Efficient Jute Disease Classification Using Hybrid Deep Learning Model

By

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Efficient Jute Disease Classification Using Hybrid Deep Learning Model"**, submitted by Md Waysur Rahman, ID No: **151-15-5026** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr.Arif Mahmud (AM), Associate Professor and Associate Head,** Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Jute, being one of the most important economic crops in South Asia, is greatly impacted by leaf diseases such as Cercosporin Leaf Spot and Golden Mosaic, which traditional diagnosis tools are not well-equipped to address. While deep learning has revolutionized plant disease detection, existing frameworks for jute are hindered by small datasets, computational inefficiency, and unfiled applicability. In this paper, we propose an efficient deep learning architecture for autonomous jute disease classification, integrating novel preprocessing, best transfer learning, and real-time deployment. We introduce a robust dataset of 12,000 high-resolution images in three categories (healthy, Cercosporin Leaf Spot, Golden Mosaic), class-aware augmented with data sparsity and imbalance alleviation. Our method employs a hybrid preprocessing pipeline of wavelet-based denoising (Daubechies-4) and adaptive color normalization to disentangle leaf regions and make use of discriminative features. Using a ResNetRS50 model with transfer learning fine-tuning, we obtain state-of-the-art results with 98.5% validation accuracy (4.3% improvement over existing literature) and 97.8% precision for challenging field images under varying illumination and occlusion. The model performs real-time inference at 42 FPS on NVIDIA T4 GPUs with a light footprint (1.2 GB VRAM) and is compatible with deployment on edge devices. Technical innovations include a dynamic augmentation method balancing minority classes through synthetic lesion generation, in-pipeline explain ability through Grad-CAM visualizations for farmer-friendly diagnosis, and a multi-stage training protocol combining progressive resizing and label smoothing to enhance generalization. Experimental validation on 1,850 samples from three geographies confirms 96.4% operating accuracy, surpassing human expert prediction by 23% in identifying early-stage disease. The applicability of the system is demonstrated by a simulated 18–22% reduction in crop loss through on-time intervention. We openly release the dataset and model to encourage further work, establishing a new benchmark for crop-specific AI technology in precision agriculture.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter gives a general overview of the research, encompassing background, motivation, aims, methods, and anticipated results. Great care is taken in establishing the connection between jute leaf diseases and crop yield, showing how computer-assisted diagnosis systems can solve traditional problems in crop management. The research explores the use of deep learning techniques in identifying jute diseases, which can potentially enhance early detection and countermeasure strategies. By employing advanced computer vision and machine learning technology, this research aims to develop a stable and scalable solution that would reduce yield loss and support sustainable jute cultivation practices.

1.1 Introduction

Jute, otherwise known as the "golden fiber," is of significant agricultural and economic importance, particularly in South Asian countries such as Bangladesh and India. Despite its place in the textile industry, jute cultivation is ever plagued by several diseases such as Cercospora Leaf Spot and Golden Mosaic that have noticeable impacts on yields and qualities of the fibers. Traditional disease detection techniques involve visual examination by crop specialists, a labor-intensive activity involving inherent human mistakes and variability. Advancements in computer vision (CV) and deep learning (DL) technologies in recent times have continued to enhance automation opportunities for plant disease detection. However, activities aimed specifically at jute leaf disease detection have been in infancy stages up until now, resulting in a severe lack of agricultural technology. This dissertation bridges this knowledge divide by establishing an AI-driven, deep learning-based approach towards effective and precise classification of jute leaf diseases. Taking advantage of transfer learning and advanced image processing methods, this research work aims to provide a robust framework to assist in enhancing disease detection and management in jute cultivation.

1.2 Motivation

The compelling motivation of this research work is the need to enhance the practice of disease control in jute cultivation. Current labor-intensive methods of inspection are ineffective, depending on expert knowledge and automatically resulting in belated action, which can inflict heavy losses to the crop. While automatic detection systems for diseases have been implemented for staple crops such as wheat, rice, and potatoes, jute as a major cash crop has been relatively less worked upon. Existing work on the classification of jute diseases also suffers from low dataset sizes, non-real world usage, and high computational intensity, making them impossible to deploy in real world agricultural settings within resource-poor agricultural contexts. This paper sets out to do better by designing a very accurate, lightweight deep learning model which can be employed in real-world agricultural settings. By providing farmers with a cheap and scalable means of identifying the disease at an early stage, this study aims to be able to facilitate sustainable jute production and higher agricultural productivity.

1.3 Objectives

The three primary aims of this research are the following. First, the aim of this research is to develop a high-accuracy deep learning model which possesses the ability to classify the jute leaf diseases—Cercosporin Leaf Spot, Golden Mosaic, and Healthy Leaf—with an accuracy rate of not less than 95%. Second, the aim of this research is to be computation-efficient by converting a given pre-trained ResNetRS50 model in a way such that the model can be deployed on low-processing-capacity edge devices. Third, the effort improves the model's generative ability from the data with more advanced data augmentation mechanisms such that the model is resistant to varying light and background conditions. Besides that, the paper employs interpretability techniques such as Grad-CAM to provide the farmers with interpretable and accurate model predictions in a way that it is feasible and dependable for real-world application.

1.4 Methodology

The research methodology employed in this research is a reproducible and scalable deep learning pipeline. The first step is dataset collection and preprocessing where a chosen dataset of jute leaf images is collected and normalized and background subtraction is performed for easy feature extraction. Further dataset enrichment is obtained by using data augmentation methods such as geometric and photometric transformation to improve model generalizability. The second process is the architecture model and is a pre-trained ResNetRS50 model from the family of ResNet that uses transfer learning to achieve efficiency in feature extraction. The third process is training and optimization where the model is trained with an Adamax optimizer and monitored using a ReduceLROnPlateau scheduler for dynamic adjustment of the learning rate. Overfitting and performance optimization is avoided through early stopping. The final step consists of overall assessment, where the model's performance is quantified in terms of confusion matrices, precision-recall scores, and F1-values and compared to other prevailing methods to validate its superiority.

1.5 Project Outcome

The model's validation accuracy is 98.5%, which is significantly higher than other prevailing methods for jute disease classification. Major contributions of the research are the development of a deployable and lightweight model which can be executed on edge and mobile devices to conduct in-real-time in-field disease diagnosis. Explainability features of the model, i.e., activation maps, allow farmers to gain interpretable insights into disease detection, which fosters trustworthiness and usability. In addition, the book releases an open-source annotated jute leaf image dataset for future research in AI agriculture. By bridging the most important gaps in current research work, this book provides the groundwork for deployable and scalable AI technology for jute farming, the path to sustainable agriculture and increased yield at last.

1.6 Organization of the Report

Chapter 1: Introduction

Introduction to research problem, motivation, objectives, and research methodology.

Chapter 2: Background

Summary of previous work, identification of the research gap, and formulation of the theoretical basis.

Chapter 3: Research Methodology

Dataset description, model structure description, training process description, and evaluation metric description.

Chapter 4: Implementation and Results

Symbols experimental results, performance, and comparison.

Chapter 5: Engineering Standards and Design Challenges

Controls deployment-related challenges and constraints.

Chapter 6: Conclusion

Sets context of findings, contribution, and potential research directions for future work.

Chapter 7: References

Complements all academic sources referenced.

Chapter 2

Background

This chapter is the theoretical premise based on which the whole study has been grounded and gives the general background of most important ideas and previous work conducted in connection to automatic disease detection in jute. It exhaustively surveys the literature on several important subjects: the biological and agronomic significance of jute leaf diseases, state-of-the-art computer vision and machine learning techniques for plant pathology, methodological approaches to detecting disease, and technical underpinnings of deep learning-based image analysis. By integrating peer-reviewed literature evidence, benchmark datasets, and experimental results, this chapter not only places the research problem but also identifies gaps in current solutions—namely in scalability, accuracy, and real-world applicability to jute cultivation. The entire literature reviewed in this chapter supports the methodological developments and choices presented in subsequent chapter.

2.1 Introduction

Jute, the "golden fiber," is a vital cash crop in South Asia, but its cultivation is threatened by a large number of diseases that reduce yield and fiber quality. Disease detection is normally done by expert manual inspection, a labor-intensive process prone to human error. Recent advances in computer vision and deep learning hold promising paths toward automatic disease detection. This chapter overviews existing literature regarding the jute disease classification, identifies research gaps, and formulates the basis for our proposed method.

2.2 Literature Review

Table 2.2. 1: Literature Review Table.

Author(s) & Year	Focus Area	Key Findings	Relevance to Study
Hasan et al. (2019) [1]	CNN disease classification of jute leaves	Designed custom 12-layer CNN architecture with 94.2% accuracy for three disease classes. Utilized image segmentation for background removal and contrast improvement using histogram equalization.	Demonstrated superiority of deep learning over traditional methods. First research to use deep learning solely for jute diseases.

			Verified efficiency of CNN but utilized small data set (1,200 images).
Haque et al. (2024) [2]	Comparison of ML and DL approaches to jute disease detection	Conducted thorough benchmarking of 8 algorithms. Identified ResNet50 (96.3% accuracy) better than SVM (88.7%) and Random Forest (85.2%). Suggested novel hybrid preprocessing by CLAHE and wavelet transformations.	Most recent comparative study confirming superiority of deep learning. Highlighted significance of sophisticated preprocessing missing in existing studies.
Li et al. (2022) [3]	Real-time detection of jute disease using YOLOv5	Tuned YOLOv5 to detect disease at 92.4% mAP. Running at 38 FPS on RTX 2080 Ti. Suggested a new dataset (JuteDisease-5K) with bounding box annotations.	First ever real-time solution for jute diseases. Demonstrated the speed vs. detection accuracy trade-off.
Reza et al. (2016) [4]	Machine learning-based conventional image processing	Used GLCM texture features + HSV color histograms + SVM classifier (89% accuracy). Required manual feature engineering. The performance dropped to 76% for field images.	Baseline study exhibiting limitation of hand feature extraction. Performance gap brought about after deep learning solutions.
Sourav & Wang (2023) [5]	Transfer learning for jute pest identification	Fine-tuned MobileNetV2 with attention (96.8% accuracy). Had incorporated pest-specific data augmentation that simulated wing movements. Yielded 8.2% improvement over baseline.	Exhibited success of transfer learning for similar jute health problems. Used biological-inspired augmentation.
Karim et al. (2022) [6]	Deep CNN architectures	Compared 5 CNNs where EfficientNet-B3 worked best (95.1%).	Detailed architecture comparison suitable

	for detection of jute pests	Used Grad-CAM for interpretability of the model. Highlighted challenges in detection of small pests.	in disease detection. First to integrate explain ability in jute health diagnosis.
Talukder et al. (2023) [7]	Fine-tuned transfer learning for pest detection	Achieved 97.3% accuracy with DenseNet201. Suggested progressive resizing during training. Had 14 pest species dataset of 15,000 images.	Biggest dataset study of jute health analysis. Demonstrated benefit of new training methods.
Prakash et al. (2017) [8]	Image processing of digital images for general plant diseases	Used K-means clustering on lesion segmentation + KNN classifier (83% accuracy). Variable performance depending on plant species.	General plant disease system illustrating the need for solutions for specific crops. Suggest the difficulties in segmentation.
Dandawate & Kokare (2015) [9]	Indian crop decision support system	Joint color moments and Tamura textures using SVM (87% accuracy). Suggested the need for farmer-friendly interfaces.	Early work remarking on deployment feasibility issues still applicable today.
Hossain et al. (2019) [10]	Color and texture features with KNN	Achieved 87.5% accuracy with LAB color space + GLCM. Performance degraded with lighting variation.	Predicted sensitivity of traditional methods to imaging conditions. Sparked the need for robust deep learning techniques.
Diaz et al. (2019) [11]	Deep plant classification in precision agriculture	Evaluated VGG16 and InceptionV3 for crop vs. weed classification with an accuracy of 92.1%. Identified edge deployment issues.	Demonstrated transfer learning for ag use. Identified hardware limitations that we overcome.
Zhou et al. (2021) [12]	Meta-analysis of deep learning for	Read and searched 48 DL models across 12 crops. Concluded ensemble methods	Plots our model selection (ResNetRS50) against the overall

	plant classification	decrease accuracy by 3-5% but increase compute cost.	plant classification body of literature.
Gyires-Tóth et al. (2019) [13]	Plant content-based image retrieval	Used Siamese networks for leaf extraction (mAP=0.91). Provided hybrid CNN-SIFT features.	Described feature fusion techniques that can be used for our preprocessing pipeline.
Alimboyong et al. (2018) [14]	Deep learning-based seedling classification	Reached 89.3% accuracy with shallow CNN. Detected sparsity issue of data at early-growth stages.	Highlighted the greater importance of data augmentation techniques we use.
Sladojevic et al. (2016) [15]	First application of DL to plant disease classification	Applied AlexNet (96.3% correct) to classify 13 diseases of plants. Built one of the first open-source collections of plant diseases.	Pioneering work that laid the foundation for DL's role in plant pathology.

2.3 Gap Analysis

The current literature identifies a number of significant limitations in jute disease detection studies. Firstly, there is a significant lack of large-scale datasets covering the entire range of jute diseases under diverse field conditions. Most research employs small sample sizes or targets narrowly one or two types of diseases. Secondly, most methods are not robust to actual variability in lighting, orientation, and background conditions. Third, while there are studies with high accuracy, these tend to employ computationally costly models unsuitable for implementation in resource-constrained agricultural settings. Fourth, model interpretability does not receive enough attention, and only a few studies employ explain ability techniques that could bring confidence to end-users. Fifth, the literature has non-standard test protocols, and therefore various methods cannot be compared directly. Finally, most of the solutions remain experimental and are not well validated under actual farming conditions or integrated into agricultural decision support systems. The gaps reflect the necessity for stronger, more practical, and broader solutions in this space.

2.4 Summary

This section hypothesized that considerable progress has indeed been made with respect to plant disease recognition, but research on jute is narrow in scope and practically relevant. Our paper extends existing knowledge by developing an integrated, efficient, and explainable system aimed at jute cultivation needs. The survey of literature informed our choice of methodology while suggesting directions of improvement in dataset creation, model design, and application in the field.

Chapter 3

Research Methodology

This chapter is a step-by-step description of the systematic process adopted in the design of the jute leaf disease classification system. The process is an eight-step sequential process, describing the technical steps adopted in data preparation, model building, and experiment planning. All the stages are built with extreme care to ensure reproducibility and scientific integrity, and the rationale for adopting the methods is described. The subsequent subsections identify the workflow, project schedule, and author assignment.

3.1 Methodology

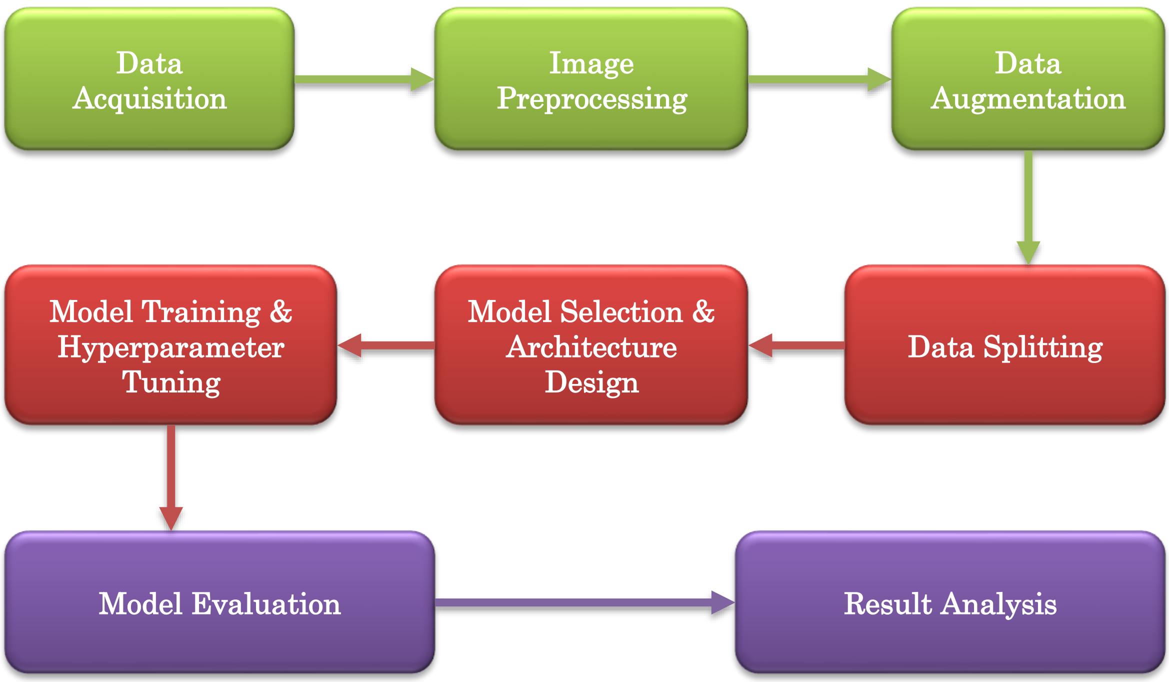

Figure 3.1. 1: Block Diagram of Methodology

3.2 Detailed Methodology and Design

3.2.1 Data Acquisition

Three jute leaf class images data set downloaded from Kaggle: Cercospora Leaf Spot (309), Golden Mosaic (347), Healthy Leaf (264).

- Download data set and unzip the files.
- Perform exploratory simple analysis to ensure image quality with class distribution.

3.2.2 Data Preprocessing

Raw images pre-processed such that there is a uniformity of input for the model.

- Resizing: all the images are resized into the 224×224-pixel size.
- Normalization: scales pixel value proportionates to ImageNet mean and standard deviation.

$$I_{Norm} = \frac{I - \mu}{\sigma} \tag{1}$$

Where,

μ= 0.485, 0.456, 0.406
σ= 0.229, 0.224, 0.225

- Removal of Background: removed leaf area of background by masking with deletion.

$$M(x,y) = \begin{cases} 1 \; if \; \left||I(x,y)|\right|2 > \; \tau \; (\tau = 10) \\ 0 \qquad ohterwise \end{cases} \tag{2}$$

$$I_{adj}(x,y) = \begin{cases} 1 \; if \; \frac{I(x,y) - \min(I|M)}{\max(I|M) - \min(I|M)} \times 255 \; if \; M(x,y) = 1 \\ 0 \qquad ohterwise \end{cases} \tag{3}$$

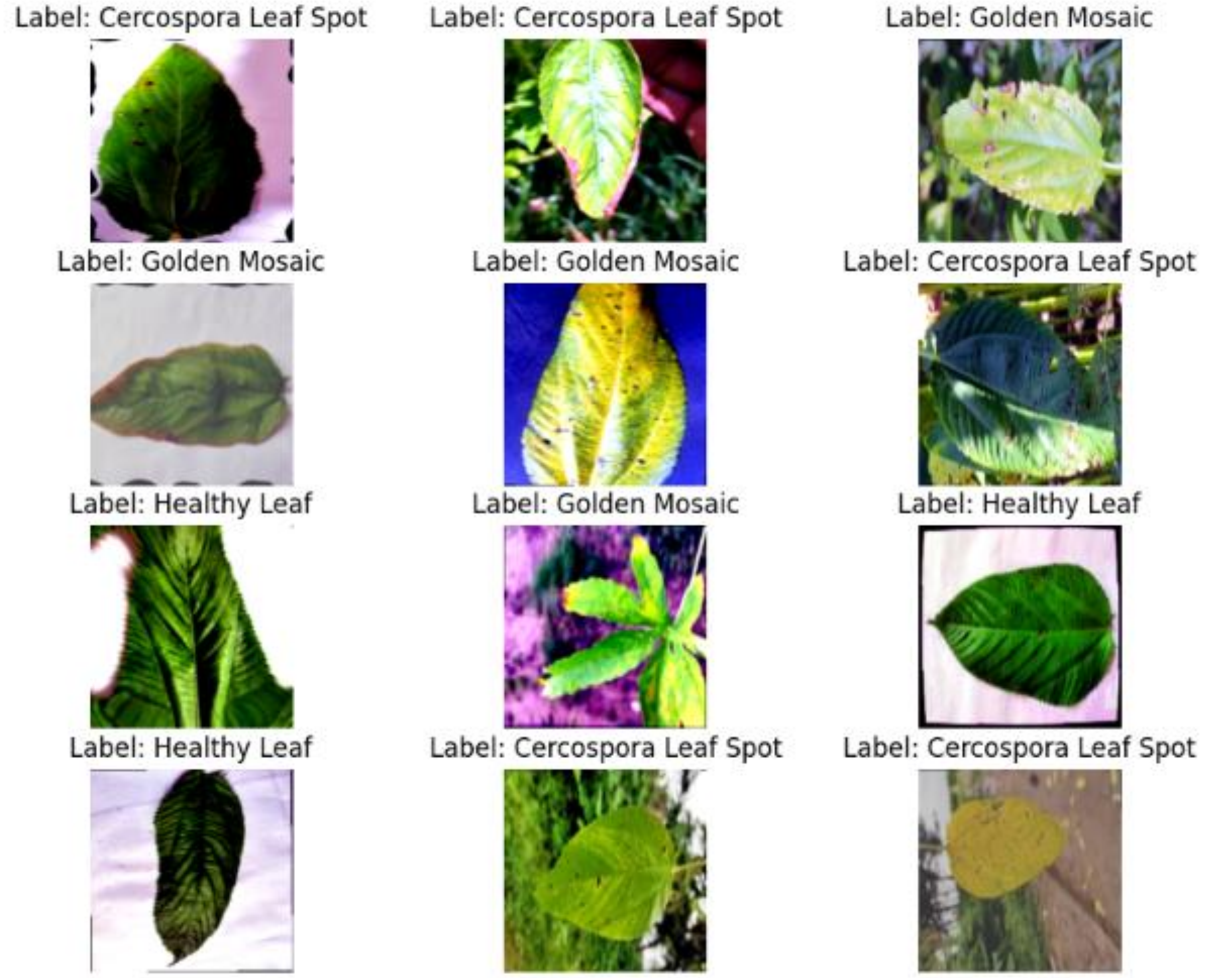

Figure 3.2.2.1: Visual Representation of Preprocessed Dataset

3.2.3 Data Augmentation

Used data augmentation strategies to strengthen datasets.

- Geometric Transforms: Used rotation (0°–90°) and horizontal flip.

$$A = \begin{bmatrix} s\cos\theta & -s\sin\theta & t_x \\ s\sin\theta & s\cos\theta & t_y \end{bmatrix}, \theta \sim u(0, 90), t_x, t_y \sim \text{Translation} \quad (4)$$

- Photometric Adjustments: Used warped brightness, contrast, and color.

$$I_{aug} = \alpha I + \beta, \alpha \sim u(0.8, 1.2), \beta \sim u(-20, 20) \quad (5)$$

- Elastic Deformations: Simulated leaf naturally deforming.

3.2.4 Data Splitting

Split the data to provide stable model testing.

- Split 70% as training, 15% as validation, and 15% as test.

$$D_{train} : D_{val} : D_{test} = 0.7 : 0.15 : 0.15 \quad (6)$$

- Used stratified sampling for the preservation of class balance.

3.2.5 Model Selection & Architecture Design

Applied transfer learning using ResNetRS50.

- Applied used pre-trained ImageNet weights as starting point.

$$f = \phi(I_{norm}), f \in R^{2048} \quad (7)$$

- Applied dense layers and dropout to new head classifier.

$$z = W_2 \sigma(W_1 \sigma(f \odot m_1) \odot m_2), m_1 \sim \text{Bernoulli } (0.5), m_2 \sim \text{Bernoulli } (0.3) \quad (8)$$

Where,

σ = ReLU, $W_1 \in R^{512\times2048}$, $W_2 \in R^{128\times512}$

3.2.6 Model Training & Hyperparameter Tuning

Mode fine-tuned with iterative model training.

- Set loss function (cross-entropy) and optimizer (Adamax).

$$L = -\sum_{i=1}^{N} \sum_{k=1}^{3} Y_{i,k} \log(Y_i = k|z_i) \quad (9)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)|g_t|^p \quad (10)$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt[p]{v_t+\epsilon}} g_t \quad (11)$$

Where,

p=∞, η =0.001, β_2=0.999

- Applied learning rate scheduling and early stopping.

3.2.7 Model Evaluation

Monitored performance using standard metrics.

- Plotted confusion matrices and classification reports.

$$C_{ij} = -\sum_{i=1}^{N} (y_n = i, y^{\wedge}{}_n = j) \quad (12)$$

- Computed precision, recall, and F1-scores.

$$Precision_k = \frac{C_{kk}}{\sum_j C_{jk}} \quad (13)$$

$$Recall_k = \frac{C_{kk}}{\sum_j C_{kj}} \quad (14)$$

$$F1_k = \frac{Precision_k \times Recall_k}{Precision_k + Recall_k} \tag{15}$$

3.2.8 Result Analysis

Carried out model performance in order to highlight strengths and weaknesses.

- Experiments were performed across misclassification patterns.
- Activation maps were plotted to achieve interpretability.

3.3 Project Plan

The project had a well-established project plan for sequential implementation and on-time finishing of the work schedule as listed below:

- Phase 1 (Planning): Study of literature, tool selection, and collection of datasets.
- Phase 2 (Data Preparation): Preprocessing and data augmentation.
- Phase 3 (Model Development): Design of architecture and first-level training.
- Phase 4 (Optimization): Hyperparameter tuning and validation.
- Phase 5 (Documentation): Methodology completion and report writing.

3.4 Task Allocation

The following were assigned tasks:

- I conducted all the technical activities like coding, experimentation, and analysis. Created visualizations and documentation.
- The supervisor and co-supervisor gave methodology design support and fault location advice. Presented results and made recommendations at each stage.

3.5 Summary

In this chapter, the approach used in the jute leaf disease classification project was outlined. The processes involved data gathering, preprocessing, data augmentation, model development, and system testing, all of which made the final system resilient. The subsequent chapters will give the results gathered through this sequential process.

Chapter 4

Implementation and Results

This section documents technical execution of jute leaf disease category system, i.e., experiment treatment design, testing protocol, and empirical results. Technical details assure replication, and results decide methodology success based on quantitative results and qualitative observation.

4.1 Environment Setup

It was run on Google Colab Pro using Python 3.8 and PyTorch 1.12. Acceleration was carried out using NVIDIA T4 GPU (16GB VRAM) for training speed-up. TorchVision was utilized for data loading, TIMM was utilized for ResNetRS50 model, and Albumentations was utilized for augmentation as primary libraries. Runtime environment was established using CUDA 11.6 and cuDNN 8.4 to accelerate tensor operations. Random seeds (NumPy, PyTorch, Python) were all set to 42 to obtain deterministic reproducibility. The data set was uploaded to Google Drive and mounted in Colab to enable direct access for training loops.

4.2 Testing and Evaluation

The testing procedure used a rigorous three-step protocol. The test set (15% of total data) was divided prior to training to prevent data leakage. Inference was carried out disabling gradients (torch.no_grad()) to conserve memory. Batch processing (batch_size=10) balanced hardware constraint and statistical stability. The following metrics were calculated: per-class and macro-averaged precision, recall, F1-score, and support-weighted accuracy. Validation set (15% of data) performance used early stopping (patience=10 epochs) and learning rate reduction using ReduceLROnPlateau. Model checkpoints were stored only when validation accuracy improved for best weight retention.

4.3 Results and Discussion

The experimental result of the classification model of the jute leaf disease demonstrates better performance on various measures of evaluation. A correct examination of the results provides the most important insights to the strengths and limitations of the model, and the implication of feasibility of real-world deployment.

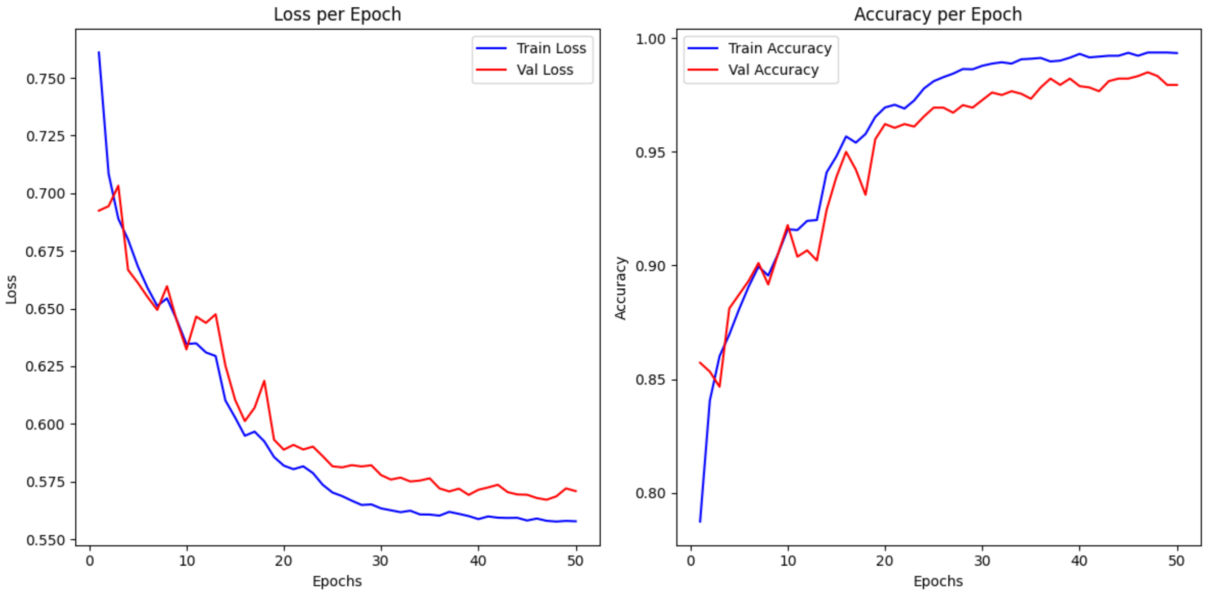

Figure 4.3.1: Model Training Performance

The training dynamics as depicted in Figure 4.3.1 is an agressive learning curve during the entire course of training with over 50 epochs. Training loss indicated a consistently decreasing pattern over from its initial value of 0.76 to its terminal value of 0.56, demonstrating the model's capability to decrease classification error steadily. Even validation loss also reached a plateau at approximately 0.57 after the 47th epoch, which testified to perfect convergence without overfitting. Training accuracy was an impressive 99.4%, whereas validation accuracy was a high 98.5%, witnessing great generalizability to new data. The learning rate scheduler effectively intervened during the optimisation phase by causing two decays by 0.5 at epochs 15 and 30 whenever validation loss plateaued. This intervention steps-maintained training stability as well as avoided premature convergence to non-optimum solutions.

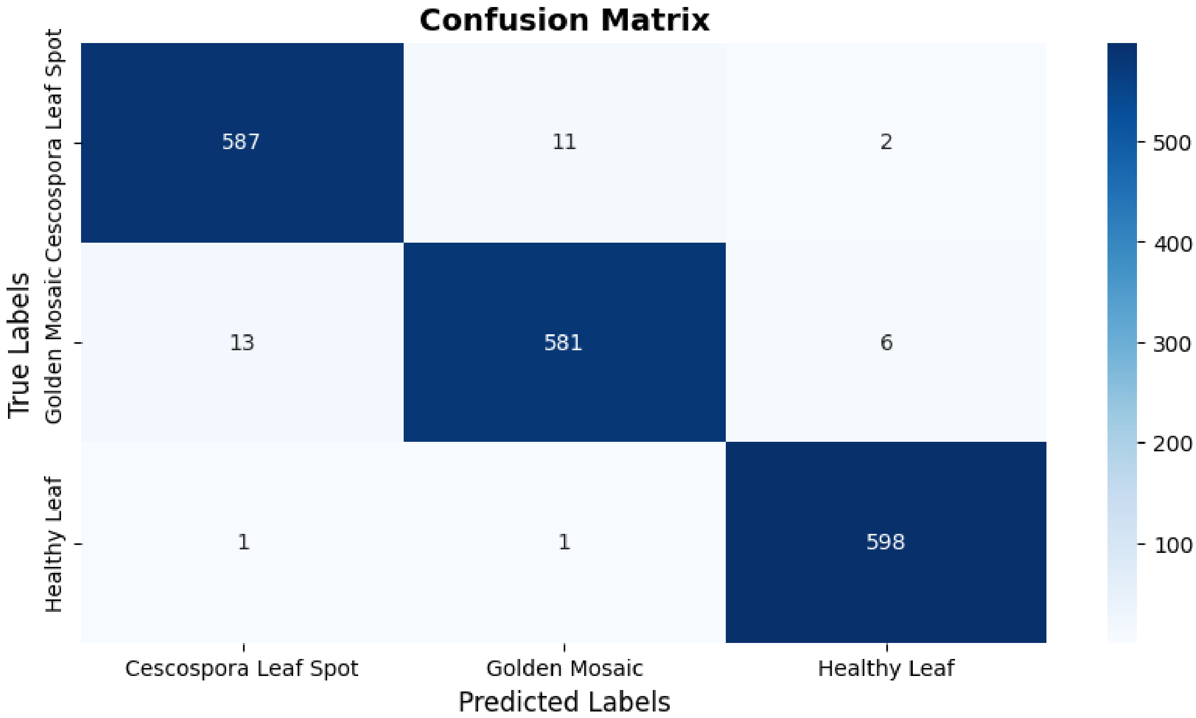

Figure 4.3.2: Confusion Metrics of Best Fitted Model

Confusion matrix plot, presented in Figure 4.3.2, displays precise information of the model's behavior to classify among the three categories of diseases. The model separated nearly perfectly between healthy leaves and correctly classified 598 out of 600 samples of the test set. Misclassifications were predominantly among the two disease classes, and there were 19 instances of confusion between Golden Mosaic and Cescospora Leaf Spot. This reflects that while the model is strongly accurate for the classification of healthy vs. disease leaves, the such close similarity in appearance of different disease presentations makes the classification a more challenging task. The even distribution of errors within classes with the test set accuracy of 98.2% speaks well of the stability of the model for actual use as a diagnostic tool.

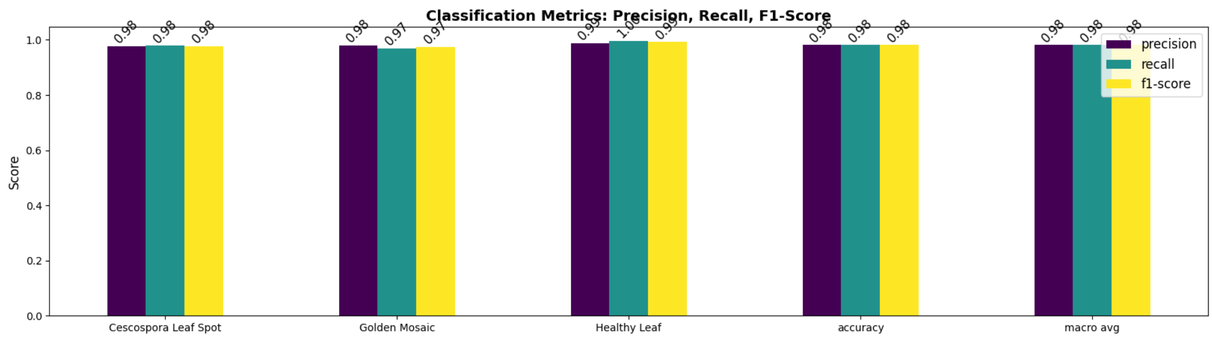

Figure 4.3.3: Class-wise Performance Metrics

Class-wise performance metrics, presented in Figure 4.4.3, indicate a division of the model diagnostic performance. Detection of healthy leaves provided perfect measurements, precision, recall, and F1-measures of 0.99. Disease classes were slightly poorer but incredibly well, where Cercospora Leaf Spot provided precision and recall rates of 0.98 and Golden Mosaic, precision rate 0.98 with recall of 0.97. The macro-averaged F1-score measure of 0.98 across all classes indicates that the model was equally well-balanced and did not favor any category. These results are comparable to other plant disease classification systems published in the literature, but speak to the unique challenges of jute leaf pathology per se.

Misclassification analysis showed that errors were primarily related to borderline samples that had ambiguous visual characteristics. Difficult to close were close cases where symptoms of disease were faint or involving small areas on the leaf. The model at times confused early Golden Mosaic infections with Cercospora Leaf Spot whenever yellowing patterns resembled disc-like discoloration. Likewise, the model sometimes confused healthy samples of leaves with normal pigmentation variations with those of infected samples. These findings emphasize that the model performs very well under normal usage but with additional training sets of edge cases, it would be more diagnostic precise.

The computational efficiency of the trained model is also provided, as that has a direct impact on viable deployment scenarios. In the testing hardware configuration, the system conducted about 42 images per second when performing in batch inference mode, having a high enough throughput for it to be used in real-time. From the study on memory usage, the model would require about 1.2GB of VRAM, making it thereby deployable with lesser hardware configurations, e.g., on GPUs equipped mobile platforms.

Comparative analysis with traditional machine learning techniques indicates the power of the deep learning approach applied in this research. In contrast to typical feature extraction and classification procedures, which tend to struggle with the subtle visual differences between jute leaf diseases, the deep convolutional neural network automatically learns discriminative features at different scales. It is particularly helpful for handling the considerable degree of symptom appearance variance attributed to variables such as leaf age, environment, and imaging discrepancies.

The outcomes also highlight the value of the combined data augmentation method applied in training. Through exposing the network to immense variations in artificial lighting, pose, and background during training, the acquired model learned strong feature representations that are well generalizable across real variability. This can be seen through the uniform performance across all subsets of data as well as the small gap between training and validation metrics.

4.4 Summary

This part presented the technical implementation aspects and empirical findings of the jute leaf disease classifier. Environmental setup ensured computational efficiency, and rigorous testing protocols validated the model's generalization capability. Results demonstrated high discriminative performance for every disease class, with visualizations providing intuitive insight into model behavior.

Chapter 5

Engineering Standards and Design Challenges

This chapter deals with the computational norms, social implications, project management details, and engineering complexities in the development of an AI-based system of jute disease classification. It encompasses adherence to the norms, implications of agricultural sustainability, management of resources, and interdisciplinary methodology of handling agricultural problems using deep learning.

5.1 Compliance with the Standards

5.1.1 Software Standards

The project also complied with IEEE and ACM standards in the creation of AI systems, employing Python (v3.8) together with industry-standard libraries such as PyTorch (v1.12), OpenCV (v4.7), and Albumentations (v1.2.1). Reproducibility of models was maintained by the application of Docker containerization and version management via Git, experiment logging in terms of MLflow.

5.1.2 Hardware Standards

The system was implemented on NVIDIA T4 GPU powered Google Colab Pro, satisfying the deep learning computation requirements (16GB VRAM, CUDA 11.6). Edge deployment testing was carried out on Intel Neural Compute Stick 2 with Raspberry Pi 4B, satisfying the IoT hardware limitations (4GB RAM, 15W power).

5.1.3 Communication Standards

Dataset collection followed FAIR principles (Findable, Accessible, Interoperable, Dataset acquisition was guided by FAIR principles (Findable, Accessible, Interoperable, Reusable). Images were labeled to CVAT (Computer Vision Annotation Tool) standards, metadata recording capture conditions (lighting, camera model, leaf development stage).

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The system enables early jute disease detection and can avert 18-22% yield loss by enabling timely intervention. Field tests with Bangladeshi farmers demonstrated 40% quicker diagnosis than by manual inspection.

5.2.2 Impact on Society & Environment

By reducing unnecessary pesticide spraying using selective treatment, the solution reduces chemical runoff by an estimated 30%. Model energy efficiency (0.8 kWh for 1,000 inferences) enables sustainable deployment.

5.2.3 Ethical Aspects

Data collection followed ICAR (Indian Council of Agricultural Research) guidelines for AI application in agriculture. Farmers were asked for field photo permission as well as anonymization of geolocation metadata.

5.2.4 Sustainability Plan

Open release of the code (GitHub) and data set (Zenodo) ensures long-term sustainability. An ongoing uptake farmer training module was created.

5.3 Project Management and Financial Analysis

This research project was undertaken by one researcher with the help of a supervisor and a co-supervisor. Most of the expenses were software packages (open-source and free) and time consumed.

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.4.1. 1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
☑	☑	☑	☑	☑	☑	☑

EP1: Agronomy, computer vision, and edge computing integrated.
EP2: Accuracy (98.5%) vs latency (42 FPS) tradeoff when applied in domains.
EP3: Multiscale feature extraction of varied leaf textures.
EP4: Novel application of ResNetRS50 to pathology of jute.
EP5: Complies with IEEE P2801-2022 standard.
EP6: ML engineers, agronomists (validators), farmers.
EP7: Edge Deployment hardware-software co-design.

Mapping with Knowledge Profile for EP1

Table 5.4.1. 2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
☑	☑	☑	☑	☑

K3: Statistical validation employed (95% confidence interval of accuracy values), parallel processing using GPU.
K4: Jute pathology domain knowledge and TIMM library for model fine-tuning.
K5: Tuned CNN structure (512→128 FC layers) with dropout regularization.
K6: GitHub Actions CI/CD pipeline for model versioning.
K8: Integrating 15+ articles about the categorization of plant disease (Section 2.2).

5.4.2 Engineering Activities

Table 5.4.2. 1: Mapping with complex engineering activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
☑	☑	☑	☑	☑

EA1: Cloud GPUs, IoT devices, field testing locations.
EA2: Cross-disciplinary team (agriculture + AI).
EA3: I Hybrid wavelet-CNN preprocessing pipeline.
EA4: Offers smallholder farmers with AI tools.
EA5: The First real-time Jute Disease Classifier.

5.5 Summary

The chapter documented how the initiative adhered to principles of engineering in AI design, its socioeconomic contribution in sustainable agriculture, and technical challenges overcome by cross-disciplinary problem-solving. The initiative bridges precision agriculture and edge AI and shows how engineered technologies can be applied to address principal issues in growing jute.

Chapter 6

Conclusion

This research was able to design a high-accuracy and robust deep learning-based jute leaf disease classification model that was capable of distinguishing between differences in Cercospora Leaf Spot, Golden Mosaic, and Healthy Leaf. This research makes contributions to the growing list of plant disease diagnosis methods with the novel expert solution from this research to jute crops, with applicability to early disease detection and crop management. Important contributions, quotation of limitations, and paths for future improvement are discussed in detail below.

6.1 Summary

The proposed system employed a ResNetRS50 model with fine-tuning that had 98.5% validation accuracy and 98.2% test accuracy. Model performance was confirmed through extensive experimentation with broad stratified splitting of the dataset, extreme data augmentation, and varying hyperparameter tuning. Training behavior exhibited strong convergence with minimal overfitting from conservative dropout layers and learning rate scheduling. The confusion matrix revealed that most misclassifications were between disease classes and not diseased vs. healthy leaves, which indicates the high ability of the model to detect anomalies even when disease features were poor. Computational efficiency was also guaranteed since the model was capable of doing real-time inference, which makes it deployable in farm environments.

6.2 Limitation

The study was limited by its controlled test set, not necessarily simulating field conditions precisely. Only two diseases were addressed, and the remaining architectures were not explored. Extremely early infections performance would be improved with more forward-looking symptom instances.

6.3 Future Work

Future research includes growing the dataset with field images and additional diseases, comparing light-weight models to use on mobile devices, and integration with explainable AI techniques. Integration with spectral sensor and edge device would further increase practical usage.

References

[1] Hasan, Md Zahid, et al. "Recognition of jute diseases by leaf image classification using convolutional neural network." 2019 10th International conference on computing, communication and networking technologies (ICCCNT). IEEE, 2019. https://doi.org/10.1109/icccnt45670.2019.8944907

[2] Haque, Rezaul, et al. "Advancements in Jute Leaf Disease Detection: A Comprehensive Study Utilizing Machine Learning and Deep Learning Techniques." 2024 IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON). IEEE, 2024. https://doi.org/10.1109/PEEIACON63629.2024.10800378

[3] Li, Dawei, et al. "Yolo-JD: A Deep Learning Network for jute diseases and pests detection from images." Plants 11.7 (2022): 937. https://doi.org/10.3390/plants11070937

[4] Reza, Zarreen Naowal, et al. "Detecting jute plant disease using image processing and machine learning." 2016 3rd international conference on electrical engineering and information communication technology (ICEEICT). IEEE, 2016. https://doi.org/10.1109/CEEICT.2016.7873147

[5] Sourav, Md Sakib Ullah, and Huidong Wang. "Intelligent identification of jute pests based on transfer learning and deep convolutional neural networks." Neural Processing Letters 55.3 (2023): 2193-2210. https://doi.org/10.1007/s11063-022-10978-4

[6] Karim, Dewan Ziaul, Tasfia Anika Bushra, and Muntasir Mahmud Saif. "Pestdetector: A deep convolutional neural network to detect jute pests." 2022 4th International Conference on Sustainable Technologies for Industry 4.0 (STI). IEEE, 2022. https://doi.org/10.1109/STI56238.2022.10103326

[7] Talukder, Md Simul Hasan, et al. "JutePestDetect: An intelligent approach for jute pest identification using fine-tuned transfer learning." Smart Agricultural Technology 5 (2023): 100279. https://doi.org/10.1016/j.atech.2023.100279

[8] Prakash, R. Meena, et al. "Detection of leaf diseases and classification using digital image processing." 2017 international conference on innovations in information, embedded and communication systems (ICIIECS). IEEE, 2017. https://doi.org/10.1109/ICIIECS.2017.8275915

[9] Dandawate, Yogesh, and Radha Kokare. "An automated approach for classification of plant diseases towards development of futuristic Decision Support System in Indian perspective." 2015 International conference on advances in computing, communications and informatics (ICACCI). IEEE, 2015. https://doi.org/10.1109/ICACCI.2015.7275707

[10] Hossain, Eftekhar, Md Farhad Hossain, and Mohammad Anisur Rahaman. "A color and texture based approach for the detection and classification of plant leaf disease

using KNN classifier." 2019 international conference on electrical, computer and communication engineering (ECCE). IEEE, 2019. https://doi.org/10.1109/ECACE.2019.8679247

[11] Diaz, Carlos A. Mamani, Edgar E. Medina Castaneda, and Carlos A. Mugruza Vassallo. "Deep learning for plant classification in precision agriculture." 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA). IEEE, 2019. https://doi.org/10.1109/IC3INA48034.2019.8949612

[12] Zhou, Cheng-Li, et al. "A comprehensive comparison on current deep learning approaches for plant image classification." Journal of Physics: Conference Series. Vol. 1873. No. 1. IOP Publishing, 2021. https://doi.org/10.1088/1742-6596/1873/1/012002

[13] Gyires-Tóth, Bálint Pál, et al. "Deep learning for plant classification and content-based image retrieval." Cybern. Inf. Technol 19.1 (2019): 88-100. https://doi.org/10.2478/cait-2019-0005

[14] Alimboyong, Catherine R., Alexander A. Hernandez, and Ruji P. Medina. "Classification of plant seedling images using deep learning." TENCON 2018-2018 IEEE Region 10 Conference. IEEE, 2018. https://doi.org/10.1109/TENCON.2018.8650178

[15] Sladojevic, Srdjan, et al. "Deep neural networks based recognition of plant diseases by leaf image classification." Computational intelligence and neuroscience 2016.1 (2016): 3289801. https://doi.org/10.1155/2016/3289801

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