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A Full Look at Deep Learning-Based Method for Finding Diseases in Tea Leaves

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Tea leaves, Leaf Disorders, Classification, Virus, Intelligent Systems, Disease Detection.

ABSTRACT

With the advent of Deep Learning (DL), researchers have taken a keener interest in recognizing images, which have applications in areas such as automated classification and the diagnosis of plant diseases. The plant's ability to grow is compromised when it becomes sick. Numerous tea leaf diseases aim specifically at slowing down the crop's growth pace. Several ways of detecting disorders in tea plants using DL are the focus of this work. In this research, the state of the art in DL-based approaches to disease detection and diagnosis in tea leaves was surveyed. Various DL-based methods, including convolutional neural networks (CNNs), are reviewed in this article, with an emphasis on their implementations, datasets used, and performance measures. Although these strategies provide encouraging outcomes in restricted environments, there are several obstacles to their actual implementation. The study points out where existing studies fall short and offers suggestions for future research to help move the area forward. To help academics and practitioners come up with creative solutions, a comprehensive examination of unresolved issues was provided.

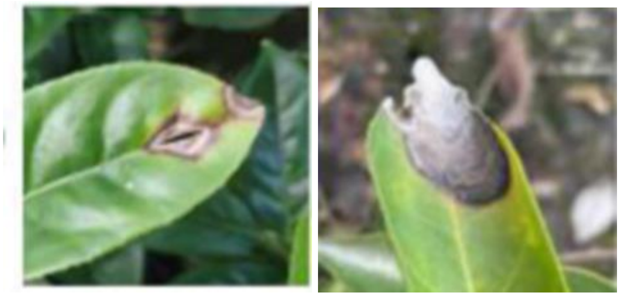
INTRODUCTION

ML and DL techniques are widely applied in every field including temperature forecasting, rainfall prediction [1], cyber security, E-Commerce, churn prediction, disease detection, price prediction, text classification, opinion mining, sentiment analysis, recommendation systems, Internet of Things (IoT) [2], agriculture, farming, Wireless Sensor Networks (WSNs), and healthcare. Because of its ability to improve crop management and decrease financial damage, DL approaches have attracted a lot of interest for usage in the agricultural sector, especially for identifying tea leaf disorders. Many industries, including farming, have benefited from the advancements in technological advances in computers that are based on intelligent systems. Fruit ripeness grading, controlling land use, plant monitoring, and identifying infections in plants are just a few of the many uses for this technology. Because it impacts the quality of the finished product, plant disease identification should be a top priority. Hence, to get proper treatment and stop the spread of plant diseases, early detection is crucial.

Some of the viral, bacterial, and fungal diseases that may affect tea plants are anthracnose, leaf spot, gray blight, and leaf blight. It is challenging to physically monitor each plant over a large territory since disease signs are usually visible on the leaves of tea plants. An advanced technique has to be created to identify and categorize tea leaf diseases in their early stages. Because DL has been so effective in disease classification for banana, tomato, tea, maize, sugarcane, apple, grape, potato, and citrus plants, it is now seeing a surge in its use. Various tea diseases can appear in the leaves area like algae leaf spots, brown blight, white spots, gray blight, helopeltis, bud blight, and red spots. The images of different types of tea leaf diseases are shown in Fig.1. Data preparation includes collecting, preprocessing, and labeling raw pictures of tea leaves with diseases matching them; this is the first step in the overall architecture of a DL-based disease detection system for tea leaves, as illustrated in Fig. 2. Next comes the learning framework, which specifies the design of the DL model—typically using transformer-based models or CNNs—trained on the pre-prepared dataset. While developing the model, iterative optimization of loss functions is used with training and validation datasets to instruct the model on how to extract features and assign them to the relevant disease classes. Once trained, the model can detect tea leaf diseases or pathology by assigning a predicted class to incoming input images. Lastly, the model's dependability and efficacy in practical situations are confirmed by performance assessment utilizing measures like accuracy, precision, recall, F1-score, and sometimes visuals like confusion matrices.

(a) Anthracnose (b)Leaf Blight

(c) Red Spot



(d) Gray Blight

Fig. 1. Types of tea leaf diseases

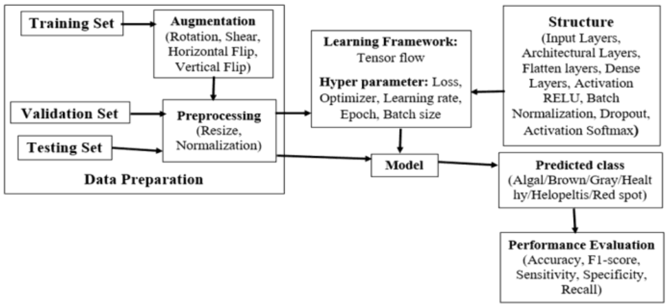


Fig. 2. General Architecture of DL-based tea leaf disease detection model

RELATED WORKS

CNNs trained on tiny, often homogenous datasets are the backbone of most current methods. When put to use in practical situations, these models often overfit and fail to generalize. Due to their capacity to extract hierarchical features, CNNs have become the most popular DL model for image-based illness identification. Also investigated were methods like transfer learning; by fine-tuning pre-trained models using pictures of tea leaves, they were able to increase classification accuracy while decreasing training time. While earlier research using CNN designs such as VGG-16 and ResNet-50 to categorize illnesses in tea leaves achieved good accuracy, it relied on short datasets, which limited its ability to generalize. Also investigated were methods like transfer learning; by fine-tuning pre-trained models using pictures of tea leaves, they were able to increase classification accuracy while decreasing training time.

The current techniques for detecting diseases in tea leaves have several serious flaws that make them unreliable, particularly when applied to real-world scenarios. A review of different CNN-based tea leaf detection systems, datasets employed, performance metrics employed, and demerits is shown in Table I. Due to their restricted datasets and poor generalization to a variety of environmental variables, existing tea leaf disease detection systems often struggle with low accuracy. Existing methods could also be less resilient to changes in illumination, scale, and leaf position, as well as overlapping symptoms. Furthermore, a lot of approaches mostly depend on manual feature extraction, which may be laborious and error-prone, which restricts scalability and the potential for real-time applications. The limited integration of real-time monitoring systems or the IoT is another problem in existing methods that makes it difficult to provide timely warnings and preventative steps for efficient disease management.

TABLE I. A REVIEW OF TEA LEAF DISEASE DETECTION TECHNIQUES

study	Method	dataset	Analysis	Demerits
[3]	CNN (EfficientNet)	public dataset downloaded from KAGGLE	Five types of tea leaf diseases were studied and obtained an accuracy of 93.60%.	Training time is more. It is 257 minutes and 15 seconds.
[4]	CNN	CIFAR-10	Seven types of tea leaf diseases were studied. Accuracy=94.45%.	Performance is measured using one hyperparameter i.e. no. of epochs. However, the model can be tested against different hyperparameters like learning rate, batch size, no. of layers, and optimizer.
[5]	CNN (GoogleNet)	Dataset built using UAV	Seven types of tea leaf diseases were studied. Accuracy=85%.	Multiple disease classification on the same leaf is not studied. Low accuracy.
[6]	CNN	Self-Built Dataset	Four types of coffee leaf diseases were studied. Accuracy=90%.	The severity of the teal leaf disease has not been studied. Low recognition rate.
[7]	CNN	Self-Built Dataset	Black rot and rust tea leaf diseases were studied. Accuracy=95.93%.	The study is limited to two types of tea leaf diseases. However, it can be extended for many other tea leaf diseases by adding more images to the dataset.
[8]	Deep Neural Networks (DNN)	self-built dataset	Five types of tea leaf diseases were studied. Accuracy=96.56%	The accuracy of gray blight and red spot leaf diseases is low.
[9]	CNN	public dataset	Accuracy=92%. Five types of tea leaf diseases were studied.	A low accuracy of 93.8% is obtained for blister blight leaf disease.
[10]	Swim transformer	self-built dataset on Yashixiang, a typical variety of tea leaf in China	Accuracy=94%. Four types of tea leaf diseases were studied.	The model is not extended to identify large no. of tea leaf diseases.
[11]	CNN	public dataset	Accuracy=73%. Seven types of tea leaf diseases were studied.	Low accuracy
[12]	Dense net	Real-time dataset obtained from tea plantations in Kothagiri, Tamil Nadu.	Accuracy=96%. Seven types of tea leaf diseases were studied.	The severity of leaf diseases was not studied.
[13]	CNN	public dataset	Accuracy=84%. Error rate=16%.	The error rate is higher.
[14]	Modified Resnet 50-V2	Real-time dataset obtained from tea plantations in Kothagiri, Tamil Nadu.	Accuracy=90.8 %	Classification of tea leaf diseases was not studied. Only binary classification that involved healthy and unhealthy leaves was studied.
[15]	CNN	KAGGLE public dataset	Accuracy=96%. Seven types of tea leaf	Only no. of epochs was considered for study. Batch size,

			diseases were studied.	optimizer, and changing layer count were not used.

ANALYSIS OF TEA LEAF DISEASE DETECTION METHODS

Hybrid and ensemble methods have been suggested as a means to circumvent the shortcomings of individual CNN models. Models, especially DNN, tend to overfit the training data when there aren't enough different datasets. While this produces impressive accuracy on test datasets, it drastically decreases performance when faced with novel situations. Shadows, occlusions (such as overlapping leaves), and background clutter are examples of real-world noise that may impact pictures and cause models to misclassify illnesses. Models work well on dominant classes but miss minority classes due to the underrepresentation of rare diseases in datasets. To increase diagnostic accuracy, most systems just use picture data and exclude additional relevant information like as soil health, climatic conditions, or pest population statistics. Not all state-of-the-art models are viable for implementation in resource-limited situations, such as rural tea plantations, since they demand large computing resources.

Due to dataset limits, ecological fluctuations, and a lack of scalability, DL-based tea leaf disease diagnosis has not yet reached its full potential, despite improvements in automation and accuracy. Tackling these drawbacks needs a comprehensive strategy that integrates developments in model design, dataset generation, and comprehensibility. To connect research prototypes with real-world applications, agricultural specialists, data scientists, and legislators must work together. The use of new technologies, such as edge AI, and investments in open-source datasets and tools will hasten the advancement of this crucial field. It is observed from the current work that most of the CNN models when employed individually achieved an accuracy ranging from 73% to 96%.

The analysis of tea leaf disease detection models based on various DL architectures reveals a diverse range of accuracies across different methods. Several studies employed CNN-based models, achieving varied accuracy results, with the highest being 96% and a lower accuracy of 73%. Other models, such as EfficientNet and GoogleNet demonstrated solid performance yielding accuracies of 93.60% and 85% respectively. Some more advanced techniques like DNN and Densenet achieved higher accuracies, with values of 96.56% and 96%, respectively. The use of specialized architectures like the swim transformer also resulted in a recognition rate of 94%. These findings highlight the potential of CNNs and other advanced models in effectively detecting tea leaf diseases, with more sophisticated models and architectures consistently leading to better performance. Overall, the accuracy of these models ranges from the low 70s to mid-90s, suggesting ongoing improvements in the detection of tea leaf diseases as more advanced models are utilized. Most of the research conducted to identify tea leaf diseases using CNN ended up with an accuracy of greater than 90% which is shown in Fig.3. Young researchers can concentrate on developing mobile-based applications for identifying tea leaf diseases and integrating models with IoT devices to deploy them in real-world applications. Based on current research, it is determined that DL-based tea leaf disease detection uses sophisticated algorithms, like CNNs and transformer models to reliably detect and categorize leaf diseases from image data. This allows for accurate and automated disease monitoring for better crop management.

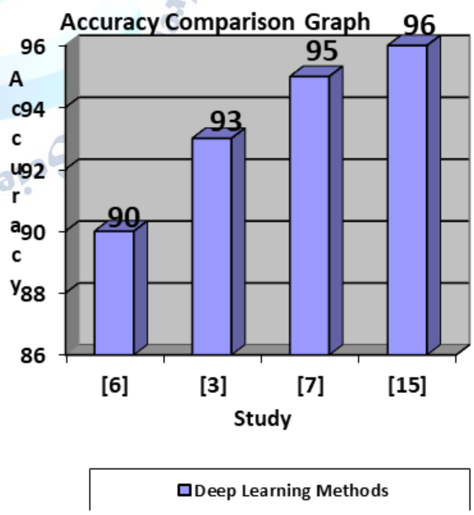


Fig. 3. Accuracy comparison graph of existing tea leaf disease detection methods

OPEN CHALLENGES

After a comprehensive examination of existing tea leaf diseases, a few open challenges were identified from the current work. These open challenges will be useful to young researchers and practitioners who are working in the field of plant leaf disease detection. These open challenges are given in Table II.

TABLE II. OPEN CHALLENGES AND SOLUTIONS

Attribute	Open Challenge	Solution
Lack of Real-Time Detection Systems	Models often lack integration with real-time monitoring systems, reducing their applicability in field scenarios.	Models can be integrated with IoT-based systems for real-time data acquisition and prediction. Cloud-based or edge computing can be employed to balance performance and latency.
Adaptation to New Disease Types	Models trained on known diseases struggle to detect emerging or previously unseen diseases.	Few-shot learning, Liquid Neural Networks (LNN), or continual learning approaches can be adapted to identify new disease types.
Models deployed in real-world applications using IoT devices	Many interfering parameters like insects, uneven lighting conditions, etc affect the accuracy of tealeaf disease identification.	Using sophisticated DL models in conjunction with preprocessing and data augmentation methods is a reliable way to increase resistance to interfering factors like insects and fluctuating illumination.

CONCLUSION

Since the introduction of DL, researchers have shown a greater interest in the process of image recognition. This is because image recognition has applications in a variety of fields, including automated categorization and the detection of plant diseases. It is detrimental to the plant's capacity for growth when it is afflicted with a disease. Numerous illnesses that affect tea leaves are particularly designed to slow down the rate at which the crop grows. This paper focused on several different methods that may be used to identify problems in tea plants by using DL. For the current study, a survey was conducted to determine the current state of the art in DL-based techniques for disease detection and diagnosis in tea leaves. Several different DL-based approaches, such as CNNs, are discussed in this work. The focus is placed on the implementations of these methods, the datasets that are used, and the performance metrics that are utilized. Although the application of these tactics in constrained circumstances may result in positive results, several barriers must be overcome before they can be executed. The research highlighted the areas in which previous studies have failed to meet expectations and provided recommendations for further research that might assist in advancing the field. An in-depth analysis of problems that have not yet been addressed is provided in this work to facilitate the development of innovative solutions by both academics and practitioners.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] G. L. V. Prasad, B. R. Teja, T. Haribabu, G. N. Pavani, D. Karunamma and K. Vivek, "A Hybrid Time Series Rainfall Prediction Model Using Neural Prophet and LS TM," 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), Erode, India, 2023, pp. 1582-1587, doi: 10.1109/ICSSAS57918.2023.10331827.

[2] Natarajan, Krishnaraj, et al. "Neural network-based secured routing protocol for IoT environment using DE algorithm." International Journal of Embedded Systems 16.5-6 (2023): 422-430.

[3] U. Hairah, A. Septiarini, N. Puspitasari, E. Romiyanto, N. A. Hadiwijaya and D. Nurcahyono, "Analysis of EfficientNet Architecture Performance for Classifying the Tea Leaves Diseases," 2023 9th International Conference on Computer and Communication Engineering (ICCCE), Kuala Lumpur, Malaysia, 2023, pp. 223-228, doi: 10.1109/ICCCE58854.2023.10246097.

[4] R. S. Latha et al., "Automatic Detection of Tea Leaf Diseases using Deep Convolution Neural Network," 2021 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2021, pp. 1-6, doi: 10.1109/ICCCI50826.2021.9402225.

[5] R. Dhivya Praba, K. Kavitha, S. Abinaya, P. Abarna, K. Shupriyaa Shri and S. N. Shivappriya, "Automatic Tealeaf Disease Detection Using Machine and Deep Learning Method," 2023 2nd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA), Coimbatore, India, 2023, pp. 1-5, doi: 10.1109/ICAECA56562.2023.10200312.

[6] G. Grimaldo, H. Rodriguez and V. L. Cabrera, "Convolutional Neural Network Model for the Detection of Diseases and Pests in Coffee Crops," 2022 8th International Engineering, Sciences and Technology Conference (IESTEC), Panama, Panama, 2022, pp. 684-690, doi: 10.1109/IESTEC54539.2022.00113.

[7] S. Bhowmik, A. K. Talukdar and K. Kumar Sarma, "Detection of Disease in Tea Leaves Using Convolution Neural Network," 2020 Advanced Communication Technologies and Signal Processing (ACTS), Silchar, India, 2020, pp. 1-6, doi: 10.1109/ACTS49415.2020.9350413.

[8] Datta, Saikat, and Nitin Gupta. "A novel approach for the detection of tea leaf disease using deep neural network." Procedia Computer Science 218 (2023): 2273-2286.

[9] J. P. Manasa and Nethravathi, "Mobile Based Application For Tea Leaf Disease Detection," 2023 IEEE 3rd International Conference on Technology, Engineering, Management for Societal impact using Marketing, Entrepreneurship and Talent (TEMSMET), Mysuru, India, 2023, pp. 1-5, doi: 10.1109/TEMSMET56707.2023.10149957.

[10] S. Xie, C. Wang, C. Wang, Y. Lin, and X. Dong, "Online Identification Method of Tea Diseases in Complex Natural Environments," in IEEE Open Journal of the Computer Society, vol. 4, pp. 62-71, 2023, doi: 10.1109/OJCS.2023.3247505

[11] K. M S, R. R. G and S. Karthik, "Streamlining Load Scheduling in Cloud Computing: A Thorough Performance Assessment and Development of Effective Methods for Design," 2024 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE), Shivamogga, India, 2024, pp. 1-7, doi: 10.1109/AMATHE61652.2024.10582239.

[12] Sai Srinivas Vellela, Roja D, NagaMalleswara Rao Purimetla, SyamsundaraRao Thalakola, Lakshma Reddy Vuyyuru, Ramesh Vatambeti, Cyber threat detection in industry 4.0: Leveraging GloVe and self-attention mechanisms in BiLSTM for enhanced intrusion detection, Computers and Electrical Engineering,Volume 124, Part A,2025,110368,ISSN 00457906,https://doi.org/10.1016/j.compeleceng.2025.110368.

[13] S. S. Vellela, L. R. Vuyyuru, K. B. S. K, N. MalleswaraRaoPurimetla, L. Dalavai and M. V. Rao, "A Novel Approach to Optimize Prediction Method for Chronic Kidney Disease with the Help of Machine Learning Algorithm," 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Gautam Buddha Nagar, India, 2023, pp. 1677-1681, doi: 10.1109/IC3I59117.2023.10397974.

[14] Kavitha Mettupalayam Subramaniam, Ramachandra Rao Goli, Karthik Subburathinam, Srihari Kannan,Optimization of pyrolysis parameters for enhanced biochar production from agricultural biomass: A study on energy efficiency and carbon sequestration potential,Science of The Total Environment, Volume 1015,2026,181362,ISSN 00489697,https://doi.org/10.1016/j.scitotenv.2026.181362.

[15] K. K. Kumar, S. G. B. Kumar, S. G. R. Rao and S. S. J. Sydulu, "Safe and high secured ranked keyword searchover an outsourced cloud data," 2017 International Conference on Inventive Computing and Informatics (ICICI), Coimbatore, India, 2017, pp. 20-25, doi: 10.1109/ICICI.2017.8365348.

[16] R. K. Yarava, G. R. C. Rao, Y. Garapati, G. C. Babu and S. D. V. Prasad, "Analysis on the Development of Cloud Security using Privacy Attribute Data Sharing," 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichy, India, 2022, pp. 1-5, doi: 10.1109/ICEEICT53079.2022.9768608.

[17] K. K. . Kommineni and A. . Prasad, “A Review on Privacy and Security Improvement Mechanisms in MANETs”, Int J Intell Syst Appl Eng, vol. 12, no. 2, pp. 90–99, Dec. 2023.

[18] Kommineni, K.K., Prasad, A. Enhancing Data Security and Privacy in SDN-Enabled MANETs Through Improved Data Aggregation Protection and Secrecy. Wireless Pers Commun 139, 855–882 (2024). https://doi.org/10.1007/s11277-024-11635-w

[19] “Blockchain-Enabled Secure Data Aggregation for SDN-Enabled Ad-Hoc Networks,” International Journal of Intelligent Engineering and Systems, vol. 18, no. 5, pp. 704–717, Jun. 2025, doi: https://doi.org/10.22266/ijies2025.0630.49.

[20] K. K. Kommineni, P. Ande, “Blockchain-driven key management and privacy-preserving data Aggregation Scheme for SDN-enabled MANETs,” International Journal of Intelligent Engineering and Systems, vol. 18–18, no. 9, pp. 601–615, 2025, doi: 10.22266/ijies2025.1031.39.