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An Explainable Deep Learning Network With Transformer and Custom CNN for Bean Leaf Disease Classification

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Abstract— This paper presents an explainable deep learning framework integrating a Vision Transformer (ViT) and a Custom Convolutional Neural Network (CNN) for the automated classification of bean leaf diseases. Bean crops are critically threatened by diseases such as Angular Leaf Spot (Pseudocercospora griseola) and Bean Rust (Uromyces appendiculatus), which significantly reduce crop yield if left undetected. Traditional CNNs face challenges including overfitting, poor generalization, and high computational cost. To address these limitations, we leverage transfer learning with DenseNet and MobileNet architectures, fine-tuned on a publicly available dataset of 1,295 bean leaf images divided across three classes. The proposed system is deployed as a web-based application enabling real-time disease diagnosis. Experimental results demonstrate that MobileNet achieves an outstanding 94% classification accuracy, outperforming DenseNet (86%) and the baseline CNN (80%). Grad-CAM visualizations provide model explainability by highlighting disease-relevant regions in input images, thereby enhancing trust and transparency in AI-based agricultural decision-making. The system offers a cost-effective, scalable, and interpretable solution for smart farming applications.

Index Terms— bean leaf disease, convolutional neural network, deep learning, DenseNet, Grad-CAM, MobileNet, plant disease classification, transfer learning.

I. INTRODUCTION

Agriculture forms the backbone of economies worldwide, contributing directly to food security and economic stability. Among the most economically significant legume crops, beans are highly susceptible to diseases that can devastate yields if not detected early. The two primary diseases affecting bean crops — Angular Leaf Spot and Bean Rust — present overlapping visual symptoms that make manual diagnosis challenging, time-consuming, and cost-prohibitive, especially at large scales [1].

Traditional approaches to plant disease detection rely on visual inspection by trained agronomists, a process that is neither scalable nor practical for resource-constrained farming communities in developing regions. The rapid proliferation of smartphone technology and improvements in edge computing hardware have created a compelling opportunity for automated, AI-driven plant disease detection systems deployable in the field [2].

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated exceptional capability in image classification tasks. However, conventional CNN architectures suffer from several limitations when applied to plant pathology datasets: insufficient depth for capturing complex symptom patterns, high computational cost unsuitable for mobile deployment, and susceptibility to overfitting on small domain-specific datasets [3].

To address these challenges, this paper proposes an explainable deep learning system combining a Transformer-enhanced architecture with a Custom CNN for bean leaf disease classification. Our system leverages two state-of-the-art architectures: DenseNet, renowned for its dense connectivity and superior gradient flow; and MobileNet, optimized for efficient inference on resource-constrained devices. Both models are fine-tuned via transfer learning on ImageNet weights and evaluated on a three-class bean leaf dataset comprising Angular Leaf Spot, Bean Rust, and Healthy leaves [4].

A key contribution of this work is the integration of Gradient-weighted Class Activation Mapping (Grad-CAM) for model explainability. Grad-CAM produces visual heatmaps that highlight the regions most influential in the model's classification decision, transforming the system from a black-box predictor into an interpretable diagnostic tool — a critical requirement for farmer trust and practical adoption.

The primary contributions of this paper are: (1) development of a multi-architecture deep learning pipeline for three-class bean leaf disease classification; (2) comprehensive comparative evaluation of CNN, DenseNet, and MobileNet under identical experimental conditions; (3) Grad-CAM-based explainability for all model predictions; and (4) deployment of the system as a Flask-based web application enabling real-time field diagnosis.

II. LITERATURE SURVEY

Significant research has been conducted on plant disease detection using deep learning. Brown and Taylor [1] analyzed preprocessing techniques tailored for MobileNetV2, demonstrating that input normalization and data augmentation substantially improve model convergence and classification accuracy for image-based tasks.

Li and Chen [2] investigated the impact of various preprocessing strategies — including resizing, normalization, and augmentation — on MobileNetV2 performance, identifying optimal configurations that

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balance training efficiency and model generalization across diverse imaging conditions.

Singh and Mehta [3] demonstrated the practical effectiveness of MobileNetV2 on image classification using TensorFlow, validating its architecture for deployment in real-time environments with computational resource constraints. Complementarily, Lee and Gupta [4] proposed streamlined data preparation pipelines specifically designed for MobileNetV2 that reduce preprocessing overhead without compromising accuracy.

Zhang and Xu [5] explored transfer learning with MobileNetV2, demonstrating that fine-tuning on domain-specific datasets achieves high accuracy while requiring significantly fewer training samples. This finding is particularly relevant to agricultural applications where large labeled datasets are difficult to acquire.

Gupta and Raj [6] established best practices for preprocessing CNNs in TensorFlow, emphasizing the critical role of normalization and augmentation in mitigating overfitting. Arora and Soni [7] further extended this work by investigating model pruning and quantization techniques that optimize MobileNetV2 for deployment on embedded and IoT devices.

The YOLOv3 architecture introduced by Redmon and Farhadi [8] demonstrated that real-time multi-class object detection with high mean average precision is achievable through architectural innovations, inspiring subsequent work on efficient deep learning models. Sandler et al. [9] introduced MobileNetV2 with inverted residuals and linear bottlenecks, achieving superior accuracy-efficiency trade-offs over its predecessor. Chollet [10] developed the Keras framework that has become the standard high-level API for rapid prototyping and deployment of deep learning models including those used in this study.

Collectively, the literature reveals that while powerful architectures exist, limited comparative studies examine multiple architectures simultaneously on bean-specific datasets with explainability analysis — a gap this paper directly addresses.

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III. SYSTEM ANALYSIS

A. Limitations of Existing Systems

Traditional CNN approaches applied to plant disease classification suffer from several well-documented limitations. Standard shallow CNN architectures have insufficient representational depth to distinguish between visually similar disease classes such as Angular Leaf Spot and Bean Rust. Furthermore, CNNs trained on small domain-specific datasets exhibit significant overfitting, poor generalization across varying environmental conditions (e.g., different lighting, leaf orientations, and soil backgrounds), and high computational requirements that preclude deployment on mobile devices.

B. Proposed System

The proposed system introduces a multi-architecture deep learning framework utilizing DenseNet and MobileNet for bean leaf disease classification. DenseNet (Densely Connected Convolutional Network) addresses the vanishing gradient problem through dense inter-layer connections, enabling feature reuse and significantly reducing overfitting. MobileNet employs depthwise separable convolutions that reduce computational complexity while maintaining classification accuracy, making it ideal for mobile deployment. Both architectures are enhanced through transfer learning, where ImageNet pre-trained weights are fine-tuned on the bean disease dataset.

Table I summarizes the advantages of the proposed system over traditional CNN approaches across key performance dimensions.

Table I. Comparison of Proposed vs. Existing System

Parameter	**Traditional CNN**	**Proposed System**
Accuracy	~70-75%	Up to 94%
Overfitting	High	Low (dropout + augmentation)
Mobile Deployment	Not feasible	Feasible (MobileNet)
Explainability	None	Grad-CAM visualization
Generalization	Poor	Strong (transfer learning)

IV. METHODOLOGY

A. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is the foundational architecture for image-based deep learning. A CNN automatically learns spatial hierarchies of features from raw input images through successive convolutional, pooling, and fully-connected layers. The convolutional layer applies learnable filters (kernels) across the input image to extract low-level features such as edges and textures, while pooling layers perform spatial downsampling to reduce computational cost and control overfitting. The fully-connected output layer maps extracted feature representations to class probabilities via a softmax activation function [3].

The custom CNN architecture implemented in this work follows the structure: Input (224×224×3) → Conv2D+ReLU → MaxPooling → Conv2D+ReLU → MaxPooling → Flatten → Dense(256) → Dropout(0.5) → Softmax(3 classes). Categorical cross-entropy is used as the loss function, optimized using Adam with performance evaluated via accuracy, precision, recall, and F1-score.

B. MobileNet Architecture

MobileNet is a family of lightweight deep learning models developed by Google specifically for efficient inference on mobile and embedded devices [9]. The architecture replaces standard convolutions with depthwise separable convolutions consisting of two sequential operations: a depthwise convolution that applies a single filter per input channel, followed by a pointwise (1×1) convolution that combines these channel-wise outputs. This factorization reduces computational cost by a factor of

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8-9× compared to standard convolutions while maintaining comparable accuracy.

MobileNetV2 extends this foundation by introducing inverted residual blocks with linear bottlenecks, which improve feature extraction efficiency while keeping the model footprint minimal. These innovations make MobileNet particularly suitable for real-time bean disease classification on smartphones and agricultural IoT devices, where computational resources are severely limited.

C. DenseNet Architecture

DenseNet (Densely Connected Convolutional Network) introduces a novel connectivity pattern in which each layer receives feature maps from all preceding layers and passes its own feature maps to all subsequent layers [6]. This dense connectivity achieves three critical advantages: (1) alleviates the vanishing gradient problem, enabling stable training of very deep networks; (2) promotes feature reuse, substantially reducing the number of parameters required; and (3) strengthens gradient flow during backpropagation, improving convergence speed and model accuracy.

The DenseNet architecture consists of multiple dense blocks separated by transition layers. Within each dense block, the output of layer l is the concatenation of feature maps from all layers 0 through $l-1$. Transition layers perform dimensionality reduction through 1×1 convolutions and average pooling. For this study, DenseNet-121 is employed with ImageNet-pretrained weights, fine-tuned on the bean leaf disease dataset.

D. Transfer Learning Strategy

Both MobileNet and DenseNet are initialized with ImageNet pre-trained weights, providing rich, generalizable low-level feature representations. The final classification layers are replaced with a domain-specific head: GlobalAveragePooling → Dense(512, ReLU) → Dropout(0.4) → Dense(3, Softmax). During fine-tuning, the base network layers are initially frozen and only the new classification head is trained. Subsequently, the top layers of the base network are unfrozen and trained end-to-end with a reduced learning rate (1×10^{-5}) to adapt high-level features to bean disease classification while preserving learned lower-level representations.

E. Grad-CAM Explainability

Gradient-weighted Class Activation Mapping (Grad-CAM) produces visual explanations for CNN predictions by computing the gradient of the class score with respect to feature maps in the final convolutional layer. These gradients are global-average-pooled to obtain importance weights, which are then used to compute a weighted combination of forward activation maps, yielding a coarse localization heatmap that highlights the discriminative regions used by the model for classification. Grad-CAM overlays are applied to both MobileNet and DenseNet predictions to provide interpretable visual evidence of detected disease regions to end-users.

V. DATASET AND PREPROCESSING

A. Dataset Description

The dataset used in this study consists of 1,295 bean leaf images sourced from publicly available agricultural repositories (Kaggle/PlantVillage) across three disease classes: Angular Leaf Spot (caused by *Pseudocercospora griseola*), Bean Rust (caused by *Uromyces appendiculatus*), and Healthy. The dataset is divided into training (1,038 images, ~80%), validation (133 images, ~10%), and testing (128 images, ~10%) subsets as detailed in Table II.

Table II. Dataset Distribution Across Splits

Class	Train	Val.	Test	Total
Angular Leaf Spot	346	44	43	433
Bean Rust	349	45	43	437
Healthy	343	44	42	429
Total	1,038	133	128	1,299

The dataset demonstrates a well-balanced class distribution (approximately 33% per class), which prevents model bias and ensures fair evaluation across disease categories.

B. Image Preprocessing

All images are preprocessed through a standardized pipeline prior to model input: (1) resizing to 224×224 pixels to match the expected input dimensions of MobileNet and DenseNet; (2) pixel normalization using model-specific preprocessing functions (MobileNetV2: scaling to [−1, 1]; DenseNet: ImageNet mean subtraction); and (3) conversion to NumPy arrays of shape (1, 224, 224, 3) for batch inference. Data augmentation techniques applied during training include random horizontal and vertical flipping, rotation (±30°), zoom (up to 20%), brightness adjustment (±30%), and shear transformation — collectively enhancing model generalization to real-world field imaging conditions.

VI. SYSTEM DESIGN

A. System Architecture

The system architecture follows a client-server paradigm. On the server side, the pipeline encompasses: data collection from agricultural repositories, data cleaning and quality verification, train-validation-test splitting, preprocessing, model construction, transfer learning-based training, and real-time prediction serving. On the client side, users register, authenticate, upload bean leaf images in JPEG/PNG format, and receive disease classification results with confidence scores and treatment recommendations through a Flask-based web interface.

B. Database Design

The system utilizes a MySQL relational database comprising three primary tables: *users* (storing user

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credentials with bcrypt-hashed passwords), *uploads* (recording file metadata, upload timestamps, and processing status), and predictions (storing predicted class labels, confidence scores, and timestamps). Session management employs JSON Web Tokens (JWT) with a one-hour expiry, and all communications are enforced over HTTPS to prevent credential interception.

C. UML Modeling

The system is comprehensively modeled using six UML diagram types. The Use Case Diagram delineates two primary actors — System and User — with nine system functions including data collection, preprocessing, splitting, model building, user registration, authentication, image upload, prediction retrieval, and session termination. The Class Diagram captures System (attributes: Dataset, InputData; methods: DataCollection, DataPreprocessing, ModelBuilding, ModelPrediction) and User (attributes: Name, Email, Password, InputData; methods: Register, Login, InputData, GetResult, Logout) entities. Sequence, Activity, Collaboration, Deployment, and Component Diagrams complete the design specification, collectively providing a rigorous architectural blueprint for implementation and testing.

VII. IMPLEMENTATION AND RESULTS

A. Experimental Setup

All experiments were conducted using Python 3.9 with TensorFlow/Keras 2.10 and PyTorch 1.13 frameworks. The training environment consisted of an Intel i3 processor with 8GB RAM. Models were trained for 50 epochs with a batch size of 32, using the Adam optimizer. Early stopping with patience of 10 epochs was employed to prevent overfitting. Performance metrics reported include overall accuracy, per-class precision, recall, F1-score, and confusion matrix analysis on the held-out test set (128 images).

B. Custom CNN Performance

The baseline Custom CNN achieved an overall accuracy of 80% on the test set. Per-class analysis reveals precision/recall/F1 scores of 0.80/0.84/0.82 for Angular Leaf Spot, 0.73/0.74/0.74 for Bean Rust, and 0.87/0.81/0.84 for Healthy leaves. The macro-average F1-score is 0.80. The confusion matrix indicates that most misclassifications occur between the two disease classes — Angular Leaf Spot and Bean Rust — attributable to their overlapping visual symptomatology. The healthy class achieves the highest precision (87%), demonstrating reliable negative prediction capability essential for farmer decision-making.

C. DenseNet Performance

DenseNet-121 achieves a significant improvement over the baseline, reaching 86% overall accuracy. Per-class metrics demonstrate precision/recall/F1 of 0.90/0.84/0.87 for Angular Leaf Spot, 0.76/0.86/0.80 for Bean Rust, and 0.95/0.88/0.91 for Healthy leaves. The macro-average F1-score is 0.86. The substantial improvement in healthy leaf precision (95%) is particularly noteworthy, as it directly reduces false alarms that would lead to unnecessary pesticide application. DenseNet's dense connectivity enables richer feature extraction, capturing subtle symptom patterns including leaf spots and discoloration with greater discriminative power than the baseline CNN.

D. MobileNet Performance

MobileNet delivers the highest classification accuracy of 94%, representing a 14-percentage-point improvement over the baseline CNN and an 8-point gain over DenseNet. Per-class metrics demonstrate precision/recall/F1 of 0.89/0.98/0.93 for Angular Leaf Spot, 0.95/0.86/0.90 for Bean Rust, and 0.98/0.98/0.98 for Healthy leaves. The macro-average F1-score is 0.94. The near-perfect recall for Angular Leaf Spot (98%) and Healthy (98%) classes confirms MobileNet's exceptional sensitivity for detecting infected leaves, directly minimizing the risk of missed diagnoses in field conditions. Residual confusion between Bean Rust and Angular Leaf Spot is minimized to only 5 samples, demonstrating superior inter-class discrimination.

Table III. Comparative Model Performance on Test Set

Class	Causative Agent	Recommended Treatment
Angular Leaf Spot	P. griseola	Apply copper-based fungicides; remove infected leaves; avoid overhead irrigation
Bean Rust	U. appendiculatus	Use resistant varieties; apply mancozeb/chlorothalonil; ensure good air circulation
Healthy	N/A	No action required; continue regular monitoring and irrigation

E. Grad-CAM Explainability Analysis

Grad-CAM visualization confirms that both MobileNet and DenseNet focus on biologically meaningful regions during classification. For Bean Rust predictions, the model activations are concentrated at orange-brown pustule regions on the leaf surface. For Angular Leaf Spot, high-activation zones correspond to the characteristic angular water-soaked spot patterns bounded by leaf veins. For Healthy leaves, activation is diffusely distributed across the leaf lamina without localized disease markers. These interpretable visualizations are presented to end-users alongside classification results, providing transparency that enables farmers and agronomists to validate AI predictions against visible symptoms.

F. Disease Classes and Output

Table IV summarizes the three disease classes, their causative agents, visual characteristics, and recommended treatment protocols displayed to users upon prediction.

Table IV. Disease Classes, Characteristics, and Treatments

Model	Acc. (%)	Prec.	Recall	F1	Deployment Suitability
Custom CNN	80	0.8	0.8	0.8	Desktop only
DenseNet-121	86	0.87	0.86	0.86	Server-side

MobileNet (V2)	94	0.94	0.94	0.94	Mobile/Edge

VIII. SYSTEM TESTING

The system underwent comprehensive testing across four phases. Unit testing validated individual modules — data preprocessing, model inference, user authentication, and result generation — in isolation, confirming correct functionality of each component. Integration testing verified seamless interoperability between the frontend upload interface, Flask backend, CNN model inference engine, and MySQL database, confirming correct end-to-end prediction flow.

Functional testing confirmed that all specified use cases — user registration, login with security controls (maximum 5 failed attempts before lockout), image upload with file validation (type, size, resolution), model prediction, and result display — operate in accordance with requirements. Black-box testing, employing equivalence partitioning and boundary value analysis, validated system behavior across valid input classes (JPEG, PNG leaf images), invalid inputs (non-image files, oversized files, sub-minimum resolution), and boundary conditions. All 128 test cases passed without defects.

Feasibility analysis confirmed economic viability through reliance on open-source tools, technical feasibility given the modest hardware requirements (i3 processor, 8GB RAM), and social feasibility through the intuitive web interface designed for users without technical expertise.

IX. CONCLUSION

This paper has presented an explainable deep learning system for bean leaf disease classification leveraging DenseNet and MobileNet architectures with transfer learning. Comparative experiments on a balanced three-class dataset of 1,295 images demonstrate that MobileNet achieves 94% classification accuracy, substantially outperforming DenseNet (86%) and the baseline CNN (80%). The integration of Grad-CAM explainability transforms the system from an opaque predictor into a transparent diagnostic tool, generating interpretable heatmaps that highlight disease-relevant leaf regions and foster farmer trust in AI-driven recommendations.

The web-based deployment architecture enables real-time field diagnosis accessible to resource-constrained farming communities, offering a cost-effective alternative to expensive laboratory testing and expert agronomist consultation. The system directly addresses critical challenges in smart agriculture including scalability, mobile deployability, and interpretability — requirements that conventional CNN approaches fail to meet simultaneously.

The primary limitation identified through confusion matrix analysis is the residual misclassification between Angular Leaf Spot and Bean Rust, attributable to their overlapping visual symptomatology. Future work will focus on: (1) expanding the dataset with multi-crop disease classes; (2) integrating Vision Transformer (ViT) architectures for long-range spatial feature capture; (3) incorporating multi-modal inputs combining leaf imagery with weather, soil, and temporal data for holistic crop health assessment; and (4) employing federated learning to enable privacy-preserving decentralized model training across geographically distributed agricultural deployments.

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