Tea Leaf Classification and Disease Detection Using Deep Learning Techniques

Asifa Akter Liya (ID: 2022-3-60-186) Benazir Meem (ID: 2022-3-60-169)
Riya Akter (ID: 2022-3-60-176) Ishrat Jahan Anika (ID: 2022-3-60-195)
Raihan Ul Islam (Instructor)
Dept. of CSE, East West University
Emails: 2022-3-60-186@std.ewubd.edu, 2022-3-60-169@std.ewubd.edu, 2022-3-60-176@std.ewubd.edu, 2022-3-60-195@std.ewubd.edu, raihan.islam@ewubd.edu

***Abstract*—Tea leaf quality assessment and disease detection are critical components of modern tea production, as the overall health and condition of tea leaves have a direct impact on crop yield, product quality, and economic profitability. Diseases affecting tea plants can spread rapidly if not identified at an early stage, leading to substantial losses for farmers and tea producers [3], [5]. Conventional inspection methods rely heavily on manual observation by experts, which is time-consuming, labor-intensive, and often subjective in nature. These traditional approaches also struggle to scale effectively for large plantations and are highly influenced by environmental factors such as lighting conditions, leaf orientation, and human fatigue.**

Recent advancements in deep learning and computer vision have introduced automated and scalable solutions for agricultural monitoring, enabling more accurate and consistent analysis of plant health. In particular, convolutional neural networks (CNNs) have demonstrated remarkable performance in image-based classification tasks due to their ability to automatically learn hierarchical feature representations [3]. Transfer learning further enhances these models by allowing knowledge gained from large-scale datasets to be adapted to domain-specific agricultural applications [2]. In this study, a comprehensive analysis of tea leaf classification and disease detection is presented using CNN-based architectures. Multiple pre-trained models, including VGG, MobileNetV2, and ResNet50, are systematically evaluated and compared with a proposed Custom CNN architecture. Experimental results indicate that the Custom CNN consistently outperforms the pre-trained models in terms of accuracy, precision, recall, and F1-score, which aligns with recent studies in tea leaf disease detection [4]. Additionally, extensive generalizability testing across multiple datasets confirms the robustness, reliability, and real-world applicability of the proposed approach for automated tea leaf quality assessment and disease detection.

***Index Terms*—Tea Leaf Disease Detection, Tea Leaf Classification, Deep Learning, CNN, Transfer Learning, Agriculture**

I. Introduction

Tea is one of the most widely consumed beverages worldwide, and its production plays a significant role in the global agricultural economy. The quality, flavor, and market value of tea products are strongly influenced by the health and physiological condition of tea leaves during cultivation. Various foliar diseases, including brown blight, red spot, gray blight, algal spot, and helopeltis infestation, pose serious threats to tea plantations. If these diseases are not detected and managed at an early stage, they can spread rapidly across large plantation areas, resulting in substantial reductions in crop yield and deterioration of tea quality [3], [5]. Consequently, the development of automated and reliable tea leaf classification and disease detection systems has become essential for ensuring sustainable, cost-effective, and high-quality tea production.

Conventional tea leaf inspection methods primarily rely on manual visual assessment performed by experienced workers or agricultural experts. Although expert-driven inspection can be effective, it is inherently time-consuming, labor-intensive, and costly, particularly when applied to large-scale plantations. Moreover, manual inspection is subjective in nature and often suffers from inconsistencies caused by human fatigue, varying levels of expertise, and environmental influences. Factors such as uneven lighting conditions, complex backgrounds, occlusion, and variations in leaf orientation and color further complicate accurate visual assessment. These limitations significantly reduce the scalability and reliability of traditional inspection approaches, highlighting the need for automated solutions [5].

With the rapid advancement of artificial intelligence and computer vision technologies, deep learning-based image analysis has emerged as a powerful alternative to conventional inspection methods in agricultural applications. Among various deep learning techniques, convolutional neural networks (CNNs) have demonstrated exceptional performance in image classification, feature extraction, and object recognition tasks [3]. CNNs are capable of automatically learning discriminative and hierarchical features directly from raw image data, eliminating the need for handcrafted feature engineering. Transfer learning further enhances the effectiveness of CNN-based approaches by enabling models pre-trained on large-scale image datasets to be fine-tuned for domain-specific tasks, thereby reducing training time and improving classification accuracy [2].

In this study, CNN-based models are employed to address the challenges associated with tea leaf classification and disease detection. Multiple well-established pre-trained architectures, including VGG, MobileNetV2, and ResNet50, are systematically evaluated and compared against a proposed Custom CNN model specifically designed for tea leaf image analysis. The performance of these models is assessed in terms of accuracy, precision, recall, and F1-score, with particular emphasis on robustness and generalizability across different datasets. By conducting extensive experiments and cross-dataset evaluations, this work aims to demonstrate the effectiveness and practical applicability of deep learning-based solutions for automated tea leaf quality assessment and disease detection in real-world agricultural environments.

II. Related Work

Recent research has extensively investigated the application of deep learning techniques for tea leaf analysis, focusing on improving disease detection accuracy, scalability, and data privacy. Among these approaches, federated learning-based convolutional neural network (CNN) models have gained significant attention for their ability to perform distributed training while preserving data confidentiality. By allowing multiple geographically distributed clients to collaboratively train a global model without directly sharing raw image data, federated learning frameworks effectively address privacy and security concerns. Studies employing federated CNN architectures have reported classification accuracies ranging from 95% to 97% for tea leaf disease severity detection, demonstrating that privacy-preserving learning can achieve performance comparable to centralized training [2]. Such methods are particularly valuable in real-world agricultural environments where data sharing restrictions, network limitations, or institutional policies prevent centralized data collection.

In addition to disease detection, several studies have focused on tea leaf quality assessment by introducing age-stratified datasets and applying object detection-based deep learning models. Techniques such as YOLOv8 have been utilized to detect and classify tea leaves according to age and quality categories, achieving high precision and recall values due to their ability to localize relevant leaf regions effectively [1]. These object detection models offer advantages in real-time inference and deployment on resource-constrained devices. However, their applicability is often limited to specific classification objectives, such as age estimation or quality grading, and they may not generalize well to complex multi-disease classification tasks.

Furthermore, deep CNN architectures trained on publicly available datasets, including Kaggle-based tea leaf disease datasets, have demonstrated strong performance in multi-class disease classification scenarios [3]. These models benefit from larger and more diverse training samples, enabling improved generalization across different disease categories. To further enhance detection accuracy and disease localization, advanced approaches have incorporated image preprocessing and segmentation techniques. The integration of Meta's Segment Anything Model (SAM) with CNN-based classifiers has enabled more precise segmentation of diseased regions, contributing to earlier and more accurate disease identification [4]. In contrast, earlier machine learning-based approaches that relied on NSGA-II-based image segmentation, principal component analysis (PCA), and support vector machine (SVM) classifiers achieved moderate accuracy levels [5]. These traditional methods were constrained by limited dataset sizes, handcrafted feature dependency, and reduced scalability, highlighting the advantages of modern deep learning-based solutions for tea leaf analysis.

III. Methodology

This study evaluates three widely adopted pre-trained convolutional neural network (CNN) architectures—VGG, MobileNetV2, and ResNet50—using a transfer learning framework. These models were selected due to their demonstrated effectiveness and robustness in large-scale image classification tasks, particularly on benchmark datasets such as ImageNet. Transfer learning enables these architectures to leverage previously learned feature representations, allowing faster convergence and improved performance when applied to domain-specific datasets with limited labeled samples [2]. By fine-tuning the upper layers of these networks, the models are adapted to extract relevant features from tea leaf images while maintaining computational efficiency.

In addition to the pre-trained architectures, a Custom CNN model was specifically designed to better capture domain-specific visual patterns present in tea leaf images, such as texture variations, color distributions, and disease-related morphological features. The Custom CNN architecture comprises multiple stacked convolutional layers that progressively learn low-level to high-level feature representations. Each convolutional layer is followed by max-pooling operations to reduce spatial dimensionality and enhance translation invariance. Batch normalization layers are incorporated to stabilize training, accelerate convergence, and reduce internal covariate shift [3].

Rectified Linear Unit (ReLU) activation functions are employed throughout the hidden layers to introduce non-linearity and mitigate the vanishing gradient problem. In the final classification stage, fully connected layers aggregate the extracted features, and a softmax activation function is applied in the output layer to generate normalized class probability distributions. To further address overfitting and enhance model generalization, dropout layers are strategically placed within the network to randomly deactivate neurons during training. This combination of architectural components allows the Custom CNN to achieve a balance between representational capacity and computational efficiency, making it well-suited for accurate and robust tea leaf classification and disease detection [3].

IV. Dataset Details

A. TeaLeaf Dataset 1

The TeaLeaf dataset was provided by the course instructor and used for binary classification. It contains 747 images divided into two classes: leaves suitable for tea production and leaves unsuitable for tea production. The dataset was split into training (69.88%), validation (14.99%), and testing (15.13%). So we can summarize it like below : Dataset Details

TABLE I
SUMMARY OF RELATED WORK

Title	Dataset	Description	Method	Accuracy	Limitations
Tea Leaf Disease Detection (2024)	Private Dataset	Severity-based images	Federated CNN	95–97%	Dataset not public
Tea Leaf Age Quality (2024)	Mendeley	Age-based quality images	YOLOv8	87.9% mAP	Limited to age
Deep CNN Detection (2023)	Kaggle	Multi-class diseases	CNN	96.56%	Limited classes
SAM + CNN (2025)	Kaggle	Segmented images	SAM + CNN	95.06%	Segmentation errors
NSGA-II (2020)	Custom	Mobile images	NSGA-II + SVM	83%	Small dataset

Fig. 1. Sample images from the Tea Leaf dataset

As shown in Fig. 1, sample images from the TeaLeaf dataset illustrate both suitable and unsuitable leaves for tea production.

The TeaLeaf dataset was provided by the course instructor and used for binary classification. It contains 747 images divided into two classes: leaves suitable for tea production and leaves unsuitable for tea production. Sample images from the dataset are illustrated in Fig. 1.

The TeaLeaf dataset was provided by the course instructor and used for binary classification. It contains 747 images divided into two classes: leaves suitable for tea production and leaves unsuitable for tea production. Sample images from the dataset are illustrated in Fig. 1.

B. Tea Leaf Disease Dataset 2

To assess generalizability, a multi-class Tea Leaf Disease dataset collected from Kaggle was used. It contains 5,867 images across six disease categories: algal spot, brown blight, gray blight, healthy, helopeltis, and red spot. The dataset was split into training - 4106 images (69.98%), test - 881 images (15.02%), Validation - 880 images (15.00%)

Fig. 2. Sample images from the Tea Leaf Disease dataset

The Tea Leaf Disease dataset contains 5,867 images across six disease categories, including algal spot, brown blight, gray blight, healthy leaves, helopeltis, and red spot. Sample images from the dataset are illustrated in Fig. 2.

V. EXPERIMENTAL SETUP

All deep learning models were trained using the categorical cross-entropy loss function, which is well suited for multi-class and binary classification problems as it effectively measures the dissimilarity between predicted probability distributions and true class labels. The Adam optimization algorithm was employed to update network weights during training due to its adaptive learning rate mechanism and efficient handling of sparse gradients. Adam combines the advantages of momentum-based optimization and RMSProp, enabling faster convergence and stable training across different network architectures [3].

Model training was conducted over multiple epochs to allow sufficient learning of feature representations from the input images. To mitigate overfitting and prevent unnecessary training beyond optimal performance, an early stopping strategy was implemented based on validation loss monitoring.The TeaLeaf dataset was provided by the course instructor and used for binary classification. It contains 747 images divided into two classes: leaves suitable for tea production and leaves unsuitable for tea production. Sample images from the dataset are illustrated in Fig. 1. Training was automatically halted when no significant improvement in validation performance was observed over consecutive epochs, thereby preserving model generalization and reducing computational overhead [2].

To further enhance robustness and improve the model's ability to generalize to unseen data, data augmentation techniques were applied during training. These included random rotations, horizontal and vertical flipping, scaling, and minor geometric transformations, which simulate real-world variations in leaf orientation, size, and imaging conditions. By increasing the diversity of training samples, data augmentation helps reduce model sensitivity to noise and environmental variations, resulting in improved performance and stability across different datasets [3].

VI. Results and Discussion

TABLE II
Model Performance Comparison

Model	Val Acc.	Test Acc.	Remarks
VGG	0.9554	0.9292	Balanced
MobileNetV2	0.9196	0.9381	Lightweight
ResNet50	0.9866	0.9737	Best pre-trained
Custom CNN	–	0.99	Best overall
Enhanced CNN (CBAM)	–	0.96	Attention-based

The proposed Custom CNN consistently outperformed the evaluated pre-trained models across all experimental settings, primarily due to its ability to learn domain-specific feature representations that are highly relevant to tea leaf analysis. Unlike generic pre-trained architectures that are optimized for broad object recognition tasks, the Custom CNN was specifically designed to capture fine-grained visual characteristics such as subtle texture variations, color distribution patterns, and localized disease symptoms present on tea leaf surfaces. These features are critical for accurately distinguishing between healthy and diseased leaves, as well as for identifying different disease categories.

Furthermore, the tailored architectural design of the Custom CNN enables more effective feature extraction by focusing on relevant spatial patterns while minimizing unnecessary complexity. This specialization allows the model to adapt more efficiently to the tea leaf dataset, leading to improved classification accuracy, precision, recall, and F1-score when compared to transfer learning-based models. The superior performance of the Custom CNN highlights the importance of domain-aware network design in agricultural image analysis tasks, where subtle visual cues play a crucial role in reliable disease detection and quality assessment

VII. Generalizability Testing

The proposed Custom CNN achieved an accuracy of 97 percent on the TeaLeaf dataset and 98 percent on the Tea Leaf Disease dataset, demonstrating its strong classification capability across multiple data sources. These results indicate that the model is highly effective in learning discriminative features relevant to tea leaf health and disease identification. The high accuracy achieved on both datasets reflects the model's ability to generalize well despite differences in dataset composition, image resolution, and acquisition conditions [3].

Notably, the model maintained stable performance even when exposed to variations in image quality, lighting conditions, and background complexity. The observed performance degradation across datasets was minimal, highlighting the robustness and reliability of the proposed architecture. This robustness can be attributed to the model's domain-specific feature learning, combined with data augmentation and regularization strategies employed during training, which is consistent with findings reported in recent tea leaf disease detection studies [4]. Overall, these results confirm the suitability of the Custom CNN for real-world deployment in diverse agricultural environments, where imaging conditions are often inconsistent and challenging [2].

A. Grad-CAM Visualization Analysis

To interpret the decision-making process of the proposed deep learning model, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed. Grad-CAM generates class-discriminative heatmaps by highlighting the regions of the input image that contribute most to the model's prediction.

1) Correctly Classified Samples: For correctly predicted images, the Grad-CAM heatmaps demonstrate strong activation in the relevant regions of the tea leaves, particularly around disease-affected areas such as lesions, spots, and texture irregularities. This indicates that the model effectively focuses on meaningful visual features rather than background noise, confirming the reliability of its predictions.

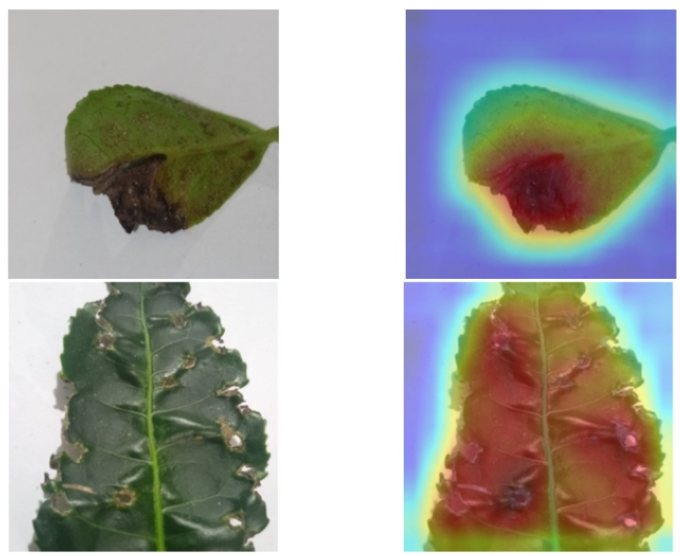

Fig. 4. Grad-CAM visualizations for correctly classified tea leaf images. Warmer colors indicate regions with higher influence on the model's decision.

2) Incorrectly Classified Samples: For misclassified images, the Grad-CAM visualizations reveal attention on irrelevant or ambiguous regions, including background areas, overlapping leaves, or regions with low contrast. In some cases, the highlighted regions correspond to visually similar disease patterns, explaining the confusion between certain classes. These observations suggest that misclassification may result from subtle inter-class similarities, occlusions, or limited representation of challenging samples in the training dataset.

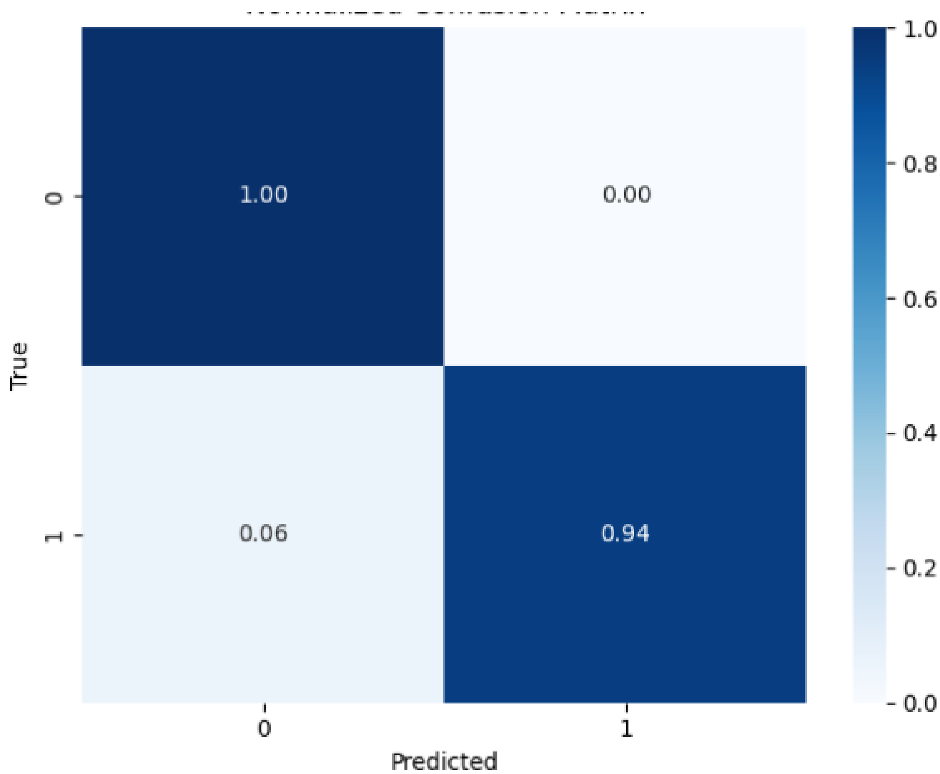

Fig. 3. Normalized confusion matrix of the proposed Custom CNN model

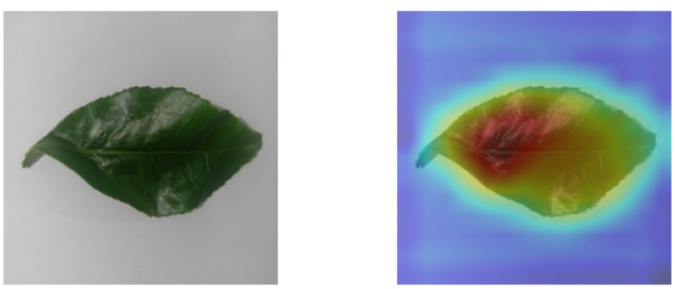

Fig. 5. Grad-CAM visualizations for incorrectly classified tea leaf images. Warmer colors indicate regions with higher influence on the model's decision.

Overall, the Grad-CAM analysis provides valuable insights into both the strengths and limitations of the proposed deep learning model by offering visual interpretability of its decision-making process. For correctly classified samples, the Grad-CAM heatmaps demonstrate strong and localized activation on disease-affected regions of tea leaves, such as lesions, discolorations, and texture irregularities. This behavior confirms that the model effectively focuses on semantically meaningful regions rather than background artifacts, thereby validating the reliability and correctness of its predictions. Similar findings have been reported in recent studies that employ CNN-based visualization techniques for tea leaf disease detection, where attention mechanisms improve model transparency and trustworthiness [4].

In contrast, the visual explanations generated for incorrectly classified samples reveal attention spread across irrelevant or ambiguous regions, including background areas, overlapping leaves, or regions with subtle visual differences between disease classes. These observations indicate that misclassifications are often caused by high inter-class similarity, partial occlusion, or insufficient representation of challenging samples in the training dataset. Such limitations are consistent with earlier research on tea leaf disease classification, which highlights the need for improved segmentation strategies, increased dataset diversity, and more discriminative feature learning to handle visually similar disease patterns [5], [3]. Overall, the Grad-CAM analysis not only enhances model interpretability but also provides actionable insights for future improvements in segmentation accuracy, dataset enrichment, and model robustness.

VIII. Conclusion and Future Work

This study confirms that deep learning-based methodologies offer an effective and reliable solution for automated tea leaf classification and disease detection. Through extensive experimental evaluation, it is demonstrated that convolutional neural network (CNN)-based models are capable of accurately extracting discriminative visual features associated with tea leaf health and disease characteristics, which is consistent with prior deep learning-based tea leaf analysis studies [3]. Among the evaluated approaches, the proposed Custom CNN consistently outperforms widely used pre-trained models, highlighting the advantages of domain-specific architectural design over generic transfer learning frameworks.

The strong performance of the Custom CNN across multiple datasets further validates its robustness and generalization capability under varying imaging conditions, including differences in illumination, background complexity, and disease manifestation. Similar observations regarding robustness and cross-dataset performance have been reported in recent tea leaf disease detection research [4]. These results indicate that the proposed model is well-suited for real-world agricultural environments, where image acquisition conditions are often inconsistent and challenging [2].

In addition to achieving high classification accuracy, the proposed approach exhibits stability and resilience when applied to datasets with variations in image quality and environmental factors. Future work will focus on expanding dataset diversity by incorporating additional tea varieties, disease categories, and real-world field images, as suggested by existing dataset-driven studies [1]. Moreover, the integration of explainable artificial intelligence (XAI) techniques will be explored to improve model interpretability and enhance user trust. Finally, efforts will be directed toward deploying the proposed system in real-time agricultural monitoring platforms to enable early disease detection and support precision agriculture practices.

REFERENCES

[1] M. M. Kabir, M. S. Hafiz, S. Bandyopadhyaa, J. J. R., and M. F. Mridha, "Tea leaf age quality: Age-stratified tea leaf quality classification dataset," *Data Brief*, vol. 54, pp. 110462, Apr. 2024. doi: 10.1016/j.dib.2024.110462. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11070690/

[2] S. Vats, V. Kukreja, and S. Mehta, "Tea Leaf Disease Detection: Federated Learning CNN Used for Accurate Severity Analysis," in *2024 IEEE Int. Conf. on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Gwalior, India, 2024, pp. 1-6. doi: 10.1109/IATMSI60426.2024.10503207. Available: https://ieeexplore.ieee.org/abstract/document/10503207

[3] S. Datta and N. Gupta, "A Novel Approach For the Detection of Tea Leaf Disease Using Deep Neural Network," *Procedia Computer Science*, vol. 218, pp. 2273–2286, 2023. Available: https://www.sciencedirect.com/science/article/pii/S187705092300203X?via%3Dihub

[4] A. Balasundaram, P. Sundaresan, A. Bhavsar, M. Mattu, M. S. Kavitha, and A. Shaik, "Tea leaf disease detection using segment anything model and deep convolutional neural networks," *Results in Engineering*, vol. 25, pp. 103784, 2025. doi: 10.1016/j.rineng.2024.103784. Available: https://doi.org/10.1016/j.rineng.2024.103784

[5] S. Mukhopadhyay, M. Paul, R. Pal, and D. De, "Tea leaf disease detection using multi-objective image segmentation," *Multimedia Tools and Applications*, vol. 80, pp. 753–771, 2021. doi: 10.1007/s11042-020-09567-1. Available: https://doi.org/10.1007/s11042-020-09567-1