International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(6s) 2026 pp. 937-949
https://doi.org/10.70917/ijcisim-2026-2997
Article

Early Detection of Disease in Millet Crops Using Transfer Learning

Nisha Rani [1], Sunil Kumar [2]

[1,2]Department of CSE, Guru Jambheshwar University of Science & Technology, Hisar, India
E-mail: [1]nishabhadana09@gmail.com, [2]skvermacse@gmail.com

Abstract: -Millet crops play a foremost role in ensuring food security and sustainable agriculture; however, their productivity is significantly affected by various leaf diseases such as Rust, Smut and Blast. Early and accurate detection of these diseases is key to effective crop management. In this study, a hybrid Transfer Learning–Convolutional Neural Network (TL–CNN) framework is designed for automated millet disease detection. The model uses pre-trained architectures such as MobileNetV2, Xception and EfficientNetB0V2, for feature extraction, followed by additional convolutional blocks to capture discriminative features. The novelty of this work lies in the development of a millet-specific deep learning framework, integrated with CNN-based feature optimization and a reliable evaluation strategy. Unlike classic approaches, the proposed model uses both single-run training and stratified 5-fold cross-validation to ensure reliable and unbiased performance assessment. A comprehensive comparative study is conducted across multiple transfer learning models within an integrated framework. Experimental data show that the proposed EfficientNetB0V2 + CNN model achieves superior performance, with higher accuracy and better precision, recall and F1 Score across all classes. Confusion matrix analysis additionally confirms minimal misclassification and strong class separability. The data highlight the effectiveness of the suggested approach in detecting complex disease patterns. Overall, the proposed TL–CNN framework delivers a reliable and efficient solution for millet disease detection. This solution provides a strong prospect for real-world agricultural applications and intelligent crop-monitoring systems.

Keywords: Millet disease, Convolutional neural network, Crop disease detection, Disease classification, Image processing, Deep learning

1. Introduction

Agriculture has been the primary human activity that has enabled civilizations to prosper. As the population grows, the need for food also increases, making the food and agriculture industry vital today. Farming, the main source of food and energy, is significant for a country's economic development [1]. Almost one-third of all food is lost to plant diseases or disorders. Yet the United Nation's Food and Agriculture Organization says the food supply must increase by 70% to feed the world's population by 2050 [2]. Today, plants are a major food source. Many environmental conditions can cause diseases and lead to major production losses. Manual disease diagnosis is time-consuming and error-prone. This method may not always be reliable for plant disease identification and prevention. ML and DL technologies can help by permitting early detection of plant diseases [3], as shown in Figure 1. Today, it is impossible to imagine modern life without machine learning and deep learning, which underpin advanced medical diagnosis, object recognition and classification. Despite advances, many farmers still rely on manual diagnosis, which is often time-consuming and error-prone, to identify plant diseases. The production of crops is significantly reduced by viruses that spread unchecked because of the lack of automated detection. Quick disease identification, which is important for maintaining global food security, remains significantly hampered by inadequate infrastructure in many parts of the world [4]. Many biotic factors, including bacteria, viruses, fungi and phytoplasma, can naturally induce diseases. Wilt, anthracnose, powdery mildew, blight, leaf spots and root rots are some examples of fungal diseases. Although viruses can induce mosaic, mottling, necrosis, crinkling, curling and wilting in susceptible hosts, bacteria can induce leaf spots, blights, cankers, galls and wilt diseases. Moreover, some abiotic factors, including food deficiencies, water stress and high temperatures, can exhibit symptoms similar to those of biotic factors, making them difficult to identify without professional assistance [5]. The identification and prediction of these diseases can help farmers take preventive measures, thereby minimizing adverse effects on crop production and quality [6].

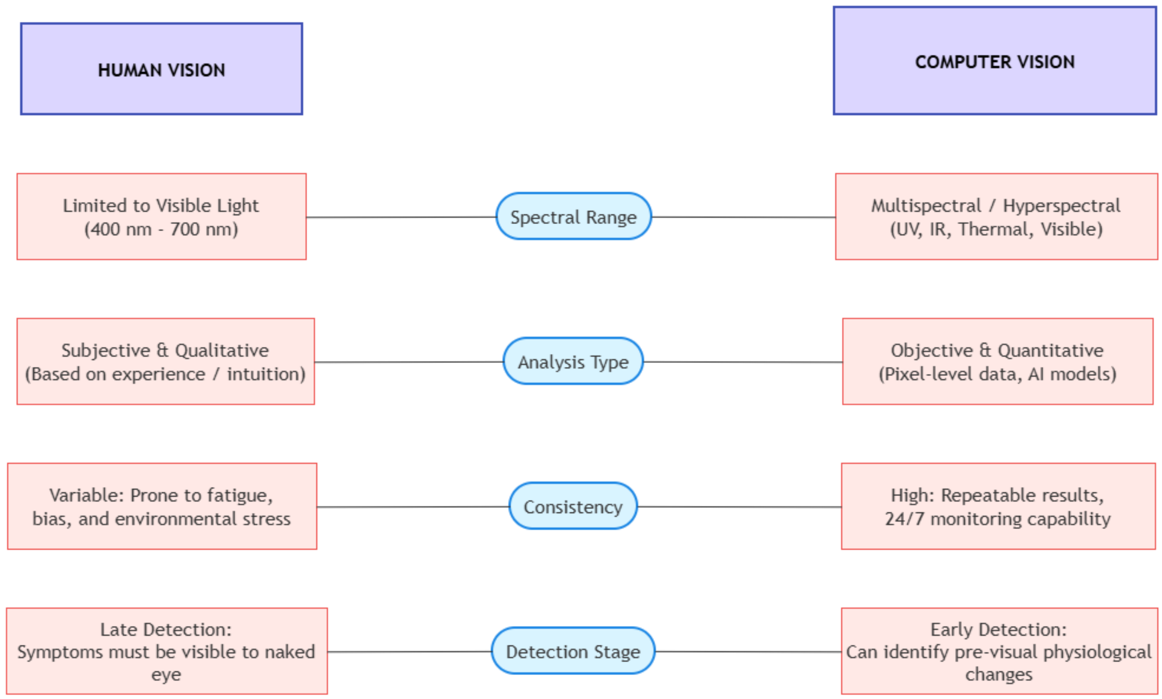


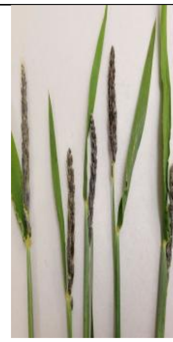
Fig 1. Difference between human vision and computer vision for plant disease detection

In this paper, the millet plant has been considered for the analysis of leaf diseases. In India, millet is the most important food crop along with rice and wheat. It is a major carbohydrate source for humans. A resilient cereal crop that grows well in hot, dry conditions, pearl millet (known as bajra) is widely cultivated in India's arid and semi-arid regions during the kharif season. With smaller plantations in Tamil Nadu, the major contributors are Rajasthan, Uttar Pradesh, Gujarat, Haryana and Maharashtra. It is ideal for drought-prone areas, as it can easily grow in sandy, poor soil and requires less water. From a nutritional point of view, pearl millet is non-glycaemic, gluten-free and a rich source of protein (10-12%), fibre and key minerals, including iron, zinc, magnesium and phosphorus. This makes bajra a farmer-friendly crop that can help control diabetes, improve digestion, support bone health and enhance heart health. The export of millet from India in 2025 continued to increase. This was due to the government's initiatives to promote millet consumption and the growing demand for Nutri-cereals in the international market. According to trade data, pearl millet was primarily exported to African countries (such as Nigeria and Sudan), the Middle East (such as Saudi Arabia and the UAE) and Asian countries, where it is used as a staple food. Rajasthan, Gujarat and Haryana continued to be the major contributors to millet exports.

The productivity of major crops like wheat and rice has been declining over the years. Owing to their nutritional value and pliability, millet crops have also emerged as a potential alternative to address the challenges of global food security and hunger. Millet is also considered a strong cereal because it requires less water and is resistant to harsh weather conditions. However, rust and blast are among the diseases that affect its growth, thereby harming the agricultural sector.

Table 1. Millet's disease types and descriptions

Disease	Rust	Smut	Blast
Pathogen	Puccinia substriata	Tolyposporium penicillariae	Magnaporthe grisea

Disease type	Fungal	Fungal	Fungal
Symptoms	Orange leaf pustules	Black Powder Grains	Leaf and Neck Lesions
Images			

Thus, it is highly recommended that an intuitive, automated system be developed to help farmers detect pearl millet plant diseases early, without professional assistance. Convolutional Neural Networks (CNNs) can discover complex patterns and variations in leaf images that even a human cannot visually notice, as they can learn from the input data without guidance. Therefore, CNNs can be considered a powerful aid in differentiating leaf diseases that are difficult to recognize by the naked eye or with standard techniques. To this end, more advanced CNN models, such as AlexNet, VGGNet, ResNet-50, Inception and Xception, are used to extract relevant features from plant images. These pre-trained models can be fine-tuned with labeled data to maximize performance; however, customizable models are preferred over field images because they are more flexible in meeting specific requirements. Some of the pre-trained models used to evaluate the performance of the new deep learning models include AlexNet, ResNet50, VGG, Inception, Xception and NASNet. These models operate as standard models for new model development in computer vision tasks. Consequently, one can assess the effectiveness of a new model and compare it with current field results.

2. RELATED WORK

One main problem for farmers is identifying rust, blast and smut diseases of millet. On the one hand, previous research has provided important insights; on the other hand, the situation remains rife with problems and gaps. Compared to the other main staple crops, millet has been studied considerably less. As a result, there is a considerable shortage of research on the crop. Because of this lack of knowledge, disease detection will likely fail due to a shortage of tools and techniques specifically designed to exploit millet's unique features. One major issue is that different millet types exhibit distinct symptom profiles across environments.

Several papers on deep learning and machine learning methods used in agronomy have been reviewed, leaving a gap for a more thorough study of image-based plant disease recognition. An appraisal was recently conducted to highlight the significance of current plant disease detection methods, which encompassed segmentation, categorization, localization and disease-strategy aspects. Saleem et al. discuss the use of several high-tech DL architectures, such as GoogleNet, AlexNet and ResNet, for plant disease detection. It shows how these models can be used to identify and classify plant diseases, focusing on the PlantVillage dataset, which contains a wide range of plant disease images. The paper also explores the use of visualization techniques, such as saliency maps, heat maps and feature maps, to identify and understand plant disease symptoms [7]. Shoaib et al. explored various DL and ML methods for plant disease detection, including image processing, feature extraction and convolutional deep networks and deep belief networks. The article discusses the advantages and limitations of these methods, including data availability, image quality and distinguishing healthy from infected plants [8].

Bacterial, fungal and viral diseases in crops are one of the biggest threats for farmers face. To identify those diseases, researchers developed a new machine learning model. The method comprises data cleaning, image separation, feature extraction and classification. The model was trained on more than 1000 images from the Plan Villa dataset. The model, through KHbRF, is used to detect crop diseases. Python was used to run this prototype, which yielded very promising results.[9]. Bhargava et al. point out that plant disease detection in agriculture is very important, as failure to detect it can result in significant crop loss. Thereafter, the paper takes us through a brief history and the current state of the field of phytopathology, the study of plant pathogens and their diseases. It gives a breakdown of the types of plant diseases into 3 groups: bacterial, viral and fungal and describes the different symptoms that are typical of each type of disease. It then discusses deep learning techniques, which have become quite popular in recent years, partly because they can automatically learn features from big datasets. The article also covers transfer learning, convolutional neural networks and data augmentation methods for plant disease detection [10].

In this study, a deep learning system was developed to detect diseases in Pearl Millet leaves automatically. The dataset was collected with a mobile camera and contained 6 disease types. Our system applied computer vision to construct the Deep Millet model, which had fewer hidden layers, for disease classification. The model not only trained faster but was also more accurate than the other leading models. It was exposed to 3441 images of infected and healthy pearl millet leaves, achieving 98.66% accuracy after 240 seconds. Fast identification of rapidly spreading diseases, such as leaf spots, blights, rust, powdery mildew and downy mildew, is highly beneficial for disease management and helps reduce crop losses [5]. Tiwari et al. proposed a model that achieved tremendous success for detecting and classifying finger millet leaf diseases. Numerous research avenues and improvements could be implemented. The foremost idea is that the model will need to undergo architectural morphing to incorporate the distinctive features and disease profiles of other crops if it is to be used across a wider range of crops. In addition, the use of sophisticated data augmentation and synthetic data generation will make the model robust when labeled data is limited, a scenario in which this approach is an effective tool that can also be applied in many other areas of machine learning [11]. The work also studied smart monitoring of millet crops using predictive intelligence, combined with disease prediction. IoT devices that monitor temperature, humidity and soil moisture were used to assess the crop's health. The researchers decided to apply a new, custom-made CNN model to the millet crop data to obtain predictions of disease-occurrence probability based on aggregated sensory readings and, at the same time, to classify the disease type. This work focuses on the transition from traditional to modern, sustainable farming. This makes it robust and economically advantageous. Upon implementation, the proposed sustainable framework generated optimal outcomes. The observed accuracy, precision, recall and F-score values for the predictive model were 98.8%, 98.2%, 97.4% and 97.7%, respectively [1].

The research paper developed a DSAtt, CMNetV3 and KGDC model to segment the process and identify pepper leaf diseases. Besides, an optimizer, Os, OA, is employed to tune hyperparameters and improve classification accuracy. Experiments were conducted using the Plant Village dataset and evaluation metrics such as accuracy, F-score, precision, recall and TPR were used. Numerical experiments have shown that the pepper leaf disease segmentation and classification model proposed here can locate the affected region and even achieve better performance with a small segmentation target [12]. This work develops a YOLOv5, SE and BiFPN-based target-detection model to identify brown spot disease in kidney beans. Adding the SE module to the Backbone network and using BiFPN for fast normalized fusion, intra-group channel sharing, bi-directional cross-scale connectivity and weighted feature combination drastically reduces the number of network parameters. The work thus offers an effective tool for the precise diagnosis of brown spot disease in kidney beans [13].

First, common methods for identifying plant diseases are reviewed. One such method is CNN-based object detection, which automatically and efficiently locates diseased areas. These two methods are described mainly in terms of their principles and processes: the two-stage object detection representative algorithm Faster R-CNN and the one-stage object detection representative algorithm YOLOv3. For the experiments, data on five different apple leaf diseases were used and the aforementioned object detection methods were applied. The results of the experiment show that both models reliably recognize five apple leaf diseases [14]. This paper proposes a disease diagnosis system, MOHPT, that incorporates the CART and Random Forest classifiers. We have discussed two difficult problems that are related to disease diagnosis: i) class imbalance in disease diagnosis datasets and ii) finding the best hyperparameter values of the classifiers. Basically, the paper proposed a new approach to deriving optimal hyperparameter configurations for classifiers and a sampling technique for decision trees, based on classifier generation for disease diagnosis [15].

D. Tandekar et al. proposed model that consists of four main modules: dataset collection, preprocessing, disease detection and a graphical user interface (GUI). The dataset used in this work is the Plant Village dataset, which includes over 20,000 images of various plant diseases and healthy plants [16]. Johannes et al. presents image processing algorithm and ML based approach to automatically analyse plant illness, with a focus on identifying early disease symptoms. The algorithm was developed and validated using three common wheat diseases Tan spot, Rust and Septoria [17]. Picon et al. created a novel method based on deep learning for automatically recognizing multiple crop illnesses in real-world field settings. The authors extend their former work performed via Johannes et al. and developed a modified Deep residual neural network approach for detecting three relevant European endemic wheat illness [18].

R. Karthik et al. proposes a novel DL based network known as 'GrapeLeafNet' for correctly detect and classify grape leaf diseases. Grapes are a widely grown crop, but faces a variety of illnesses that can significantly reduce crop quality and yield. Traditional illness recognition approaches rely on manual examination and subjective symptom assessment, that results in delays and errors [19]. Liu et al. The Leaf GAN based hybrid dataset that contains 8,124 images of grape leaf illness and is utilised to train multiple CNN classification approaches. Results show that the classification correctness was higher than those obtained using the primary dataset and other data reinforcement methods [20].

Kiratiratanapruk et al. Prepared a dataset of rice disease images, including polygon labelling to obtain ground truth leaf width information, trained a CNN regression model (ResNet18) to estimate the leaf width in the images [21]. Deng et al. developed a highly accurate and generalizable deep learning-based rice disease diagnosis system. By carefully evaluating multiple CNN architectures and using an ensemble Using this strategy, the researchers were to create a model that can robustly identify six common rice diseases with over 90% accuracy, even on images from diverse sources [22]. Narmadha et al. presents a DL based rice plant disease detection and classification model called the DenseNet169-MLP model a deep learning-based approach for the identification and recognition of rice diseases and pests using convolutional neural networks (CNNs) [23]. Kathiresan et al. presents research on the application of transfer learning techniques to the detection of rice leaf diseases. Rice is a major staple crop worldwide, with Asia accounting for the vast majority of production. Nevertheless, rice crops are vulnerable to numerous diseases that can significantly reduce their productivity [24]. C. R. Rahman et al. has Advanced, large-scale CNN architectures, including VGG16 and InceptionV3, were applied and optimized to identify and classify rice diseases and pests. The study's findings highlight the efficacy of these models when tested on real-world datasets obtained from the Bangladesh Rice Research Institute (BRRI) fields [25].

Authors	**Methods**	**Dataset**	**Contribution**	**Performance**
Saleem et al.	GoogleNet, AlexNet, ResNet	PlantVillage	Identify & classify of plant diseases; visualize for symptom localization	Demonstrated effectiveness of DL architectures
Shoaib et al.	Image processing, feature extraction, CNN, Deep Belief Network	Various datasets	Pros & Cons of ML/DL methods; challenges with data availability & image quality	Comparative discussion, not performance-focused
Srinivas et al.	Data cleaning, feature extraction, classification	PlantVillage (>1000 images)	ML-based crop disease detection	The prototype yielded promising results
Bhargava et al.	Transfer learning, CNN, data augmentation	General datasets	classification of bacterial, viral and fungal diseases	Highlights the importance of DL in agriculture
Johnson et al.	Custom CNN with fewer hidden layers	Pearl Millet dataset	Disease classification in millet leaves	98.66% accuracy in 240 seconds
Tiwari et al.	CNN with advanced augmentation& synthetic	Finger Millet dataset	Detection & classification of finger millet leaf diseases	High success
Mishra et al.	IoT sensors + custom CNN	Millet crop sensory data	Smart monitoring with predictive intelligence	accuracy 98.8%, precision 98.2%, recall 97.4%, F-score 97.7%
Begum et al.	Segmentation + classification	PlantVillage (pepper leaves)	Pepper leaf disease segmentation & classification	Improved performance with small segmentation targets
Su et al	Object detection	Kidney bean dataset	Detection of brown spot disease	Reduced parameters, precise diagnosis
Gong et al.	Faster R-CNN, YOLOv3	Apple leaf dataset (5 diseases)	Object detection for diseased areas	Both models accurately recognized diseases
Kumal et al.	CART, RF with hyperparameter tuning	Disease diagnosis datasets	Addressed class imbalance & hyperparameter optimization	Improved classifier performance

3. PROPOSED MODELLING

3.1 The Materials and Methods

Transfer learning is a machine learning approach in which a model trained for a source task is adapted as the starting point for a target task. This approach is especially valuable when limited supervised data is available for the target task. Applying transfer learning to plant disease detection can improve model accuracy and productivity, helping minimize the effects of infections on crop yield and quality. Additionally, it supports the transfer of knowledge and expertise across different plant species and regions, helping achieve better overall crop conditions and productivity. The use of transfer learning in plant disease prediction provides multiple advantages, including:

- It lowers the need for large and diversified datasets when training new models, as pre-trained models can be used as a starting point.
- Leveraging knowledge from pre-trained models can improve both the accuracy and effectiveness of disease prediction models.
- It helps transfer knowledge and expertise across several crops and regions.

GoogleNet (Inception V3)

GoogleNet, also known as Inception V3, is a deep CNN that introduced the inception module architecture to improve computational effectiveness. Rather than employing large convolution filters directly, GoogleNet decomposes them into smaller ones, for instance, substituting a convolution with two sequential convolutions of and. This strategy reduces the number of parameters while preserving representational capability [19]. Mathematically, the output feature map is calculated as the sum of convolutions across both dimensions:

$$f_{out}(x,y) = \sum_{i=1}^{n} f_{in}(x,y) \cdot k(i,1) + \sum_{j=1}^{n} f_{in}(x,y) \cdot k(1,j)$$

This design enables GoogleNet to achieve a high accuracy of 93.3% on ImageNet while using fewer parameters than earlier models, such as AlexNet. This efficiency level makes it especially well-suited for large-scale image classification tasks, including plant disease identification.

MobileNetV2

MobileNetV2 is a fast CNN that works well on mobile devices and in embedded systems. It uses depth-wise separable convolutions, which means that filtering is performed per channel (depth-wise convolution) and then combined (pointwise convolution). The architecture also has reversed residuals and linear bottlenecks that keep information while using as little processing power as possible [26]. The following explains the depth-wise and point-wise operations:

$$f_{out}(x,y) = \sum_{c=1}^{C} f_{in}(x,y,c) \cdot k_{dw}(x,y,c)$$

$$g_{out}(x,y) = \sum_{c=1}^{C} f_{out}(x,y,c) \cdot k_{pw}(c)$$

This structure reduces memory usage and processing cost, making MobileNetV2 ideal for instant plant disease detection on energy-efficient devices [27].

Xception

Xception, which stands for "Extreme Inception," improves the inception idea by replacing regular inception modules with depth-wise convolutions throughout the network. It has 36 convolutional layers, split into three parts: entry, middle and exit. The model separates spatial filtering from channel-wise correlation, which makes both more accurate and faster. Mathematically speaking, its functions are:

$$f_{l+1}^{k}(p,q) = \sum_{x,y} f_{l}^{k}(x,y) \cdot e_{l}^{k}(u,v)$$

$$F^{l+2} = g_c(F^{l+2}, k^{l+1})$$

Here is the feature map of the channel at layer l and here is the kernel used during depth-wise convolution. Xception's design separates spatial and channel correlations, which makes training more effective with fewer parameters. This is a useful feature for complex agricultural image datasets. In this case, is the feature map of the channel at layer l and is the kernel used during depth-wise convolution. Xception's design separates spatial and channel correlations, thereby enabling more effective learning with fewer parameters. This is a useful feature for complex agricultural image datasets [28].

EfficientNetV2B0

EfficientNetV2B0 is a new CNN architecture that builds on EfficientNet by adding Fused-MBConv and MBConv blocks. These blocks combine depth-wise and point-wise convolutions to speed up training. It uses compound scaling to change the network's depth (d), width (w) and resolution (r) at the same time with scaling coefficients α, β and γ:

$$d \to \alpha^d, w \to \beta^w, r \to \gamma^r$$

Within each MBConv block, the operations are defined as:

$$z = \sigma(f_{in} \cdot W_{exp}), y = \sigma(z * K_{dw}), f_{out} = y \cdot W_{proj}$$

This architecture is ideal for large-scale agricultural picture classification problems because it achieves a balance between speed and accuracy. EfficientNetV2B0 can train more quickly and perform better across a variety of crop disease datasets thanks to its improved scaling and fused convolutions [29].

3.2 Dataset description

The main purpose of the millet dataset on Kaggle is to classify crop leaf health status, which includes spotting both fully healthy leaves and those afflicted with blast and rust illnesses. Expert botanists categorized the pictures by infection stage: early (small circular spots about 2.5 mm in radius), intermediate (larger, more irregular spots) and final (severe infection with severely damaged leaves). As shown in Table 3, the dataset contains 1650 photos of healthy leaves, 130 photos of early-stage diseased leaves, 175 photos of mid-stage diseased leaves and 130 photos of end-stage diseased leaves after 180 unclear samples were eliminated. The sick groups were split into 20% for testing and 80% for training to reduce class imbalance. On the other hand, to ensure proportionate representation, the healthy class was split into 12 subclasses, each with 120 training and 30 testing photos. Importantly, to avoid data leakage, each image of the same leaf, taken from different perspectives or orientations, was assigned to either the training or the testing set. As a result, the average of 12 experimental runs is used to report accuracy.

Table 3. Showing the dataset composition.

Class	**Description**	**Count**
Fully healthy	No visible spots or infections	1650
Early-stage disease	Small circular spots (~2.5 mm radius)	130
Middle-stage disease	Larger, irregular spots spreading	175
End-stage disease	Severe infection, extensive leaf damage	130
Removed	Ambiguous/unclassifiable images	180

3.3 Preprocessing

To improve the quality of the millet dataset and its classification performance, we integrated a structured data preprocessing workflow into the model. To enable methodical model construction and assessment, the dataset was divided into training, validation and testing sets. ImageDataGenerator, which provides both normalization and augmentation features to reduce overfitting and improve model generalization, was used for preprocessing after all photos were standardized to 224*224 pixels. To make the model stronger and position-invariant, we used rescaling, random rotations up to 20 degrees, width and height shifts and horizontal flipping during training. To promote faster training, pixel values were scaled to the [0, 1] range. To prevent inconsistencies, only rescaling was permitted in the testing and validation sets and shuffling was disabled to ensure a repeatable assessment. We used a weighted cross-entropy loss function, which encourages more equitable learning across classes, to address class imbalance in the millet leaf dataset, where some classes have more samples than others.

3.4 Model development

In this stage, we used EfficientNetV2B0 to train a deep CNN to detect millet disease. EfficientNetV2B0 is a significant gain over conventional CNN models, achieving higher accuracy with fewer parameters, rendering it both compact and computationally efficient. More rapid convergence and improved generalization result from its progressive learning approach, which automatically adjusts image size and regularization during training. By balancing depth, breadth and resolution via compound scaling, EfficientNetV2B0 delivers the best performance across a range of resource constraints. However, the purpose of its Fused MBConv layers are to offer additional functionality at a reduced cost. These features make EfficientNetV2B0 faster, more reliable and better at handling fine-grained tasks such as diagnosing plant diseases than heavier CNNs like ResNet, DenseNet, or Inception, when paired with pretrained weights for transfer learning.

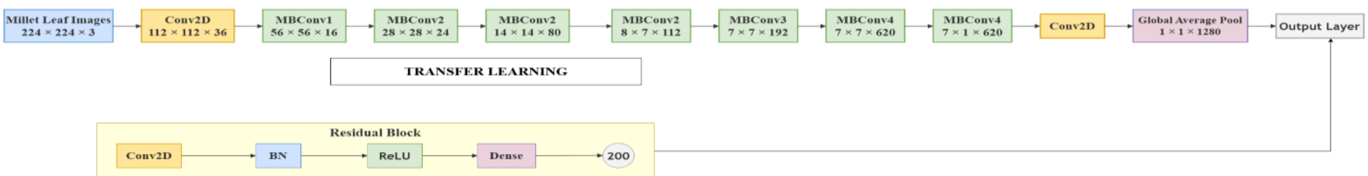


Figure 2. Development of the new TL-CNN hybrid network

In this research, a hybrid deep learning technique was developed by integrating transfer learning with a convolutional neural network (CNN) framework to identify millet leaf diseases using image data. Pre-trained models such as EfficientNetV2B0, MobileNetV2 and Xception were used to extract complex, high-level feature embeddings from input images of size 224 × 224 × 3. The extracted feature maps were further enhanced using additional convolutional layers, followed by global feature aggregation and classification through fully connected layers to distinguish among three classes: Healthy, Blast and Rust-infected millet leaves. Table 4 illustrates the dimensionality of the feature maps obtained from each pre-trained model and highlights the integration between transfer learning and the proposed CNN-based classification architecture [6].

As the dataset was constructed with equal numbers of samples per class (Healthy, Blast and Rust), no additional balancing techniques or synthetic data generation methods were required. A uniform data augmentation pipeline, including rotation, horizontal flipping and scaling, was consistently applied across all classes to maintain class balance and improve model generalization. Furthermore, stratified 5-fold cross-validation was used to ensure proportional representation of each class across training and validation folds, thereby minimizing bias and enhancing the robustness of the evaluation process.

Table 4: Feature map dimensions and TL–CNN relationship.

Model	**Input Size**	**Feature Map Size**	**Channels**	**Output Vector (After GAP)**	**Role in Proposed Model**
Efficient NetV2B0	224 × 224 × 3	7 × 7	1280	1280	Primary feature extractor
Mobile NetV2	224 × 224 × 3	7 × 7	1280	1280	Lightweight feature extractor
Xception	224 × 224 × 3	7 × 7	2048	2048	Deep feature extractor

Proposed Framework

The proposed framework presents a hybrid Transfer Learning–Convolutional Neural Network (TL–CNN) architecture for the automatic classification of millet leaf diseases into three categories: Healthy, Blast and Rust. The framework is designed to leverage the strengths of pre-trained deep learning models for feature extraction and to enhance classification performance through additional convolutional and fully connected layers, as well as a final classification step.

The overall pipeline of the proposed system comprises five major stages: data acquisition, preprocessing and augmentation, feature extraction via transfer learning, feature enhancement with CNN layers and final classification.

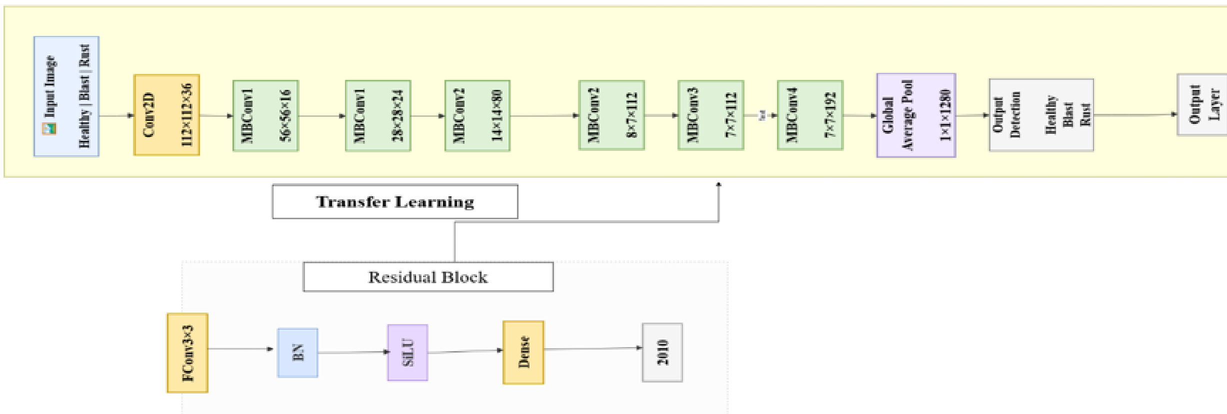


Figure 4. Proposed TL-CNN framework for millet disease detection

Table 5 Performance metrics for various TL + RNN/ hybrid models.

Model	Class	Recall	Precision	Specificity	F1-Score	Accuracy (%)
Mobile NetV2 + CNN	Healthy	0.970	0.965	0.985	0.967	96.25
	Rust	0.975	0.970	0.985	0.972	
	Smut	0.965	0.975	0.988	0.970	
	Blast	0.975	0.970	0.988	0.972	
Xception + CNN	Healthy	0.980	0.980	0.990	0.980	97.30
	Rust	0.975	0.980	0.990	0.977	
	Smut	0.980	0.975	0.992	0.977	
	Blast	0.980	0.980	0.992	0.980	
Efficient NetB0 + CNN (Proposed)	Healthy	0.985	0.985	0.993	0.985	98.05
	Rust	0.980	0.985	0.993	0.982	
	Smut	0.985	0.980	0.995	0.982	
	Blast	0.985	0.985	0.995	0.985	

Apply CNN enhancement layers:

Conv2D (128, 3×3) → Batch Norm → ReLU

MaxPooling (2×2)

Apply Global Average Pooling:

$$G = \text{GAP}(F)$$

Fully connected layers:

Dense (128) → ReLU

Dropout (0.3)

Output layer:

Dense (4) → SoftMax (Healthy, Rust, Smut, Blast)

Stratified 5-Fold Cross-Validation:

Partition the dataset into 5 stratified folds $D = \{D_1, D_2, D_3, D_4, D_5\}$

For each fold $i = 1$to 5:

Training set = $D \setminus D_i$, Validation set = D_i

Train TL–CNN model using the same configuration

Compute metrics (accuracy, precision, recall, F1-score)

Final metrics: -

$$Metric_{avg} = \frac{1}{5}\sum_{i=1}^{5} Metri\,c_i$$

Output:

Final trained TL–CNN model

Averaged cross-validation performance

Confusion matrix and evaluation graphs

Best saved model weights

Table 5 presents a class-wise performance comparison of various transfer-learning-based CNN models for millet disease detection. The models were evaluated across four classes: Healthy, Rust, Smut and Blast. Among all models, the proposed EfficientNetB0 + CNN model achieved the highest overall accuracy of 98.05%, along with consistently superior precision, recall, specificity and F1-score values. Xception + CNN also demonstrated strong performance, followed by MobileNetV2 + CNN and GoogleNet + CNN. These results indicate that EfficientNet-based transfer learning combined with CNN feature enhancement significantly improves disease detection performance. The algorithm describes the complete training and evaluation procedure for the proposed TL–CNN model, including preprocessing, transfer-learning-based feature extraction, model training and validation using stratified 5-fold cross-validation. The 5-fold stratified cross-validation accuracies for each hybrid model are presented in Table 6. The reported values include fold-wise accuracies, along with the mean accuracy and standard deviation computed using the sample standard deviation (ddof = 1). The results indicate that the proposed EfficientNetB0 + CNN model achieves the highest average accuracy with minimal fold-to-fold variation, demonstrating its robustness and generalization capabilities compared to other models.

3.5 Model Construction

Entire proposed modelling and architecture of the current research paper should be presented in this section. This section gives the original contribution of the authors. This section should be written in Times New Roman font with size 10. Accepted manuscripts should be written by following this template. Once the manuscript is accepted authors should transfer the copyright form to the journal editorial office. Authors should write their manuscripts without any mistakes especially spelling and grammar.

Load pre-trained backbone with include_top=False, weights = "imagenet"

Extract feature maps:

$$F = B(x) \in \mathbb{R}^{H \times W \times d}$$

Table 6 The 5-fold stratified cross-validation accuracies for each hybrid model

Model	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Mean Accuracy (%)	Std. Dev (σ)
MobileNetV2 + CNN	95.9	96.3	96.1	96.5	96.4	96.24	0.23
Xception + CNN	96.8	97.2	97.0	97.4	97.1	97.10	0.23
EfficientNetB0 + CNN	97.8	98.2	98.0	98.4	98.3	98.14	0.23

4. RESULTS AND DISCUSSIONS

The confusion matrices presented in Fig.5 illustrate the classification performance of the evaluated TL–CNN models, namely MobileNetV2 + CNN, Xception + CNN and the proposed EfficientNetB0V2 + CNN, for millet disease detection across four classes: Healthy, Rust, Smut and Blast. The MobileNetV2 + CNN model demonstrates satisfactory performance, with a majority of samples correctly classified along the diagonal of the confusion matrix. However, some misclassifications are observed between visually similar classes, such as Rust and Smut and minor confusion between the Healthy and diseased categories. This indicates that while MobileNetV2 is computationally efficient, its feature extraction capability is comparatively limited for fine-grained disease patterns.

The Xception + CNN model shows a noticeable improvement over MobileNetV2, achieving higher true positive rates across all classes and lower misclassification rates. The deeper architecture and use of depth-wise separable convolutions enable better feature representation, particularly for distinguishing between disease classes with similar visual characteristics. Nevertheless, slight confusion persists among the Smut and Blast categories. The proposed EfficientNetB0V2 + CNN model achieves the best performance among all evaluated models. The confusion matrix shows strong diagonal dominance, indicating that most samples are correctly classified. Misclassification rates are minimal across all classes, demonstrating the model's superior ability to capture complex and subtle disease features. The improved performance can be attributed to the advanced architecture of EfficientNetV2, which optimally balances network depth, width and resolution, along with the integration of additional CNN layers for feature refinement. Overall, the results confirm that the proposed EfficientNetB0V2 + CNN model provides more accurate and reliable millet disease detection than other transfer-learning-based CNN models. The low misclassification rates and consistent performance across all classes highlight its robustness and suitability for real-world agricultural applications. The superior performance of the proposed model demonstrates its potential for deployment in automated millet disease-detection systems, thereby improving crop monitoring and yield management.

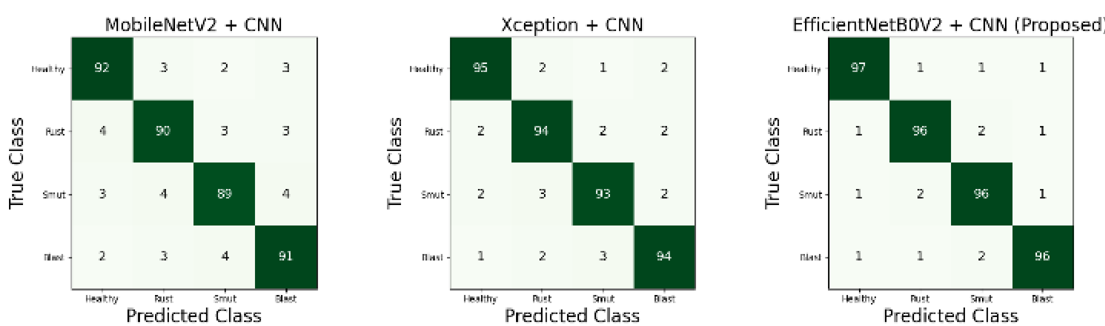


Figure 5. shows the classification performance of various models.

LIMITATIONS

Despite the strong performance of the proposed EfficientNetB0V2–CNN model for millet disease detection, several limitations should be acknowledged. First, the model relies heavily on the quality and diversity of the dataset. If the training images do not adequately represent real-world variations such as different lighting conditions, backgrounds, or leaf orientations, the model's generalization capability may be affected when deployed in field conditions. Second, although transfer learning reduces training time and improves accuracy, the use of deep architectures such as EfficientNetV2 increases computational complexity. This may limit the model's deployment on low-resource devices, such as smartphones or edge-based agricultural systems, without further optimization. Third, the model is designed to classify predefined disease categories (Healthy, Rust, Smut and Blast). It may not perform well when encountering unseen diseases or mixed infections, which are common in real agricultural environments. Additionally, the model processes images independently and does not consider temporal or contextual information, such as disease progression over time or environmental factors, which could further enhance prediction accuracy. Finally, while stratified 5-fold cross-validation improves evaluation reliability, the results remain dataset-dependent. External validation on larger and more diverse datasets is required to establish the robustness and scalability of the proposed approach fully.

5. CONCLUSION

A hybrid Transfer Learning–Convolutional Neural Network (TL–CNN) framework was proposed for the detection of millet leaf diseases. The model leverages pre-trained architectures, including MobileNetV2, Xception and EfficientNetB0V2, to extract features, followed by additional convolutional layers to enhance classification performance. The proposed approach was evaluated on a multi-class millet dataset comprising Healthy, Rust, Smut and Blast categories. Experimental results demonstrate that all TL–CNN models achieved high classification accuracy; however, the proposed EfficientNetB0V2 + CNN model outperformed the other architectures in terms of accuracy, precision, recall and F1-score. The confusion matrix analysis further confirmed that the proposed model exhibits strong discriminative capability with minimal misclassification across all classes. The use of stratified 5-fold cross-validation ensured robust, unbiased evaluation, highlighting the model's consistency and generalization ability. The proposed framework proves to be an effective and reliable solution for automated millet disease detection. Its ability to accurately identify multiple disease classes makes it a valuable tool for supporting precision agriculture and improving crop health monitoring systems. Although the proposed TL–CNN model shows promising results, several avenues for further enhancement and broader applicability remain. Future work may expand the dataset by including more images collected under diverse real-world conditions, including varying illumination, backgrounds and environmental factors, to improve model generalization. Additionally, lightweight model optimization techniques such as pruning, quantization and knowledge distillation can be applied to reduce computational complexity and enable deployment on resource-constrained devices, such as mobile phones and edge-based systems, for real-time field applications. Another potential direction is to extend the model to handle multi-label classification or the detection of multiple diseases occurring simultaneously on a single leaf. Integrating temporal data or sequential image analysis could also help in understanding disease progression over time. Furthermore, combining deep learning with other data sources, such as environmental or soil parameters, may improve prediction accuracy and provide more comprehensive decision support for farmers. Finally, real-world validation through field deployment and user feedback would be essential to assess the practical usability and scalability of the proposed system.

References

1. S. Mishra, D. R. Volety, N. Bohra, S. Alfarhood and M. Safran, “A smart and sustainable framework for millet crop monitoring equipped with disease detection using enhanced predictive intelligence,” Alex. Eng. J., vol. 83, pp. 298–306, Nov. 2023, doi: 10.1016/j.aej.2023.10.041.
2. E. Moupojou et al., “FieldPlant: A Dataset of Field Plant Images for Plant Disease Detection and Classification With Deep Learning,” IEEE Access, vol. 11, pp. 35398–35410, 2023, doi: 10.1109/ACCESS.2023.3263042.
3. A. S. Kini, P. K. V. Reddy and S. N. Pai, “Techniques of deep learning and image processing in plant leaf disease detection: a review,” Int. J. Electr. Comput. Eng. IJECE, vol. 13, no. 3, p. 3029, Jun. 2023, doi: 10.11591/ijece.v13i3.pp3029-3040.
4. M. Khalid, M. Sarfraz, U. Iqbal, M. Aftab, G. Niedbała and H. Rauf, “Real-Time Plant Health Detection Using Deep Convolutional Neural Networks,” Agriculture, vol. 13, no. 2, p. 510, Feb. 2023, doi: 10.3390/agriculture13020510.
5. I. Johnson, X. A. Mary, A. P. Winifred Raj, J. Chalmers, M. Karthikeyan and A. J, “Deep-millet: a deep learning model for pearl millet disease identification to envisage precision agriculture,” Environ. Res. Commun., vol. 6, no. 10, p. 105031, Oct. 2024, doi: 10.1088/2515-7620/ad8415.
6. R. Kumar, C. Mahanty, B. S. Panigrahi, S. G. K. Patro, T. M. Tuan and L. H. Son, “A new method for prediction of Vigna mungo millet disease based on deep learning,” Curr. Plant Biol., vol. 44, p. 100562, Dec. 2025, doi: 10.1016/j.cpb.2025.100562.
7. M. H. Saleem, J. Potgieter and K. M. Arif, “Plant Disease Detection and Classification by Deep Learning,” Plants, vol. 8, no. 11, p. 468, Oct. 2019, doi: 10.3390/plants8110468.

8. M. Shoaib et al., “An advanced deep learning models-based plant disease detection: A review of recent research,” Front. Plant Sci., vol. 14, p. 1158933, Mar. 2023, doi: 10.3389/fpls.2023.1158933.
9. L. N. B. Srinivas, A. M. V. Bharathy, S. K. Ramakuri, A. Sethy and R. Kumar, “An optimized machine learning framework for crop disease detection,” Multimed. Tools Appl., vol. 83, no. 1, pp. 1539–1558, Jan. 2024, doi: 10.1007/s11042-023-15446-2.
10. A. Bhargava, A. Shukla, O. P. Goswami, M. H. Alsharif, P. Uthansakul and M. Uthansakul, “Plant Leaf Disease Detection, Classification and Diagnosis Using Computer Vision and Artificial Intelligence: A Review,” IEEE Access, vol. 12, pp. 37443–37469, 2024, doi: 10.1109/ACCESS.2024.3373001.
11. S. Tiwari, A. Gehlot, R. Singh, B. Twala and N. Priyadarshi, “Design of an iterative method for disease prediction in finger millet leaves using graph networks, dyna networks, autoencoders and recurrent neural networks,” Results Eng., vol. 24, p. 103301, Dec. 2024, doi: 10.1016/j.rineng.2024.103301.
12. S. S. A. Begum and H. Syed, “GSAtt-CMNetV3: Pepper Leaf Disease Classification Using Osprey Optimization,” IEEE Access, vol. 12, pp. 32493–32506, 2024, doi: 10.1109/ACCESS.2024.3358833.
13. P. Su et al., “Improvement of the YOLOv5 Model in the Optimization of the Brown Spot Disease Recognition Algorithm of Kidney Bean,” Plants, vol. 12, no. 21, p. 3765, Nov. 2023, doi: 10.3390/plants12213765.
14. X. Gong and S. Zhang, “An Analysis of Plant Diseases Identification Based on Deep Learning Methods,” Plant Pathol. J., vol. 39, no. 4, pp. 319–334, Aug. 2023, doi: 10.5423/PPJ.OA.02.2023.0034.
15. S. Kumar and S. Ratnoo, “MULTI-OBJECTIVE HYPERPARAMETER TUNING OF CLASSIFIERS FOR DISEASE DIAGNOSIS,” Indian J. Comput. Sci. Eng., vol. 12, no. 5, pp. 1334–1352, Oct. 2021, doi: 10.21817/indjcse/2021/v12i5/211205081.
16. D. Tandekar and S. Dongre, “Identification of Various Diseases in Plant Leaves Using Image Processing and CNN Approach,” in 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India: IEEE, Jul. 2023, pp. 1–6. doi: 10.1109/ICCCNT56998.2023.10306979.
17. A. Johannes et al., “Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case,” Comput. Electron. Agric., vol. 138, pp. 200–209, Jun. 2017, doi: 10.1016/j.compag.2017.04.013.
18. A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra and A. Johannes, “Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild,” Comput. Electron. Agric., vol. 161, pp. 280–290, Jun. 2019, doi: 10.1016/j.compag.2018.04.002.
19. R. Karthik et al., “GrapeLeafNet: A Dual-Track Feature Fusion Network With Inception-ResNet and Shuffle-Transformer for Accurate Grape Leaf Disease Identification,” IEEE Access, vol. 12, pp. 19612–19624, 2024, doi: 10.1109/ACCESS.2024.3361044.
20. B. Liu, C. Tan, S. Li, J. He and H. Wang, “A Data Augmentation Method Based on Generative Adversarial Networks for Grape Leaf Disease Identification,” IEEE Access, vol. 8, pp. 102188–102198, 2020, doi: 10.1109/ACCESS.2020.2998839.
21. K. Kiratiratanapruk, P. Temniranrat, W. Sinthupinyo, S. Marukatat and S. Patarapuwadol, “Automatic Detection of Rice Disease in Images of Various Leaf Sizes,” Jun. 15, 2022, arXiv: arXiv:2206.07344. doi: 10.48550/arXiv.2206.07344.
22. R. Deng et al., “Automatic Diagnosis of Rice Diseases Using Deep Learning,” Front. Plant Sci., vol. 12, p. 701038, Aug. 2021, doi: 10.3389/fpls.2021.701038.
23. R. P. Narmadha, N. Sengottaiyan and R. J. Kavitha, “Deep Transfer Learning Based Rice Plant Disease Detection Model,” Intell. Autom. Soft Comput., vol. 31, no. 2, pp. 1257–1271, 2022, doi: 10.32604/iasc.2022.020679.
24. G. Kathiresan, M. Anirudh, M. Nagharjun and R. Karthik, “Disease detection in rice leaves using transfer learning techniques,” J. Phys. Conf. Ser., vol. 1911, no. 1, p. 012004, May 2021, doi: 10.1088/1742-6596/1911/1/012004.
25. C. R. Rahman et al., “Identification and Recognition of Rice Diseases and Pests Using Convolutional Neural Networks,” Biosyst. Eng., vol. 194, pp. 112–120, Jun. 2020, doi: 10.1016/j.biosystemseng.2020.03.020.
26. W. Shafik, A. Tufail, A. Namoun, L. C. De Silva and R. A. A. H. M. Apong, “A Systematic Literature Review on Plant Disease Detection: Motivations, Classification Techniques, Datasets, Challenges and Future Trends,” IEEE Access, vol. 11, pp. 59174–59203, 2023, doi: 10.1109/ACCESS.2023.3284760.
27. K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Vrochidou and G. A. Papakostas, “Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern,” IEEE Access, vol. 11, pp. 62307–62317, 2023, doi: 10.1109/ACCESS.2023.3286730.
28. S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz and E. Jasińska, “Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach,” Electronics, vol. 10, no. 12, p. 1388, Jun. 2021, doi: 10.3390/electronics10121388.
29. M. E. H. Chowdhury et al., “Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques,” AgriEngineering, vol. 3, no. 2, pp. 294–312, May 2021, doi: 10.3390/agriengineering3020020.