International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://www.theaspd.com/ijes.php

Automated Detection of Eggplant Diseases Using Custom Convolutional Neural Network (CNN) and Transfer Learning Models

Putra Sumari[1]*, Mustafa M. Abd Zaid[2], Ahmed Kateb Jumaah Nussairi[3], Abdullah Saud Fatmi[1], Zannatul Sanzida[1], Bilal Muhammad[1], Abdulkarem Khaled[1] and Cheah Jun Hong[1]
[1]School of Computer Science, University Sains Malaysia, 11800 Peneng, Malaysia
[2]College of Technical Engineering, Islamic University, Najaf, Iraq
[3]Al-Manara College for Medical Sciences, Amarah, Iraq
*Corresponding author: putras@usm.my

Abstract: *Eggplant is a crop with substantial economic value; it is at risk for several illnesses, including small leaf, mosaic virus, bacterial wilt, and leaf spot. Timely and accurate identification of these illnesses is essential for efficient handling and increased crop productivity. This project aims to use transfer learning and convolutional neural networks (CNN) to create an automated system for diagnosing and categorizing eggplant illnesses. A 4-6 convolutional layer and 2-3 classification layer bespoke CNN model was constructed, and its performance was assessed against three pre-trained models: VGG16, InceptionV3, and MobileNetV2. We carefully adjusted the models using optimizers, epochs, and other hyperparameters to determine the best method for identifying eggplant illness. This showed that the custom CNN outperformed all models applied in this study and yielded 96.09%, which refers to the capacity of the deep learning model to classify plant diseases correctly.*
Keywords: *Eggplant disease, CNN , VGG16, InceptionV3, MobileNetV2.*

1. INTRODUCTION

Eggplant farming is of significant economic importance although it is highly susceptible to several diseases that can induce poor output and quality. These diseases need early and accurate diagnosis to enhance effective management of the disease and optimal health of the crops. Among the most common diseases that can affect eggplant plants include Bacterial Wilt, Mosaic Virus, Leaf Spot as well as Small Leaf. When not identified and treated in their early stages, such diseases can cause massive damages.

Classically, the diagnosis and classification process of these diseases involved a manual review process by human experts which is time consuming, subjective and error prone. The possibility of automated systems predicated upon computational vision and methods of machine learning has suggested new ways of diagnosing diseases more effectively and accurately. In the current paper, we strive to devise a system that will automatically detect and classify most prevalent diseases found in eggplant leaves basing on the implementation of a convolutional neural network (CNN) architectural design and implementation the transfer learning technique to identify the most suitable model.

Machine learning and deep learning methods have become trends in a set of fields same medicine [1] and agriculture [2], [3], geographic [4], [5], especially CNNs have exhibited excellent identification in image identification challenges owing to their capability to automatically obtain significant characteristics from entered photos and generate exact predictions [6], [7]. The adoption of deep learning methods, notably CNNs, has transformed the area of image identification and classification, giving remarkable accuracy and efficiency [8]. By applying CNNs, we may construct a robust system capable of properly identifying and categorizing diseases affecting eggplant leaves. Transfer learning has proven to be a valuable method for boosting the performance of CNN models by using pre-trained networks on large datasets [9]. This strategy may boost the model's capacity to identify and categorize varied pathology signs in eggplant leaves, even with insufficient labeled data. In the broader context of data-driven approaches in agriculture and public health, time series analysis and machine learning techniques have demonstrated substantial value in forecasting and anomaly detection. For example, exponential smoothing methods have been effectively applied to predict the progression of COVID-19 cases using real-world datasets, showing the importance of robust models for handling noisy or limited data [10].

The successful deployment of a CNN-based disease detection system for eggplant leaves will have important practical ramifications. It would help farmers identify infections at an early stage, thereby minimizing crop losses and enhancing total productivity. "Automated disease detection systems in agriculture not only enhance productivity but also contribute to sustainable farming practices [11]. Additionally, such a system may serve as a basis for creating more sophisticated, intelligent agricultural systems.

2. RELATED WORKS

A. Kaniyassery et al. [12] examined the correlations between weather parameters and the incidence of diseases in Mattu Gulla; it considered leaf spot and fruit rot. The authors also determined that there was a high negative correlation between leaf spot and minimum temperature, and a positive correlation between DI (%) and fruit rot. Di (%) in the case of FR showed a positive relationship with wind speed and temperature, as well as the highest relative humidity and rainfall. A good RH I of 86-87% was reported to be conducive to the incidence of fruit infections in fields. The project has produced an Android application called Leaf Guard, which has been tested for AI-powered eggplant disease detection, achieving an accuracy level of 98.2 %.

J. Liu and X. Wang [13] introduced a lightweight algorithm concerning the YOLOv8 model to enhance the detection of eggplant diseases under complex settings. The significant improvements of this work include FasterNet, efficient feature extraction, TAM attention modules for enhanced feature representation, a small-object detection head, and an adaptive WIoU loss function for optimizing bounding box regression features. Through experiments, it is revealed that the method obtains a mean Average Precision of 92.61% and a speed of 88.39 frames per second to offer an optimal balance between accuracy and speed.

An agricultural and medical expert system, which is based on machine vision, has also been suggested by I. H. Saad et al. [14]. The system calculates photos that are taken either by using a mobile phone or any handheld appliance and classifies the diseases and allows the individuals to find solutions to their problems. The authors used a convolutional neural network (CNN) transfer learning model, e.g., DenseNets, Xception, and ResNets and achieved the greatest accuracy of 99.06 percent with DenseNet201.

In addition, other researchers came up with a methodology based on Ensemble Transfer Learning (ETL) by I. Hossain Siddiqui et al. [15] to obtain minimal errors at the level of classification of the disease of eggplants in terms of concatenating ConvNeXt, EfficientNetV2, NFNet, and RegNet. It had two datasets, where over 19,800 images were trained and validated, and where advanced data augmentation and preprocessing methods were used. The superb classification effectiveness of 99.76% and the model exceeds the already existing methods and displayed satisfactory generalization on other conditions.

A. Suryavanshi et al. [16] studied the opportunity of using Federated Learning (FL) and Convolutional Neural Networks (CNN) to detect and identify five diseases in Brinjal leaves. In the project, there were five different customers, and their data sets identified symptoms that represented their respective illnesses. Besides the virtue of CNNs to serve as image processing machines, the research exploited the privacy by design and distributed capability of FL to construct a strong model that can recognize several signs of ill-health. That research involved Federated Averaging, the new methodology that consolidates the learning process on regional data into a single, more generalizable model. The measures of performance were built in terms of macro and micro averages and weighted ones. The findings were staggering, with significant differences between customers, which is expected given the substantial variation in the data sets. Client io-1 recorded an overall average, weighted average, and micro average of 87.68%, 87. 54%, and 87. 54%, respectively, which implies its capability to recognize different situations. Client io-3 performed exceptionally well, achieving a 97.20% macro average, a 97.54% weighted average, and a 97.54% micro average.

S. A., R. Kamal G., M. S. Sayeed, and V. T. [17] proposed a deep learning model that can classify images of a single leaf as healthy or infected for the sake of early disease detection and effective preventive measures. Pre-trained Convolutional Neural Network (CNN) architecture was used in three datasets, with an accuracy that spanned from 0.82 to 0.97. The study's findings will enable farmers to utilize the model in a mobile app, confidently classify healthy and infected single leaf pictures, and take timely action to eradicate the disease, thereby preventing its spread.

A. Anu Priya and K. Rajaram [18] have introduced the concept to diagnose these diseases through the VGG16 CNN model, which is more effective compared to traditional ones, where these diseases could only be identified through a manual examination. This approach adopts the VGG16 architecture in the process of extracting meaningful features of leaf images and classifying them with high accuracy. To complete the task, it is proposed to operate with the Eggplant Leaf Disease Dataset that consists of six classes. VGG16 uses fully connected activations after the deep convolutional layers, which extract discriminative features and are then classified using their fully connected layers and the softmax activation. The model achieves 98.2% synthesis accuracy, enabling the diagnosis of Brinjal diseases. This is a crucial role for agriculture, as the research aims to develop a faster, automatic model for early disease diagnosis, thereby minimizing crop yield loss and increasing production.

A method of classification based on a few-shot was proposed by D. Meng, D. Ma and M. Ma [19]. First, the diversity of the image features is increased with the application of the Randaugment approach. Afterwards, an optimal MCA-RepVGG-A-B3 is employed as the backbone to enlarge the characteristic dimensions at each learning step, thus enhancing the concentration and acquisition of multidimensional collaborative key characteristics. Moreover, the concept of transfer learning is used, whereby the model has been trained on a miniImageNet dataset and fine-tuned on an open-source dataset of eggplant leaves that can suffer from diseases to counter the effects of overfitting. As the experimental findings indicate, a classification accuracy of 89.76% and an F1 score of 89.69% can be obtained using the given method, which proved superior to models like VGG16, ResNet50, Convnext(tiny), VIT, and YOLOv5.

A. Sandhya et al. [20] provided a method through which brinjal disease identification would be automatic, and they used the YOLOv8 algorithm, which shows higher accuracy on object detection efforts. A detailed dataset of brinjal leaves images affected by diseases of various natures was used to train the system with the specific aim of correctly labelling the symptoms of the diseases. The YOLOv8 algorithm demonstrated a significant improvement over its predecessors, achieving an impressive accuracy of 95%. A comparison across previous versions of YOLO and other state-of-the-art object detection algorithms was considered, and it was found that YOLOv8 had better accuracy and a lower processing time, and thus better fits in real-time applications. The offered system will allow accurate recognition and categorization of the various ailments that arise in brinjal with a high degree of accuracy and therefore be able to implement precautionary measures in time.

R. Gayathri and K. Umadevi [21] leveraged advanced deep learning, including a transformative attention mechanism, the integration of YOLOv8's most sophisticated model, and bounding box regression accuracy enhancement. The method provides a mean average precision of 92.61% and 88.39% Frames per second. Other pre-trained models such as DenseNet201, Xception and ResNet152V2 are also employed; the accuracy of the DenseNet201 is 99.06%. The use of multispectral imaging in combination with VGG16-triplet attention allows the early diagnosis of illnesses such as Verticillium wilt with 86.73% precision. To provide a correct assignment of up to 99.4 %, extensive data are generated to produce results.

3. METHODOLOGY

In this paper, we aim to develop a robust system for the accurate detection and categorization of brinjal (eggplant) diseases such as Mosaic Virus, Small Leaf, Leaf Spot, and Bacterial Wilt (caused by Ralstonia Solanacearum). To achieve this, we will employ Convolutional Neural Networks (CNNs) and leverage pretrained models to enhance the accuracy and efficiency of our disease classification system. The methodology is divided into three main sections: Data Preprocessing, CNN Model, and Pretrained Models.

3.1 Dataset Collection:

This dataset consists of a set of images indicating various diseases affecting the leaves of the eggplant crop. The images were collected from various sources, including Google Photos, Kaggle, and Adobe Stock. A total of 500 images were collected and divided into four classes: 100 for bacterial wilt, 150 for leaf spot, 190 for small leaf, and 60 for mosaic virus. Figure 2 shows samples of this dataset.

Figure 2: Classes of diseases in dataset

3.2 Preprocessing

Data preprocessing is a critical step in ensuring the quality and effectiveness of the machine learning models. To ensure uniformity and avoid duplication, all images are renamed according to a standard naming convention (disease_type_image_number.extension).

Given that the images are of different formats (.jpg, .png, .jpeg) and sizes, standardization is required. Using the Python Imaging Library (PIL), each image file is opened and resized to a uniform size of 224x224 pixels while maintaining the aspect ratio. This is done using the thumbnail method of PIL, which ensures that the image does not become distorted during the resizing process. When the image size permits, the image is resized to 224x224 pixels (with padding to preserve the original aspect ratio without distorting/stretching or squashing the image). The finally processed images are then saved to the suitable output folder with a different name indicating that the image has been resized.

Class imbalance is the tendency of the data sets to be skewed with one group heavily underrepresented in comparison with another. This can impact negatively on the performance of machine learning models. To rectify this, we used the method of data augmentation to have a balanced dataset. The augmentation of the images that belong to the minority classes will keep all the classes of diseases well represented, therefore, contributing to the enhancement of the model generalization, both in the training and testing stages.

To further increase the number of images and enhance the model's robustness, systematic data augmentation techniques are applied. This includes rotating the images (e.g., 90°), flipping them horizontally and vertically, adjusting brightness and contrast, and adding random noise. These augmentations are performed with a probability of 0.5 for each operation, ensuring a diverse dataset. The augmented images are saved locally, and this process is repeated until a predefined number of images is achieved for each class. The number of images for each category has been increased to 250, resulting in a total of 1000 images. Figure 3 explains the difference in the dataset between before and after augmentation

The data are next divided into training, validation and test sets (8:1:1). Stratification has been carried out in the split to balance the number of locations of the images in the training, validation, and testing sets. A training set is what is used as a model to adjust the mode parameters to the validation set and finally to test the overall performance of the model trained.

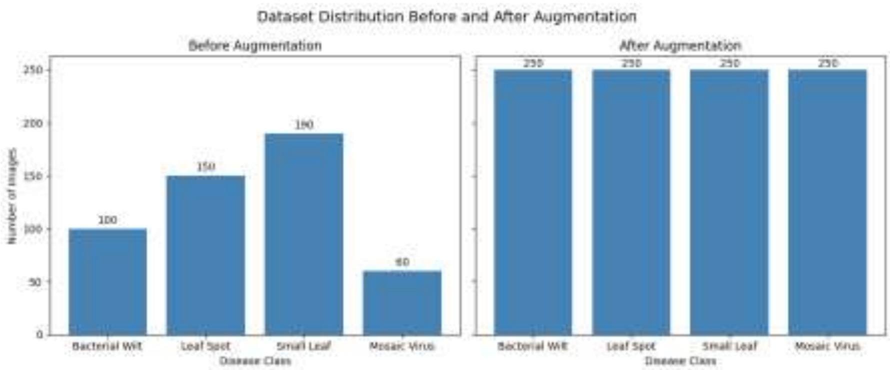

Figure 3: Class distribution before and after augmentation

3.3 Classification Model

3.3.1 Convolutional Neural Network

CNN is well-known in image-based classification tasks. CNNs process the input data using several interconnected layers. The first hidden layer of a CNN is usually a convolutional layer, which applies filters to the input data to detect specific patterns. These networks are built to automatically extract significant features at various degrees of abstraction from raw pixel input and learn hierarchical representations. Convolutional layers in CNNs allow for the extraction of regional patterns and structures. In contrast, pooling layers make it easier to down-sample spatial data, improving the model's ability to identify essential features. Based on the retrieved features, fully connected layers provide the final categorization.

In this study, we will design a custom CNN architecture tailored to the specific characteristics of brinjal disease images. The architecture will include several convolutional layers with ReLU activation functions, followed by max-pooling layers to reduce the spatial dimensions and capture the most salient features. Dropout layers will be added to prevent overfitting, and the final fully connected layers will output the probability distribution over the four disease classes.

3.3.2 Transfer Learning Models

In addition to the proposed CNN, transfer learning models such as MobileNetV2, VGG19 and InceptionV3 are used to compare the accuracy with our CNN model. Transfer learning is a powerful technique in computer vision tasks which enables models to leverage knowledge learned from pre-trained models trained on large-scale datasets. By transferring this knowledge to a new task, transfer learning can significantly enhance classification performance. In our approach, we harness the benefits of transfer learning by utilizing pre-trained models from the literature, such as MobileNetV2, VGG19 and InceptionV3. In this study, the classification layers of the transfer learning models were dropped and replaced with a new classification layer like the proposed CNN model. The weights are initialized to the models' weights trained on ImageNet. All the transfer learning layers were allowed to be trained in this study.

1. MobileNetV2: A compact convolutional neural network architecture called MobileNetV2 was created for effective mobile and embedded vision applications. It is appropriate for devices with limited resources because it uses depth-wise separable convolutions and inverted residual blocks to simplify computations while retaining competitive accuracy.
2. VGG19: convolutional neural network architecture VGG19 is renowned for its efficiency and simplicity. There are 19 layers, including several 3×3 convolutional layers followed by max-pooling layers. Although VGG19 has more parameters than other architectures, it performs image classification tasks with high accuracy.
3. InceptionV3: the deep convolutional neural network architecture known as InceptionV3 uses inception modules. These modules use parallel convolutional layers with various kernel sizes to capture features at various scales. InceptionV3 reduces the number of parameters using dimensionality reduction techniques to obtain high accuracy in image recognition tasks while retaining computing efficiency.

3.4 Hyperparameter Tuning

To achieve the best-performing model, hyperparameter tuning was performed. In this study, three hyperparameters were tested, namely, epochs, learning rate and batch size. The learning rate is a hyperparameter which dictates the extent of change in a deep learning model in response to the estimated error each time the model weights are updated. Batch size, meanwhile, refers to the number of samples processed before the model is updated. Various studies have concluded that learning rate and batch size significantly impact neural networks' performance.

3.5 Performance Metric

During the testing phase, the CNN models' performance is evaluated. Accuracy is one of the most used measures for evaluating the performance of a Convolutional Neural Network (CNN). Accuracy is the ratio of accurately predicted images to all images. The formula for accuracy is:

- TP: True Positive is when the model correctly predicts a sample as belonging to a specific class.
- TN: True Negative is when the model correctly predicts a sample as not belonging to a specific class.
- FP: False Positive is when the model incorrectly predicts a sample as belonging to a specific class.
- FN: False Negative is when the model incorrectly predicts a sample as not belonging to a specific class, but it belongs to that class.

4. RESULTS AND DISUSSION

The first model was made using six convolutional layers and two feed-forward layers, whereas model 2 was made using six convolutional layers, a batch normalization layer and 2 feed-forward layers. The basic structure is the same for both models, with the only difference being the batch normalization layer and the number of epochs. Model 1 had 50 epochs, and model 2 had 30 epochs.

Neural network epochs are one of the most important hyperparameters for Neural Networks. Increasing epochs trains the model for longer periods, enabling it to learn more and perform better. Generally, we wish to have as many epochs as reasonably possible, while balancing the time needed and avoiding model overfitting. A lower number of epochs leads to underfitting, whereas a higher number of epochs can lead to overfitting. Model 1's performance was still lower than Model 2, which could be attributed to model overfitting. When we look at the learning rate and train-validation accuracy graph, we notice that around epoch 25, the training accuracy becomes higher than the validation accuracy. This indicates that the model performs better on its training data than on its validation data, suggesting the model has begun overtraining. This leads to it having lower overall testing accuracy. Compared to model 2's graph, we notice that the training accuracy does not surpass the validation accuracy nor the learning rate, which suggests it has no overtraining. Hence, the overall test accuracy is much higher. Figure 4 explains the results of each one. The structure of both proposed models is the same as that explained in Figure 5.

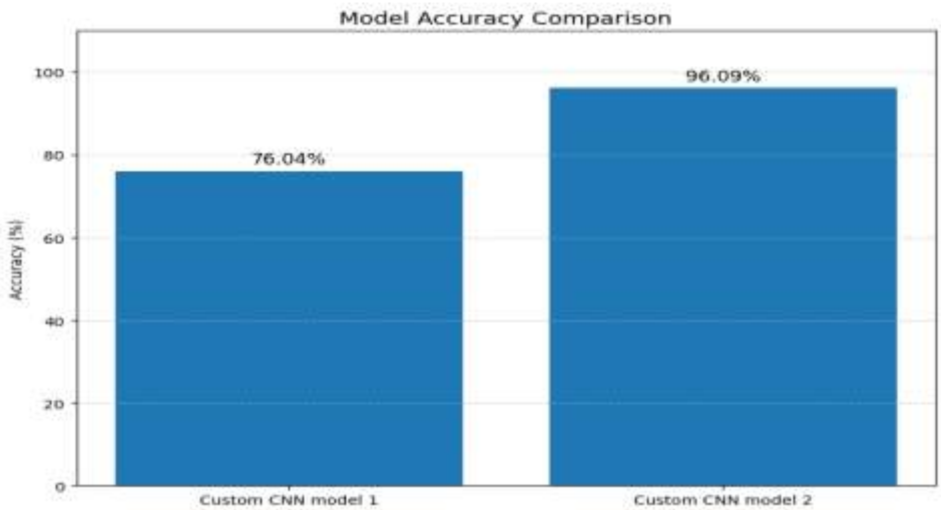

Figure 4: Result of proposed models

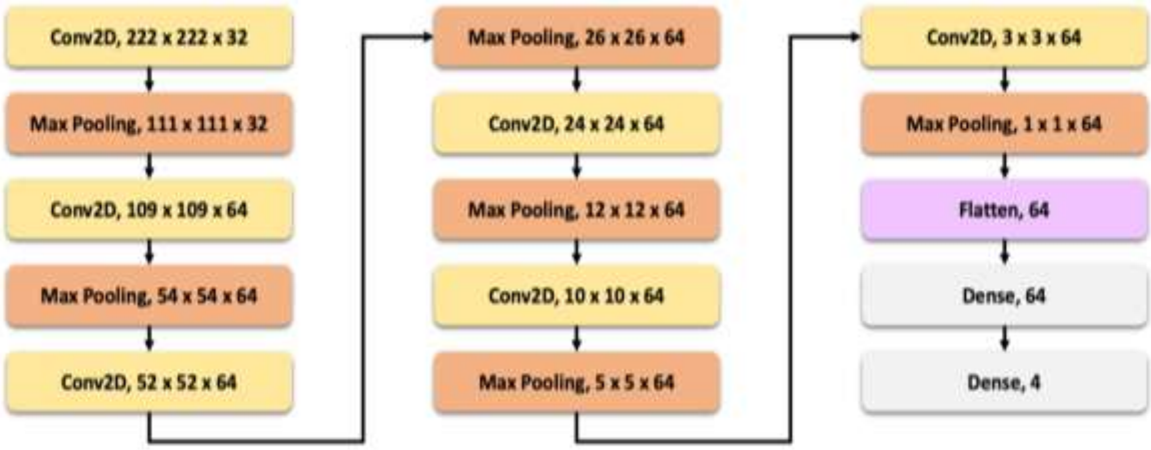

Figure 5: Structure of both proposed custom CNN

According to the original paper, many of the top-performing models of ImageNet were created using batch normalizations. It is a regularization layer that optimizes a model without the need for additional steps. It counteracts the effects of internal covariate shift in a model. Batch normalizations also help prevent overfitting of models and often replaces the function of having a dropout layer. Having an optimal number of epochs and Batch Normalization layers enables us to create a model that significantly outperforms model 1. Figures 6 and 7 explain performance of both proposed models.

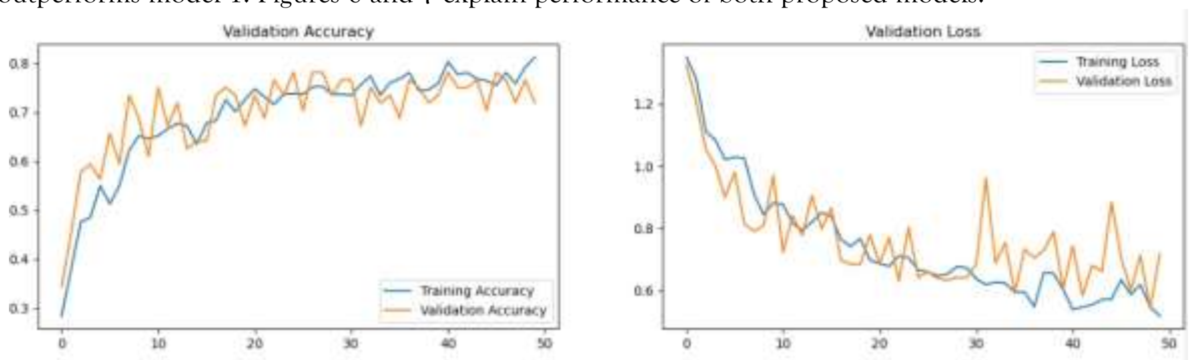

Figure 6: Performance of first custom CNN

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://www.theaspd.com/ijes.php

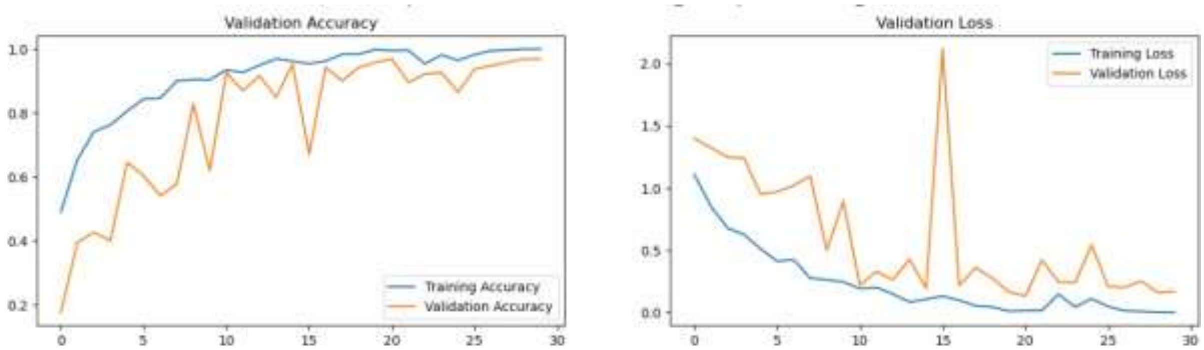

Figure 7: Performance of second custom CNN

Our custom model 1 achieved 76.04% accuracy, whereas custom model 2 scored 96.09%. In contrast, the VGG19, MobileNetV2, and Inception v3 models scored 87.50%, 80.20%, and 63.54%, respectively, as shown in Table 1. The pretrained models perform worse compared to our second model. These performance differences can be attributed to one primary reason: highly specialized training.

Table 1: Performance of the models

Model	Accuracy
First Custom CNN	76.04%
Second Custom CNN	96.09%
Inception v3	63.54%
VGG19	87.50%
Mobilenetv2	80.20%

Our model is specifically trained to classify brinjal leaf diseases. In contrast, other pretrained models are more general, having been trained on the ImageNet dataset. In terms of general object classification, the retrained models will be significantly better, but they lose out to custom models when it comes to specialized tasks. The feature extraction of our model was done only for brinjal leaves, whereas the pretrained models' feature extraction was done for general objects and shapes. They may be able to differentiate between cars and cats very well, but they cannot differentiate between one lead with another. To compare, the MobileNet model has 53 layers, whereas the VGG19 model boasts 19 layers. Compared to our model, which only had seven layers total. This means that, despite the higher number of layers, our model 2 was able to extract more important features from the data, thereby improving its classification prowess. Most pretrained models were too general and were not as optimized for feature extraction of brinjal leaves. It is important to note, however, that without parameter tuning, pretrained models perform much better. Understanding why people prefer pretrained models is important, and it's because of the ease of use. By not optimizing parameters, it is significantly faster to use transfer learning than to create a custom solution. For people who do not have the expertise or time to go through several renditions, pretrained models are far more convenient and still boast a respectable performance.

5. CONCLUSION AND FUTURE WORK

The final accuracy of our best model was around 96.1% which is considered a resounding success. The model is suitable enough to be used confidently for brinjal disease identification. For this project, we created a custom CNN model and evaluated its performance on the task of recognizing brinjal disease against three pre-trained models (VGG16, InceptionV3, and MobileNetV2). The final performances for VGG16, InceptionV3, and MobileNetV2 were: 87.50%, 80.20% and 63.54% respectively. Early on in our experimentation, the CNN model produced was mediocre, and the pre-trained models fared better. With further Hyperparameter tuning and Batch Normalization, we created a much stronger model, highlighting the importance of hyperparameter tuning in neural networks. It is still essential to emphasize that transfer learning offers benefits in handling more complex, significant, and challenging picture classification problems.

The early diagnosis and efficient treatments for crop diseases made possible by this automated system for the detection of brinjal disease presents farmers with a viable option that will ultimately improve production and promote sustainable agricultural practices. The final model produced is highly accurate and, after further testing, would be considered ready to deploy. In future work, suggest expanding the dataset and using other models.

REFERENCES

[1] A. Abed Mohammed, P. Sumari, and kassem Attabi, "Hybrid K-means and Principal Component Analysis (PCA) for Diabetes Prediction," International Journal of Computing and Digital Systems, vol. 15, no. 1, pp. 1719–1728, Jun. 2024, doi: 10.12785/ijcds/1501121.

[2] B. H. Jawad, O. A. Alwesabi, N. Abdullah, and A. A. Mohammed, "Hybrid Artificial Neural Network Activation Function to Reduce Water Wastage in Agricultural Irrigation," IEEE Access, vol. 13, pp. 93302–93322, 2025, doi: 10.1109/ACCESS.2025.3573678.

[3] A. A. Mohammed, H. Alqaseer, P. Sumari, and M. M. A. Zaid, "Durian Fruit Diseases Detection Using Convolutional Neural Networks (CNN) and Pre-trained Models," 2025, pp. 97–116. doi: 10.1007/978-981-96-5220-4_9.

[4] M. M. Abd Zaid, A. A. Mohammed, and P. Sumari, "Remote Sensing Image Classification Using Convolutional Neural Network (CNN) and Transfer Learning Techniques," Journal of Computer Science, vol. 21, no. 3, pp. 635–645, Mar. 2025, doi: 10.3844/jcssp.2025.635.645.

[5] M. M. Abd Zaid, A. Abed Mohammed, and P. Sumari, "Classification of Road Features Using Convolutional Neural Network (CNN) and Transfer Learning," International Journal of Computing and Digital Systems, vol. 17, no. 1, pp. 1–12, Jan. 2025, doi: 10.12785/ijcds/1571031764.

[6] L. S. Ashour et al., "Non-overlapping Patch-Based Pre-trained CNN for Breast Cancer Classification," Iraqi Journal for Computer Science and Mathematics, vol. 6, no. 2, Jun. 2025, doi: 10.52866/2788-7421.1271.

[7] M. M. Abd Zaid, A. A. Mohammed, and P. Sumari, "Classification of Geographical Land Structure Using Convolution Neural Network and Transfer Learning," Journal of Computer Science, vol. 20, no. 12, pp. 1580–1592, Dec. 2024, doi: 10.3844/jcssp.2024.1580.1592.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in Advances in Neural Information Processing Systems, vol. 25, pp. 1097–1105, 2012.

[9] Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How transferable are features in deep neural networks?. Advances in neural information processing systems.

[10] F. A. Abidi and Z. H. Radiy, "Using exponential smoothing methods to analysis COVID-19 time series," AIP Conference Proceedings, vol. 3092, no. 1, p. 070014, Mar. 2024. DOI: 10.1063/5.0200417.

[11] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, Apr. 2018. DOI: 10.1016/j.compag.2018.02.016

[12] A. Kaniyassery et al., "Association of meteorological variables with leaf spot and fruit rot disease incidence in eggplant and YOLOv8-based disease classification," Ecological Informatics, vol. 83, p. 102809, Nov. 2024, doi: 10.1016/j.ecoinf.2024.102809.

[13] J. Liu and X. Wang, "EggplantDet: An efficient lightweight model for eggplant disease detection," Alexandria Engineering Journal, vol. 115, pp. 308–323, Mar. 2025, doi: 10.1016/j.aej.2024.12.037.

[14] I. H. Saad, Md. M. Islam, I. K. Himel, and Md. J. Mia, "An automated approach for eggplant disease recognition using transfer learning," Bulletin of Electrical Engineering and Informatics, vol. 11, no. 5, pp. 2789–2798, Oct. 2022, doi: 10.11591/eei.v11i5.3575.

[15] M. I. Hossain Siddiqui et al., "Eggplant Disease Diagnosis Using a Robust Ensemble of Transfer Learning Architectures," in 2025 International Conference on Electrical, Computer and Communication Engineering (ECCE), IEEE, Feb. 2025, pp. 1–6. doi: 10.1109/ECCE64574.2025.11013918.

[16] A. Suryavanshi, V. Kukreja, P. Srivastava, S. Mehta, and K. Joshi, "Smart Farming: Integrated Federated Learning CNNs for Brinjal Leaf Disease Detection," in 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), IEEE, Mar. 2024, pp. 1–6. doi: 10.1109/IATMSI60426.2024.10503064.

[17] S. A, R. Kamal G, M. S. Sayeed, and V. T, "Vellore Spiny Brinjal Leaf Disease Classification," in 2025 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE), IEEE, May 2025, pp. 1–6. doi: 10.1109/ICCRTEE64519.2025.11053030.

[18] A. Anu Priya and K. Rajaram, "Brinjal Leaf Diseases Detection Based on Deep Convolutional Neural Network," in 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL), IEEE, Feb. 2025, pp. 1478–1483. doi: 10.1109/ICSADL65848.2025.10932993.

[19] D. Meng, D. Ma, and M. Ma, "Applying Few-Shot Transfer Learning with RandAugment and MCA-RepVGG-A-B3 Network for Eggplant Leaf Disease Classification," in 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON), IEEE, Aug. 2024, pp. 1–7. doi: 10.1109/NMITCON62075.2024.10698826.

[20] A. Sandhya, P. Babu, U. M. Srinivas, B. Sravanthi, K. Phani Kumar, and N. Rajeswaran, "Enhanced Detection of Brinjal Diseases using YOLOv8: A High-Accuracy Real-Time Model for Precision Agriculture," in 2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA), IEEE, Nov. 2024, pp. 1075–1081. doi: 10.1109/ICECA63461.2024.10800784.

[21] R. Gayathri and K. Umadevi, "Early Identification of Eggplant Diseases using Cutting-Edge Deep Learning

Models," in 2025 3rd International Conference on Data Science and Information System (ICDSIS), IEEE, May 2025, pp. 1–7. doi: 10.1109/ICDSIS65355.2025.11070910.