m@gmail.com

B. Muthu Kumar

Professor, School of Computing and Information Technology,

REVA University, Bengaluru,
Karnataka 560064, India
muthukumar@gmail.com

Abstract—Among the many beverages served globally, coffee is certainly one of the most popular and it largely depends on the health status of the coffee plants on the quality of coffee beans. Coffee plants can be affected by different diseases and pests, one of which is coffee leaf disease which constitutes a serious threat to global coffee production. The appropriate and early diagnosis of these diseases is important in a bid to prevent their spread as well as maintain the wellbeing of the coffee leaf. Given that the coffee is an integral component of the global economic structure and diseases especially impact its productivity and quality, therefore, it is important to have an automatic mechanism for detecting coffee plant diseases. This research is focusing on the new deep learning technologies which are developed in the recent past experiences for the identification of coffee leaf diseases. The current trends, and the limiting factors hindering coffee leaf disease identification using deep learning and advanced imaging methods are reviewed. In addition, we applied various deep learning frameworks and validated the results obtained from every architecture. The result of this comparison shows a neural network representing the combination is more effective in diagnosing diseases of coffee leaves. MobileNet, ResNet50, and hybrid models display a detection accuracy in the range of 82% to 99.3%. Based on the analysis, the success rate of the MobileNet model reached 99.93% of the success rate of other deep learning frameworks for coffee leaf disease classification. This shows the power of deep learning algorithms to decide coffee leaf diseases on their early stage.

Keywords—Coffee leaf disease, Deep learning, Machine learning, Production quality.

I. INTRODUCTION

Coffee is grown in 50+ countries around the globe and among the most popular drinks and important legacies. Billion of cups are used in drinking coffee around the world daily. India has one of the leading manufacturers of the coffee in the world. The best-made coffee anywhere in the world is not under direct sunlight, rather in the shade. During the two-year period of 2018-2019, an estimated 319,500 tons of coffee beans will be produced, of which approximately 80% will be exported. The industry is expected to manufacture \$ 987 million in 2020 while its market is projected to register an annual growth of 7.4 %. Coffee plants are extremely vulnerable not only to different insects but also to diseases. 20–30% of national total of coffee will have been devastated by these same pathogens [5, 6]. Mostly, coffee leaf disease targets on the leaves, but it also affects the beans negatively. The very minimum needed time for a coffee germination is 1-2 months and the plant takes about 3 years to mature and grow fruit. Spending longer days under mild temperatures definitely bring up flower buds as

drier conditions start to appear [7, 8]. The life expectancy of a coffee tree grown in an agroforestry system is usually thirty years. Coffee plants may suffer heavy leaf infection leading to severe coffee leaf disease which may make them weak and more vulnerable to other stresses like drought, pests and diseases [9, 10]. The plant can produce smaller, lower-quality coffee beans because it is weak. The affected leaves may omit the greening and fall off the coffee plant, if coffee leaf illness occurs in a similar severe condition. While the nature of coffee leaf disease determines where disease strikes, progressing towards the leaves, the consequent substantial drop in leaf area and overall plant health may critically affect how many coffee beans are harvested. There is a possibility of the health of coffee trees falling down and that will affect the development of coffee cherries to an extent that the beans grown will be of low quality [11].

The deep learning algorithms [12] achieve impressive performance in the classification of coffee leaf diseases, so that reliable detection is possible already at the early stages of disease development that is the key in case of any effective intervention. The use of deep learning automation reduces a huge amount of time and labor required for manual spotting of coffee plants, hence making disease diagnosis process efficient and inexpensive [13]. AI advanced techniques are employed from AI, deep learning and CNN [14], making it hard to predict coffee leaf diseases. The existing methods of coffee leaf disease prediction are clarified in a brief way [15] and the several approaches of CNN [16] are tested well for the detection of diseases. The analysis models developed for this task were all of the type namely RegNet, MobileNet, Google Net, and Efficient Net which were all ‘fine tuned’ by the new batch of the net layers implemented instead of head. Recently, a novel sampling technique was created so as to be able to carry out a study that debated the inequality of learning in the process itself. The purpose of the primary goal of the research is to assess the current techniques of DL in coffee leaf diseases detection. The most highlighted deep learning research for detecting coffee leaf disease is presented in this paper along with a deep study of the apparent benefits and drawbacks of the existing employs. Utilizing capable deep learning models such as CNN, LSTM, YOLO etc play an important role in visualizing the different sorts of diseases. The study's main objective is described as follows: The study's main objective is described as follows:

- Investigating and reviewing all deep learning networks on recognition of coffee leaf disease taking the collected images.

- For the purpose of integrating reviews of different verified data sources on coffee leaf disease.
- In view of the shortcomings of the previous review articles on disease identification, a survey of recent research has been done on the identification of coffee leaf disease using image processing techniques.
- To present the future model capable of solving the current limitation and developing the most reliable coffee leaf disease detection method.

And finally the rest of the paper is organized as follows; section II deals with the analysis of datasets concerning coffee leaf disease. To ensure all details are covered on the deep architecture, this is thoroughly discussed in Section III. Participant discussion is detailed in section IV whereas the results of the surveys are expressed in section V.

II. STUDY ON COFFEE LEAF DISEASES

The dataset for the coffee leaf disease is briefly detailed below, along with some of the more advanced methods currently used to identify the coffee leaf disease are mentioned in this section.

A. Review on different dataset

In the next part, I will cover a short, high-level summary of the deep learning investigation on the coffee leaf disease dataset. It consists of the major reliable sets of data on coffee leaf disease among others, namely. The Arabica set is constructed of 58,555 leaf images divided into five classes, namely 'Phoma', 'Cercospora', 'Rust', 'Miner', and 'Healthy'. The Arabica data can serve as training and validation for deep learning when employed to characterize and classify coffee plant leaf diseases. The leaf image dataset contains coffee leaf visuals and has a CSV file that is labeled according to the various biotic stressors that are included in the leaf dataset. 2048x1024 pixels are the dimensions of the original image for each pixel. As for the file, there are 1747 images that you can see! They are classified into 5 categories: healthy leaves, leaf infected with phoma, leaf miners, coffee leaf rust, and cercospora spots.

A PlantVillage collection of 54303 pictures of good and bad leaves separated into 38 groups corresponding to species and diseases forms the dataset. With a view to supplying the demands of mobile diagnostics for plant diseases, an open access gallery of plant health photos. The dataset ImageNet consisted on 14 million images, being used for constructing the weights for each of these 1000 categories. The computer vision task considers 1300 images in total, and each class is 260 images. The ImageNet class consists of 260 images for each of the 1300 total images of that class. Keras has these weights imported for its use. The fundamental pre-initialized models' weights, which were already trained with the ImageNet weights, enable them to perform an immediate use of the present features and form their ability of image recognition quickly.

Imagery for the coffee leaf database was taken with 300-dpi resolution of a coffee crop. The images of 128x128 pixels in size are obtained from sub-images of the affected area. Every one of the three versions of datasets Cercospora, Rust, and healthy leaves, is independent of one another. This indeterminacy of crop is dealt with by data augmentation techniques such as mirroring. At the pre-augmentation stage

of the study, there were about 500 initial images for each group of images and 750 sub-images.

B. Review on Disease Classification techniques

In the following years there were lots of researches using deep learning and machine learning methods for the coffee leaf disease prediction. Next is the part where latest scientific researches are highlighted.

A mobile computing framework MobileNetV3, Swin Transformer and variational autoencoder (VAE) approach for coffee leaf disease classification was proposed. The hybrid feature fusion approach we propose was assessed using a diverse Robusta coffee leaves dataset (RoCoLe), containing among others red spider mite and leaf rust, which is a synthetic dataset. The achieved precision of 84.29% for the coffee leaf disease detection is through the performance of the experiment. Yamashita and Leite suggested modeling coffee leaf disease classification using cascade and single-stage method. BRALC and LiColedatasets are used. Total images are 1747 and 4667. The test results in detecting the coffee leaf illness with the 96% accuracy. The proposed cascade and single technique, both show less accuracy when compared with other state-of-the-art methods. Tuesta-Monteza et al., introduce deep learning methods for the presence/non-presence of disease in coffee leaves. Peruvian coffee leaf data set is used and an initial set of 1000 images are loaded from the suggested data set. The nutritional requirements necessary for coffee plant have influence on productivity, hence early detect (of these requirements) is very critical. Proposed method has an accuracy 87.75% for discrimination of disease and healthy leaves.

Deep neural network model as proposed by Martinez et al., is used for classification of coffee leaf diseases. For detecting coffee leaf diseases the objective is 1250 images which are from the real world or laboratories are gathered. The suggested procedure returns 2.5 percentage error and the success rate is still not satisfactory compared with other methods. Yebasse et al. declared the Visualization and Diagnosis of Coffee Disease on Robusta coffee leaf image dataset, with the guided method have an accuracy of 98% against the basic strategy of 77%. Grad-CAM, Grad-CAM++, score-CAM were used for the classification visualization. The dataset has 1560 visuals used in the process of disease detection. Mobilenet, VGG16-net, and Inception_V3 networks are the most studied types of structural networks for identifying coffee leaf diseases. The approach has been modeled on the jimmaandlimmu coffee farm data set of 422 images that were contributed for the detection of coffee leaf disease. The established method gives 98.8% average of success rate. Among the methods highlighted the approach of MobileNet stands out with the highest reliability rate. The discovery of the YOLOv5 algorithm for coffee leaf disease detection by splitting a dataset into multiple test sets has been put forward recently. Via merge of deep metric learning and object detection algorithms a detection system that is able to detect and recognize types of plant leaves and diseases was built. The Plant Village, coffee leaf, and citrus leaf weights are used for disease detection in coffee leaf. The plans created by us led to 98.8% of the success rate achieved.

Arabica and Robusta coffee plants were into the picture for the identification of coffee leaf diseases in 2022. LeNet, AlexNet, ResNet-50, and the Google Net models are constructed and they result in an accuracy rate of 97.67% for

classification. The coffee-kind discriminator algorithm based on modified-CNN approach yielded the required accuracy. Compared with the traditional-CNN systems when detecting different coffee varieties, the modified-CNN one achieved an acceptable accuracy. In 2020, deep learning-based convolutional neural networks were suggested for coffee bean disease classification. The developed model used the dataset I have self-prepared for its diagnosis which consisted of 1000 good beans images and 1000 bad beans images. The study shows an affection for disease classification in coffee bean with a percentage of 93% success rate and 0.1007% error rate is obtained. The research group of Chang designed a model called AlexNet for the detection of coffee bean disease in 2021 with an accuracy rate of 95.2%. Use of dataset manually prepared with 3621 pictures is employed in the detection of disease. In the selection of eight types of coffee beans, the proposed model can be quite precise in distinguishing the defects of coffee beans.

The author is Marcos and was involved in developing “Convolutional neural network” for rust infection detection in coffee leaves in 2019 . The obtained hit rate 81% of the proposed CNN method provides the same precision as other known methods. By designing a self-built dataset that contained 51462 images, the methods which were evaluated were employed. Mask R-CNN was applied as a means for disease detection in coffee leaf by Tassis, hitting 95.63% accuracy rate in 2021. BRACOT and BRACOL dataset have 500 leaf images and its total 1662(!) cases of disease in 300 images used for coffee leaf disease classification. The existing model also lacks of some factors when combined with other approaches. Aupar and Knolaka represented the MobileV2Net derivative of deep learning convolutional neural network in 2022 for the detection of coffee leaf illness. The accuracy of the model was 99.93% when using the dataset that consists of 1560 images of the Robusta coffee leaf disease. Similar architectures than MobileNetV2: DenseNet169 give 99.74% accuracy rate, ResNet50 give 99.41%, InceptionResNetV2 give 99.09%.

In the year 2022 Paulos and Woldeyohannis structured a resnet 50 deep learning based model for the detection of coffee leaf disease. The designed model realign the initial target, which was 99.87% success rate, after using 3,360 images of coffee leaves that were self-prepared from the Wolaita Sodo agricultural research institute. In 2023, seven models, including ResNet50, InceptionResNetV4, MobileNetV2, and DensNet169, were proposed for detecting

coffee leaf disease. To evaluate the effectiveness of CNN architecture in identifying images of Arabica coffee leaf disease, 5000 image data was sorted into five classes: Phoma, Rust, Cercospora, healthy, and Mite. The ratio of training data to validation data to testing data is 80:10, 10. This research uses dataset Arabica contains 58,555 images diseased and healthy leaves, which are used for the classification. The model is credited with 97.67% of accuracy for the detection of coffee leaf disease.

III. MATERIALS AND METHODS

A. Deep learning

Training deep learning for leaf disease detection means labeling leaf images datasets and then using the networks’ to recognize the disease symptoms and patterns. Deep neural networks can attain an unparallel level of classification of leaf diseases and many times they supersede traditional machine learning algorithms because of their capacity to learn complex features without any human supervision.

We describe both the specific deep learning models for identifying coffee leaf disease and some variations of the CNNs like RegNet, MobileNet, Google Net, and Efficient Net.

Diminished models that can align with various resource restrictions and growth rate needs are for example RegNet, MobileNet, Google Net and Efficient Net. The customized architectures also fulfil important function of developing more accurate and robust models for detecting coffee leaf disease. Figure 1 illustrates the basic framework of CNN structure. As compared to Convolutional Neural Network to the conventional feed-forward neural networks, the need for far fewer number of neurons and hyper-parameters is the most obvious advantage.

For application of dealing with the difficult visual imaging problems in image recognition issues, a variety of CNN design benchmarks have been introduced. However, in the current research, RegNetMobileNet, Google Net, and Efficient Net are recommended pre-trained models.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The methodologies for classifying and identifying coffee leaf diseases are briefly compared in the section below.

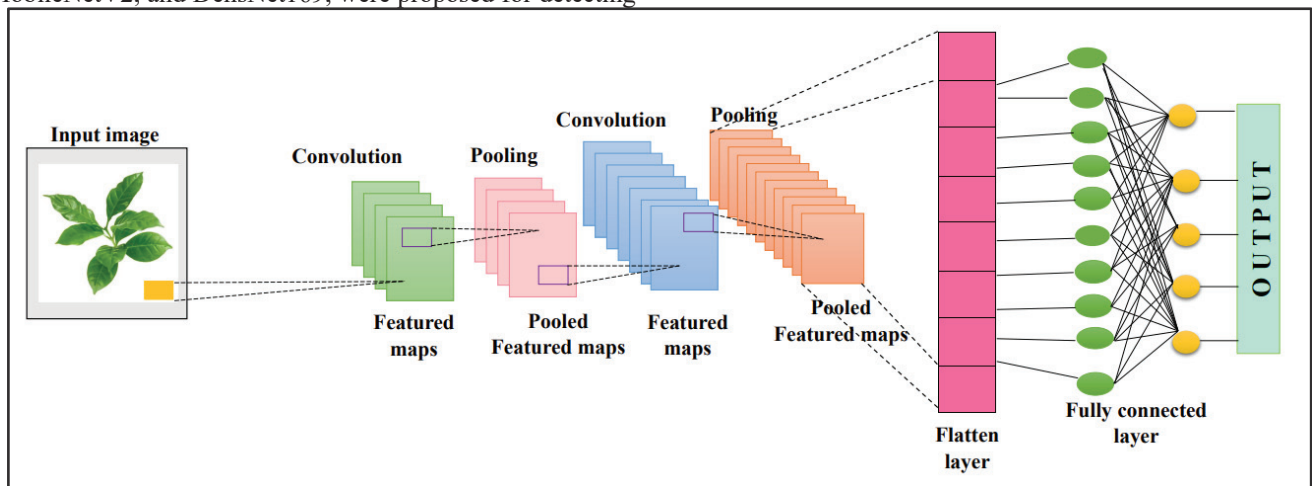


Fig. 1. Architecture of Convolutional Neural Network

TABLE I. COMPARISON OF VARIOUS TECHNIQUES FOR DETECTION OF COFFEE LEAF DISEASE IMAGES

Author& year	Dataset	Data description	Pre-processing methods	Network model	Partitioning	Validation results
Jepkoech, J et al.,	Arabica dataset	58,555 images of diseased and healthy leaves	Gaussian and averaging filters	Machine learning model	Traning-80% Testing-20%	Accuracy-97.7%
Kumar, M et al.,	Leaf image dataset	1747 images of coffee leaf with size 2048x1024 pixels	Mini-Batch Gradient Descent (MBGD)	Convolutional neural network (CNN)	Traning-80% Testing-20%	Accuracy-97.61%
Esgario, J.G et al.,	Plant village dataset	54303 images healthy and diseased leaves	Data augmentation via mirroring, and random crops	Convolutional neural network (CNN)	Traning-80% Testing-20%	Accuracy-94.05%
Novtahaning, D et al.,	Image Net dataset	1300 total images are included in the dataset	Resize the image, data augmentation	Ensemble Learning Technique	20% used for validation and 80% used for training	Accuracy-97.31%

A. Experimental Results

In this paragraph, the deep learning model for coffee leaf disease diagnosis is pointed out and explained. The pre-process models and various datasets employed in detecting coffee leaf disease are given below. As perceived by comparing with the models below, MobileNet gives good result and outperformed others with the performance of 99.93%. The table below renders a comparison of the different techniques for coffee leaf disease classification.

Datasets of coffee leaf diseases that are commonly used have demonstrated promising outcomes, with models being able to classify healthy and infected ones with a high accuracy. The flexibility and superiority of the CNN system was demonstrated in a few notable comparative studies where it outperformed other machine learning approaches.

Applying cognitive network for coffee leaf identification, CNN (CNN) showed good performance by taking into account the leaf image, plant village, self-prepared, robusta, and self-prepared at 97.61%, 94.05%, 81%, 97.67%, and 93% respectively. Robusta dataset produces a better result of 3.62%, 0.06%, 4.67%, and 15.87% of high reliability rate than Plant village, self-prepared, leaf image, and self-prepared. The crop Robusta coffee leaf, Arabica, and self molded dataset are used on MobileNet model for the medical examination of coffee leaf disease by the accuracy of 99.93%, 97.67%, and 98.8% respectively. After detailed results and insights, Robusta coffee leaf dataset achieve 99.93% of the success rate that are the highest among Arabica, BRACO and BRACOL, Self-prepared, and PlantVillage dataset.

MobileNet , MobileNetV3 and Swin Transformer visualization methods: The three approaches for detecting the coffee leaf diseases by Grad-CAM, Grad-CAM++ and Score-CAM as well as the Google Net approach is adopting the Robusta coffee leaf dataset. OmniPow applies Robusta coffee leaf dataset to come up with 99.93%, 84.9%, 98%, and 82.16% success rate using deep learning techniques. In Arabica dataset where Deep Learning and DenseNet , and AlexNet models are utilized for the detection of coffee leaf with 97.7%, 99% and 95% of success rate respectively. Recognition of coffee bean disease obtained the best result when dataset Arabica was used in DenseNet model for the disease classification in coffee leaf. The Self prepared dataset

and research papers based ResNet50 , DNN , CNN , MobileNet, and AlexNet models are developed for the detection of coffee leaf disease which obtain 99.89%, 96.5%, 81%, 93%, 98.8%, and 95.2% of success rate. The framework ResNet50 is more reliable compared to existing modern approaches. Without doubt, the review of MobileNet information show that this model is more accurate compared with other state of approaches.

V. CONCLUSION

This paper introduces an extensive review of the research on detection and classification of the coffee leaf disease using the deep learning method, mostly in the period of 2019 and 2023, especially the DL algorithms to improve the tools for the coffee leaf disease. A deep learning model takes advantage of the complex visual data sets processed by neural networks and offers an efficient solution which can be easily scaled to the coffee leaf disease. To avoid the overfitting problem and generalize the deep learning models for coffee leaf diseases, deep learning models should be designed carefully. Robusta Coffee Leaf Dataset has done a 99.93% of success rate which is highest among Arabica, BRACO and BRACOL, Self-Prepared and Plant Village dataset. The MobileNet model on a normal basis, would achieve the highest accuracy of 99.993% for the classification of coffee leaf diseases as compared the other state-of-the-art approaches. The entire study focuses on the success rates that are between the highest 82% and the lowest 99.93% for coffee leaf pathology identification using the newest deep learning models. A combination of deep learning methods is being used in this system for coffee leaf disease prevention by early diagnosis and accurate monitoring. Moreover, the key agricultural practices such as planting at right spacing, i shade management, and soil management can benefit the plants and make them strong enough resistant leaf diseases.

ACKNOWLEDGMENT

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

- [1] R. Jhaveri, "Coffee: More Than Just Your Morning Pick-Me-Up. Clinical Therapeutics," vol. 43, no. 3, pp. 431-433, 2021.

- [2] A.B. Storm, "The Climate Institute". 2016.
- [3] K.R. Nethrayini, V. Naik, and R. Rangegowda, "Impact of COVID-19 pandemic on coffee production and exports in India," ANGRAU, pp. 80, 2020.
- [4] S. zu Lynar, "Agroforestry Certification and Tree Cover Protection in Cocoa and Coffee Production Systems". 2021.
- [5] E. Guirado, S. Tabik, D. Alcaraz-Segura, J. Cabello, and F. Herrera, "Deep-learning versus OBIA for scattered shrub detection with Google earth imagery: Ziziphus Lotus as case study," *Remote Sens.*, vol. 9, no.12, pp.1220, 2017.
- [6] G. Debry, *Coffee and health*. John Libbey Eurotext. 1994.
- [7] A.S. Abu Mettleq, and S.S. Abu-Naser, "A rule-based system for the diagnosis of coffee diseases," *International Journal of Academic Information Systems Research (IJASIR)*, vol. 3, no. 3, pp.1-8, 2019.
- [8] F.M. DaMatta, C.P. Ronchi, M. Maestri, and R.S. Barros, "Ecophysiology of coffee growth and production," *Brazilian journal of plant physiology*, vol. 19, pp.485-510, 2007.
- [9] C. Sarkar, D. Gupta, U. Gupta, and B.B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges," *Appl. Soft Comput.*, pp.110534, 2023.
- [10] H. A. Patil et al., "A syllable-based framework for unit selection synthesis in 13 Indian languages," 2013 International Conference Oriental COCOSDA held jointly with 2013 Conference on Asian Spoken Language Research and Evaluation (O-COCOSDA/CASLRE), Gurgaon, India, 2013, pp. 1-8, doi: 10.1109/ICSDA.2013.6709851.
- [11] Kolita, S., Acharjee, P.B. (2022). Analysis on Syllable-Based Intonational Features of Assamese Speech Signals. In: Srivastava, P., Thivagar, M.L., Oros, G.I., Tan, C.C. (eds) *Mathematical and Computational Intelligence to Socio-scientific Analytics and Applications*. Lecture Notes in Networks and Systems, vol 518. Springer, Singapore. https://doi.org/10.1007/978-981-19-5181-7_18.
- [12] L. K. Thakuria, P. Acharjee, A. Das and P. H. Thakdar, "Integrating Rule and Template-Based Approaches to Prosody Generation for Emotional BODO Speech Synthesis," 2014 Fourth International Conference on Communication Systems and Network Technologies, Bhopal, India, 2014, pp. 939-943, doi: 10.1109/CSNT.2014.193.
- [13] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—a review," *IEEE Access*, vol. 9, pp.56683-56698, 2021.
- [14] R. Kanthavel, R. Dhaya, and A. Ahilan, "AI-Based Efficient WUGS Network Channel Modeling and Clustered Cooperative Communication," *ACM Trans. Sens. Netw.*, vol. 18, no. 3, 2022.
- [15] B. Sivasankari, M. Shunmugathammal, A. Appathurai, and M. Kavitha, "High-Throughput and Power-Efficient Convolutional Neural Network Using One-Pass Processing Elements," *J. Circuits, Syst. Comput.*, vol. 31, no.13, pp.2250226, 2022.
- [16] M. Nawaz, T. Nazir, A. Javed, S.T. Amin, F. Jeribi, and A. Tahir, "CoffeeNet: A deep learning approach for coffee plant leaves diseases recognition," *Expert Syst. Appl.*, pp.121481, 2023.