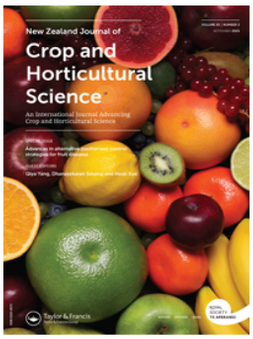

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Hybrid deep learning model for maize leaf disease classification with explainable AI

Yıldırım Özüpak [a], Feyyaz Alpsalaz[b], Emrah Aslan[c] and Hasan Uzel[b]

[a]Department of Electricity and Energy, Dicle University, Diyarbakır, Turkey; [b]Department of Electricity and Energy, Yozgat Bozok University, Yozgat, Turkey; [c]Department of Computer Engineering, Faculty of Engineering and Architecture, Mardin Artuklu University, Mardin, Turkey

ABSTRACT

This study presents a hybrid learning model that integrates MobileNetV2 and Vision Transformer (ViT) with a stacking model to classify maize leaf diseases, addressing the critical need for early detection to improve agricultural productivity and sustainability. Utilising the 'Corn or Maize Leaf Disease Dataset' from Kaggle, comprising 4,062 high-resolution images across five classes (Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight, Not Maize Leaf), the model achieves an impressive accuracy of 96.73%. Transfer learning from ImageNet, coupled with data augmentation (rotation, flipping, scaling, brightness adjustment), enhances generalisation, while a 20% dropout rate mitigates overfitting. The key advantage of the hybrid model lies in its ability to combine the strengths of MobileNetV2's localised feature extraction and ViT's global context understanding, enhanced by the stacking model's ability to reduce the weaknesses of either model. Explainable AI techniques, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Grad-CAM, provide transparent insights into model decisions, fostering trust among agricultural stakeholders. Comparative analysis demonstrates the model's superiority over prior works, with F1-scores ranging from 0.9276 to 1.0000. Despite minor misclassifications due to visual similarities, the model offers a robust, interpretable solution for precision agriculture.

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Maize leaf disease; hybrid deep learning; MobileNetv2; vision transformer; explainable AI

Introduction

Maize is one of the most widely produced and consumed agricultural crops in the world and is important for food, feed and industrial uses. However, various fungal, bacterial and viral diseases that threaten maize production can result in reduced product quality and severe economic losses (Thai and Le 2025). Early detection and correct classification of these diseases can not only increase agricultural productivity, but also contribute to environmental sustainability by optimising the use of chemical pesticides (Barman et al. 2024). Traditional methods of disease detection usually involve visual inspection by agricultural experts, which is time consuming, costly and requires expertise

CONTACT Yıldırım Özüpak yildirim.ozupak@dicle.edu.tr
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(Pfordt and Paulus 2024). In addition, manual diagnostic methods are often subjective and diagnostic accuracy may vary depending on personal experience and observational skills (Elmasry et al. 2024). In this context, artificial intelligence and deep learning-based approaches have the potential to automate agricultural diagnostic processes and provide faster, more reliable and cost-effective solutions (Malik et al. 2024). In recent years, deep learning and computer vision methods have played an important role in plant disease detection. In the literature, the effectiveness of Convolutional Neural Networks (CNN), Transfer Learning and Transformer-based models in this field has been widely documented (Abbod et al. 2025). For example, models based on Faster-RCNN and ResNet-50 detected maize leaf diseases with high accuracy (Verma et al. 2024), segmentation-based models such as Attention U-Net have been shown to distinguish specific disease regions with precision, and real-time detection systems such as YOLO (You Only Look Once) can be integrated with mobile applications (Agarwal et al. 2024). However, most of these studies have focused on specific model architectures and have some limitations in terms of generalisability, computational efficiency and explainability of model decisions (Dolatabadian et al. 2025).

Maize, a cornerstone of global agriculture, is vital for food, feed and industrial applications. However, fungal, bacterial and viral diseases threaten its yield and quality, resulting in significant economic losses. Early and accurate disease detection is critical to increasing productivity and promoting sustainable agriculture by reducing pesticide use. Traditional visual inspection by experts is labour-intensive, costly and prone to subjective errors, requiring automated solutions. Deep learning, particularly CNNs and transformer-based models, has shown promise in automating plant disease diagnosis with high accuracy. This study proposes a hybrid deep learning model combining MobileNetV2 and ViT to classify maize leaf diseases, using transfer learning and data augmentation for improved generalisation. To further improve performance, a stacking ensemble model was incorporated, integrating support vector machine (SVM), random forest, logistic regression and k-nearest neighbour (KNN) as base models, with a logistic regression meta-model trained via 5-fold cross-validation to combine their predictions. An alternative stacking approach aggregated probability predictions from these base models, refined by a logistic regression meta-model, to capture complex patterns and improve classification accuracy. The model achieves high accuracy and computational efficiency suitable and incorporates Explainable AI (XAI) techniques such as SHAP, LIME and Grad-CAM to improve interpretability. By overcoming limitations in generalisability and computational requirements, this work aims to advance precision agriculture and support farmers with reliable, transparent and scalable disease detection tools.

In recent years, advancements in artificial intelligence (AI), particularly in deep learning and computer vision, have transformed plant disease detection, offering faster, more precise, and cost-effective alternatives to conventional methods. CNNs transfer learning, and transformer-based models have demonstrated remarkable success in identifying disease symptoms with high accuracy, as evidenced by studies employing architectures like Faster-RCNN, ResNet-50, and YOLO for real-time detection. Despite these advancements, existing approaches often struggle with generalisability across diverse datasets, computational efficiency in resource-constrained environments, and interpretability of model decisions, which are critical for fostering trust among agricultural stakeholders.

To address these challenges, this study proposes a novel hybrid deep learning model that integrates MobileNetV2 and ViT with a stacking ensemble framework to classify maize leaf diseases. This work stands out for three key reasons:

- The hybrid model achieves an impressive accuracy of 96.73% on the Kaggle 'Corn or Maize Leaf Disease Dataset,' surpassing state-of-the-art models such as 3DCNN-RNN and AlexNet, by effectively combining MobileNetV2's localised feature extraction with ViT's global contextual understanding and a stacking ensemble's robust classification.
- The integration of explainable AI techniques, including SHAP, Local Stuarts, LIME, and Grad-CAM, provides transparent visualisations of disease-specific features, enabling farmers and agronomists to understand and trust model decisions.
- Leveraging MobileNetV2's lightweight architecture, the model is optimised for resource-constrained devices, facilitating potential deployment in field applications for real-time maize disease detection, thus enhancing its practical utility in precision agriculture.

The proposed model leverages MobileNetV2's efficiency in extracting localised features and ViT's strength in capturing global contextual dependencies, achieving superior classification performance. The stacking ensemble, incorporating SVM, random forest, logistic regression, and KNN as base models, further enhances accuracy through a logistic regression meta-model trained via 5-fold cross-validation. Data augmentation techniques, including rotation, flipping, and brightness adjustment, are employed to improve robustness and generalisation. Evaluated on the 'Corn or Maize Leaf Disease Dataset' from Kaggle, comprising 4,062 high-resolution images across five classes (Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight, and Not Maize Leaf), this study delivers a computationally efficient, interpretable, and highly accurate solution for automated disease detection.

In conclusion, this study aims to contribute to the literature on deep learning-based and stacking integration maize foliar disease diagnosis and make disease management more effective in agricultural production. Due to the high accuracy, computational efficiency and explainability of the model, it is expected to be widely used in agricultural applications in the future to help farmers in early diagnosis.

Literature review

Maize is a critical crop for global food and industrial needs, but fungal, bacterial, and viral diseases can significantly reduce its yield and quality. Traditional disease diagnosis is slow, expensive, and requires expertise. Deep learning and AI-based methods provide fast, accurate, and cost-effective alternatives by automating detection. Techniques like image processing, object recognition, CNNs, machine learning, transfer learning, and transformer models have shown success in identifying disease symptoms on maize leaves. This section reviews AI, deep learning and stacking learning applications for maize disease diagnosis.

Ashwini et al. proposed a hybrid 3DCNN-RNN model optimised by JSWOA for maize leaf disease prediction. The model enhances 3D image recognition with optimised

hyperparameters. It achieved over 90% performance on Maize_in_field and KaraAgro AI datasets (Ashwini and Sellam 2024). Mafukidze et al. developed a CNN-based system for maize leaf disease classification and quantification without expert input. Using transfer learning, they achieved up to 99% classification accuracy. An adaptive thresholding technique extracts regions of interest from class activation maps to estimate disease severity accurately (Mafukidze et al. 2022). Albahli et al. proposed EANet, an end-to-end CNN based on EfficientNetv2, for multi-class maize leaf disease identification. Incorporating a spatial-channel attention mechanism and trained with focal loss and transfer learning, EANet enhances feature representation and achieves superior performance on diverse, noisy datasets (Albahli and Masood 2022). Zhang et al. proposed a CNN with a Multi-Activation Function (MAF) module for maize leaf disease detection, achieving 97.41% accuracy. Using image pre-processing and transfer learning, it detects maculopathy, rust, and blight. MAF, with Sigmoid, ReLU, and Mish, boosted ResNet50 accuracy by 2.33% (Zhang et al. 2021). Singh et al. utilised the AlexNet model for accurate maize leaf disease detection, achieving 99.16% accuracy on the PlantVillage dataset. The model identifies Cercospora, Grey leaf-spot, and Common rust diseases, automatically extracting features from raw images, offering a practical tool for farmers (Singh et al. 2022).

Singh et al. developed a novel approach using Random Forest Classifiers and CNNs for diagnosing maize diseases like Maize Dwarf Mosaic Virus and Northern Corn Leaf Blight. By leveraging a diverse dataset with image augmentation and preprocessing, the model accurately detects diseases, aiding farmers in improving maize yield (Singh et al. 2024). Verma et al. developed a lightweight CNN model for disease detection in corn, rice, and wheat, achieving 84.4% accuracy with 387,340 parameters. Using variable-sized convolution layers, it outperforms VGG16 and ResNet50, enabling efficient, real-time crop disease detection in resource-constrained settings (Verma et al. 2024). Ahadiana et al. used CNNs to classify maize plant diseases, leveraging ResNet-18, VGG16, and EfficientNet on two datasets (4144 and 5155 images). VGG16 achieved 97.146% accuracy on the first dataset, while EfficientNet with weighted loss reached 94.798% on the imbalanced second dataset using SGD optimisation (Ahadian et al. 2024). Gopalan et al. developed a ResNet152 model with Grad-CAM for classifying corn leaf diseases, using 4188 images across four classes. Achieving 99.95% training and 98.34% testing accuracy, the model offers interpretable heatmaps, enhancing trust and aiding farmers in accurate disease diagnosis to improve yields (Gopalan et al. 2025). Thanjaivadivel et al. proposed an enhanced CNN with depthwise separable convolution and inverted residual blocks for detecting leaf diseases in plants like corn and tomato. Using global average pooling, the model achieves high accuracy across 39 classes, outperforming traditional ML and deep learning approaches (Thanjaivadivel et al. 2025).

Rahman et al. developed a real-time plant disease detection system using deep learning, with a dataset of 30,945 images across eight plants, including corn. A custom CNN achieved 95.62% accuracy, with corn disease detection at 98%. A web/mobile app was created for disease identification and treatment suggestions (Rahman et al. 2025). Khandagale et al. proposed FourCropNet, a deep learning model for disease detection in cotton, grape, soybean, and corn. Using residual blocks, attention mechanisms, and lightweight layers, it achieved high accuracy for corn and 95.3% for combined datasets,

outperforming MobileNet, VGG16, and EfficientNet (Khandagale et al. 2025). Handrizal et al. utilised a CNN to identify diseases in corn leaves, addressing the inefficiencies of manual diagnosis. Trained on a labelled dataset of corn leaf images, the model achieved 95% accuracy, precision, recall, and F1 score, enabling efficient early disease detection (Yustika Manik and Sianturi 2024). Iftikhar et al. developed an optimised E-CNN model for early detection of leaf diseases in apple, corn, and potato crops, achieving 98.17% accuracy in fungal classes. Fine-tuned with data augmentation, the model integrates with a mobile app for real-time disease detection and treatment guidance, enhancing agricultural productivity (Iftikhar et al. 2024). Dash et al. applied 13 pre-trained CNN models to detect maize diseases (Leaf-blight, Common Rust, Grey Leaf Spot) using 4,988 images. DenseNet201 achieved the highest accuracy and lowest False Positive Rate, while VGG-19 performed the worst, as evaluated through multiclass statistical analysis (Dash and Sethy 2024).

Material and method

This study proposes a hybrid deep learning model combining MobileNetV2 and ViT to classify maize leaf diseases. The model processes RGB images of 224 × 224 pixels, extracting features through three convolutional layers in the MobileNetV2 branch, capturing basic (edges, textures) to complex (disease patterns) features. The ViT branch processes image patches to capture global dependencies. To prevent overfitting, a dropout rate of 20% was applied, determined through empirical tuning to balance model capacity and generalisation. The Adam optimizer and Sparse Categorical Crossentropy loss function were used, with a learning rate of 0.001 and batch size of 32 over 50 epochs. Data augmentation techniques, including rotation, flipping, scaling, and brightness adjustment, were employed to enhance model robustness. To further improve classification performance, a stacking ensemble was integrated, combining predictions from support vector machine, Random Forest, Logistic Regression, and k-nearest neighbours' models through a cross-validated learning framework, with an additional probability-based stacking variant to optimise decision boundaries. Performance was evaluated using accuracy, precision, recall, and F1-score, ensuring comprehensive assessment across the dataset's five classes.

Dataset

The study utilised the 'Corn or Maize Leaf Disease Dataset' from Kaggle (Corn or Maize Leaf Disease). which includes four common maize leaf diseases: Healthy, Cercospora Leaf Spot, Common Rust, and Northern Leaf Blight. This dataset contains 4,062 high-resolution JPG images, divided into training (80%), testing (10%), and validation (10%) subsets. Images were captured under varying lighting, leaf angles, and scales, with data augmentation techniques like rotation and flipping applied to increase diversity. A slight class imbalance was addressed through strategic sampling or weighting during model training. Structured to evaluate deep learning models, such as Convolutional Neural Networks, the dataset supports the development of automated disease detection systems for agriculture. Accessible via Kaggle, it serves as a valuable resource for AI

research, promoting sustainable farming by enabling early disease diagnosis to minimise crop losses.

Figure 1 presents six different images of maize leaves and illustrates the various conditions (Healthy, Northern Leaf Blight, Grey Leaf Spot and Common Rust). The healthy leaf is characterised by its green hue and undamaged structure, while Northern Leaf Blight is characterised by longitudinal grey-brown lesions. Grey Leaf Spot contains oblong-shaped brown spots surrounded by a yellowish ring, while Common Rust is characterised by small, reddish-brown pustules. These visual differences reveal the distinctive features of the disease symptoms observed on maize leaves from an academic perspective.

Figure 2 shows the class distribution in the maize leaf dataset with a histogram and pie chart. The histogram shows the numerical distribution of the classes Common Rust (1907), Northern Leaf Blight (1908), Healthy (1859), Grey Leaf Spot (1642) and Non-Corn Leaf (1536). The pie chart shows the percentages of these classes: Common Rust 21.5%, Northern Leaf Blight 21.6%, Healthy 21.0%, Grey Leaf Spot 18.5% and Non-Corn Leaf 17.4%. This distribution assesses the class balance and diversity in the dataset from an academic perspective.

Deep learning

Deep learning has revolutionised artificial intelligence by leveraging its ability to process vast datasets. A key driver of this transformation is computer vision, which empowers machines to interpret visual information. This technology finds applications in diverse fields, including facial recognition, self-driving cars, medical imaging, object detection,

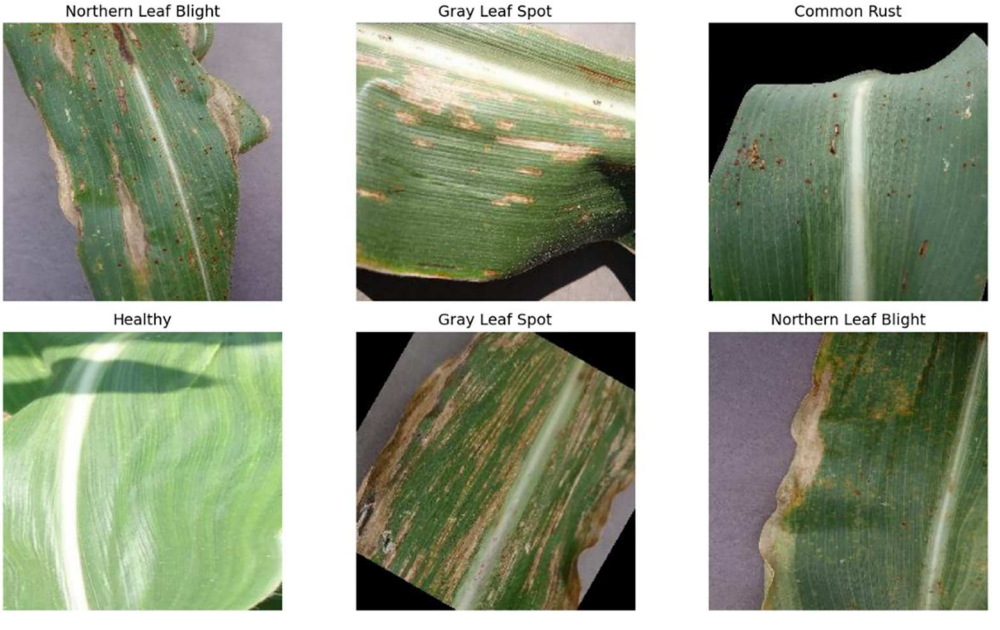

Figure 1. Example pictures of healthy and diseased maize leaves.

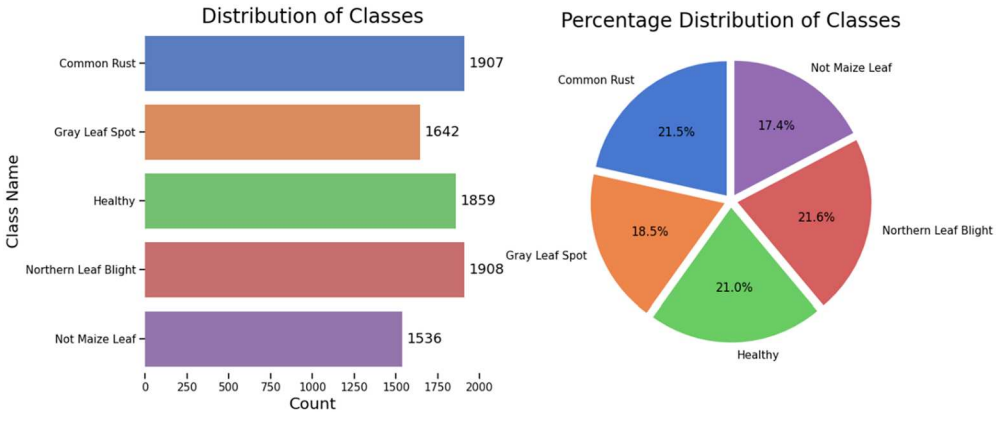

Figure 2. Class distribution of the corn leaf dataset.

and industrial quality control. Among deep learning frameworks, CNNs stand out for their exceptional ability to analyse and classify visual data. With their multi-layered architecture, CNNs extract features at varying levels of complexity: early layers capture simple elements like edges and textures, while deeper layers identify intricate patterns, object parts, and overall forms. Convolution filters enable the model to detect specific image characteristics, and pooling techniques enhance efficiency by reducing data dimensions. This layered approach allows CNNs to build increasingly abstract representations, leading to impressive accuracy. As a cornerstone of computer vision, CNNs, with their diverse variants, are widely adopted across numerous domains with remarkable success (Chen et al. 2024).

Vision transformer

The ViT, introduced in 2020 by Dosovitskiy et al., is a groundbreaking deep learning model for computer vision, adapting the Transformer architecture from natural language processing. Unlike CNNs, ViT processes images by splitting them into fixed-size patches (e.g. 16×16 pixels), flattening them into tokens, and adding positional encodings to preserve spatial context. These tokens are fed into a Transformer encoder, which uses self-attention to capture global relationships across the image, enabling ViT to model long-range dependencies effectively. ViT excels in tasks like image classification and object detection, especially when trained on large datasets like ImageNet, often surpassing CNNs. However, its data and computational demands are significant, lacking CNNs' inductive biases like locality. Variants like DeiT address these limitations. ViT's global feature extraction makes it ideal for applications such as medical imaging and agricultural disease detection, redefining computer vision research (Aslan and Özüpak 2024).

MobileNetv2

MobileNetV2 is a lightweight CNN architecture designed for efficient image classification, particularly on resource-constrained devices like mobile phones. Introduced by Sandler et al. in 2018, it builds on MobileNetV1 by incorporating inverted residual

blocks and linear bottlenecks, enhancing performance while maintaining computational efficiency. MobileNetV2 processes images through depthwise separable convolutions, reducing parameters and computational cost compared to traditional CNNs. This makes it ideal for applications like maize leaf disease detection in agricultural settings, where real-time processing on edge devices is valuable. The architecture consists of 17 building blocks, followed by a global average pooling layer and a classification head. Pre-trained on ImageNet, MobileNetV2 supports transfer learning, enabling effective adaptation to specific tasks with limited data. Its balance of accuracy and efficiency makes it a robust choice for scalable, on-field AI-driven diagnostics (Chen et al. 2024).

Stacking learning

Stacking learning, also known as stacked generalisation, is an advanced ensemble learning technique designed to improve predictive performance by combining the strengths of multiple base models through a meta-learning framework. Unlike simpler ensemble methods such as bagging or boosting, stacking uses a two-layer architecture: the first layer consists of different base models that generate predictions, while the second layer uses a meta-model to learn an optimal combination of these predictions (Lu et al. 2024). This approach mitigates individual model biases and variances by exploiting complementary information across heterogeneous algorithms, such as support vector machines, decision trees or neural networks. Typically, base models are trained on the same dataset and their predictions (or probability outputs) are used as features for the meta-model, which is trained via cross-validation to avoid overfitting. Stacking is particularly effective for complex tasks where no single model consistently outperforms others, offering improved generalisation and robustness, as demonstrated in applications ranging from classification to regression in diverse domains.

Local interpretable model-agnostic explanations

LIME is a technique designed to explain the predictions of complex machine learning models in a human-interpretable way. Introduced by Ribeiro et al. in 2016, LIME addresses the challenge of understanding 'black-box' models, such as deep neural networks, by providing local explanations for individual predictions. It is model-agnostic, meaning it can be applied to any machine learning model, including those used in computer vision tasks like maize leaf disease detection. LIME works by approximating a complex model's behaviour around a specific prediction. It generates a perturbed dataset by slightly modifying the input (e.g. altering image pixels or patches) and observes how the model's predictions change. A simpler, interpretable model, such as a linear regression or decision tree, is then trained on this perturbed data to mimic the complex model's behaviour locally. The resulting explanation highlights which features (e.g. image regions) most influenced the prediction. For example, in classifying a maize leaf image as 'Northern Leaf Blight,' LIME might identify specific leaf patterns or discolouration as key contributors. This interpretability is crucial in domains like agriculture, where trust and actionable insights are essential. Despite its strengths, LIME's

explanations are local and may vary across instances, and its reliance on perturbations can introduce instability. Nonetheless, LIME remains a vital tool for enhancing transparency in AI applications (Parisineni and Pal 2023).

SHapley Additive exPlanations

SHAP is a powerful framework for interpreting machine learning model predictions, introduced by Lundberg and Lee in 2017. Grounded in cooperative game theory, SHAP leverages Shapley values to fairly allocate the contribution of each feature to a model's output, providing consistent and interpretable explanations. It is model-agnostic, applicable to any model, including deep learning architectures used in tasks like maize leaf disease detection. SHAP works by computing the marginal contribution of each feature (e.g. pixels or image patches) to a prediction, considering all possible feature combinations. For a given image, SHAP assigns importance scores to features, indicating how they influence the model's decision, such as identifying a leaf as 'Cercospora Leaf Spot.' Visualisations like summary plots or force plots help users understand feature impacts intuitively. SHAP's strengths include its theoretical rigour and consistency, but it can be computationally intensive for high-dimensional data. In agriculture, SHAP enhances trust in AI by clarifying model decisions, supporting precise interventions (Li 2022).

Gradient-weighted Class Activation Mapping

Grad-CAM is a visualisation technique for interpreting CNN predictions, introduced by Selvaraju et al. in 2017. Designed to highlight regions of an input image most relevant to a model's decision, Grad-CAM is particularly useful in computer vision tasks like maize leaf disease detection. It is model-specific, tailored to CNN architectures, and provides intuitive, class-specific heatmaps. Grad-CAM works by computing gradients of the target class score with respect to feature maps in a CNN's final convolutional layer. These gradients are globally averaged to obtain weights that reflect each feature map's importance for the class. The weighted feature maps are combined and passed through a ReLU activation to produce a heatmap, highlighting image regions that positively influence the prediction. For instance, in classifying a maize leaf as 'Common Rust,' Grad-CAM may highlight rust-coloured spots. While computationally efficient and visually clear, Grad-CAM's coarse resolution can miss fine details. Nonetheless, it is widely used to build trust in AI-driven agricultural diagnostics (Raghavan et al. 2024).

Proposed model

The proposed model for maize leaf disease classification, as shown in Figure 3, implements a comprehensive approach to achieve accurate and interpretable classification results. The computational environment was initialised by installing essential libraries and defining key parameters, including an image resolution of 256×256 pixels, a batch size of 32, and a fixed random seed for reproducibility. A distributed training strategy was used to take advantage of multiple GPUs and optimise

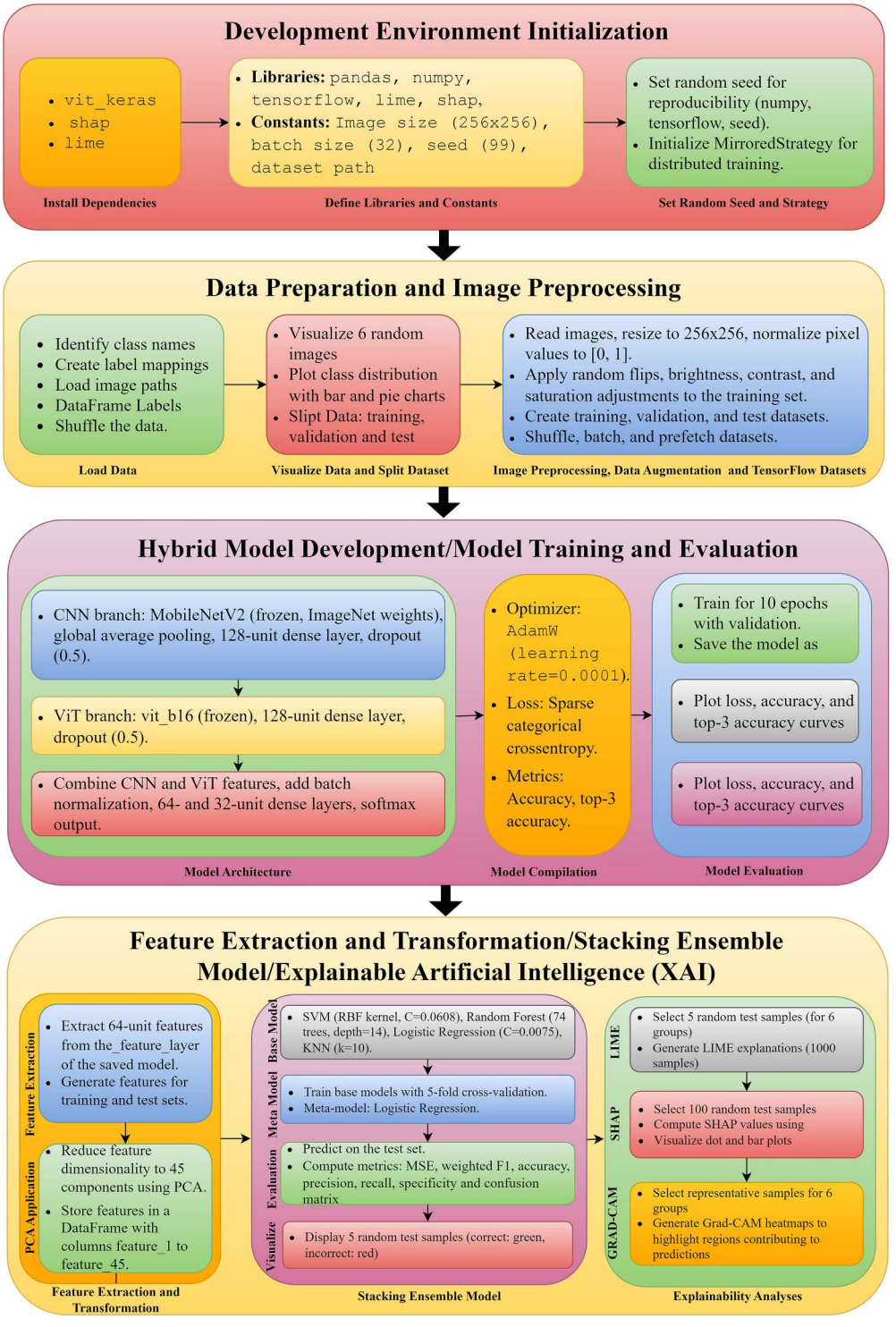

Figure 3. Structure of the Proposed Mode.

computational efficiency. The dataset was loaded with class labels mapped and image paths organised into a shuffled Data Frame. Initial data exploration involved visualising random samples and generating bar and pie charts to illustrate class distributions. The dataset was divided into training (80%), validation (10%) and test (10%) sets, with the training set further divided into training (89%) and validation (11%) subsets. Images were pre-processed by resizing to 256×256 pixels and normalising pixel values to the range [0, 1]. Data enhancement, applied to the training set only, included random flipping and brightness, contrast and saturation adjustments. TensorFlow datasets were constructed, shuffled, batched and prefetched to ensure efficient data handling. A hybrid model was developed integrating a frozen MobileNetV2 CNN and a frozen ViT-B16. Features from both branches were concatenated, followed by batch normalisation, dense layers of 64 and 32 units, and a SoftMax output layer. The model was built using the Adam optimizer (learning rate = 0.0001), sparse categorical cross-entropy loss, and accuracy and top-3 accuracy metrics, and trained for 10 epochs. Training performance was assessed by loss, accuracy and top-3 accuracy curves, and the model was evaluated on validation and test sets to determine loss and accuracy. Features were extracted from a 64-unit dense layer, reduced to 45 components using Principal Component Analysis (PCA), and stored in a Data Frame. A stacking ensemble model was constructed using SVM, random forest, logistic regression and KNN as base models, with a logistic regression meta-model trained by 5-fold cross-validation. The performance of the stacking model was evaluated on the test set by calculating mean squared error (MSE), weighted F1 score, accuracy, precision, recall and specificity, with a confusion matrix visualised to summaries the classification results. Random test samples were displayed to highlight correct and incorrect predictions. An alternative stacking model was developed by aggregating the probability predictions from the base models using a logistic regression meta-model and evaluated similarly, including confusion matrix visualisation and test sample displays. To improve interpretability, LIME were applied to five random test samples (e.g. one sample per class), generating explanations for the top five labels and visualising positive contributions. SHAP were computed on 100 random test samples (seed = 99) using a Kernel Explainer, with dot and bar plots illustrating feature importance. In addition, Grad-CAM was used to generate heat maps for six groups (e.g. one sample per class), highlighting image regions critical to predictions. This integrated pipeline ensures robust classification performance while providing transparent and interpretable insights into the model's decision processes.

Evaluation metrics

Deep learning models are assessed using various performance metrics to enhance accuracy, detect errors, and improve prediction reliability. Solely depending on accuracy can be misleading, particularly with imbalanced datasets. Key metrics like precision, recall, and F1 score offer a fuller picture of model performance. Accuracy measures the proportion of correct predictions, while precision gauges the model's ability to minimise false positives. Recall assesses how well the model identifies true positives. The F1 score, as the harmonic mean of precision and recall, provides a balanced evaluation. Together, these metrics enable a thorough analysis of model effectiveness across

diverse scenarios, ensuring robust performance evaluation, especially for skewed data distributions. The equations for these metrics are provided in (1)–(4) (Rainio et al. 2024).

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Number\ of\ Total\ Prediction} \tag{1}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$Recall = Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$F1_{score} = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Results

The proposed hybrid model demonstrates exceptional performance, achieving an overall accuracy of 96.73% on the 'Corn or Maize Leaf Disease Dataset' from Kaggle, as detailed in Table 1. Evaluated across five classes Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight, and Not Maize Leaf the model excels, with F1-scores ranging from 0.9276 to 1.0000. The integration of MobileNetV2 and ViT, combined with a stacking classifier, ensures robust feature extraction and classification, outperforming several state-of-the-art models (Table 2). Visualisations from Grad-CAM, SHAP, and LIME provide clear insights into model decisions, enhancing trust for agricultural applications.

The performance of the deep learning model for maize leaf disease classification, as presented in Table 1, demonstrates robust effectiveness across multiple classes, with an overall accuracy of 96.73% on a dataset of 886 samples. The model was evaluated using precision, recall, and F1-score metrics for five classes: Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight, and Not Maize Leaf. Common Rust achieved near-perfect performance with a precision, recall, and F1-score of 0.9948, reflecting the model's ability to accurately identify this disease with minimal errors. The Healthy and Not Maize Leaf classes also exhibited exceptional results, with F1-scores of 0.9922 and 1.0000, respectively, indicating flawless recall for Healthy samples and perfect classification for non-maize leaves. Grey Leaf Spot and Northern Leaf Blight showed slightly lower but still strong performance, with F1-scores of 0.9345 and 0.9276, respectively, suggesting minor challenges in distinguishing these diseases, possibly due to visual

Table 1. Maize leaf disease classification performance metrics.

Class	Precision	Recall	F1-Score	Support
Common Rust	0.9948	0.9948	0.9948	194
Grey Leaf Spot	0.9632	0.9075	0.9345	173
Healthy	0.9846	1.0000	0.9922	192
Northern Leaf Blight	0.9185	0.9454	0.9276	183
Not Maize Leaf	1.0000	1.0000	1.0000	144
Accuracy			0.9673	886
Macro Avg	0.9766	0.9695	0.9698	886
Weighted Avg	0.9699	0.9695	0.9695	886

Table 2. Comparison of maize leaf disease classification models.

Study	Model	Accuracy
Proposed Model	Hybrid Model	96.73%
Ashwini and Sellam (2024)	3DCNN-RNN with JSWOA	90.00%
Mafukidze et al. (2022)	CNN with Transfer Learning	95.00%
Zhang et al. (2021)	CNN with MAF Module	94.41%
Singh et al. (2022)	AlexNet	95.16%
Handrizal et al. (2024)	CNN	95.00%

similarities or class imbalance. The macro-average F1-score of 0.9698 and weighted-average F1-score of 0.9695 underscore the model's balanced performance across classes, despite varying support sizes (144–194 samples). These results highlight the model's reliability for automated disease detection in maize, with potential for real-world agricultural applications. However, the slightly lower scores for Grey Leaf Spot and Northern Leaf Blight suggest opportunities for further optimisation, such as incorporating advanced data augmentation or feature extraction techniques to enhance differentiation of visually complex diseases.

Figure 4 shows the training and validation performance of a deep learning model over 10 epochs in three graphs: Training and Validation Loss, Training and Validation Accuracy, and Training and Validation Top-3 Accuracy. The first graph shows that the training and validation loss stabilises with a sharp decrease from epoch 0 to epoch 2 to 0.2 and 0.3 respectively, indicating effective learning and minimal overlearning. The second graph shows that the training accuracy increases rapidly from 0.65 to 0.95 in epoch 2 and stabilises around 0.98, while the validation accuracy follows a similar trend, reaching around 0.90, demonstrating the strong generalisation ability of the model. The third graph shows the top-3 accuracy, where the training top-3 accuracy approaches 1.0 at epoch 4, while the validation top-3 accuracy stabilises around 0.96, reflecting the model's high capacity to rank the correct classes in the top three predictions; these metrics highlight the model's consistent improvement and reliability in classifying maize leaf diseases in an academic evaluation framework.

The confusion matrix obtained from the MobileNetV2 and ViT model for corn leaf classification, as shown in Figure 5, quantitatively demonstrates the performance of the developed classification model on five different maize leaf classes: Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight, and Not Maize Leaf. High values on the diagonal of the matrix reflect the success of the model in accurate classifications, while values off the diagonal represent error rates. In particular, it is seen that the model classifies Common Rust (193/194), Healthy (192/192) and Not Maize Leaf (144/

Figure 4. Variation of training and validation performance metrics over epochs.

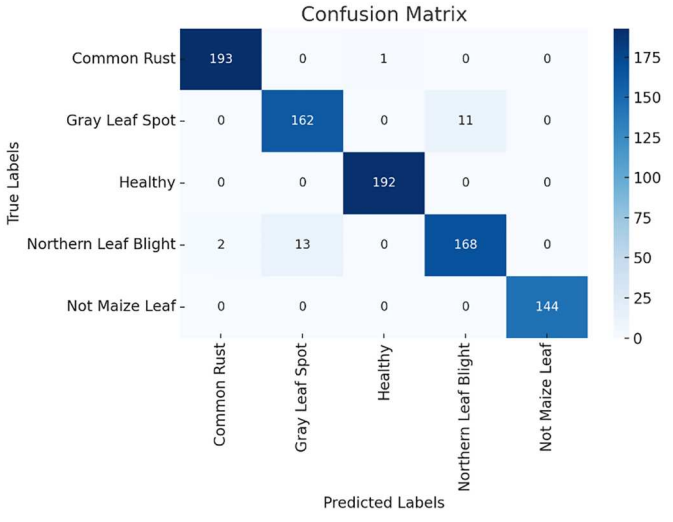

Figure 5. Confusion matrix obtained from the MobileNetV2 and ViT model for corn leaf classification.

144) with very high accuracy. On the other hand, 13 samples were misclassified as Grey Leaf Spot in the Northern Leaf Blight class. This suggests that there may be visual similarities between these two disease types and that the model is limited in discrimination. In general, the classification performance of the model is high, with only a limited number of inter-class confusions. This suggests that the developed method is an effective tool for automatic diagnosis of corn leaf diseases.

The confusion matrix obtained from the proposed model for corn leaf classification, as shown in Figure 6, illustrates the prediction performance of the model across five classes. The classes 'Healthy' and 'Not Maize Leaf' are completely correctly classified with 192

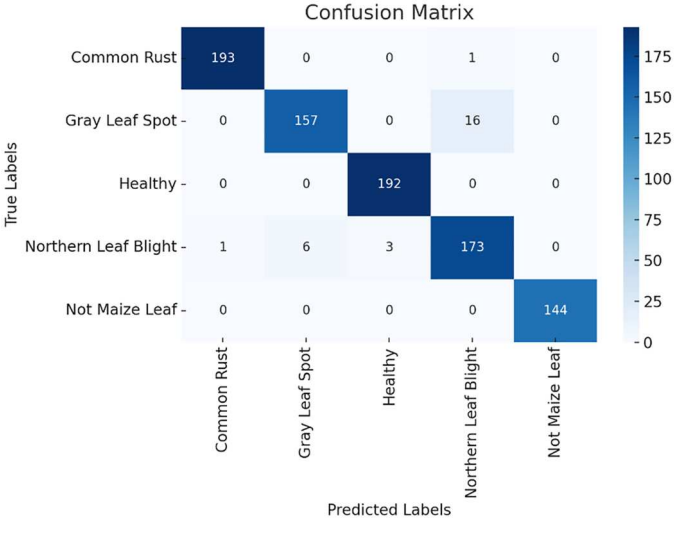

Figure 6. Confusion matrix obtained from the proposed model for corn leaf classification.

and 144 instances respectively. The 'Common Rust' class exhibited high accuracy, misclassifying only one out of 193 instances. In the 'Grey Leaf Spot' class, 16 samples were mistaken as 'Northern Leaf Blight' against 157 correct predictions. Similarly, in the 'Northern Leaf Blight' class, 10 instances were confused with other classes against 173 correct classifications. This suggests that visual similarities between leaf spot species affect classification accuracy. Overall, the model showed a strong classification performance, but the limited distinction between leaf diseases led to some confusion.

Figure 7 contains 15 images representing healthy and diseased maize leaves; these images cover the Northern Leaf Blight (nos. 143, 408, 783, 0), Common Rust (nos. 23, 811, 810, 767, 197), Grey Leaf Spot (nos. 789, 657), Healthy (nos. 336, 352) and Non-Corn Leaf (nos: 754, 836), Northern Leaf Blight shows grey-brown lesions, Common Rust shows reddish-brown pustules, Grey Leaf Spot shows brown spots with yellow rings, Healthy leaves are undamaged and green, and Non-Corn Leaves show morphological characteristics of different plant species; these visual examples reveal the diversity of data used in the training and testing processes of classification models and the distinctive features of disease symptoms in an academic framework.

Figure 8 visualises the importance of the features used by a Proposed model to classify corn leaf diseases through their SHAP values; the features (feature_1 to feature_23) are ordered on the y-axis, while the x-axis shows the SHAP values (between −2.0 and 2.0), with the colour scale indicating low (blue) and high (red) feature values. Feature_1 has the highest SHAP values and has the largest impact on the model output, indicating that

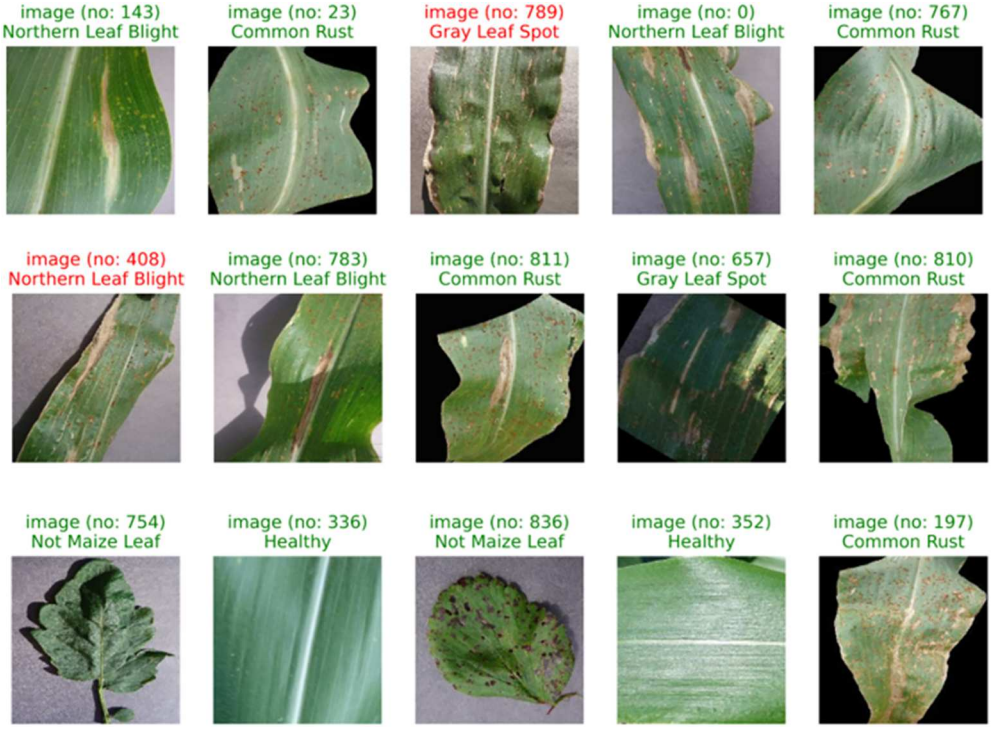

Figure 7. Visual examples of healthy and diseased maize leaves.

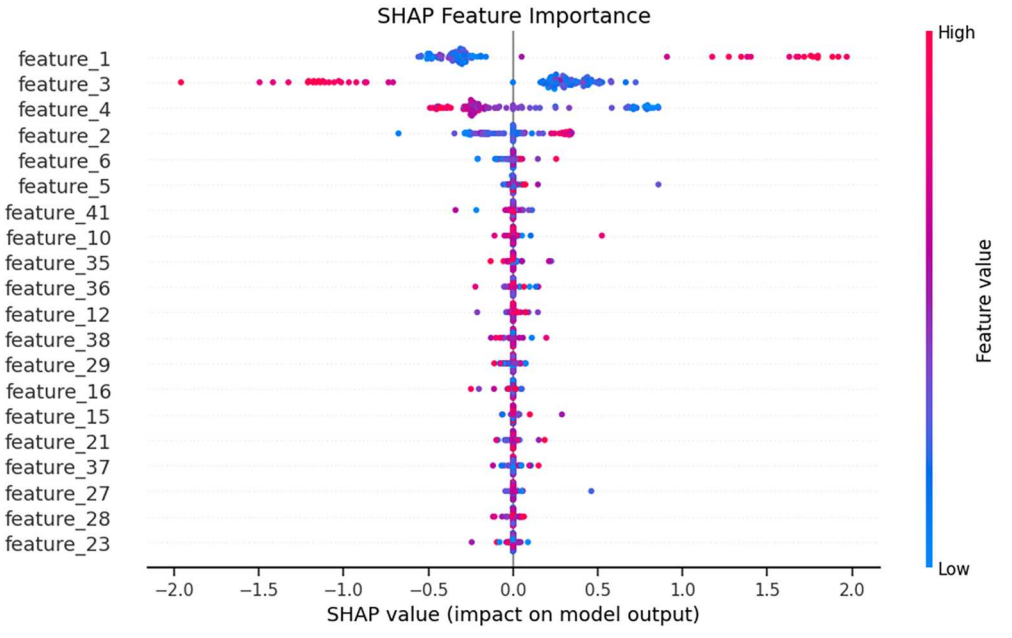

Figure 8. SHAP feature importance analysis.

this feature is dominant in classification decisions; feature_3 and feature_4 also have significant impacts, while lower ranked features such as feature_23 have less impact on the model. The distribution of SHAP values reveals that features affect the model predictions in both positive and negative directions, explaining in an academic framework which features are more decisive in the classification process; this analysis improves the interpretability of the model and makes an important contribution to understanding which visual features are critical in the diagnosis of corn leaf diseases.

Figure 9 presents the global feature importance of a machine proposed model for maize leaf disease classification as a bar graph of SHAP values; the y-axis is ordered by features (feature_1 to feature_23), while the x-axis shows the average |SHAP value| (between 0.0 and 0.6) and the average impact on the model output. Feature_1 has the highest average |SHAP value| of about 0.55, indicating that it is the most decisive feature in the model's predictions, followed by feature_3 (about 0.45), feature_4 (about 0.35) and feature_2 (about 0.25), while features ranked lower, such as feature_23, make a minimal contribution, with an impact below 0.05. This analysis makes an important contribution to understanding the importance of visual features in the diagnosis of corn leaf diseases by showing in an academic framework which features are more dominant in the model's classification decisions; in particular, the dominant effect of feature_1 highlights the critical role of this feature in detecting disease symptoms.

Figure 10 presents five different images, applying the LIME method to interpret the predictions of a machine learning model for the classification of maize leaf diseases; each image highlights with yellow lines the regions that influenced the model's decision, along with the true and predicted classes. The first image (Image 162) is correctly

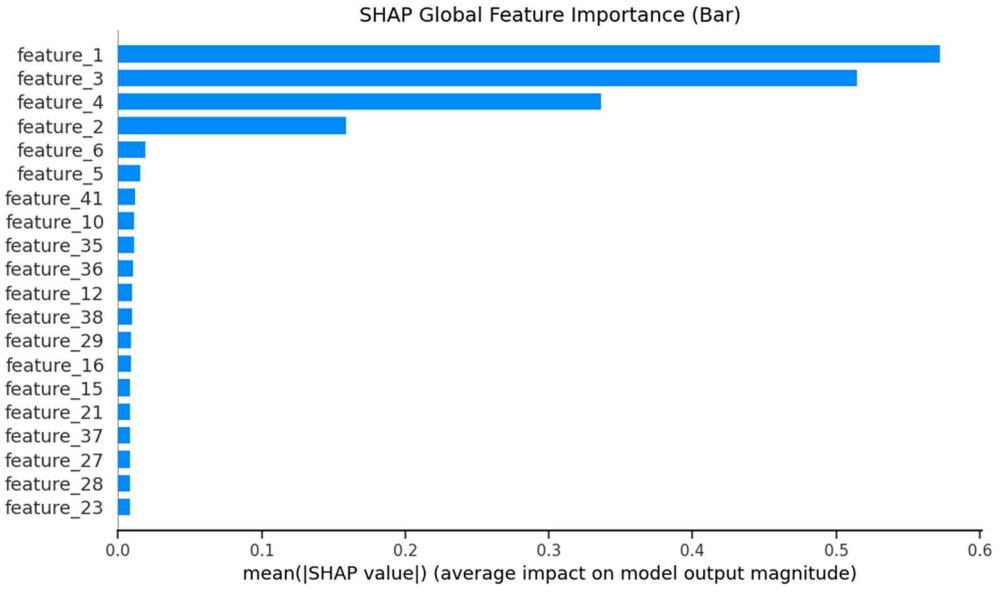

Figure 9. SHAP global feature importance analysis (bar chart).

classified as Northern Leaf Blight, with the yellow lines indicating grey-brown lesions in the central part of the leaf, indicating that the model considered this area as a disease symptom. The second image (Image 279) was correctly predicted as Common Rust and the yellow lines highlight the reddish-brown pustules on the surface of the leaf, indicating that the model detected this characteristic feature. The third image (Image 555) is correctly classified as Healthy, with the yellow lines focusing on the undamaged and smooth green surface of the leaf, indicating that the model correctly distinguished the healthy structure. The fourth image (Image 310) was correctly predicted as Grey Leaf Spot, and the yellow lines indicate brown spots with yellow rings concentrated on the edges of the leaf, making it clear that the model considers these areas as signs of disease. The last image (Image 481) is correctly classified as Not Maize Leaf, with the yellow lines highlighting the morphological features of the leaf that are specific to different plant species (e.g. wider and different vein structure), indicating that the model correctly distinguishes Not Maize Leaf. This analysis shows that the LIME method improves interpretability by visualising which visual features the model makes decisions based on, and supports the accuracy and reliability of the deep learning model for maize leaf disease diagnosis in an academic framework; in particular, the accurate detection of distinctive regions specific to each class proves that the model effectively learns visual disease symptoms.

Figure 11 presents six different images applying the Grad-CAM method to visualise the predictions of a deep learning model for the classification of corn leaf diseases; each image highlights the regions that influence the model's decision with a heat map (temperature scale from blue to red) and a green bar graph, along with the true and predicted classes. The first image (True: Common Rust, Predicted: Common Rust) shows that areas with dense reddish-brown pustules in the Common Rust class are marked with red hues and the model correctly identified these areas; the second image (True:

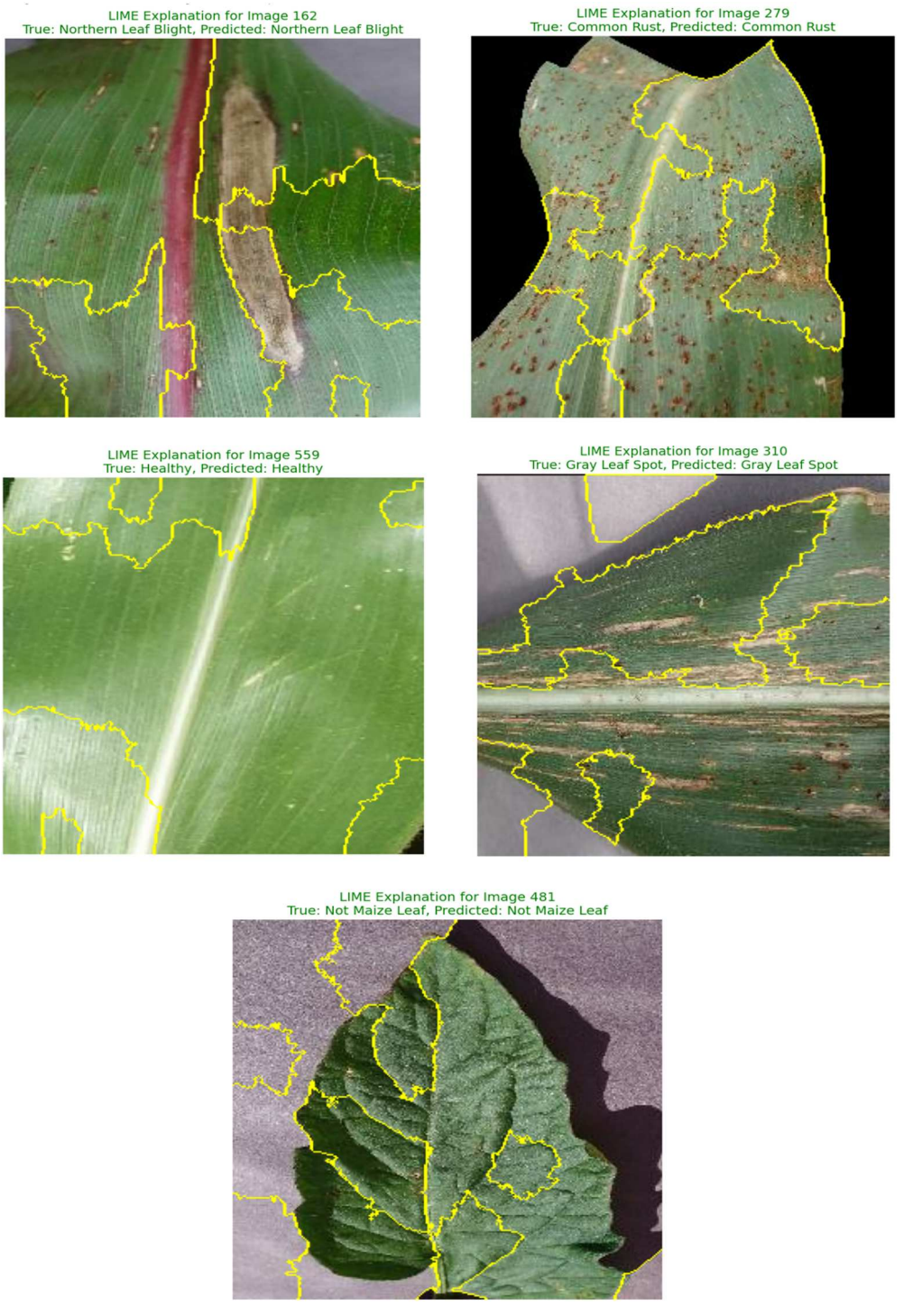

Figure 10. LIME annotation analysis for maize leaf classification.

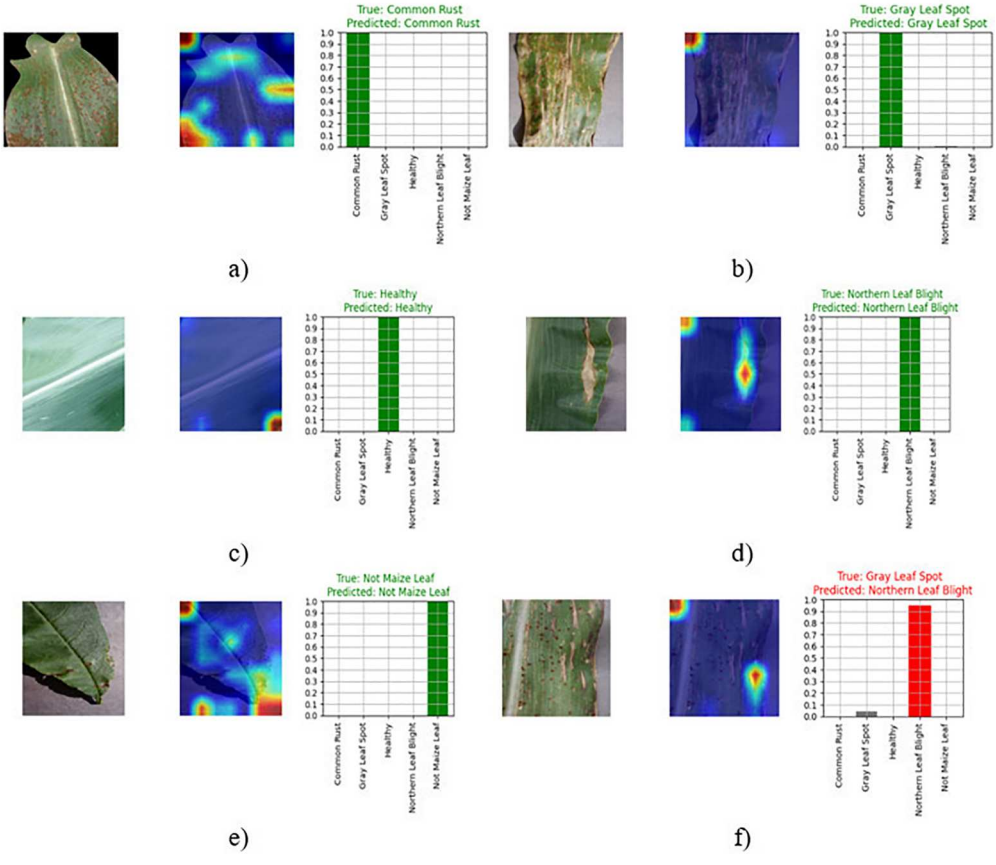

Figure 11. Grad-glass annotation maps for corn leaf classification.

Grey Leaf Spot, Predicted: Grey Leaf Spot) reveals that brown spots with yellow rings in Grey Leaf Spot are highlighted with blue–green hues, reflecting the correct classification. The third image (True: Healthy, Predicted: Healthy) shows low activity (blue tones) on the undamaged green surface of the healthy leaf, indicating that the model correctly recognised the healthy state; the fourth image (True: Northern Leaf Blight, Predicted: Northern Leaf Blight) shows that grey-brown lesions in Northern Leaf Blight are marked with red regions and were correctly predicted. The fifth image (True: Not Maize Leaf, Predicted: Not Maize Leaf) indicates that the morphological differences of the non-maize leaf are highlighted by blue tones and classified correctly, while the sixth image (True: Grey Leaf Spot, Predicted: Northern Leaf Blight) reveals that the regions of concentrated red tones reflect confusion in the misclassification of Grey Leaf Spot as Northern Leaf Blight. These Grad-CAM maps improve interpretability by explaining which visual features the model is based on and provide academic evidence of high reliability for correct classifications (values between 0.9 and 1.0 in the green bar graph) and confusion for misclassifications (values between 0.5 and 0.6 in the red bar graph); in particular, they support the conclusion that misprediction can be caused by similar visual features.

Discussion

The proposed hybrid learning model, integrating MobileNetV2 and ViT with a stacking classifier, achieves an outstanding accuracy of 96.73% in classifying maize leaf diseases, as detailed in Table 1. This performance outperforms other state-of-the-art models evaluated on similar datasets, as shown in Table 2, which compares our model with five recent studies. The hybrid approach exploits the efficiency of MobileNetV2 in extracting local features, the strength of ViT in capturing global dependencies, and a stacking model that improves overall performance by combining the strengths of individual models while mitigating their weaknesses through a meta-learner. The result is improved generalisation and robustness. As a result, the model achieves superior discriminative power across classes such as Common Rust, Grey Leaf Spot, Healthy, Northern Leaf Blight and Not Maize Leaf. The incorporation of Grad-CAM, SHAP, and LIME enhances interpretability, addressing a critical need in agricultural applications where trust and transparency are paramount. For instance, Grad-CAM heatmaps (Figure 11) and LIME annotations (Figure 10) pinpoint disease-specific regions, aiding farmers in understanding model decisions.

Compared to prior works, our model's accuracy exceeds that of Mafukidze et al. (2022) (95.00%), Singh et al. (2022) (95.16%), Zhang et al. (2021) (94.41%), Ashwini and Sellam (2024) (90.00%), and Handrizal et al. (2024) (95.00%). While Mafukidze et al. and Singh et al. achieved high accuracy using CNN-based models, their approaches lack the global context provided by ViT, limiting their ability to handle complex visual patterns. Zhang et al.'s MAF module improved ResNet50 but fell short of our hybrid model's feature fusion. Ashwini et al.'s 3DCNN-RNN model, while innovative, was less accurate due to its complexity on smaller datasets. Handrizal et al.'s CNN model, though efficient, did not incorporate advanced interpretability techniques like ours.

The confusion matrices (Figures 5 and 6) reveal minor misclassifications, particularly between Grey Leaf Spot and Northern Leaf Blight, likely due to visual similarities. This suggests future improvements could focus on advanced data augmentation or feature enhancement techniques. Additionally, the model's computational efficiency, driven by MobileNetV2, supports its potential deployment on mobile devices, making it practical for field applications. However, limitations include the dataset's specific imaging conditions, which may affect generalisability across diverse environments. Future work should explore cross-environmental testing and optimisation for real-time mobile integration to enhance practical utility in precision agriculture.

Conclusion

This study successfully demonstrates the efficacy of a hybrid learning model for maize leaf disease classification, achieving a state-of-the-art accuracy of 96.73% on the Kaggle 'Corn or Maize Leaf Disease Dataset.' The model's integration of local and global feature extraction, enhanced by transfer learning and data augmentation, ensures robust performance across diverse classes, with F1-scores ranging from 0.9276 to 1.0000. Its computational efficiency supports potential deployment on resource-constrained, addressing practical needs in precision agriculture. The incorporation of explainable AI tools SHAP, LIME, and Grad-CAM enhances interpretability, providing

clear visualisations of disease-specific features, which is crucial for building trust among farmers and agronomists. Comparative analysis (Table 2) confirms the model's superiority over existing approaches, highlighting its balanced accuracy and efficiency. However, challenges remain, including minor misclassifications between visually similar diseases and the dataset's specific imaging conditions, which may limit generalisability. Future research should prioritise cross-environmental validation, advanced augmentation techniques, and seamless mobile integration to ensure scalability and real-world impact. This work advances automated disease detection, contributing to sustainable maize production and global food security.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Yıldırım Özüpak http://orcid.org/0000-0001-8461-8702

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