Research Repository

Detection of Tea Leaf Diseases Using Deep Transfer Learning

G. Vijayakanthan, Dept of Physical Science, University of Vavuniya, Vavuniya, Sri Lanka

R. Vaishali, Dept of Physical Science, University of Vavuniya, Vavuniya, Sri Lanka

Vahid Abolghasemi, School of Computer Science & Electrical Engineering, University of Essex,

Accepted for the 2024 Moratuwa Engineering Research Conference (MERCon).

Detection of Tea Leaf Diseases Using Deep Transfer Learning

Abstract—**Tea leaf diseases significantly impact both the quantity and quality of tea production in Sri Lanka, a country where tea cultivation holds considerable economic importance, contributing significantly to its GDP and serving as a major export to consumer markets. Existing computer vision and machine learning methods require a large number of image samples for accurate classification, leading to a time-consuming process. To address this limitation, we propose a novel approach utilizing deep transfer learning to train classification models efficiently with limited samples, leveraging cross-domain knowledge transfer. Our method aims to detect tea leaf diseases early, thereby preserving tea quality and fostering sustainable agricultural practices. The unique contributions of this study are a) collecting a comprehensive set of tea leaf images from different tea gardens representing six tea leaf conditions, annotated manually and b) developing a pre-trained convolutional neural network (CNN) architecture, with 256, 128, and 6 fully connected layers, including Xception, DenseNet201, VGG16, InceptionV3, EfficientNetB0, and MobileNetV2, to transfer classification knowledge. Through several experimentations with various fine-tuning techniques, we achieved a notable average accuracy of 99.58% in classifying tea leaf diseases.**

Keywords: Convolutional Neural Network, Deep Transfer Learning, Image Classification, Tea leaf diseases

I. Introduction

Sri Lanka is globally recognized as a premier tea exporter, a reputation it has maintained for over a century. In 2019, Sri Lanka's tea cultivation covered an expansive area of approximately 202,985 hectares, yielding an annual production of around 300 million kilograms, sustaining year-round harvests [1]. Notably, in 2023, the country exported 256.04 million Kgs of tea, representing a significant portion of its total production [2]. Sri Lanka stands as the foremost producer of orthodox tea on a global scale. This demands intense care of tea plant health in Sri Lanka. Therefore, the identification and detection of tea leaf diseases play a crucial role in ensuring the growth safety and quality of tea production [3].

There are various practices carried out to monitor the condition of tea leaves in tea estates using manpower and Information Technology. The traditional disease identification and detection methods in tea plants often rely on manual inspection, which can be time-consuming and prone to errors. Furthermore, these traditional methods may require extensive knowledge and expertise in tea plant diseases, making them less accessible to farmers and researchers without specialized training. To address these problems, in recent years, the advent of deep learning technology has opened up new possibilities for automating the detection and identification of tea leaf diseases [3][4][5][6][7] [8][9]. It is possible to develop accurate and efficient models that can classify different diseases and other common tea leaf diseases by training deep-learning neural networks on large datasets of tea leaf images [4]. These deep learning models can help to distinguish healthy leaves and diseased leaves, leading to early detection and classification [10]. Moreover, deep learning models can potentially improve the accuracy and reliability of tea leaf disease detection by extracting significant features from tea leaf images [11]. This can help overcome the limitations of subjective and time-consuming manual inspection methods, providing a more efficient and objective approach to tea leaf disease diagnosis. However, the absence of robust datasets, variability in disease presentations, and the necessity for automated, non-invasive detection methods provide both challenges and opportunities for innovative research and technological progress.

Despite the predominant focus of prior research on detecting blister blight in tea leaves in Sri Lanka [12], our study aims an approach to present a robust disease detection framework for automatically identifying five tea leaf diseases (algal leaf spot, grey blight, black blight, blister blight, and spider mites). Our objective is to achieve state-of-the-art accuracy in disease detection, addressing the need for comprehensive solutions in managing tea plant health. Utilizing a pre-trained CNN architecture, augmented by data augmentation and transfer learning techniques, our approach addresses the challenge of limited sample availability, achieving a classification accuracy of 99.58%. Through the collection of 607 tea leaf image samples from the central region of Sri Lanka, we constructed a comprehensive database covering six tea leaf conditions. Our work contributes to the advancement of tea leaf disease classification by employing deep transfer learning techniques to achieve remarkable accuracy.

This paper is presented with a literature review to highlight the existing research in tea leaf disease detection. Following that, the methodology section describes the dataset used, preprocessing techniques applied, and details of the experiments conducted. Section 4 reports the results of these experiments, including the accuracy and performance of the deep-learning models in tea leaf disease detection. Finally, the conclusion in Section 5 summarizes the findings of the study and discusses potential future directions for research in tea leaf detection using deep learning.

TABLE I
COMPARATIVE ANALYSIS OF EXISTING WORKS

Paper	Year	Disease type	No. of images	Method	Accuracy
[13]	2021	Algal leaf spot, grey blight, white spot, brown blight, red scab, bud blight, and grey blight	860	Custom DCNN	94.45
[14]	2021	Red rust, red spider, thrips, helopeltis, and sunlight scorching	1000	PCA and SVM	83
[15]	2021	Leaf blight	970	Retinex algorithm and faster RCNN	84.45
[16]	2021	Brown blight, blister blight, and leaf spot	4295	Cascade RCNN (CRCNN)	76.60
[17]	2022	Leaf spot, rhizome rot, powdery mildew, and leaf blotch	630	Hybrid filter and support vector machine	92.84
[18]	2022	Red leaf spot, algal leaf spot, bird's eyespot, grey blight, white spot, anthracnose, and brown blight	885	Improved retina-net	93.83
[19]	2022	Blister blight	60000	Deep hashing with integrated autoencoders (DHIA)	98.50
[20]	2022	White scab, leaf blight, red scab, and sooty mould	634	Custom DCNN and generative adversarial network (GAN)	93.24
[21]	2022	tea white star, tea leaf blight, tea wheel spot	694	Inception V3	90.42
[22]	2023	Grey blight	634	DCNN	98.99
[12]	2023	Blister blight	3102	YOLOv8, ResNet50	88.26
[4]	2023	Red spider, Tea mosquito bug, Black rot, Brown blight, Leaf rust.	4000	YOLOv7	97.30

II. LITERATURE REVIEW

In recent years, a small number of methods for detecting tea leaf diseases have been introduced, utilizing computer vision, image processing, and machine learning techniques. This section elaborates on the most relevant frameworks and methodologies. Table I presents a comparative analysis of various detection methodologies proposed in different articles. Arnal Barbedo [23] investigated the identification of multiple plant diseases on the same leaf from individual lesions and spots using deep learning, demonstrating that this approach significantly enhances data variability without requiring additional images. Furthermore, an approach proposed by G. Hu et al. [24], a low-shot learning method for tea leaf disease identification employs Support Vector Machine (SVM) for image segmentation and improved conditional deep convolutional generative adversarial networks (C-DCGAN) for data augmentation.

The identification of plant diseases from individual lesions and spots using deep learning has also been explored, showing that this approach can significantly increase data variability without the need for additional images and can identify multiple diseases on the same leaf [23]. In the context of tea leaf disease identification, a low shot learning method has been proposed, which leverages SVM for image segmentation and improved conditional deep convolutional generative adversarial networks (C-DCGAN) for data augmentation, resulting in high identification accuracy [24].

Several other studies have investigated the detection of tea leaf diseases using YOLO models [4][25]. Notably, Xue et al. [8] developed the YOLO-Tea model, an extension of YOLOv5, which integrates self-attention and convolution (ACmix) along with the convolutional block attention module (CBAM) to enhance detection capabilities for specific diseases in tea plants. This model enhances focus, replaces modules to improve feature extraction, and optimizes resource consumption for edge devices. However, this paper focuses only in tea leaf blight disease.

In a different approach to detecting tea leaf diseases, many authors have proposed custom CNN models [25][15][22]. In which, Gayathri et al. [6] introduced a CNN approach aimed at detecting tea plant diseases from leaf images, particularly focusing on common diseases like Blister Blight and Leaf Blight in India. The method utilizes data annotation and augmentations, with the CNN model LeNet providing the output.

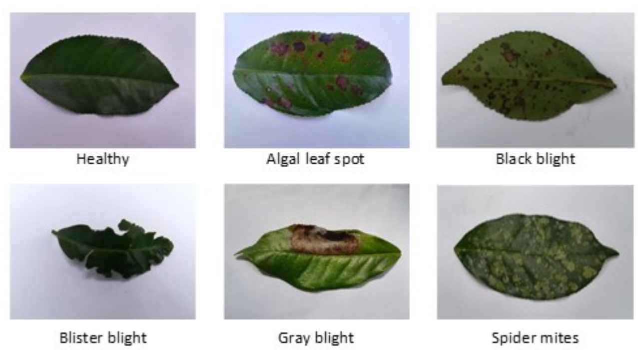

Fig. 1. Sample images of tea leaf conditions

However, there are only a few tea leaf disease detection methods employing deep transfer learning techniques have been proposed. These methods involve the direct transfer of features from a pre-trained CNN architecture. J. Chen et al. [26] applied deep transfer learning to plant disease identification. They adapted pre-trained models such as VGGNet and the Inception module for specific tasks, resulting in substantial performance improvements. Other similar approaches [16][18][21][12] and various techniques applied for detecting tea leaf disease are presented with a comparative analysis in

Table I.
Based on the extensive literature review, it is evident that transfer learning plays a crucial role in tea leaf disease detection. However, existing techniques face several challenges. Firstly, the visual symptoms of diseases such as algal leaf spot and grey blight are often similar, leading to misclassifications by disease detection models. Secondly, there is a limited number of research studies dedicated to diagnosing tea leaf diseases, despite their significant impact on tea crop yields in Sri Lanka. Lastly, existing techniques have not consistently achieved high performance across all tea leaf diseases, with the maximum classification accuracy of 98.99% observed in a model specifically trained for detecting grey blight disease [22]. These findings highlight the importance of proposing a novel approach that can accurately differentiate between the symptoms of algal leaf spot, blister blight, black blight, grey blight, and spider mites, thus surpassing the performance of existing methods.

III. Methodology

A. Dataset

For the dataset acquisition process, a selection of image samples was carefully gathered to depict six distinct classes of tea leaf conditions: algal leaf spot, blister blight, black blight, grey blight, spider mites, and healthy leaves as shown in Figure 1. These samples were obtained from tea plantations situated in the central province of Sri Lanka, renowned for its extensive tea cultivation. A comprehensive representation of the various conditions observed in tea leaves was achieved by capturing a total of 607 images using a smartphone camera. However, the number of images for each class varied, with some classes having fewer images than others. The distribution of images for each class is detailed in Table II, providing insights into the dataset composition across different disease categories and healthy leaves.

TABLE II
COLLECTED NUMBER OF IMAGE SAMPLES

Tea leaf diseases	Number of images
Algal leaf spot	86
Blister blight	36
Black blight	109
Grey blight	199
Spider mites	69
Healthy	111

The varying quantities of images obtained for each class can be attributed to the various effects of environmental conditions and weather patterns on tea leaves afflicted by different diseases. This variability emphasizes the dynamic nature of disease prevalence within tea estates. It highlights the imperative of capturing a comprehensive spectrum of samples to faithfully represent real-world scenarios in the dataset collected for tea leaf disease detection. The images were resized before training, with two models utilizing captured images resized to 299x299 pixels and the remaining models using images resized to 224x224 pixels.

B. Data Augmentation

Following the data preprocessing, the data was augmented to expand the dataset by generating additional samples from the collected images to alleviate the data deficiency during the training phase. Basic image processing algorithms were employed for this purpose. Since Convolutional Neural Networks (CNNs) exhibit invariance to factors like scale ,translation, illumination, and viewpoint, data augmentation was deemed essential to augment the samples for each disease category [27]. In this proposed approach, seven new samples were created from each raw image through various augmentation techniques, including , height shift,width shift, shear, zoom, rotation, , horizontal flip and fill mode. The utilization of synthetic data, generated through imaging algorithms, significantly improved the feature extraction capabilities of the CNN model.

C. Transfer learning

Transfer learning is a technique used to improve the accuracy of tea leaf disease prediction models. It involves using pre-trained models on large datasets, such as ImageNet, and retraining them on tea leaf disease data. Several models, including VGG16, VGG19, 10-DCNN, Inception V3, ResNet-50, MobileNetV2, and DenseNet20, have been used for transfer learning in tea leaf disease identification. The use of transfer learning has been found to be effective in improving the performance of the models, achieving high accuracy, precision, sensitivity, specificity, and F1-score.
Additionally, the lightweight deep convolutional neural network MobileNetV2 has been used for tea disease classification, and its knowledge has been transferred to the task of tea disease identification. This approach has resulted in higher recognition rates for tea disease.

D. Proposed Approach

As depicted in Figure 2, the proposed architecture utilizes a shallow convolutional feature extraction block followed by three fully-connected layers for classification. The feature extraction block leverages pre-trained convolutional layers from established image classification models, including Xception [28], InceptionV3 [29], VGG16 [19], EfficientNetB0 [30], DenseNet201 [31], and MobileNetV2 [32]. These pre-trained layers were originally trained on the large-scale ImageNet dataset. The architecture of the network incorporated a dropout layer inserted between the fully-connected layers. The convolutional layers leveraged the pre-trained model's parameters without further optimization. The design of the fully connected layers was determined based on validation results, with neurons set to 256, 128, and 6. The proposed network required input of size 299 × 299 x 3 for Xception and InceptionV3 models, and 224× 224x 3 for VGG16, EfficientNetB0, DenseNet201, and MobileNetV2, produced output for the six corresponding disease classes.

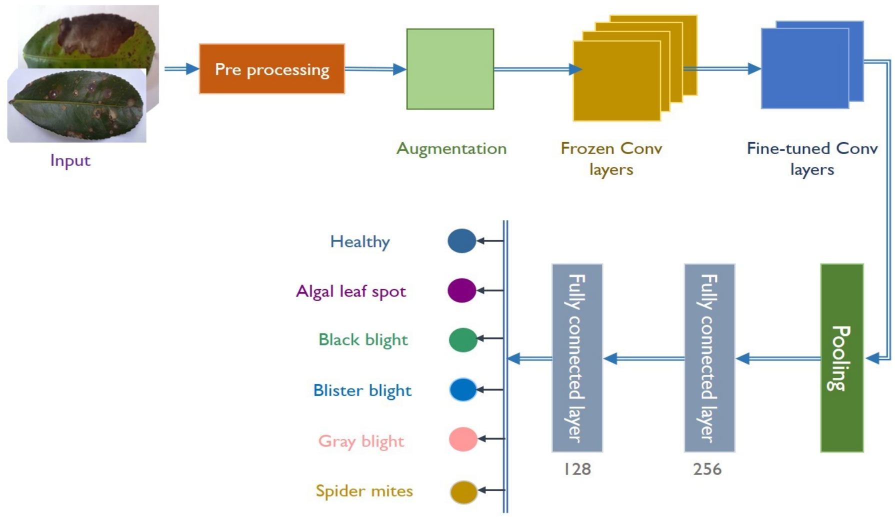

Fig. 2. Proposed architecture

The convolutional layers in the proposed CNN architectures were initialized using weights pre-trained on models developed for the ImageNet classification task. These models are characterized by fully connected layers containing 1000 neurons tailored for classifying respective classes. Given our focus on a 6-class classification task, the final fully-connected layers of the pre-trained models were replaced with a custom architecture designed for this specific output dimensionality. The design changes were made based on the experimental results, resulting in the utilization of fully connected layers with 256, 128, and 6 neurons in the proposed approach. In all six pre-trained models, a staged fine-tuning approach was employed. The initial convolutional layers were maintained in a frozen state, leveraging their ability to extract generic image features. Subsequent convolutional layer blocks, progressing from the final layers, were progressively fine-tuned using the tea leaf image dataset. This targeted fine-tuning strategy aimed to capture class-specific features while preserving the general feature extraction capabilities of the pre-trained model. The optimal number of fine-tuned convolutional layer blocks was determined empirically through model performance evaluation.

As described earlier, the proposed approach utilized transfer learning techniques to train a convolutional neural network (CNN) model for tea leaf disease classification. This architectural design leverages pre-trained convolutional layers, with most initial layers remaining static during the training process. This approach mitigates the limitations imposed by the relatively small dataset of tea leaf images. Fine-tuning is strategically applied only to a select number of later layers, facilitating the model's ability to capture class-specific features for tea leaf classification. The selection of convolutional layers for fine-tuning was guided by empirical evaluation of model performance. Conversely, the fully-connected layers were initialized with random weights, allowing their parameters to be optimized during the training process.

The performance of the CNN model is highly dependent on hyperparameters such as batch size, learning rate, optimization function, and dropout value. These hyperparameter values were fine-tuned based on validation results to achieve optimal performance. To enhance the generalizability and robustness of the proposed network architecture, k-fold cross-validation was employed for training and evaluation. Within each fold, the tea leaf image dataset was stratified and randomly partitioned into an 80% training and validation set, with the remaining 20% designated for testing. The network architecture underwent training for a predefined number of epochs. Subsequently, the model exhibiting the optimal performance on the validation set, as determined by a pre-defined metric, was selected for final evaluation.

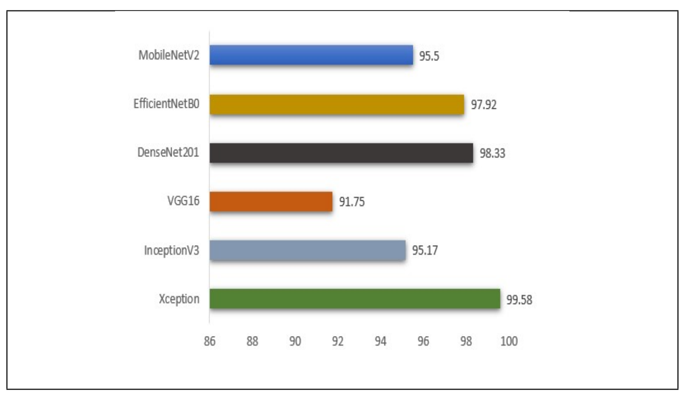

Fig. 3. Comparison between proposed models

IV. EXPERIMENTAL RESULTS

A. *Proposed Approach*

In our proposed methodology, we utilized convolutional layers from well-established pre-trained models such as Xception, InceptionV3, VGG16, EfficientNetB0, DenseNet201, and

MobileNetV2. Each model's performance was individually assessed to determine its suitability within our framework. Consistent parameter settings for the convolutional layers were maintained across all models to ensure methodological coherence. We set the dropout parameter within the range of 0.3 to 0.5 based on empirical findings to address potential overfitting. Optimization of the models was achieved using the Adam[33] algorithm, with performance evaluations conducted for each model separately. During training, the softmax cross entropy loss function was employed with a fixed learning rate of 0.0001 to facilitate model convergence.

For both training and testing phases, image data underwent pre-processing to normalize color intensity values between 0 and 1. The CNN architecture was trained extensively over 100 epochs, employing a batch size of 32 to achieve a balance between computational efficiency and model performance. Implementation of our methodology was carried out using the Keras tool within the Python programming environment. We leveraged the computational capabilities of the NVIDIA Tesla K80 GPU through the Google Colab cloud platform for efficient algorithm execution. The dataset and source code have been publicly shared to uphold scientific transparency, enabling reproducibility of the findings and fostering collaboration within the scientific community (see supplementary materials).

B. Evaluation protocols

Based on the related studies, Accuracy and F1-score are the most commonly used evaluation metrics for plant disease classification. Accuracy measures the overall correctness of a machine learning model by comparing its predictions to the actual labels (ground truth). However, accuracy may be biased towards the majority class in imbalanced datasets, potentially overestimating model performance. To address this issue, we also consider the F1-score, which provides a balanced measure of precision and recall.

Classification accuracy serves as the metric for assessing the performance of the proposed six pre-train models. In particular, F1-score, precision and recall are calculated to the outperformed proposed Xception model. Those are calculated using the following formulas:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score, = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Here, TP represents true positives, FP stands for false positives, FN denotes false negatives, and TN indicates true negatives. To evaluate the performance, a 5-fold cross-validation method was employed. The average of these cross-validations is regarded as the comprehensive performance measure of the proposed approach.

C. Testing Results

The effectiveness of the proposed approach was demonstrated through the utilization of the k-fold cross-validation technique, a method commonly employed by researchers to evaluate deep learning models when faced with a limited number of samples. The dataset was stratified and randomly partitioned into five folds of equal size. In each fold, four folds were designated for training and validation, while the remaining fold served for testing. This process iterated through all five folds, ensuring each fold served as the testing set exactly once. The final classification accuracy of the proposed model was determined by averaging the performance metrics across all five iterations of the cross-validation process.

TABLE III
CLASSIFICATION PERFORMANCE METRICS FOR VARIOUS LEAF CONDITIONS: XCEPTION-BASED MODEL

Class	**Precision**	**Recall**	**F1-score**
Algal leaf spot	0.97	1.00	0.99
Black blight	1.00	0.97	0.99
Blister blight	1.00	1.00	1.00
Gray blight	1.00	1.00	1.00
Healthy leaf	1.00	0.97	0.99
Spider mites	0.98	1.00	0.99

Figure 3 illustrates the test accuracy of each pre-trained model employed in our methodology. In comparison to the lightweight models EfficientNetB0 and MobileNetV2, EfficientNetB0 exhibited notably higher accuracy. Among the four depth models: Xception, VGG16, InceptionV3 and DenseNet201 examined, the Xception model showed inferior performance with an accuracy of 99.58%. The accuracy achieved closely aligns with precision and recall values ranging from 0.97 to 1.00. These high precision and recall values indicate the model's capability in correctly classifying each leaf condition and effectively capturing instances of each condition, as illustrated in Table III. Furthermore, with F1-score values consistently surpassing 0.99, our model shows a robust balance between precision and recall, reflecting its strong overall performance. This comparison affirms the efficacy of our model in accurately classifying various leaf conditions.

When comparing the results of our study with those presented in Table I, our work demonstrates notable accuracy in detecting five distinct diseases in tea leaves. While some existing studies exhibit significant accuracy in disease detection, they are primarily focused on individual diseases, unlike our proposed approach, which addresses multiple diseases comprehensively.

V. Conclusion

This paper introduces a deep transfer learning-based framework for classifying tea leaf diseases. Image samples, comprising five disease classes and healthy leaves, were collected from Sri Lanka's central province across various lighting conditions and preprocessed to form an image dataset. Data augmentation strategies were implemented to artificially expand the training dataset. Leveraging six pre-trained CNN models (Xception, InceptionV3, DenseNet201, VGG16, EfficientNetB0, and MobileNetV2) trained on the ImageNet dataset, we fine-tuned them using a limited number of tea leaf image samples. The proposed approach was evaluated using a 5-fold cross-validation technique, resulting in a classification accuracy of 99.58%. The future work of this study involves developing a lightweight model suitable for integration into embedded systems.

Acknowledgment

We sincerely thank Mr. Dilhara Gamage for his invaluable contribution to our research. His dedication to capturing tea leaf sample images significantly enhanced the quality of our study. His meticulous work ensured accurate visual representations, enriching our findings.

References

[1] S. L. Export Development Board (EDB), "SRI LANKA - INDUSTRY CAPABILITY REPORT," 2022. [Online]. Available: https://www.srilankabusiness.com/ebooks/industry-capability-report-tea-2021.pdf

[2] "Tea Export Association, Sri Lanka." [Online]. Available: https://teasrilanka.org/market-reports

[3] G. Yashodha and D. Shalini, "An integrated approach for predicting and broadcasting tea leaf disease at early stage using IoT with machine learning – A review," Mater. Today Proc., vol. 37, pp. 484–488, 2021, doi: 10.1016/j.matpr.2020.05.458.

[4] M. J. A. Soeb et al., "Tea leaf disease detection and identification based on YOLOv7 (YOLO-T)," Sci. Rep., vol. 13, no. 1, p. 6078, Apr. 2023, doi: 10.1038/s41598-023-33270-4.

[5] F. Ahmed, M. T. Ahad, and Y. R. Emon, "Machine Learning-Based Tea Leaf Disease Detection: A Comprehensive Review," Nov. 2023, [Online]. Available: http://arxiv.org/abs/2311.03240

[6] S. Gayathri, D. C. J. W. Wise, P. B. Shamini, and N. Muthukumaran, "Image Analysis and Detection of Tea Leaf Disease using Deep Learning," in 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), IEEE, Jul. 2020, pp. 398–403. doi: 10.1109/ICESC48915.2020.9155850.

[7] Saleem, Potgieter, and Mahmood Arif, "Plant Disease Detection and Classification by Deep Learning," Plants, vol. 8, no. 11, p. 468, Oct. 2019, doi: 10.3390/plants8110468.

[8] Z. Xue, R. Xu, D. Bai, and H. Lin, "YOLO-Tea: A Tea Disease Detection Model Improved by YOLOv5," Forests, vol. 14, no. 2, p. 415, Feb. 2023, doi: 10.3390/f14020415.

[9] Y. Xu et al., "A deep learning model for rapid classification of tea coal disease," Plant Methods, vol. 19, no. 1, p. 98, Sep. 2023, doi: 10.1186/s13007-023-01074-2.

[10] J. Wu, U. Dar, M. H. Anisi, V. Abolghasemi, C. N. Wilkin, and A. I. Wilkin, "Plant Disease Detection: Electronic System Design Empowered with Artificial Intelligence," in 2023 IEEE Conference on AgriFood Electronics (CAFE), IEEE, Sep. 2023, pp. 30–34. doi: 10.1109/CAFE58535.2023.10291622.

[11] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," Plant Methods, vol. 17, no. 1, p. 22, Dec. 2021, doi: 10.1186/s13007-021-00722-9.

[12] G. H. A. U. Hewawitharana et al., "Effectiveness of Using Deep Learning for Blister Blight Identification in Sri Lankan Tea," in 2023 International Research Conference on Smart Computing and Systems Engineering (SCSE), IEEE, Jun. 2023, pp. 1–6. doi: 10.1109/SCSE59836.2023.10215029.

[13] X.-M. Chen, C.-C. Lin, S.-R. Lin, and S.-F. Chen, "Application of Region-based Convolution Neural Network on Tea Diseases and Harming Insects Identification," in 2021 ASABE Annual International Virtual Meeting, July 12-16, 2021, St. Joseph, MI: American Society of Agricultural and Biological Engineers, 2021. doi: 10.13031/aim.202100872.

[14] S. Krishnan Jayapal and S. Poruran, "Enhanced Disease Identification Model for Tea Plant Using Deep Learning," Intell. Autom. Soft Comput., vol. 35, no. 1, pp. 1261–1275, 2023, doi: 10.32604/iasc.2023.026564.

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

[16] W. Bao, T. Fan, G. Hu, D. Liang, and H. Li, "Detection and identification of tea leaf diseases based on AX-RetinaNet," Sci. Rep., vol. 12, no. 1, p. 2183, Feb. 2022, doi: 10.1038/s41598-022-06181-z.

[17] T.-X. Jiang, T.-Z. Huang, X.-L. Zhao, and T.-H. Ma, "Patch-Based Principal Component Analysis for Face Recognition," Comput. Intell. Neurosci., vol. 2017, pp. 1–9, 2017, doi: 10.1155/2017/5317850.

[18] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," Jan. 2018, doi: https://doi.org/10.48550/arXiv.1801.04381.

[19] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," Sep. 2014, [Online]. Available: http://arxiv.org/abs/1409.1556

[20] G. G. and A. P. J., "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," Comput. Electr. Eng., vol. 76, pp. 323–338, Jun. 2019, doi: 10.1016/j.compeleceng.2019.04.011.

[21] W. Wu, "Identification of tea leaf diseases based on deep transfer learning," Front. Comput. Intell. Syst., vol. 2, no. 3, pp. 75–77, Feb. 2023, doi: 10.54097/fcis.v2i3.5218.

[22] J. A. Pandian, S. N. Nisha, K. Kanchanadevi, A. K. Pandey, and S. K. Rima, "Grey Blight Disease Detection on Tea Leaves Using Improved Deep Convolutional Neural Network," Comput. Intell. Neurosci., vol. 2023, pp. 1–11, Jan. 2023, doi: 10.1155/2023/7876302.

[23] J. G. Arnal Barbedo, "Plant disease identification from individual lesions and spots using deep learning," Biosyst. Eng., vol. 180, pp. 96–107, Apr. 2019, doi: 10.1016/j.biosystemseng.2019.02.002.

[24] G. Hu, H. Wu, Y. Zhang, and M. Wan, "A low shot learning method for tea leaf's disease identification," Comput. Electron. Agric., vol. 163, p. 104852, Aug. 2019, doi: 10.1016/j.compag.2019.104852.

[25] J. Lin, D. Bai, R. Xu, and H. Lin, "TSBA-YOLO: An Improved Tea Diseases Detection Model Based on Attention Mechanisms and Feature Fusion," Forests, vol. 14, no. 3, p. 619, Mar. 2023, doi: 10.3390/f14030619.

[26] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," Comput. Electron. Agric., vol. 173, p. 105393, Jun. 2020, doi: 10.1016/j.compag.2020.105393.

[27] G. Vijayakanthan, T. Kokul, S. Pakeerathan, and U. A. J. Pinidiyaarachchi, "Classification of Vegetable Plant Pests using Deep Transfer Learning," in 2021 10th International Conference on Information and Automation for Sustainability (ICIAfS), IEEE, Aug. 2021, pp. 167–172. doi: 10.1109/ICIAfS52090.2021.9606176.

[28] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," Oct. 2016, [Online]. Available: http://arxiv.org/abs/1610.02357

[29] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," Dec. 2015, doi: https://doi.org/10.48550/arXiv.1512.00567.

[30] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," May 2019, [Online]. Available: http://arxiv.org/abs/1905.11946

[31] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," Aug. 2016, [Online]. Available: http://arxiv.org/abs/1608.06993

[32] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," Jan. 2018, [Online]. Available: http://arxiv.org/abs/1801.04381

[33] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," Dec. 2014, [Online]. Available: http://arxiv.org/abs/1412.6980