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RESEARCH ARTICLE

Cucumis callosus (Rottl.) Cogn. leaf classification and identification using deep learning: A novel agricultural dataset

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Abstract

Agriculture is fundamental to human civilization and every plant has a unique life cycle influenced by environmental conditions, species and growth stage. Early identification of leaf stages and health status can prevent plant loss. Still, manual classification is time-consuming and may not accurately detect diseases or determine the correct life cycle stage. This study uses transfer learning to detect *Cucumis callosus* (Rottl.) Cogn. (herbaceous plant) leaves using base models, including Densely Connected Convolutional Networks (DenseNet121), InceptionV3, MobileNet and Extreme Inception Network (XceptionNet). Transfer learning plays an important role in ensuring high accuracy in results. Data augmentation techniques were employed to balance the images into categories. This study proposes a lightweight leaf-recognizing convolutional neural network (CNN) model. In comparison, 4 pre-trained models, DenseNet121, InceptionV3, MobileNet and XceptionNet, are used to validate the proposed approach results. The training and validation accuracies are nearly the same for all models. It ranges from 95 to 99 %. The proposed CNN achieved 100 % testing and validation accuracy with 285027 trainable parameters, demonstrating its suitability for future applications. The proposed CNN offers a reliable, practical and portable method for identifying *C. callosus* leaves.

Keywords: classification; CNN; *Cucumis callosus*; DenseNet121; InceptionV3; MobileNet; XceptionNet

Introduction

Cucumis callosus (Rottl.) Cogn. is a minor vegetable belonging to the Cucurbitaceae. Due to its perishable nature and oversupply during harvest, *C. callosus* has post-harvest losses ranging from 30 to 40 %, lowering the fruit's market value (1). *Cucumis callosus* is an excellent source of carbohydrates, fiber, protein, hydration, minerals and vitamin C. It also includes carotenoids, ascorbic acid and polyphenolic substances. The fruit seeds also contain omega-3 fatty acids and vitamin E. *Cucumis callosus* has good medicinal value, such as antidiabetic, antioxidant and anti-hyperlipidaemic (2). *Cucumis callosus* is the scientific name of Kachri (3). It is a wild vegetable/fruit that belongs to the Cucurbitaceae family (1). It is found in arid and semi-arid regions of South Asia, especially India and Pakistan. It resembles a small watermelon. It is mainly used as a spice and has unique health benefits. This brown-yellowish cucumber type is called *C. callosus* and is primarily produced in desert regions. As it ripens, its bitter flavor changes to sour melon. It can be plucked or cooked in regular meals like other vegetables, although it is also occasionally consumed raw.

Cucumis callosus, a wild vine with cucumber-like leaves. The blooms it bears are yellow. Vegetables are made from fruit. It is an excellent remedy for various ailments, such as diabetes, bile, phlegm, constipation and severe colds. A peculiar vegetable, *C. callosus*, is frequently confused with a fruit. It is well known that *C. callosus* stimulates appetite. Eating *C. callosus* as a side dish or adding it to food increases appetite (4). This study focuses on developing deep learning (DL) models capable of reliably recognizing, identifying and classifying *C. callosus* leaves. Using DL techniques, farmers can classify the leaves of *Cucumis callosus* at an earlier stage, whether they are healthy or not. This moves farmers towards precision agriculture.

Previous studies have analyzed and classified various plant leaf diseases using different computational techniques. Artificial neural network (ANN) and K-means-based segmentation approaches have been utilized to identify 5 common leaf diseases (cottony mold, ashen mold, early scorch, late scorch and small whitening) from the Al-Ghor region of Jordan (5). This research focuses on 3 common diseases (bacterial leaf spot, black spot and downy mildew) affecting sunflower leaves and presents an image-processing-based method for diagnosing sunflower leaf diseases. MATLAB's graphical user interface (GUI) toolkit was used to implement the suggested solution (6). This study was focused on evaluating the antioxidant properties and anticancer potential of *C. callosus in vitro*. Although the study demonstrated that *C. callosus* had a strong anticancer effect on the A549 human lung cancer cell line, it did not compare the fruit extract to other cancer cell lines or types, which would have helped assess its broader applicability and efficacy in treating different kinds of cancer (7).

Cucumis callosus was cultivated in the hot and arid regions of northwestern Rajasthan. The researchers find that the balanced combination of nitrogen phosphorus potassium (NPK) and farm yard manure (FYM), enhances crop productivity and soil fertility (8). This study examined the genetic diversity and germplasm utilization of *C. callosus* to develop varieties that are resilient to hot and dry climates

(9). Thirty-nine accessions were studied and 4 were selected for floral diversity and nutritional analysis. Based on their study, choti *C. callosus* and badi *C. callosus* were grouped (10). Various researchers have employed advanced techniques, including machine learning (ML) and DL, to develop disease detection systems for different types of leaves. However, similar studies are lacking for *C. callosus* leaves.

Deep learning models, Convolutional Neural Network (CNN), Residual network (ResNet-9) and lightweight 4 pre-trained Densely Connected Convolutional Network (DenseNet169, MobileNet, Extreme Inception Network (XceptionNet) and Visual Geometry Network (VGG16)) were used to detect potato leaf diseases such as early blight and late blight. Convolutional Neural Network achieved an accuracy of 97.4 % with a total of 600 images and ResNeT-9 achieved a test accuracy of 99.25 % on the PlantVillage dataset. The lightweight 4 pre-trained models achieved an accuracy of around 90-97 %. These models improve diagnostic accuracy and show promising results in practical applications by utilizing environmental parameters and imaging data (11-13). Developed a CNN model that outperforms state-of-the-art models such as VGG19, Residual Network (ResNet152), InceptionV3, You Look Only Once (YOLOv5), YOLOv6 and YOLOv7 for classification and detection of tomato leaf disease. Convolutional Neural Network achieved a 98.49 % accuracy rate and improved the yield and production of tomatoes (14-16).

Real-time soybean crop insect identification and detection DL techniques, utilizing YOLOv5, CNN and InceptionV3, were developed to achieve accuracies of 98.75, 97 and 97 %, respectively (17). The research presented a maize leaf disease detection model based on the attention mechanism of YOLOv5n, achieving an accuracy of 95.2 %. Utilizing the YOLOv5n algorithm with an attention mechanism to identify maize leaf diseases is a noteworthy development in agricultural technology (18). The proposed DL novel models, deep CNN and plant leaf detection transformer with improved deNoising anchOr boxes (PL-DINO), were used to detect and identify plant leaf disease. The deep CNN achieved an accuracy of 96.46 % and PL-DINO achieved an average precision of 70.3 % (19, 20).

Soft computing and image processing techniques were utilized for plant leaf disease detection, achieving an average accuracy of 97.6 %, which enhances sustainability and production. These technologies reduce crop losses by using advanced image processing techniques to enable early and accurate disease detection (21). Deep learning models, including DenseNet121, VGG16, InceptionV3, XceptionNet and MobileNetV2, were selected for plant leaf classification and detection. This study utilized Mendeley (containing 4590 leaf images) and PlantVillage (the Cherry Dataset, comprising 2052 images) datasets. MobileNetV2 outperformed the others for the plant leaf dataset with an accuracy of 98.9 %, while DenseNet121 outperformed the others for the cherry dataset, achieving an accuracy of 99.9 % (22).

The research mentioned above primarily focuses on detecting, classifying and analyzing various plant leaf diseases using ML, DL, soft computing, image processing and real-time object detection techniques. However, it does not address the identification, detection, classification and recognition of *C. callosus* plant leaves, as the *C. callosus* dataset is specifically designed for this task. Therefore, this article uses different high-performance pre-trained DL models to identify and classify *C. callosus* leaves based on their life cycle process. The main contributions of this article are given below:

Novel dataset: No dataset exists for *C. callosus* leaves. The dataset was collected under natural, uncontrolled field conditions, representing the life cycle stages of *C. callosus* plants using images of their leaves and categorizing them into 3 different classes: healthy, unhealthy and dead. Healthy leaves are green and functioning well. These leaves are free from diseases and do not have any white or black spots. Unhealthy leaves are yellow and show signs of nutrient deficiencies. Dead leaves are dry and no longer functioning, indicating the plant is completely dead.

Medicinal and nutritional properties: Previous studies primarily focused on medicinal and nutritional aspects (2), whereas the present work emphasizes recognition using DL. However, the current research recognizes *C. callosus* leaves using DL models.

Develop lightweight model: A lightweight, streamlined CNN model is developed to recognize *C. callosus* leaves, which is superior to many existing models. It also outperforms DenseNet121, MobileNet and InceptionV3.

Comparison with transfer learning model: The proposed CNN model is compared with 4 transfer learning models (MobileNet, InceptionV3, XceptionNet and DenseNet121). It outperformed better than most of these models and achieves good results using a significantly smaller trainable parameter set.

Prediction and identification of trustworthy models: This research suggests that the proposed CNN and InceptionV3 are effective and reliable models for recognizing *C. callosus* leaves. The model's confidence level is obtained using test images from the *C. callosus* leaves dataset. This contribution not only progresses the discipline but also assists researchers and practitioners in making informed choices about model selection and implementation in practical *C. callosus* recognition applications.

Materials and Methods

Dataset collection and description

Images of *C. callosus* leaves were captured from agricultural fields using a camera. The dataset contains 3 classes of leaves, as shown in Fig. 1.

These categories were designed to aid in the systematic classification of leaves for effective plant management and model training. One class represents healthy leaves, another represents dead leaves and the third class represents leaves infected with a disease, referred to as unhealthy.

Healthy: In a healthy state, plants are active and grow well. The leaves are green and function well. They are free from diseases and do not have any white or black spots on them. Healthy leaves are nutrient-rich, including nitrogen, phosphorus and potassium.

Unhealthy: The unhealthy state occurs when plants are not functioning well and are experiencing stress or damage due to a nutritional deficiency. In this state, the leaves change color from green to yellow or brown, show signs of nutrient deficiencies and are also affected by diseases.

Dead: Dead leaves occur at the end of the plant's life cycle or due to complete tissue dehydration, becoming partially dehydrated and nonfunctional. Table 1 shows the *C. callosus* leaf dataset before augmentation, which comprises 1858 images: 991 healthy, 568 unhealthy and 299 dead.

Proposed methodology

This study was conducted using Anaconda Navigator Jupyter Notebook. Before being fed into pre-trained models (CNN,

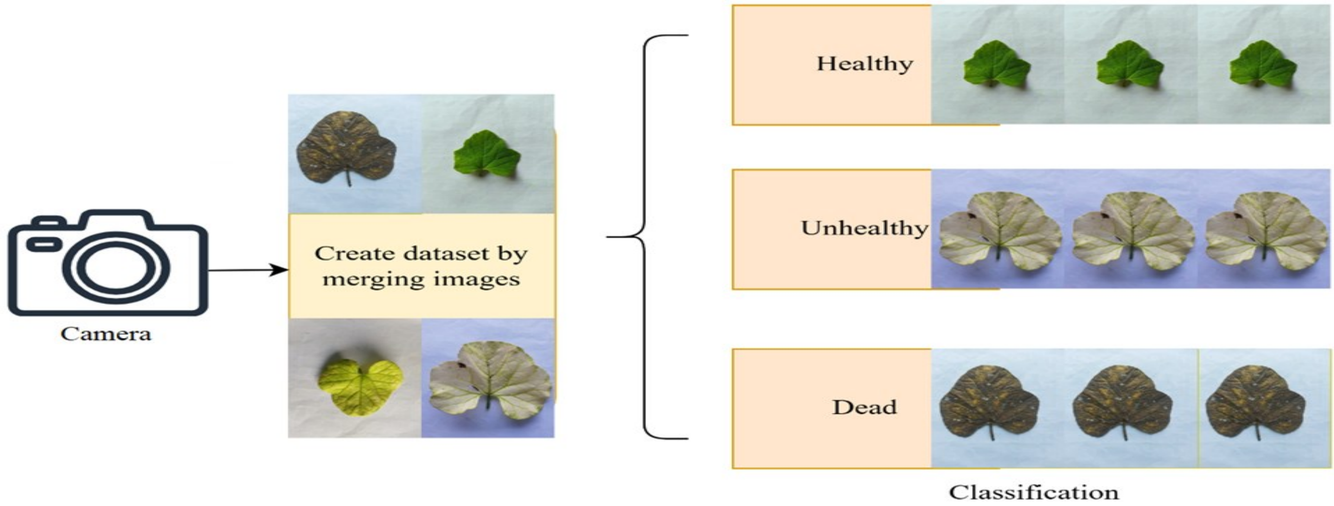


Fig. 1. Classes of *C. callosus* with their respective labels.

Table 1. Summary of the *C. callosus* dataset

Name of class labels	No. of images in sample
Healthy	991
Unhealthy	568
Dead	299
Total = 1858	

MobileNet, InceptionV3, XceptionNet and DenseNet121), the input images were enhanced to increase their diversity. A global average pooling layer was applied before the dense layers to extract key features from the images. The GlobalAveragePooling layer reduces model complexity and mitigates overfitting. It is a pooling operation to replace fully connected layers in classical CNNs and generate one feature map for each category. The proposed methodology is depicted in Fig. 2.

To enhance and handle the leaf images of the *C. callosus* dataset, the Keras function Image Data Generator was used. Using the Keras function, the training images were preprocessed. The pre-trained models' architecture included a global average pooling layer, a dense layer with an activation function Rectified Linear Unit ('ReLU') and a final output layer with a 'softmax' function. 'Adam' optimizer was used for model optimization.

Fundamental architecture of pretrained models

The transfer learning models used in this study are DenseNet121, MobileNet, InceptionV3 and XceptionNet. The summary of these models are as follows:

DenseNet121

DenseNet, connects each layer to every other layer. DenseNet121, or Dense Convolutional Network 121 (with 121 layers), is a variant of DenseNet architecture (23). It is pre-trained on the ImageNet dataset. It has 4 dense blocks with 6, 12, 24 and 16 layers sequentially shown in Fig. 3. This makes this model a promising choice for *C. callosus* leaf recognition.

XceptionNet: XceptionNet uses depthwise separable convolutions instead of standard convolutions, reducing computational complexity while retaining performance. Hence, this reduces the connections and makes the model lighter to use in this study. The complexity of different pre-trained models varies according to the architecture of the models.

InceptionV3: InceptionV3 is a 48-layer model developed by researchers at Google in 2014 called GoogleNet. It is also trained on the ImageNet dataset. This model has 2 predecessors, i.e., VI and V2 (24). This study uses this model due to its multi-scale feature and high accuracy.

MobileNet: MobileNet was developed by researchers at Google. It is a simple, straightforward and effective model for mobile (fine-tuned on mobile Central Processing Unit (CPU)) vision applications and is based on depth wise separable convolutions to build a lightweight deep CNN. In many real-world applications, such as object detection and face attributes, MobileNet models are used. It has two variants,

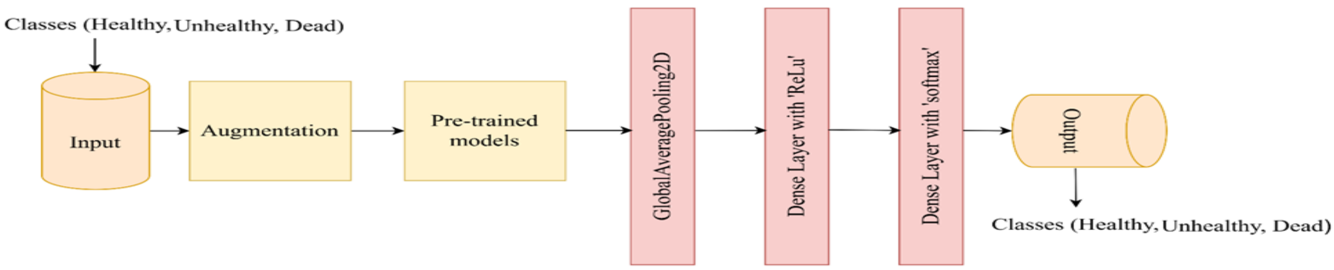


Fig. 2. Proposed methodology for *C. callosus* dataset.

Table 2. Characteristics of transfer learning models

Model name	Complexity	No. of parameters	Features
DenseNet121	High	Approximate 8 million parameters	Reuse, fewer parameters
MobileNet	Low	Approximate 4.2 million parameters	Depth wise separable, light weight
Inception	Moderate	Approximate 23.9 million parameters	Filters are multi-scale, high-accuracy
InceptionV3	High	Approximate 22.9 million parameters	Extreme depth wise separable, high performance

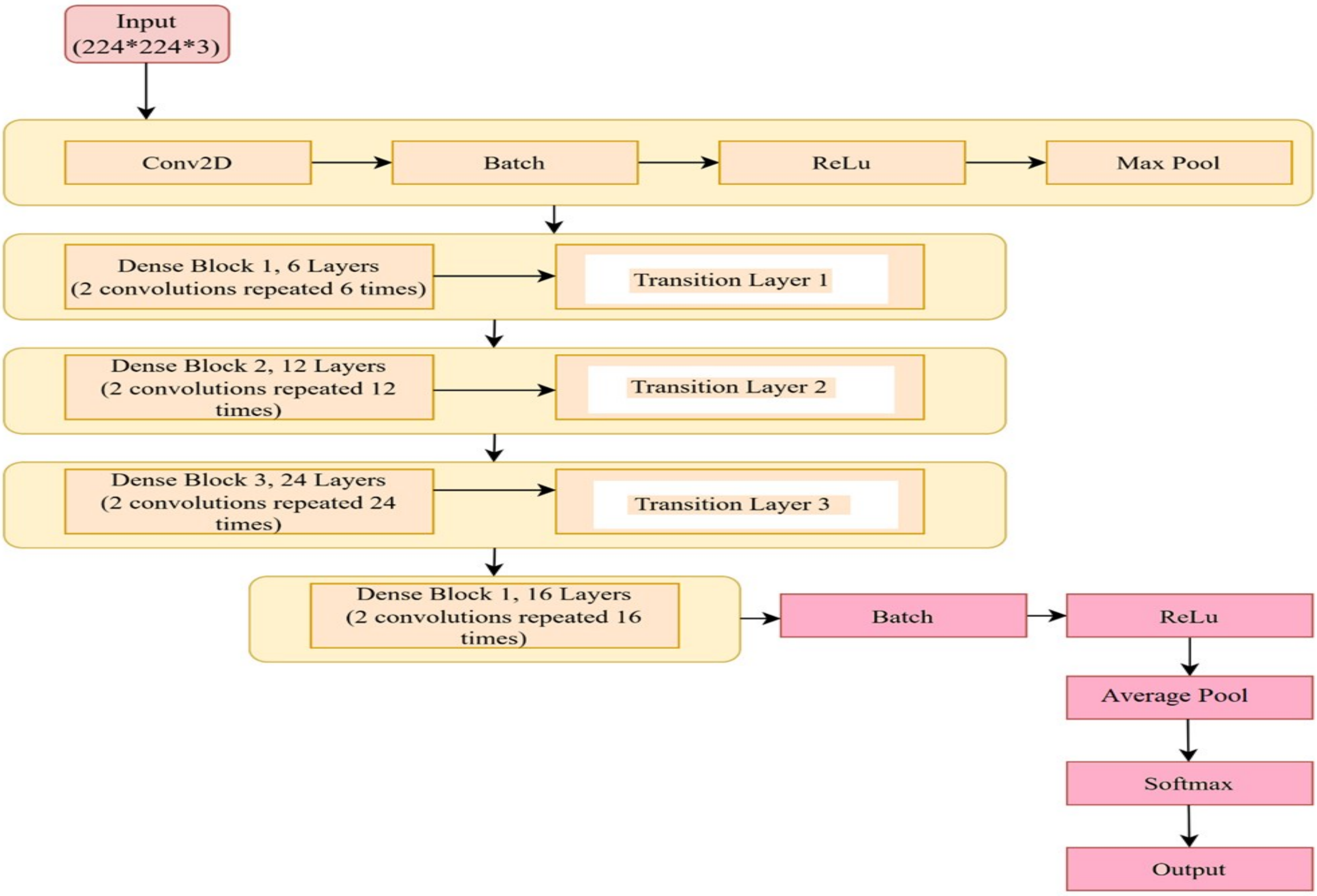


Fig. 3. DenseNet121 architecture with blocks.

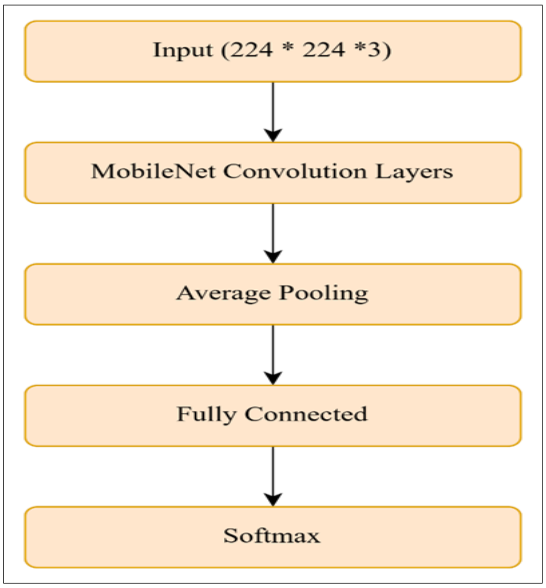


Fig. 4. MobileNet architecture with different layers.

i.e., MobileNet V1 and MobileNet V2 (25). Fig. 4 illustrates MobileNet architecture. This makes MobileNet an excellent choice for this study. It consists of convolution, average pooling, fully connected and softmax layers. The characteristics of all models are described in Table 2.

Augmentation

Due to the limited number of images in unhealthy and dead states, we applied augmentation to *C. callosus* dataset: the rotation range is 40, the height, width and zoom range are 0.2, the horizontal flip set is' true' and the fill mode is' closest'. After augmentation, the total number of images becomes 3689, with 1117 dead images and 1581 unhealthy images. Some images after augmentation are shown in Fig. 5. The augmented dataset was partitioned into training (70 %), validation (10 %) and testing (20 %) summarized in Table 3. DenseNet121, MobileNet, InceptionV3 and XceptionNet were selected for this work. This dataset compares the proposed CNN technique with 4 transfer learning models: DenseNet121, MobileNet, InceptionV3 and XceptionNet.

Evaluation metrics

To evaluate the performance of all the models used in this study, the following evaluation metrics have been applied:

Accuracy: It is the proportion of all correct classifications, whether positive or negative.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \quad \text{(Eqn. 1)}$$

Where:

True Positives (TP) are the instances where the model correctly predicts the positive class. True Negatives (TN) are the instances where the model correctly predicts the negative class. False Positives (FP) are the instances where the model incorrectly predicts the positive class (i.e., the actual class is negative). False Negatives (FN) are the instances where the model incorrectly predicts the negative class (i.e., the actual class is positive).

Precision: It is obtained by dividing the summation of true positives by the summation of true positives plus the summation of false negatives.

Recall: It is calculated by dividing the summation of true positives by

$$Precision = \frac{\sum True\ Positive}{\sum True\ Positive + \sum False\ Positive} \quad \text{(Eqn. 2)}$$

Fig. 5. Images of *C. callosus* dataset with their respective labels name.

Table 3. Summary of the *C. callosus* dataset after augmentation

***C. callosus* leaves set**	**Samples**
Training	2580
Testing	741
Validation	368
Total = 3689	

the summation of accurate positives plus the summation of false positives.

F1-Score: It is defined as the harmonic mean of precision and recall.

$$Recall = \frac{\sum True\ Positive}{\sum True\ Positive + \sum False\ Negative} \quad \text{(Eqn. 3)}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \quad \text{(Eqn. 4)}$$

Results and Discussion

The standard parameters used for all the models presented in this study are displayed in Table 4 with their values. The transfer learning models DenseNet121, MobileNet, InceptionV3, XceptionNet and the proposed CNN have been trained on the *C. callosus* dataset. All models except the XceptionNet model have been implemented with their default image size.

Table 4. Summary of common parameters

Name of parameter	**Value of parameter**
Batch size	32
Optimizer	Adam
Epochs	10
Input shape/size	(224, 224)
Loss function	Sparse categorical crossentropy

Implementation steps for all pre-trained models

1) Set the input shape to (224, 224, 3) to match the expected size and channel dimensions RGB (red green blue) colours for the learning model.
2) Call Learning model by a predefined function from \`tensorflow.keras.applications\` with \`include_top=False\` to load pre-trained weights from ImageNet while excluding the top fully connected layers.
3) Add a \`GlobalAveragePooling2D\` layer to reduce the spatial dimensions of the feature maps to a single vector per input image.
4) Add a \`Dense\` layer and ReLU activation to introduce non-linearity and learn higher-level representations.
5) Add a final \`Dense\` layer with 3 units and softmax activation for multi-class classification, matching the number of classes in the *C. callosus* dataset.
6) Combine the pre-trained base model and the newly added layers using the \`Model\` class to form the final model architecture.
7) Freeze all layers in the pre-trained base model by setting \`layer.trainable = False\` to preserve learned features from ImageNet.
8) Compile the model with the adam optimizer, a learning rate of 0.0001, a sparse categorical cross-entropy loss function and an accuracy metric for evaluation during training.

Using pre-trained models as feature extractors, this method adapts the classifier to the specific number of classes needed for *C. callosus* leaf classification. We only train the final classifier layer by freezing the parameters of the pre-trained layers, ensuring adequate training even with sparse input. By customizing the model for *C. callosus* imaging, this approach makes the best use of previously learned information. The obtained accuracy distribution is presented in Table 5 and the losses after 10 epochs are shown in Table 6. The InceptionV3 model has obtained the highest training and testing accuracies and the DenseNet model has obtained the lowest validation and training accuracies. Among all models, the XceptionNet model has achieved 100 % validation accuracy. The InceptionV3 model obtained a minimum training and testing loss, which is 0.034. In contrast, the XceptionNet model had the lowest validation loss, i.e., 0.032, as displayed in Table 6.

The precision, recall and F1-score achieved by each model on the test dataset are listed in tables 7, 8 and 9, respectively. Fig. 6 shows the accuracy and loss curves of the proposed CNN model. Fig. 7 shows training and validation loss of DenseNet121, MobileNet, InceptionV3 and XceptionNet. Fig. 8 displays the training and validation accuracy of DenseNet121, MobileNet, InceptionV3 and XceptionNet models. However, our proposed CNN model has achieved the lowest training, testing and validation loss and obtained 100 % training, 100 % testing and 100 % validation accuracy. The proposed CNN model has been thoroughly used in machine vision to classify and identify *C. callosus* leaves. It consists of 2 convolution layers, 2 max-pooling layers, 1 flattened layer and 1 dense layer, as shown in Fig. 9. This makes it lightweight compared to pre-trained models. This model has only 285027 total trainable parameters. Fig. 10 shows the heatmap representation of DenseNet121, MobileNet, InceptionV3 and XceptionNet on the *C. callosus* test set. Out of 741 images, it can be observed that the DenseNet121 model made only 3 misclassified images from the unhealthy class. Except for these misclassifications, this model performed well and made accurate predictions for other classes. While the MobileNet model incorrectly labeled 5 images as unhealthy, this model has a strong overall performance. The XceptionNet model achieved highly accurate results as it hid 4 misclassified images as unhealthy and the InceptionV3 model had just 1 misclassification. Table 10 shows the parameters used by models. Fig. 11 (heatmap and predictions) presents the heatmap representation and predictions of the proposed CNN. Fig. 11 (a) shows no misclassified images out of 741. The confidence level of the proposed CNN model, ranging from 98 % to 100 %, is demonstrated in Fig. 11 (b), along with its actual and predicted values.

Table 5. Training, testing and validation accuracies of all models

Model	**Accuracy in (%)**		
	Training	**Testing**	**Validation**
DenseNet121	99.22	99.59	99.18
MobileNet	99.84	99.32	99.18
InceptionV3	99.92	99.86	99.72
XceptionNet	99.84	99.46	100.0
Proposed CNN	100.0	100.0	100.0

Table 6. Training, testing and validation losses of all models

Model	**Loss**		
	Training	**Testing**	**Validation**
DenseNet121	0.060	0.048	0.057
MobileNet	0.052	0.051	0.052
InceptionV3	0.034	0.034	0.040
XceptionNet	0.039	0.038	0.032
Proposed CNN	0.0050	0.0065	0.0052

Table 7. Obtained precision of all models with their respective classes

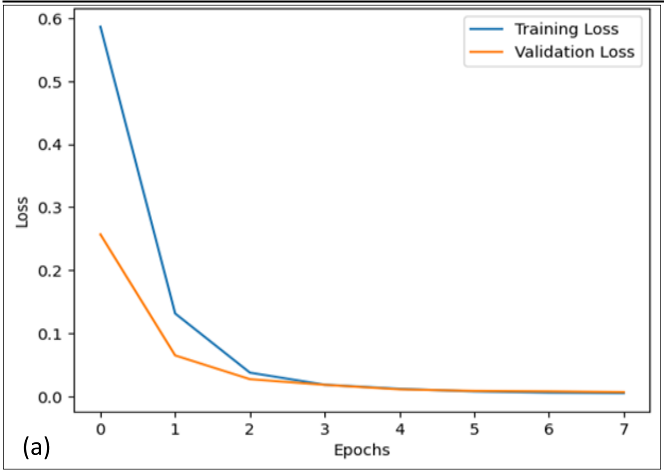
Model	Loss		
	Training	Testing	Validation
DenseNet121	0.060	0.048	0.057
MobileNet	0.052	0.051	0.052
InceptionV3	0.034	0.034	0.040
XceptionNet	0.039	0.038	0.032
Proposed CNN	0.0050	0.0065	0.0052

Table 8. Recall of all models with their respective classes

Class name	Recall				
	DenseNet121	MobileNet	InceptionV3	XceptionNet	Proposed CNN
Dead	1.00	1.00	1.00	1.00	1.00
Healthy	0.98	0.97	1.00	0.98	1.00
Unhealthy	1.00	1.00	1.00	1.00	1.00

Table 9. F1-score of all models with their respective classes

Class name	F1-score				
	DenseNet121	MobileNet	InceptionV3	XceptionNet	Proposed CNN
Dead	1.00	1.00	1.00	1.00	1.00
Healthy	0.99	0.99	1.00	0.99	1.00
Unhealthy	1.00	0.99	1.00	0.99	1.00



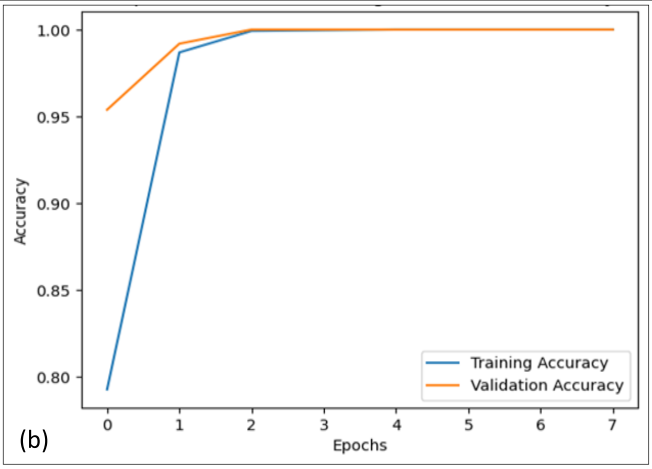


Fig. 6. (a) Loss, (b) Accuracy curve of the proposed CNN.

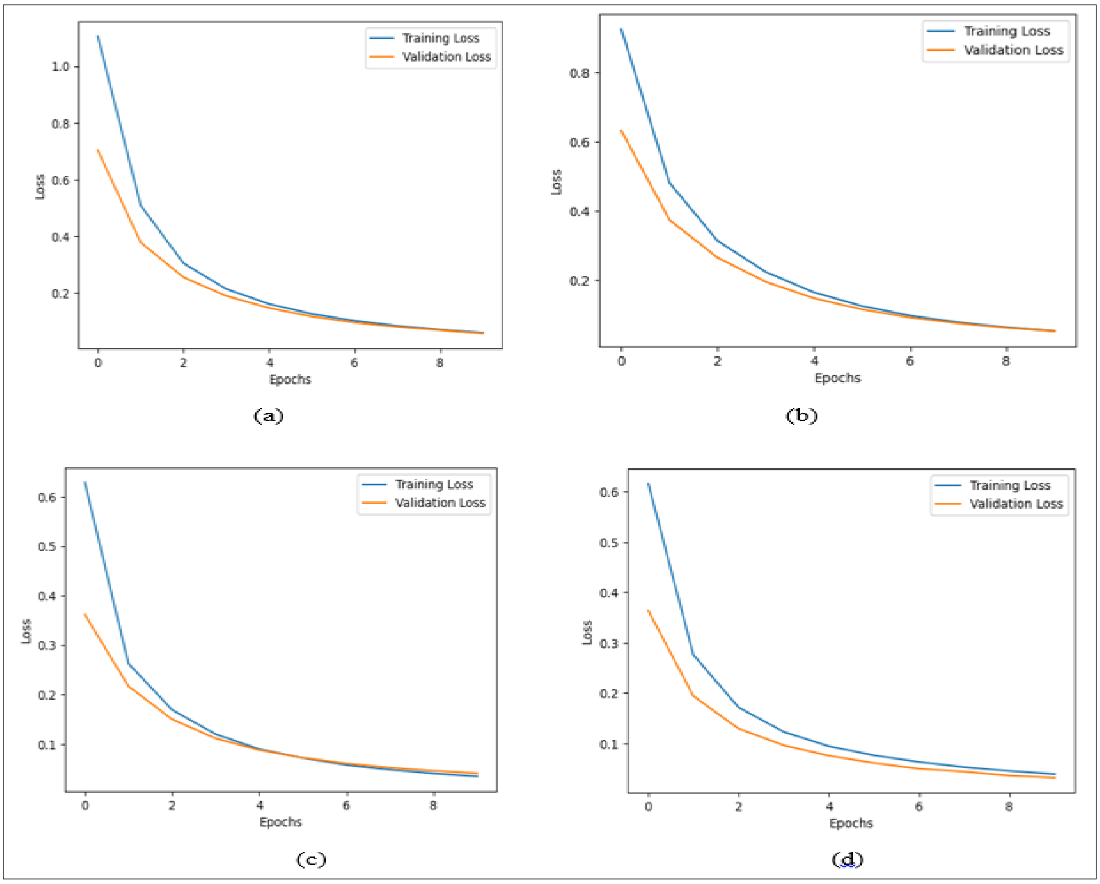


Fig. 7. Training and validation loss curve of (a) DenseNet121, (b) MobileNet, (c) InceptionV3, (d) XceptionNet.

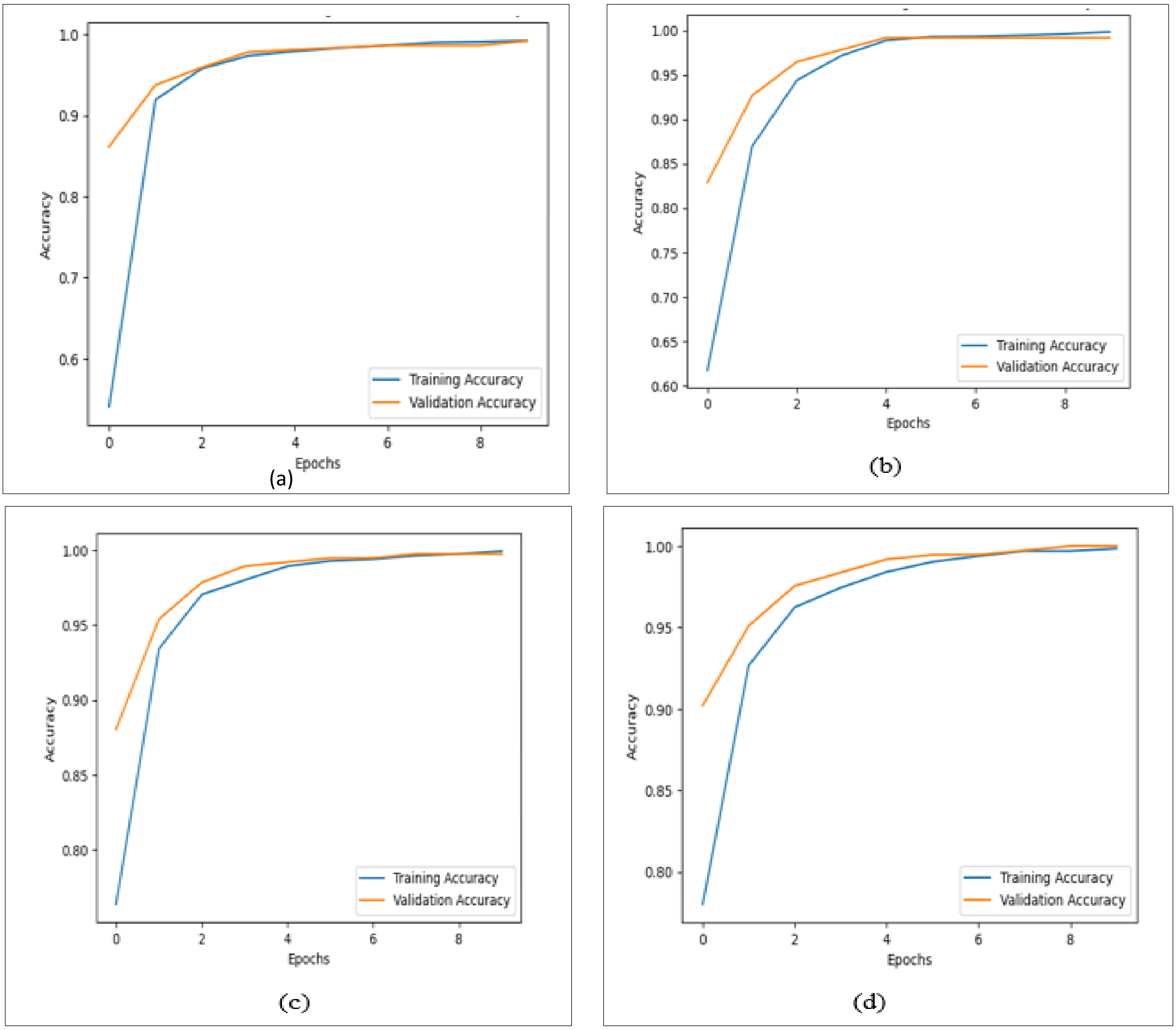


Fig. 8. Training and validation accuracy curves (a) DenseNet121, (b) MobileNet, (c) InceptionV3, (d) XceptionNet.

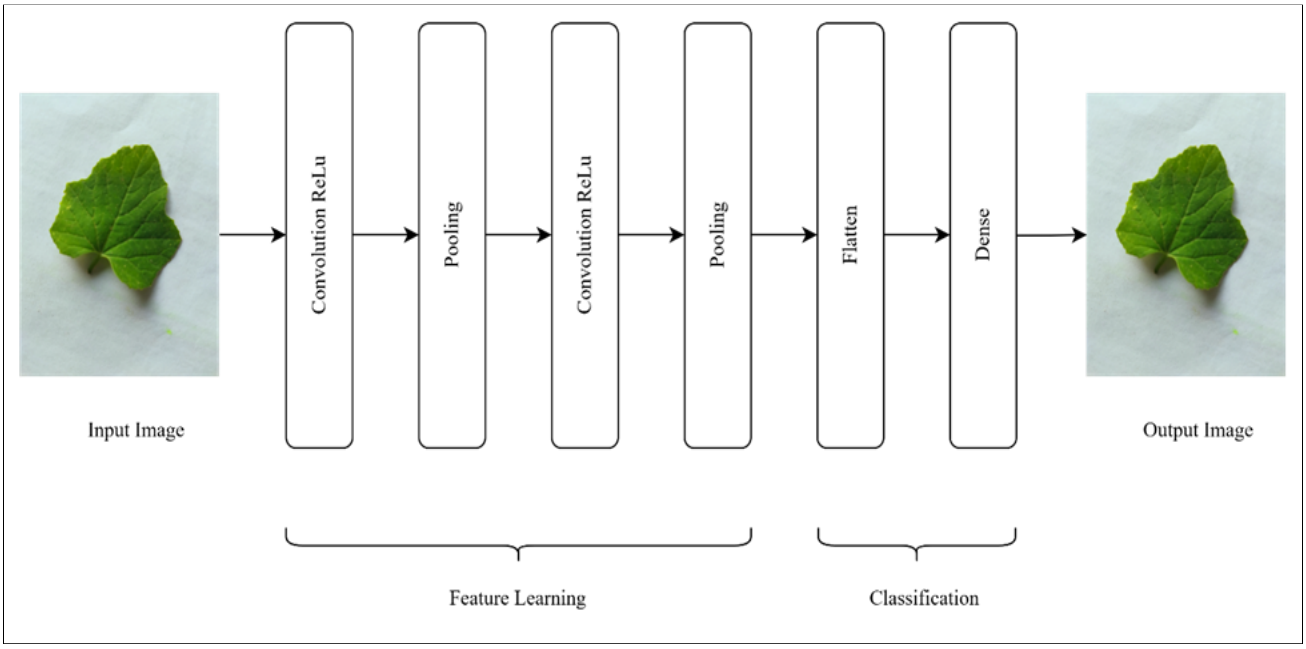


Fig. 9. Architecture of the proposed CNN model for *C. callosus* leaf classification.

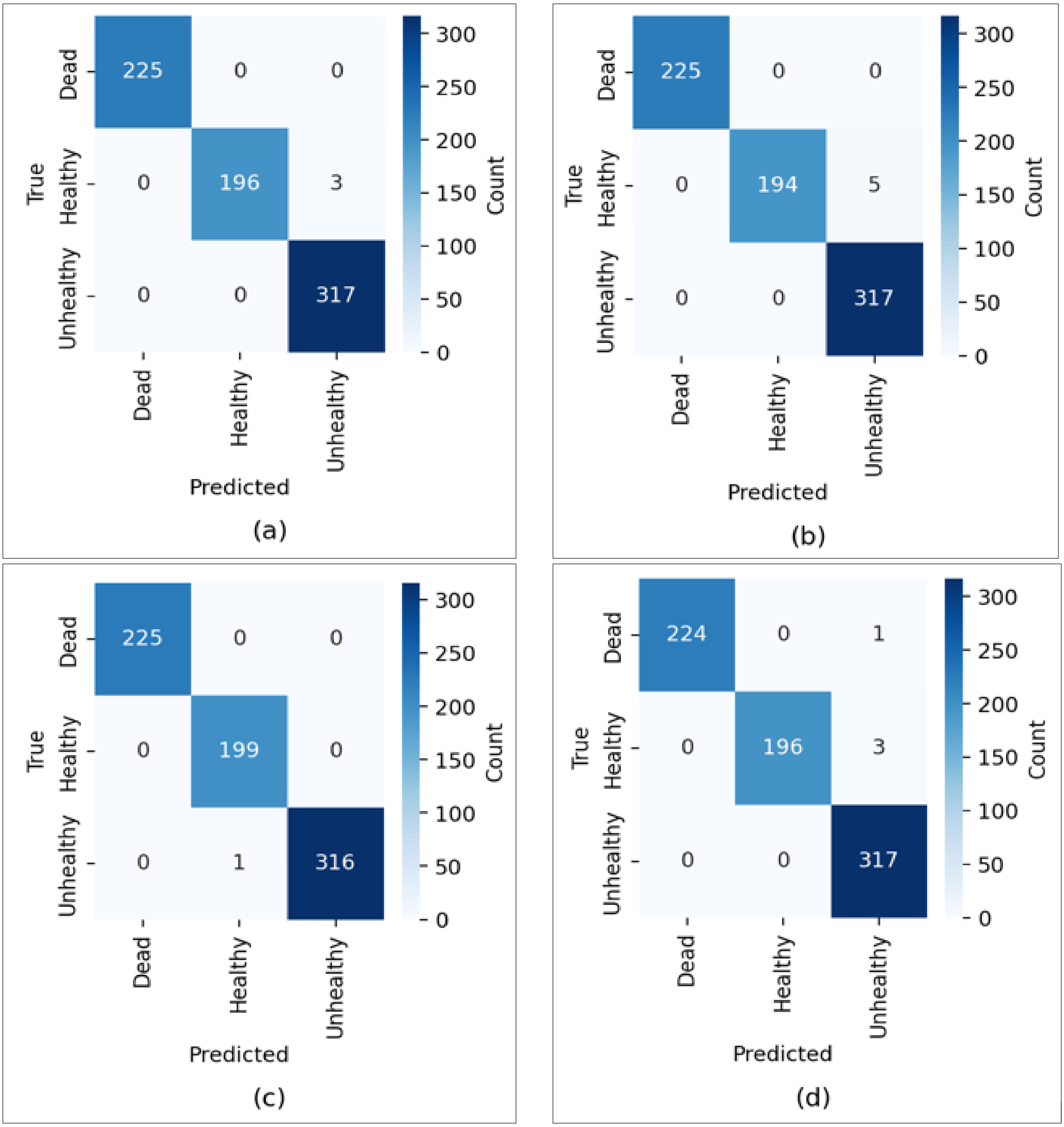
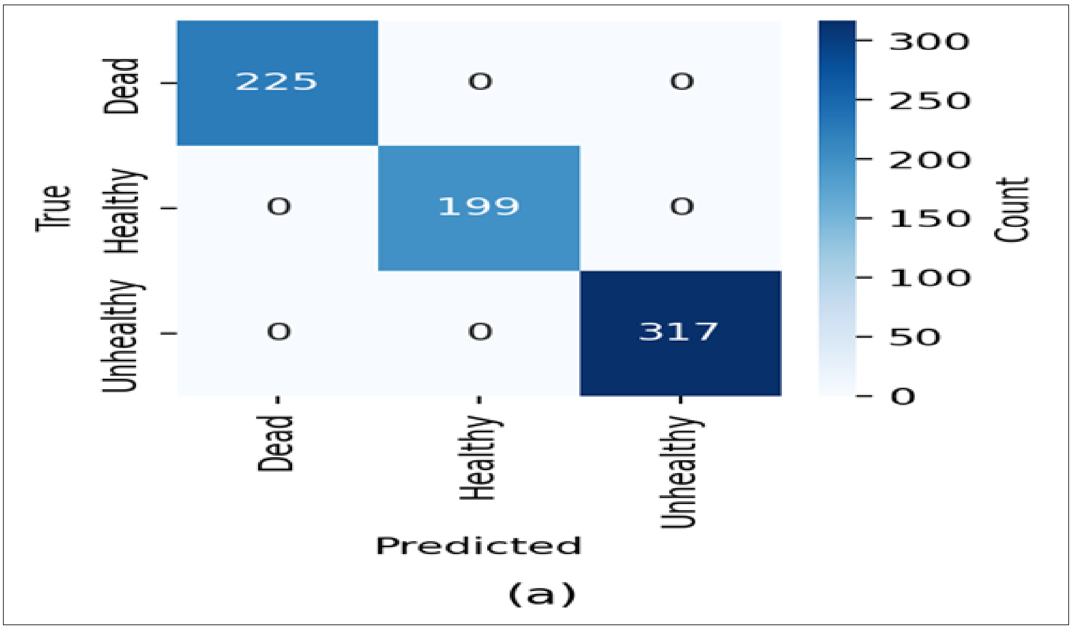


Fig. 10. Heatmaps of *C. callosus* leaf predictions using (a) DenseNet121, (b) MobileNet, (c) InceptionV3, (d) XceptionNet.

Table 10. Parameters used by models

Model name	No. of parameters
DenseNet121	7062187
MobileNet	3241211
InceptionV3	21852043
XceptionNet	20910739
Proposed CNN	285027



(b)

Fig. 11. (a) Heatmap, (b) predictions *of C. callosus* leaves using the proposed CNN model.

Fig. 12 and Fig. 13 display the actual labels, predicted labels and confidence levels of all models used in this research. The actual label represents the true class of each data point and serves as a benchmark for model performance. The predicted level indicates the output predicted by the model, while the confidence level shows the model's confidence in its predictions. The confidence score was calculated from the output of the softmax function. A higher confidence level indicates that the model is more confident in its predictions and vice versa. The confidence level of DenseNet121 ranges from 94 % to 99 % shown in Fig. 12 (a), while MobileNet ranges from 92 % to 99 %. Fig. 12 (b). The confidence level of InceptionV3 differs slightly from that of the proposed CNN, which ranges between 90 % and 100 %, as shown in Fig. 13 (a). In contrast, the confidence level of the XceptionNet model lies between 98 % and 99 %, as demonstrated in Fig. 13 (b). Table 11 describe comparison of existing work with the proposed work in this paper. Additionally, while analyzing the literature on studies on leaf images of various plants, it was found that suggested approaches only perform well on leaf images taken under controlled conditions. However, our proposed CNN and other models work well with unseen data.

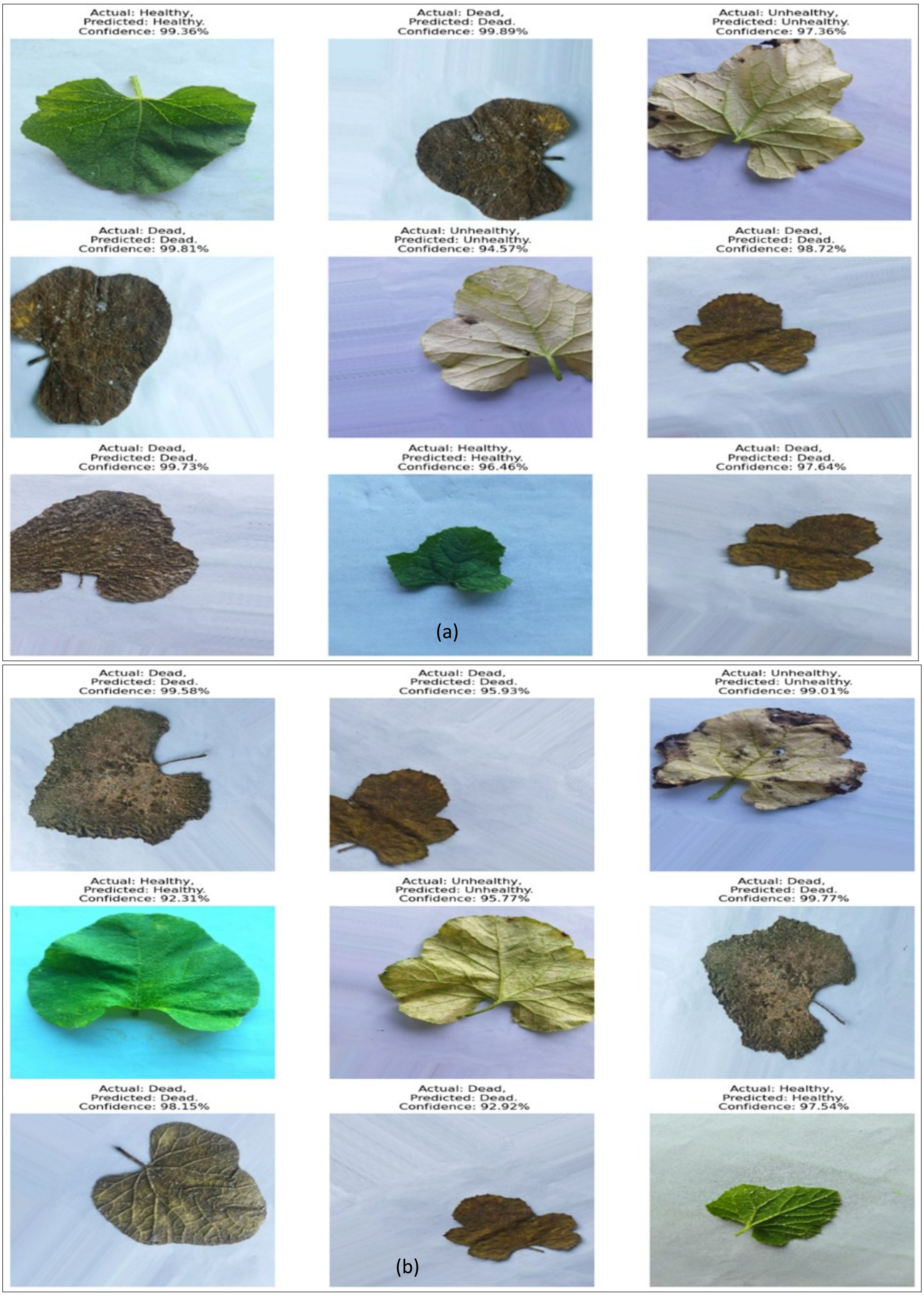
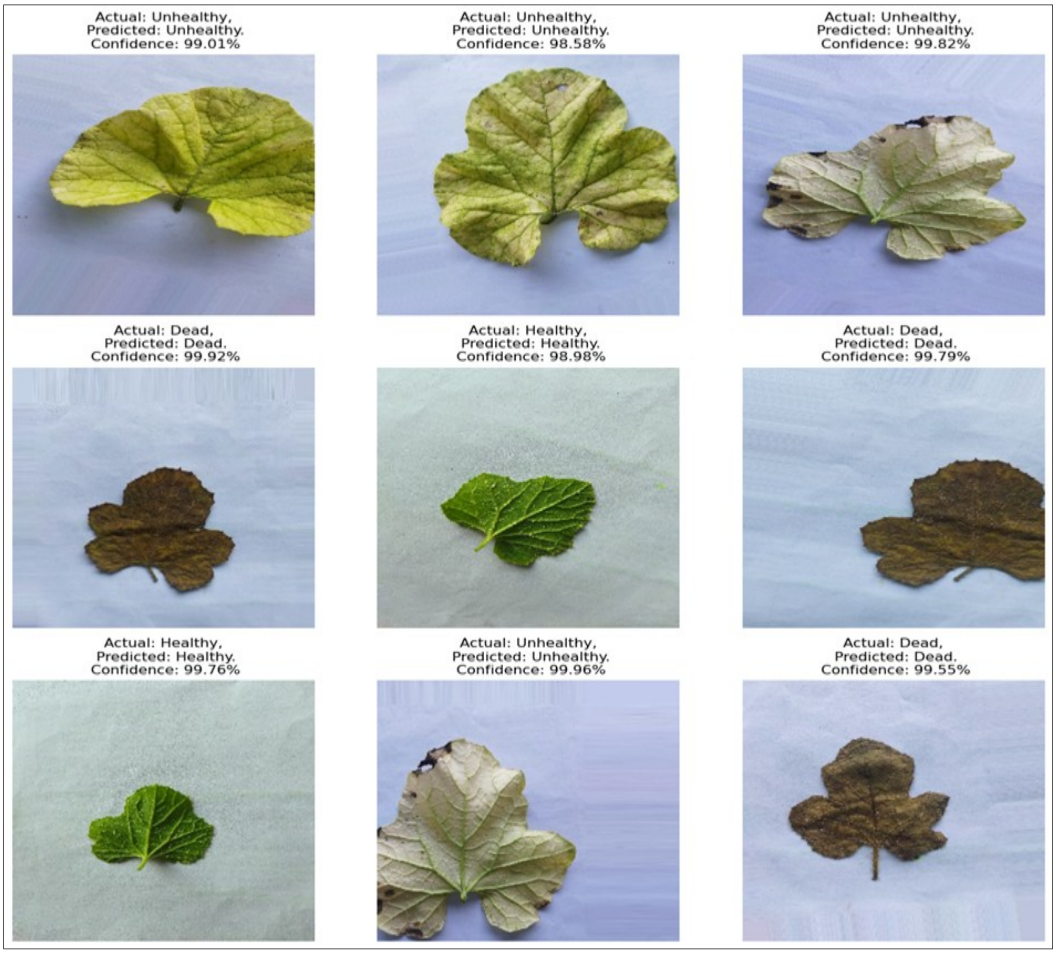


Fig. 12. Predictions of *C. callosus* leaves using (a) DenseNet121, (b) MobileNet.

(a)



(b)

Fig. 13. Predictions of *C. callosus* leaves using (a) InceptionV3, (b) XceptionNet.

Table 11. Comparison with existing models

Methods used	Accuracy	Classes	Same or Different (√or ×) dataset	References
AlexNet	95.75 %	3	×	(26)
EfficientNetV2	98.26 %	3 and 4	×	(27)
CNN	97.62 %	3	×	(28)
DenseNet121	99.59 %	3	√	-
MobileNet	99.32 %	3	√	-
InceptionV3	99.86 %	3	√	-
XceptionNet	99.46 %	3	√	-
Proposed CNN	100 %	3	√	-
ML	79.23 %	Not found	×	(29)
Particle Swarm Optimization (PSO)	98 %	6	×	(30)

Conclusion

Based on the life cycle process, *C. callosus* leaves were classified into 3 categories: healthy, unhealthy and dead, using the proposed CNN and pre-trained models. The proposed CNN achieved a testing and validation accuracy of 100 %. Transfer learning models, such as DenseNet121, MobileNet, InceptionV3 and XceptionNet, achieved accuracy rates of 95 to 99 %. Transfer learning and augmentation techniques contributed significantly to achieving high accuracy and model reliability.

This study presents a novel and practical method for classifying *C. callosus* leaf stages, contributing to deep-learning applications in agriculture and supporting disease management. Although a limited dataset was used, the results demonstrate the potential of the proposed models. Future work should focus on creating a more diverse dataset and developing user-friendly tools, such as mobile or IoT (internet of things)-based applications, to facilitate real-world deployment.

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Authors' contributions

A carried out the problem statement, methodology, dataset, writing and visualization of original manuscript. SA and A performed the writing, editing and validation of the review part of this manuscript. SA contributed conceptualization, supervision and project administration. All authors have read and agreed to the published version of the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

References

1. Meena ML, Lal L. Effect of different treatments on drying and quality of *Cucumis callosus*. Ind J Hortic. 2005;62(1):99–101.
2. Panda S, Chakraborty M, Majumder P, Mazumder S, Das S, Haldar PK. Antidiabetic, antioxidant and anti-hyperlipidaemic activity of *Cucumis callosus* in streptozotocin-induced diabetic rats. Int J Pharm Sci Res. 2016;7(5):1978–84. https://doi.org/10.13040/IJPSR.0975-8232.7(5).1978-84
3. Deepika, Kumari A, Prajapati P, Sarita, Kumar S, Aluko RE, et al. Pharmacological and therapeutic potential of *Cucumis callosus*: a novel nutritional powerhouse for the management of non-communicable diseases. Plant Foods Hum Nutr. 2023;78(4):630–42. https://doi.org/10.1007/s11130-023-01098-y
4. Boora N, Singh J, Gunjal M, Assouguem A, Ercisli S, Rasane P. *Cucumis callosus*: a valuable neglected crop as an alternative source of nutrition. CABI reviews. 2025;20(1):0056. https://doi.org/10.1079/cabireviews.2025.0056
5. Al Bashish D, Braik M, Bani-Ahmad S. A framework for detection and classification of plant leaf and stem diseases. 2010 International Conference on Signal and Image Processing; Chennai, India. 2010. p. 113–18. https://doi.org/10.1109/ICSIP.2010.5697452
6. Xu H, Lv F, Yue XM. Discussion on sunflower leaf disease diagnosis based on imaging identification. Appl Mech Mater. 2014;577:1202–6. https://doi.org/10.4028/www.scientific.net/AMM.687-691.1202
7. Sundari T, Kavitha R, Mythili Gnanamangai B, Saranya S. Assessment of *in vitro* antioxidant properties and anticancer potential of *Cucumis pubescens* Willd, a medicinal fruit, utilizing Human Lung cancer Cell line (A549). J Appl Biol Biotechnol. 2024;12(6):185–92. https://doi.org/10.7324/JABB.2024.194161
8. Jatav MK, Sharma BD, Samadia DK, Meena SR. Yield of kachri (*Cucumis callosus*) as influenced by organic and inorganic sources of nutrients in arid zone. Indian J Agric Sci. 2016;86(7):961–3. https://doi.org/10.56093/ijas.v86i7.59857
9. Samadia DK, Haldhar SM, Ram H, Verma AK, Gurjar PS. Kachri melon (a non-dessert form of *Cucumis melo*) diversity, germplasm utilization and varietal development under hot arid climate: approaches and realization. J Agric Ecol. 2024;18:14–27. https://doi.org/10.58628/JAE-2418-103
10. Pandey A, Ranjan P, Ahlawat SP, Bhardwaj R, Dhariwal OP, Singh PK, et al. Studies on fruit morphology, nutritional and floral diversity in less-known melons (*Cucumis melo* L.). Genet Resour Crop Evol. 2021;68:1453–70. https://doi.org/10.1007/s10722-020-01075-3
11. Pasalkar J, Gorde G, More C, Memane S, Gaikwad V. Potato leaf disease detection using machine learning. Curr Agric Res J. 2023;11(3):949-54. https://doi.org/10.12944/CARJ.11.3.23
12. Anim-Ayeko AO, Schillaci C, Lipani A. Automatic blight disease detection in potato (*Solanum tuberosum* L.) and tomato (*Solanum lycopersicum* L.) plants using deep learning. Smart Agric Technol. 2023;4:100178. https://doi.org/10.1016/j.atech.2023.100178
13. Kasana SS, Rathore AS. Attention-based lightweight deep learning models for early potato disease detection. Appl Sci. 2024;14(17):8038. https://doi.org/10.3390/app14178038
14. Trivedi NK, Gautam V, Anand A, Aljahdali HM, Villar SG, Anand D, et al. Early detection and classification of tomato leaf disease using high-performance deep neural network. Sensors. 2021;21(23):7987. https://doi.org/10.3390/s21237987
15. Sakkarvarthi G, Sathianesan GW, Murugan VS, Reddy AJ, Jayagopal P, Elsisi M. Detection and classification of tomato crop disease using

convolutional neural network. Electronics (Basel). 2022;11(21):3618. https://doi.org/10.3390/electronics11213618

16. Wang Y, Zhang P, Tian S. Tomato leaf disease detection based on attention mechanism and multi-scale feature fusion. Front Plant Sci. 2024;15:1382802. https://doi.org/10.3389/fpls.2024.1382802
17. Tirkey D, Singh KK, Tripathi S. Performance analysis of AI-based solutions for crop disease identification, detection and classification. Smart Agric Technol. 2023;5:100238. https://doi.org/10.1016/j.atech.2023.100238
18. Ma L, Yu Q, Yu H, Zhang J. Maize leaf disease identification based on YOLOv5n algorithm incorporating attention mechanism. Agronomy. 2023;13(2):521. https://doi.org/10.3390/agronomy13020521
19. Geetharamani G, Pandian A. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Comput Electr Eng. 2019;76:323–38. https://doi.org/10.1016/j.compeleceng.2019.04.011
20. Li W, Zhu L, Liu J. PL-DINO: an improved transformer-based method for plant leaf disease detection. Agriculture. 2024;14(5):691. https://doi.org/10.3390/agriculture14050691
21. Singh V, Misra AK. Detection of plant leaf diseases using image segmentation and soft computing techniques. Inf Process Agric. 2017;4(1):41–9. https://doi.org/10.1016/j.inpa.2016.10.005
22. Srivastava M, Meena J. Plant leaf disease detection and classification using modified transfer learning models. Multimed Tools Appl. 2024;83(13):38411–41. https://doi.org/10.1007/s11042-023-16929-y
23. Li G, Zhang M, Li J, Lv F, Tong G. Efficient densely connected convolutional neural networks. Pattern Recognit. 2021;109:107610. https://doi.org/10.1016/j.patcog.2020.107610
24. Chen HY, Su CY. An enhanced hybrid MobileNet. 2018 9th International Conference on Awareness Science and Technology (iCAST) 2018; Fukuoka, Japan. p. 308-12. https://doi.org/10.1109/ICAwST.2018.8517177
25. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. Proceedings of the IEEE conference on computer vision and pattern recognition 2016; p. 2818-26.
26. De Luna RG, Dadios EP, Bandala AA. Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. ENCON 2018 – 2018 IEEE Region 10 Conference; 2018; Jeju, Korea (South). p. 1414–9. https://doi.org/10.1109/TENCON.2018.8650088
27. Sunil CK, Jaidhar CD, Patil N. Cardamom plant disease detection approach using EfficientNetV2. IEEE Access. 2021;10:789–804. https://doi.org/10.1109/ACCESS.2021.3138920
28. Liu B, Zhang Y, He D, Li Y. Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry (Basel). 2017;10(1):11. https://doi.org/10.3390/sym10010011
29. Panigrahi KP, Das H, Sahoo AK, Moharana SC. Maize leaf disease detection and classification using machine learning algorithms. In: Das H, Pattnaik P, Rautarary S, Li KC, editors. ICCAN2019: proceedings of ICCAN progress in computing, analytics and networking; 2019; Singapore; 2020. p. 659–69. https://doi.org/10.1007/978-981-15-2414-1_66
30. Singh V. Sunflower leaf diseases detection using image segmentation based on particle swarm optimization. Artif Intell Agric. 2019;3:62–8. https://doi.org/10.1016/j.aiia.2019.09.002

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