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ORIGINAL

Empowering Date Palm Disease Management with Deep Learning: A Comparative Performance Analysis of Pretrained Models for Stage-wise White-Scale Disease Classification

Potenciando la gestión de enfermedades de la palmera datilera con aprendizaje profundo: Un análisis comparativo del rendimiento de modelos preentrenados para la clasificación de enfermedades de la escala blanca por etapas

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ABSTRACT

Deep Learning (DL) has revolutionized crop management practices, with disease detection and classification gaining prominence due to their impact on crop health and productivity. Addressing the limitations of traditional methods, such as reliance on handcrafted features, sensitivity to small datasets, limited adaptability, and scalability issues, deep learning enables accurate disease detection, real-time monitoring, and precision agriculture practices. Its ability to analyze and extract features from images, handle multimodal data, and adapt to new data patterns paves the way for a more sustainable and productive agricultural future. This study evaluates six pre-trained deep-learning models designed for stage-wise classification of white-scale date palm disease (WSD). The study assesses key metrics such as accuracy, sensitivity to training data volume, and inference time to identify the most effective model for accurate WSD stage-wise classification. For model development and assessment, we employed a dataset of 1,091 colored date palm leaflet images categorized into four distinct classes: healthy, low infestation degree, medium infestation degree, and high infestation degree. The results reveal the MobileNet model as the top performer, demonstrating superior accuracy and inference time compared to the other models and state of the art methods. The MobileNet model achieves high classification accuracy with only 60 % of the training data. By harnessing the power of deep learning, this study enhances disease management practices in date palm agriculture, fostering improved crop yield, reduced losses, and sustainable food production.

Keywords: Precision Agriculture; Date Palm (Phoenix Dactylifera); White-Scale Disease; Deep Learning; Transfer Learning.

RESUMEN

El aprendizaje profundo (deep learning, DL) ha revolucionado las prácticas de gestión de cultivos, y la detección y clasificación de enfermedades han cobrado importancia por su impacto en la salud y la productividad de los cultivos. Al abordar las limitaciones de los métodos tradicionales, como la dependencia de características artesanales, la sensibilidad a conjuntos de datos pequeños, la adaptabilidad limitada y los problemas de escalabilidad, el aprendizaje profundo permite la detección precisa de enfermedades, la supervisión en tiempo real y las prácticas de agricultura de precisión.

Su capacidad para analizar y extraer características de imágenes, manejar datos multimodales y adaptarse a nuevos patrones de datos allana el camino para un futuro agrícola más sostenible y productivo. Este estudio evalúa seis modelos de aprendizaje profundo preentrenados diseñados para la clasificación por etapas de la enfermedad de la palmera datilera blanca (WSD). El estudio evalúa métricas clave como la precisión, la sensibilidad al volumen de datos de entrenamiento y el tiempo de inferencia para identificar el modelo más eficaz para la clasificación precisa de la WSD por etapas. Para el desarrollo y la evaluación del modelo, empleamos un conjunto de datos de 1 091 imágenes coloreadas de foliolos de palmera datilera clasificados en cuatro clases distintas: sana, con bajo grado de infestación, con grado de infestación medio y con grado de infestación alto. Los resultados revelan que el modelo MobileNet es el más eficaz, con una precisión y un tiempo de inferencia superiores a los de los demás modelos y a los de los métodos más avanzados. El modelo MobileNet logra una alta precisión de clasificación con sólo el 60 % de los datos de entrenamiento. Aprovechando el poder del aprendizaje profundo, este estudio mejora las prácticas de gestión de enfermedades en la agricultura de la palmera datilera, fomentando la mejora del rendimiento de los cultivos, la reducción de las pérdidas y la producción sostenible de alimentos.

Palabras clave: Agricultura de Precisión; Palmera Datilera (Phoenix Dactylifera); Enfermedad de la Escala Blanca; Aprendizaje Profundo; Aprendizaje de Transferencia.

INTRODUCCIÓN

Agriculture, the fundamental basis of human nourishment, is the foundation of global food security, protecting the welfare of a world dealing with a growing population and increasing food needs. Nevertheless, farmers encounter an enduring obstacle: effectively controlling crop diseases that cause significant damage to crop productivity and quality. The emergence of artificial intelligence (AI) has initiated a revolutionary period filled with immense possibilities to address these difficulties, namely in disease detection and classification.[1] Deep learning algorithms, which utilize neural networks and large datasets, have demonstrated exceptional ability to detect and classify diseases in various crops.[1]

Date palm cultivation plays a pivotal role in agriculture, holding immense economic and cultural importance. Ensuring the health and vitality of date palm trees is paramount, making disease detection and classification at different stages a critical concern. Deep learning technology has emerged as a powerful tool for computer vision tasks, including disease detection and classification.[2,3] However, deep learning models face two primary challenges: the need for large, diverse datasets and the requirement of substantial computational resources for efficient results. Acquiring and curating such datasets can be challenging, and training deep learning models using these datasets can be computationally intensive and time-consuming. Transfer learning techniques have emerged as a valuable solution to address these challenges.

This study delves into a comprehensive performance evaluation of pre-trained transfer learning models tailored explicitly for date palm disease classification. The overarching goal is to gauge the efficacy of these models in accurately identifying and classifying the distinct stages of White Scale Disease (WSD) afflicting date palm trees.[4,5] This proposed solution aims to overcome the limitations of traditional WSD detection methods, such as their inability to detect early infestations, the time-consuming nature of visual inspections, the vulnerability to human error, and the potential for delayed diagnosis. The key contributions of this research encompass:

• Proposing a novel solution for automated stage-wise classification of White Scale Disease (WSD) employing a transfer learning technique.

• Conducting a comprehensive performance evaluation of six pre-trained convolutional neural networks (CNNs) for WSD classification.

• Identifying the most effective model based on a comprehensive evaluation that encompasses stage-wise evaluation metrics (Precision, Sensitivity, F1-score, and Accuracy), tolerance to variations in training data size, and inference time.

In the realm of crop disease identification and classification, deep learning has attracted considerable interest due to its promising applications and demonstrated effectiveness. Despite recent advancements in technology, there is a paucity of research focused on the early detection and classification of date palm diseases using deep learning technique.[6]

Few studies investigated the use of deep learning in the context of detecting, and classifying date palm diseases, for example, Alaa et al.[3] demonstrated the feasibility of using CNNs to classify certain date palm diseases, such as blight spots and leaf spot infection, achieving an accuracy rate of 97,9 %. Also, Magsi et al.[27] further demonstrated the potential of deep learning for diagnosing Sudden Decline Syndrome disease in Date palms. Their proposed approach involves image preprocessing, feature extraction from both color and texture information, and a stage-wise CNN classification method.[8] Furthermore, Al-Shalout et al.[6] highlighted the promising results of CNNs in identifying and classifying date palm diseases. To classify the infestation degree of WSD in date palms, a deep learning-based model is proposed in the proposed solution suggest the use of a VGG16 backbone for deatures extraction, then a fine tunned fully connected neural network (FCNN) was developed to perform the classification task.[10] The proposed solution achieves an accuracy of 98,06 %. Additionally, a robust detection system for recognizing red palm weevil (RPW) larvae during the early stages of infection using the Internet of Things was developed by Karar et al.[24]. Their proposed detection strategy, based on a modified convolutional network with mixed depths (MixConvNet), achieved an accuracy rate of 97,38 %.[11]

Table 1 provides an overview of recent research employing transfer learning approaches for plant/crop disease classification.

Table 1. Results of previous work using transfer learning for identification of plant diseases

Reference	Crop/Plant	Disease	Dataset	DL Models	Result
Emmanuel et al.[13]	Cassava	Leaf diseases	Cassava leaf disease dataset	MobileNet V2, Inception-ResNet V2	98,5 % accuracy
Osco-Mamani et al.[30]	Olive	Leaf diseases	Imagenet dataset, olive leaf disease images	Modified VGG16	100 % accuracy for training, validation, and test sets
Borugadda et al.[8]	Tomato	Leaf diseases	Tomato leaf dataset	Multi-level dimensional reduction on VGG16	95,68 % accuracy, 0,9566 weighted average F1 score
Sandhya et al.[32]	Cassava,	Plant diseases and pests	PlantVillage, IP102	EfficientNet-V2	99,5 %, 97,5 %, and 80,1 % accuracy for Cassava, PlantVillage, and IP102 datasets, respectively
Fan et al.[14]	Apple, Coffee	Leaf diseases	Three datasets of diseased plant leaves	Adapted CNN model based on transfer learning and auxiliary discriminative constraint	99,79 %, 82,59 %, and 97,12 % accuracy for the two apple datasets and coffee leaf dataset, respectively
Al-gaashani et al.[5]	Tomato	Leaf diseases	Dataset of tomato leaf images	Transfer learning and feature concatenation on deep learning models	98,5 % accuracy
Gulzar et al.[16]	Sunflower	Various	Sunflower disease image dataset	AlexNet, VGG16, InceptionV3, MobileNetV3, EfficientNet	EfficientNetB3 97,9 % accuracy
Attallah[7]	Tomato	Various	Tomato leaf disease image dataset	Three compact CNNs with transfer learning and feature selection	K-nearest neighbor and support vector machine: 99,92 % and 99,90 % accuracy
Nigam et al.[29]	Wheat	Wheat rusts	WheatRust21 dataset	VGG19, ResNet152, DenseNet169, InceptionNetV3, MobileNetV2, EfficientNet (various variants)	EfficientNet B4 99,35 % accuracy
Kaur et al.[25]	Tomato	Various	Public dataset and self-collected dataset	Modified InceptionResNet-V2 (MIR-V2) with transfer learning	98,92 % accuracy and 97,94 % F1 score
Shahoveisi et al.[33]	Rust disease	Rust disease on three commercially important field crops	Dataset of 857 positive and 907 negative samples	Xception, Residual Networks (ResNet)50, EfficientNetB4, MobileNet	EfficientNetB4: 94,29 % average accuracy

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Hadi-pour-Rokni et al.[17]	Citrus fruit	Mediterranean fruit fly	1519 images of healthy fruit and fruit infected with the Mediterranean fly	ResNet-50, GoogleNet, VGG-16, AlexNet with SGDm, RMSProp, and Adam optimization algorithms	VGG-16 with SGDm: 98,33 % detection accuracy and 98,36 % F1 for pest outbreak stage; AlexNet with SGDm: 99,33 % detection accuracy and 99,34 % F1 for third stage
Nayak et al.[28]	Rice	Various	Dataset of 2259 smartphone images of various rice (Oryza sativa) plant parts under various classes and 250 real-time validation images	DenseNet201, Xception, MobileNetV2, ResNet50	DenseNet201: 0,9803 validation accuracy; ResNet50: best for cloud architectures; MobileNetV2: best for smartphone application
Liu et al.[26]	Various	Various	Public dataset	Selective Kernel MobileNet (SK-MobileNet)	99,28 % accuracy
Ahmed et al.[2]	Palm tree	Various	Date Palm dataset of 2631 colored images	Residual Network (ResNet) and transfer learning of Inception ResNet	ResNet: 99,62 % accuracy; Inception ResNet: 100 % accuracy

MATERIALS AND METHODS

This study evaluated six pre-trained deep learning models from four different families: VGG16 and VGG19 from the VGG family,[27] Xception as an independent architecture,[28] ResNet50 and ResNet50v2 representing the ResNet family,[29,30] and MobileNet from the MobileNet family.[31] Comparing the performance of different pre-trained deep learning model families is crucial for various purposes, including model selection, benchmarking, trade-off analysis, generalization assessment, and research advancement. Furthermore, the tested models were primarily designed for stage-wise classification of WSD. This section provides an overview of the dataset used and the proposed methodology to achieve the aforementioned objectives.

The dataset employed in this study consists of 1,091 date palm leaflet images categorized into four classes representing the severity of WSD: healthy, low-degree infestation (Stage 1), medium-degree infestation (Stage 2), and high-degree infestation (Stage 3).[10] The dataset composition comprises 320 healthy leaflet images, 311 images with a low degree of infestation, 350 with a medium degree of infestation, and 110 with a high degree of infestation. Figure 1 illustrates samples from the original dataset.

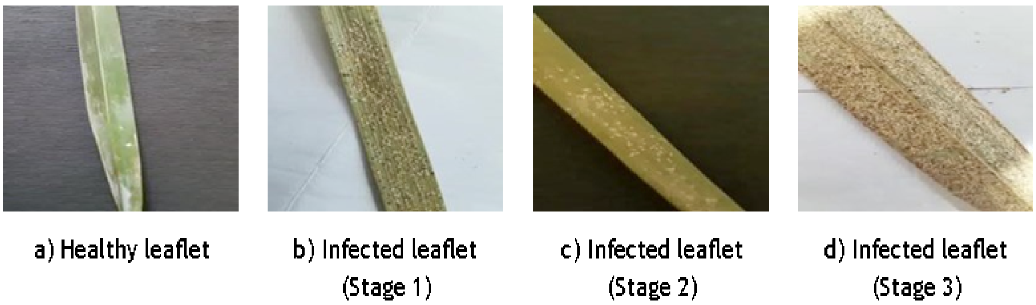

Figure 1. Samples from the used dataset

To prepare the dataset for deep learning analysis, essential preprocessing steps were applied using the preprocessing module provided by Keras, a well-established deep learning library. This module offers a variety of preprocessing functions, including data normalization, resizing, and data augmentation techniques. Data augmentation techniques were specifically employed to mitigate the risk of overfitting and enhance the model's generalization capability. These techniques involve applying random transformations to the training images, such as rotation, translation, scaling, and flipping. Figure 2 demonstrates the data augmentation technique used in the context of this study.

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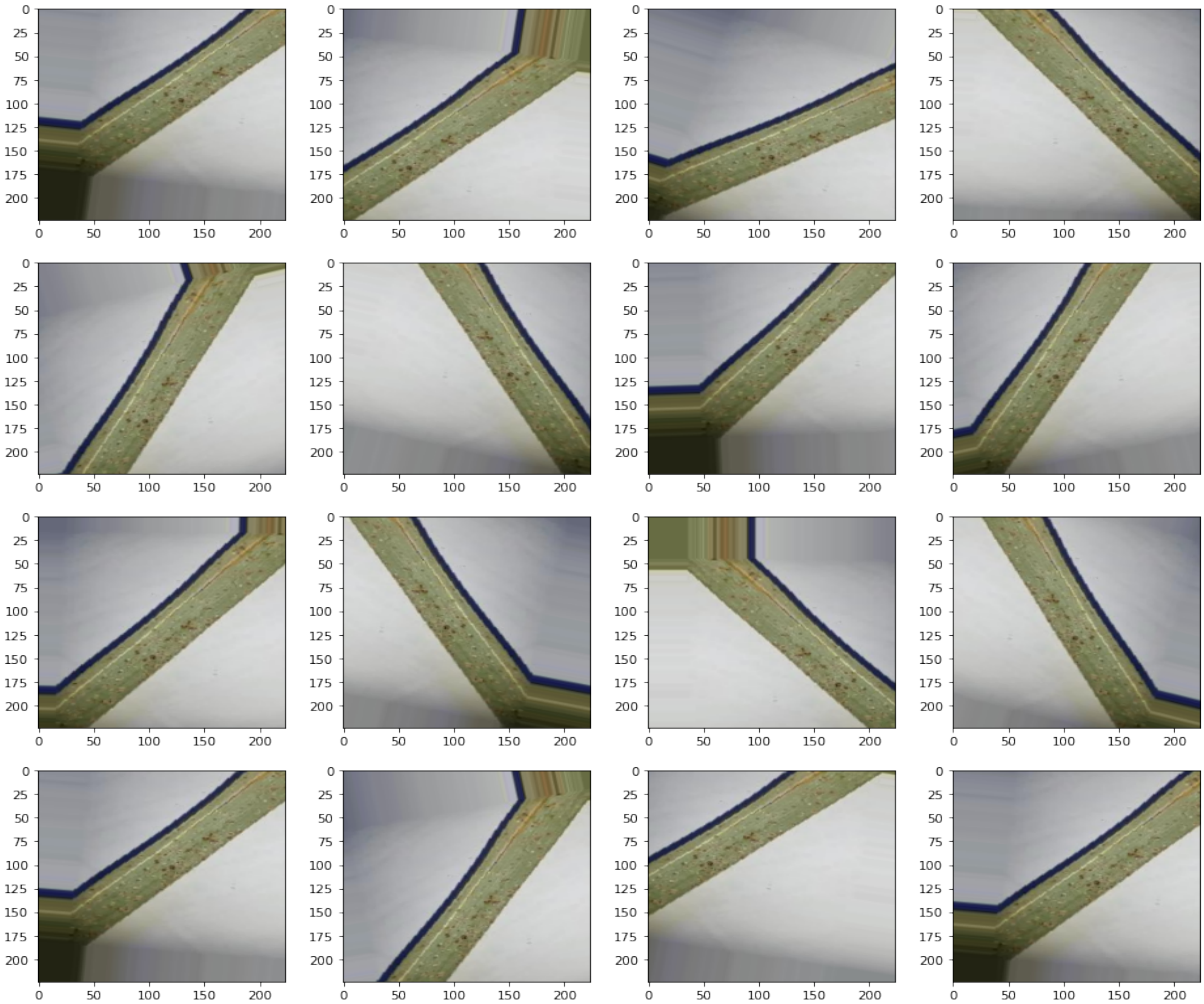

Figure 2. Data augmentation step, the original image is in the top right corner of the figure

Transfer learning approach

Leveraging pre-trained models developed using massive datasets; transfer learning facilitates fine-tuning on smaller, task-specific datasets. This approach eliminates the necessity for extensive data and computational resources, saving time and enhancing performance by transferring relevant knowledge from related domains. Transfer learning has emerged as a powerful tool for accelerating the development and deployment of deep learning models, expanding their accessibility to a broader range of applications and practitioners.

To accurately classify WSD in its four stages, we propose a robust transfer learning solution that leverages a pre-trained neural network trained on a massive dataset like ImageNet. This pre-existing model possesses a deep understanding of complex image features, which can be effectively transferred to the task at hand despite the limited size of the specialized WSD dataset. By freezing the initial layers of the network, we maintain the model's ability to recognize general visual patterns. Conversely, the final layers are fine-tuned using date palm disease images to capture the specific indicators of WSD stages. This approach significantly reduces the need for large datasets and extensive computational power that would otherwise be required to train a deep learning model from scratch, making it an efficient and practical strategy for disease classification in agricultural settings. Figure 3 illustrates the proposed transfer learning-based solution.

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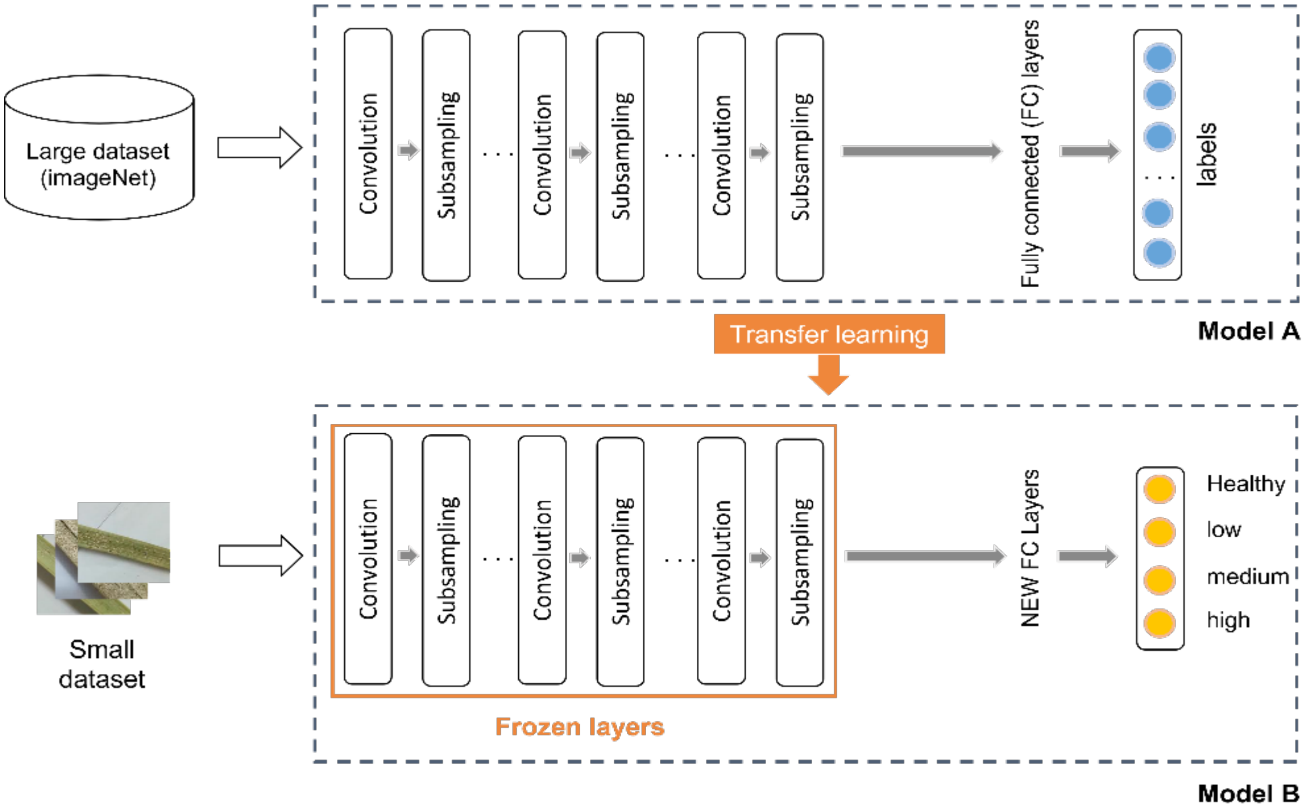


Figure 3. Transfer learning-based proposed solution

Deep Learning Models

Deep learning models are of utmost importance in the process of transfer learning, where pre-trained models are utilized to address novel tasks despite having limited data. Deep learning models facilitate transfer learning by extracting high-level features from massive datasets. This allows for domain adaptation, representation learning, and enhanced performance. Transfer learning applications require deep learning models because of their capacity to scale to large datasets and consistently outperform conventional machine learning techniques.

VGG

The VGG16 and VGG19 models belong to the Visual Geometry Group family, it is characterized by deep architectures with small 3x3 convolutional filters and max-pooling layers. VGG models are known for their simplicity and strong performance. They have a large number of parameters, which allows them to capture detailed features but can also make them computationally expensive.

Xception

Xception is an independent architecture inspired by the Inception family. It utilizes depthwise separable convolutions instead of traditional Inception modules. This design choice enhances computational efficiency while maintaining strong performance. Xception models excel in tasks where efficiency and accuracy are both important.

ResNet

The ResNet (Residual Network) family introduced residual connections, which address the vanishing gradient problem and enable the training of very deep networks. Models like ResNet50 and ResNet50v2 have residual blocks with skip connections, allowing them to learn and capture complex features effectively. ResNet models are widely used and have demonstrated exceptional performance in various computer vision tasks.

MobileNet

The MobileNet family is specifically designed for mobile and embedded devices, where computational resources are limited. These models employ depthwise separable convolutions, which reduce the number of parameters and computational complexity without significantly sacrificing accuracy. MobileNet models are lightweight and efficient, making them suitable for real-time applications on resource-constrained devices. Table 2 summarizes the description of the investigated deep learning models.

All the investigated models were pretrained using the ImageNet dataset,[11] and the final fully connected layers of each model were modified to cater to the specific requirements of the stage-wise WSD classification task. To evaluate the effectiveness of the various models, crucial performance metrics such as accuracy, precision, recall, and F1-score were calculated. Furthermore, inference time and the models' sensitivity to the training data used were meticulously assessed to identify the most suitable model for practical implementation. All experiments were conducted using the gradient tools provided by Paperspace on the machine specifications outlined in table 3.

Table 2. Specifications of Pre-trained Deep Learning Models for WSD Classification

Model	Depth	Parameters (Million)	Input Image Size	Key Features
VGG16	16	138	224x224	Deep network with 13 convolutional layers, widely used for image classification.
VGG19	19	143	224x224	Similar to VGG16, but with 16 convolutional layers.
Xception	71	22	299x299	Depthwise separable convolutions, efficient architecture for large image sizes.
ResNet50	50	25	224x224	Identity shortcut connections, enables training of very deep neural networks.
ResNet50v2	50	25	224x224	Improved version of ResNet50 with additional optimizations
MobileNet	88	4	224x224	Depthwise separable convolutions, designed for low computational resources.

Table 3. Machine specifications outlined

GPU	GPU RAM	CPU	RAM	Storage
Nvidia M4000 and P5000	8 Gb	8 x vCPU	30 Gb	5 Gb

RESULT AND DISCUSSION

To achieve the objectives of this study, a series of experiments were conducted with the primary goal of thoroughly evaluating the performance of each pre-trained model in terms of stage-wise classification performance, sensitivity to training data amount, and inference time.

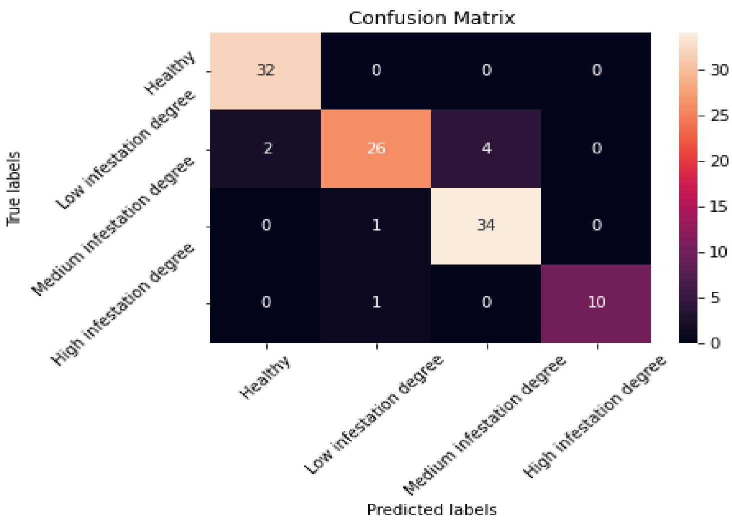
Stage-wise classification performance

As the training data volume increases from 60 % to 80 %, the performance of most models generally improves. MobileNet consistently outperforms other models in terms of average precision, average recall, and average F1-score across all three training data configurations. Additionally, Xception and ResNet50 demonstrate robust performance across all three training data volumes, consistently achieving high scores for all three metrics. In comparison, VGG16 and VGG19 exhibit slightly lower scores, particularly for average precision and average recall. Finally, ResNet50v2's performance varies, achieving competitive scores in some cases but slightly lower scores in others. Table 3 summarizes the average precision, average recall, average F1-score, and average accuracy metrics for different models trained on varying amounts of training data. The test set, representing 10 % of the dataset, remained constant across the varying training data percentages. Furthermore, the confusion matrices presented in figures 4, 5, and 6 offer valuable insights into the class-specific performance of the various models under different training data percentages.

Table 3. Performance metrics of different models across various amounts of the training set

Training Data Amount	Model	Average Precision	Average Recall	Average F1-score	Average Accuracy
60 %	VGG16	0,9411	0,9233	0,9301	0,9273
	VGG19	0,9292	0,9232	0,9247	0,9091
	Xception	0,9727	0,9688	0,9692	0,9636
	ResNet50	0,9720	0,9851	0,9780	0,9818
	ResNet50v2	0,9853	0,9844	0,9847	0,9818
	MobileNet	0,9924	0,9922	0,9922	0,9909
70 %	VGG16	0,9570	0,9389	0,9468	0,9455
	VGG19	0,9406	0,9388	0,9394	0,9273
	Xception	0,9865	0,9844	0,9850	0,9818

	ResNet50	0,9865	0,9844	0,9850	0,9818
	ResNet50v2	0,9640	0,9779	0,9705	0,9727
	MobileNet	0,9853	0,9844	0,9844	0,9818
80 %	VGG16	0,9453	0,9233	0,9321	0,9273
	VGG19	0,8973	0,8933	0,8946	0,8727
	Xception	0,9702	0,9694	0,9695	0,9636
	ResNet50	0,9931	0,9922	0,9925	0,9909
	ResNet50v2	0,9803	0,9766	0,9774	0,9727
	MobileNet	0,9853	0,9844	0,9844	0,9818



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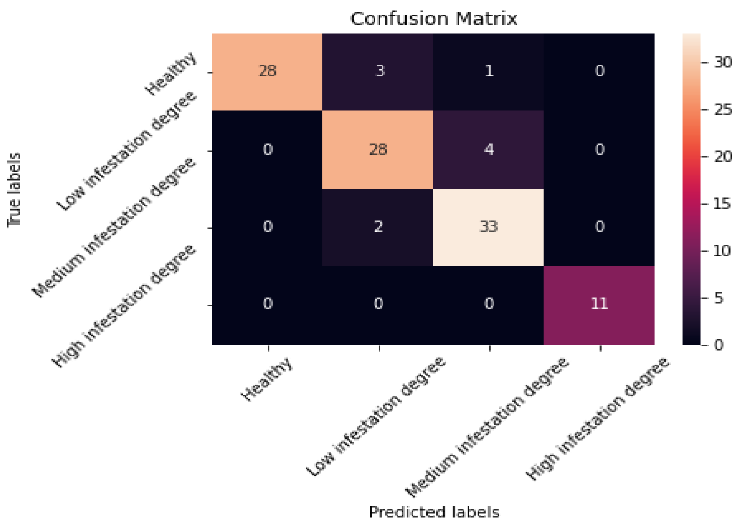

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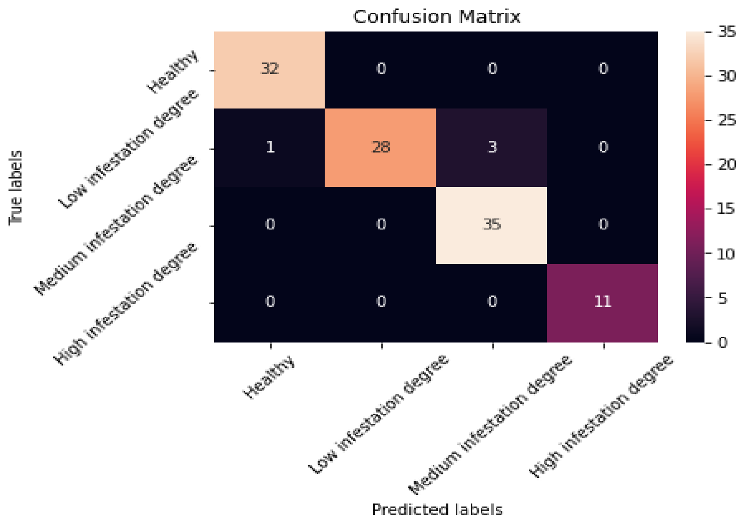

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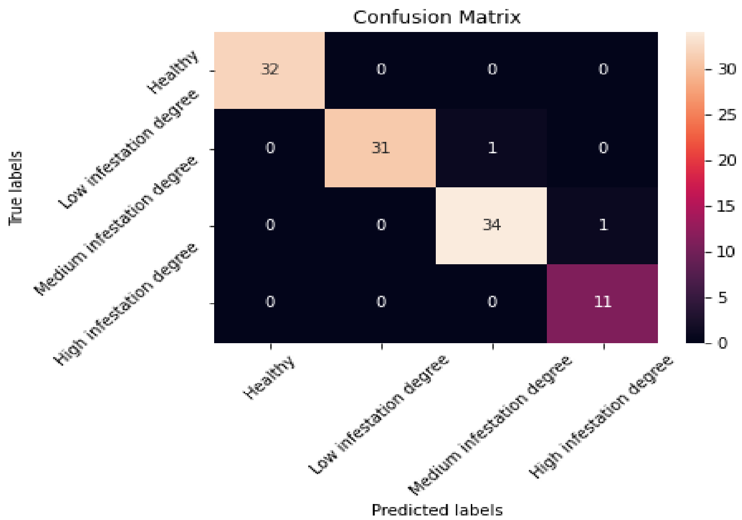

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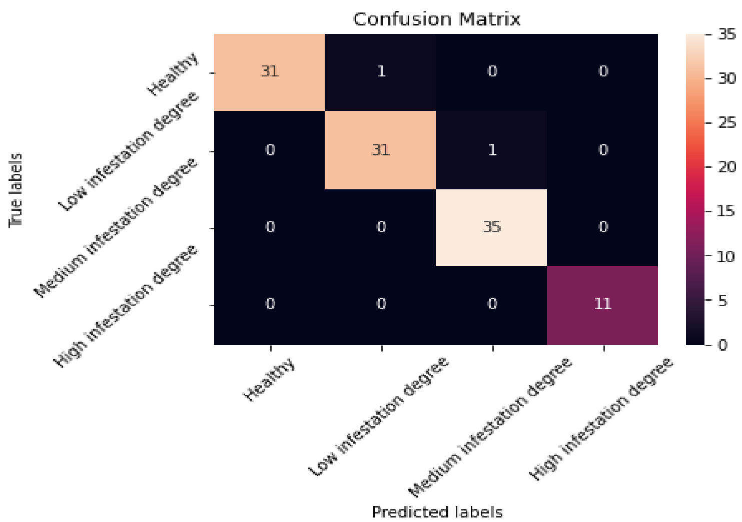

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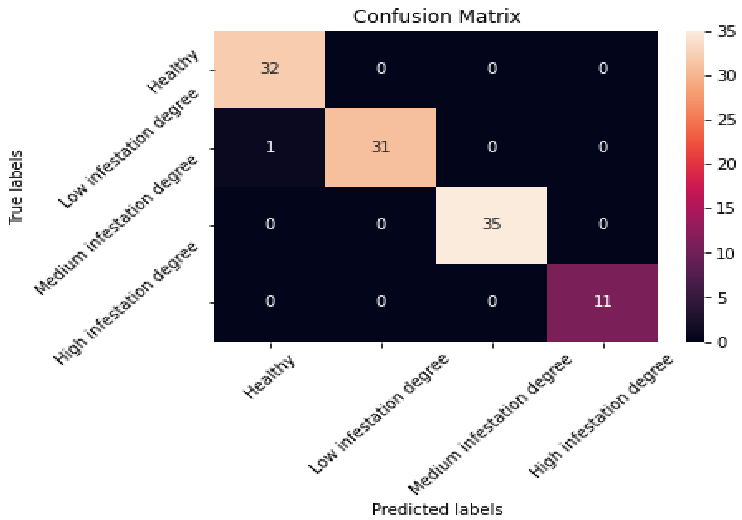
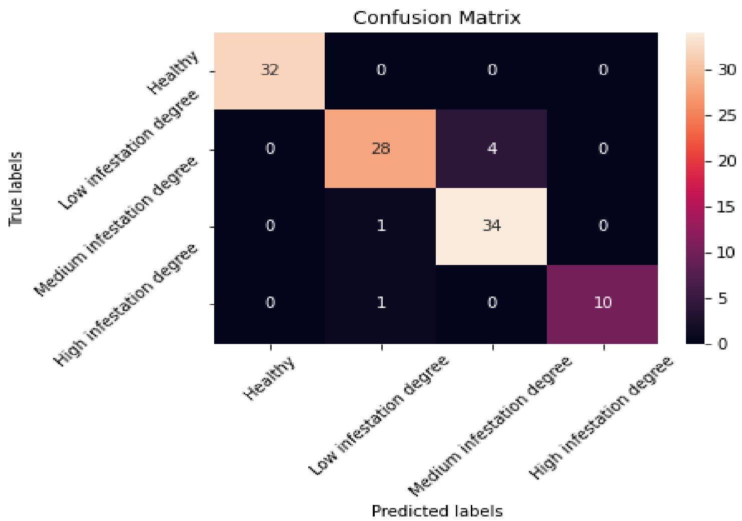


F

Figure 4. Confusion matrix of **A)** VGG16 model, **B)** VGG19 model, **C)** Xception model, **D)** ResNet50 model, **E)** ResNet50v2 model, **F)** MobileNet model, respectively, trained using 60 % of the dataset



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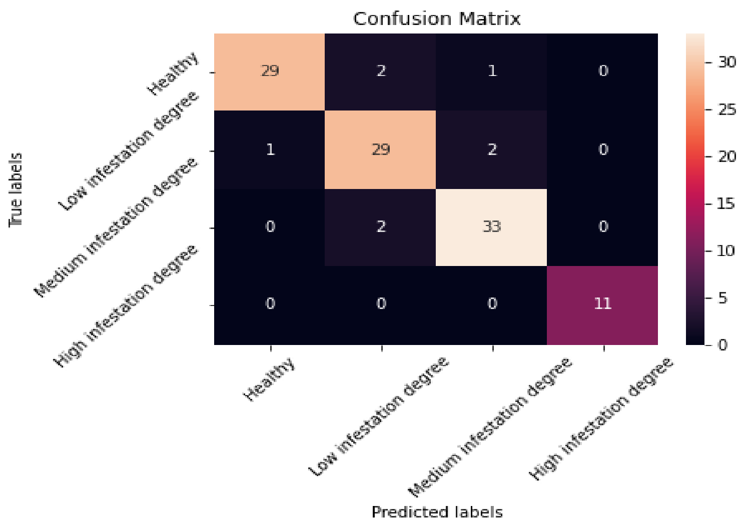

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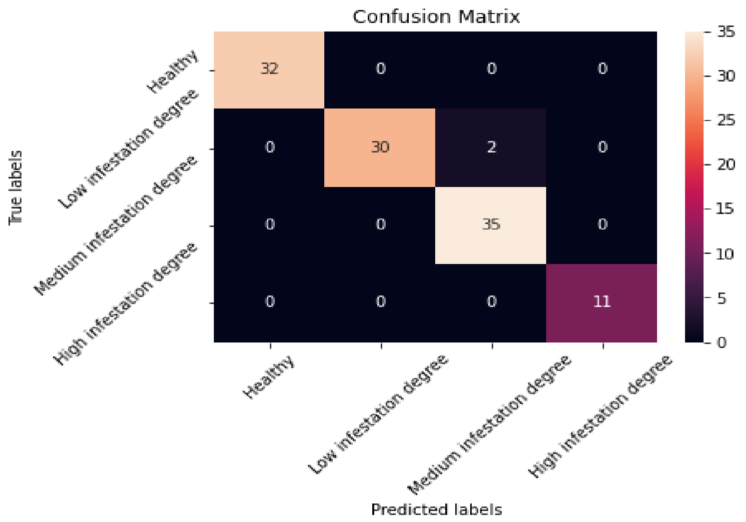
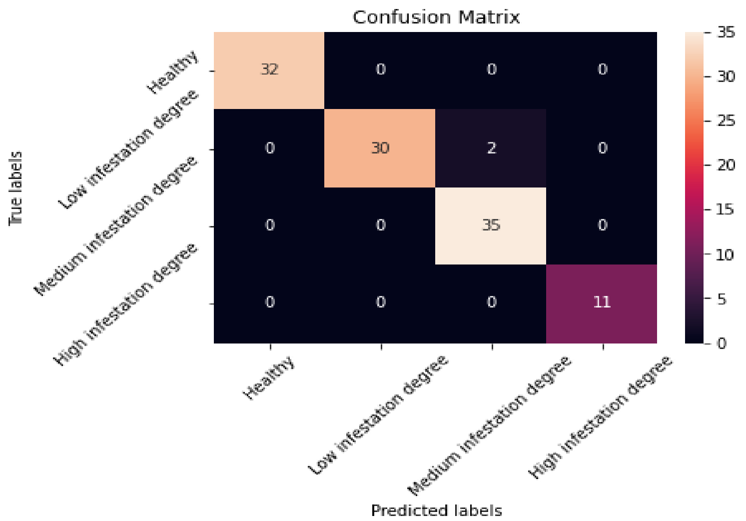

Confusion Matrix
True labels
Healthy
Low infestation degree
Medium infestation degree
High infestation degree
32 0 0 0
0 30 2 0
0 0 35 0
0 0 0 11
Predicted labels
35
30
25
20
15
10
5
0

C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Predicted labels
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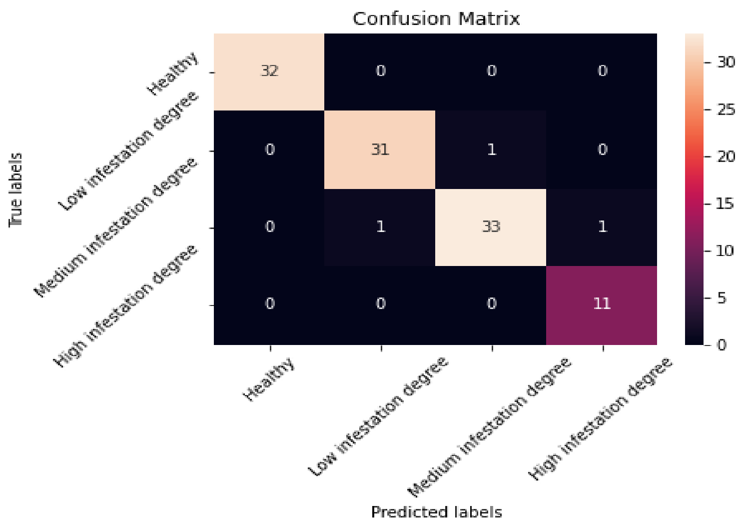
D


Confusion Matrix
True labels
Healthy
Low infestation degree
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High infestation degree
32 0 0 0
0 31 1 0
0 1 33 1
0 0 0 11
Predicted labels
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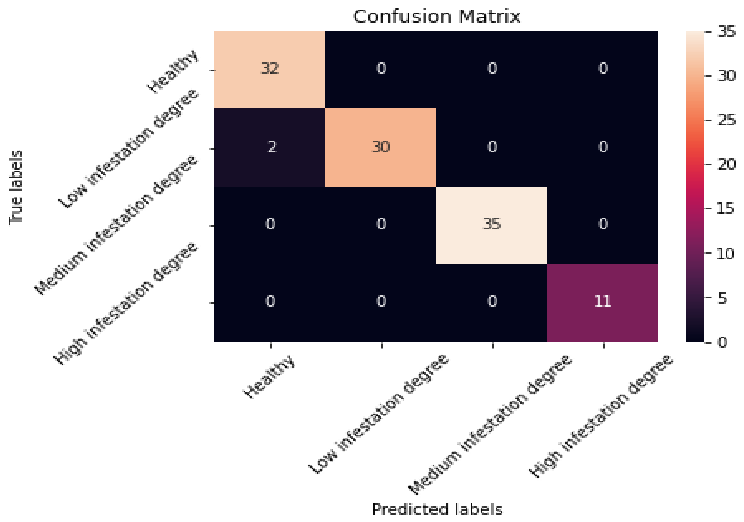
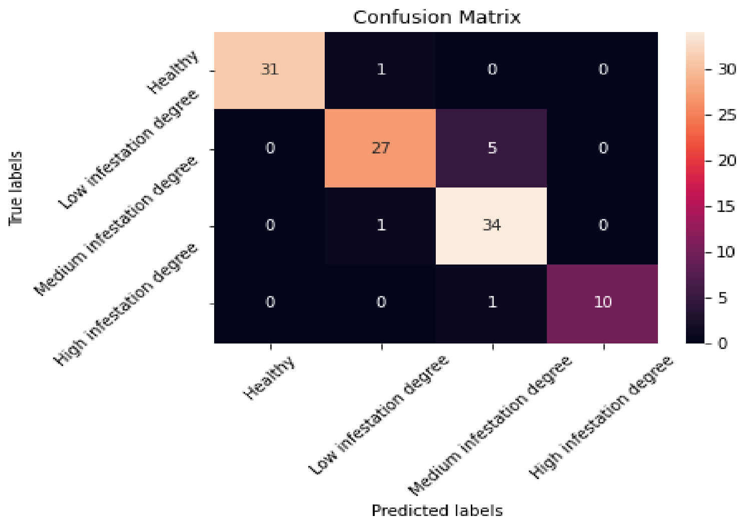
E



F

Figure 5. Confusion matrix of **A)** VGG16 model, **B)** VGG19 model, **C)** Xception model, **D)** ResNet50 model, **E)** ResNet50v2 model, **F)** MobileNet model, respectively, trained using 70 % of the dataset



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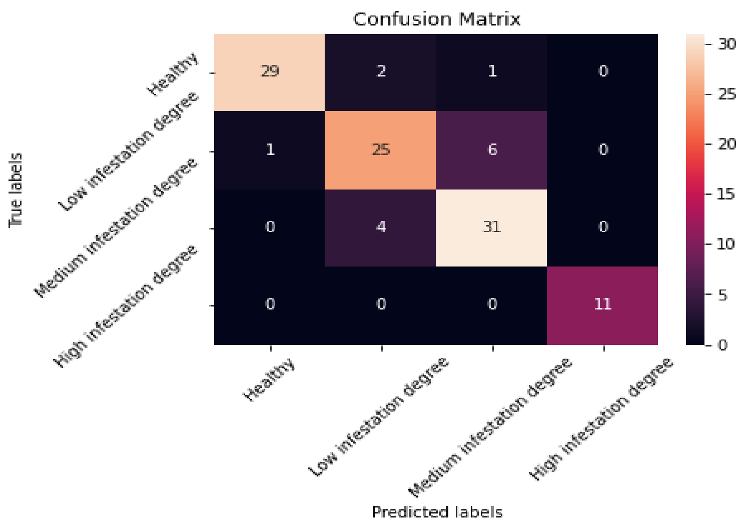

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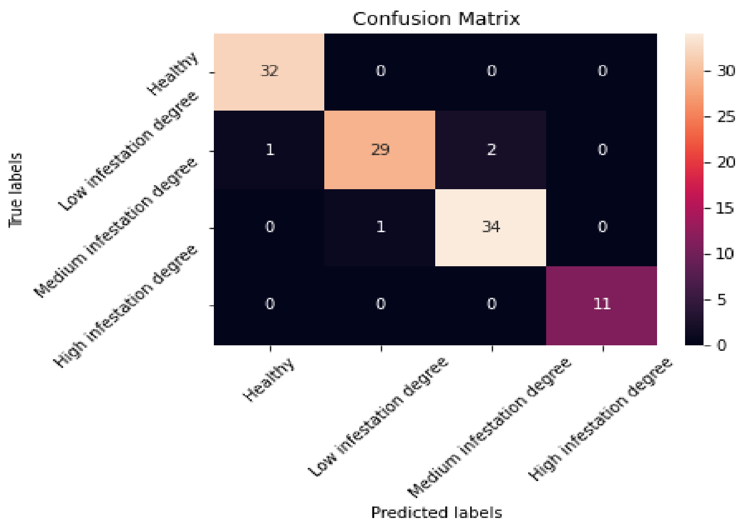
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1 29 2 0
0 1 34 0
0 0 0 11
Predicted labels
0
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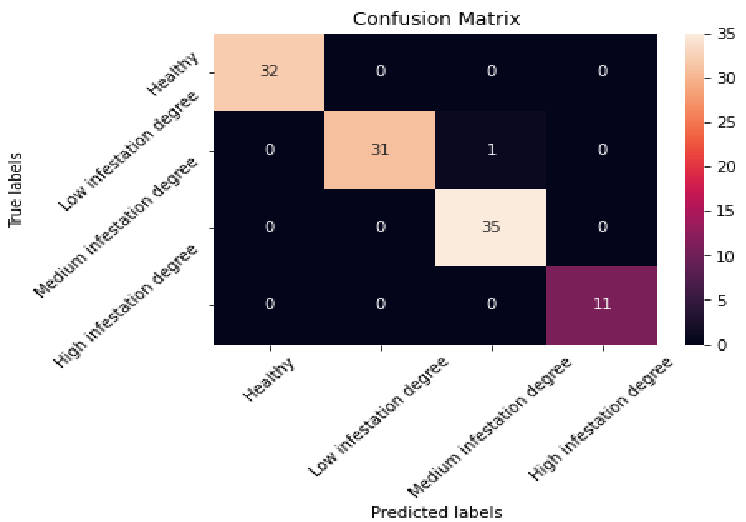
C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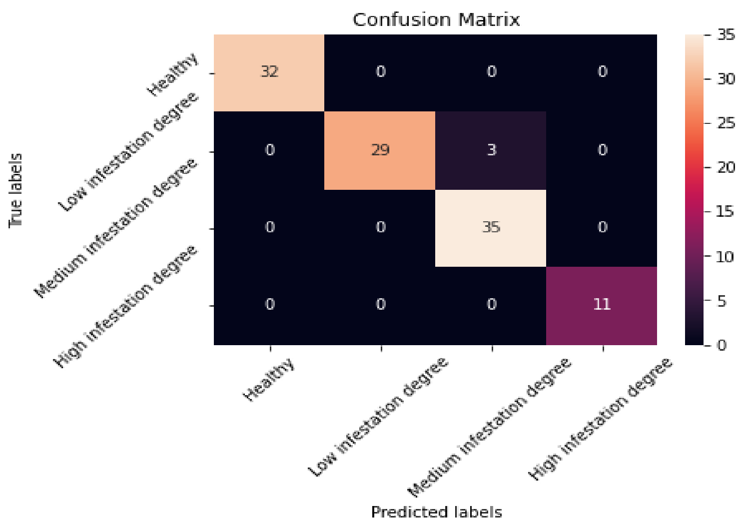
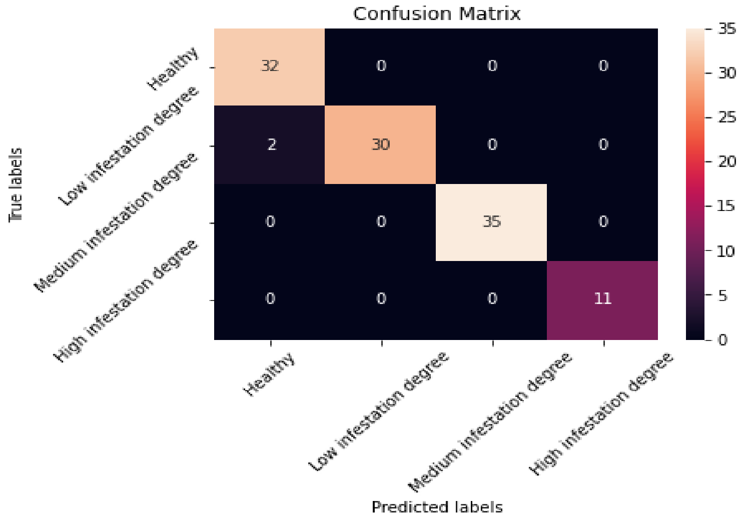
35

D


Confusion Matrix
True labels
Healthy
Low infestation degree
Medium infestation degree
High infestation degree
32 0 0 0
0 29 3 0
0 0 35 0
0 0 0 11
Predicted labels
0
5
10
15
20
25
30
35

E



F

Figure 6. Confusion matrix of **A)** VGG16 model, **B)** VGG19 model, **C)** Xception model, **D)** ResNet50 model, **E)** ResNet50v2 model, **F)** MobileNet model, respectively, trained using 80 % of the dataset

Sensitivity towards the amount of training data

The sensitivity of the models to the amount of training data used varies considerably. VGG16, VGG19, and Xception show notable sensitivity to training data volume changes. VGG19 exhibits the most pronounced sensitivity among these models, experiencing substantial performance improvements (6,24 % and 4,16 %) when the dataset size is reduced by 10 % and 20 %, respectively. This sensitivity stems from the model's tendency to overfit, highlighting the need for regularization techniques and data augmentation during VGG19 training. Conversely, models like ResNet and MobileNet demonstrate resilience to changes in training set size. These models maintain consistent performance across different training set sizes, with performance variations ranging from -0,92 % to 0,94 %. This consistency reflects their reliability, robustness, and ability to effectively learn from available data, regardless of the specific amount used.

Inference time

MobileNet consistently exhibits the fastest inference time across all training dataset sizes, with the best recorded time being 0,0337 seconds per image. This superior computational efficiency stems from the model's utilization of depthwise separable convolutions, a lightweight architecture, parameter optimization techniques, and model optimization strategies. These techniques collectively reduce the computational burden and model complexity, enabling faster predictions. MobileNet's design specifically targets efficient deep learning implementation on mobile and embedded devices. Figure 7 illustrates the inference time performance of the models, measured in seconds per image.

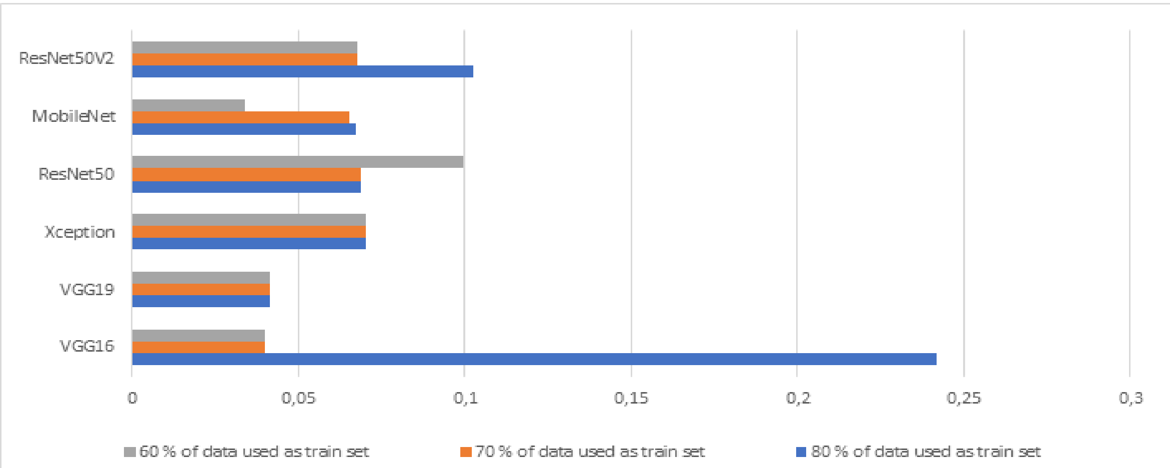


Figure 7. Inference time of different models with varying training dataset sizes

Comparing the best model with existing models

To assess the robustness of the proposed solution, we conducted a comparative evaluation with previous work addressing the same problem. The results revealed that the proposed approach of utilizing pre-trained MobileNet outperforms existing methods, achieving an improvement of 0,81 % over the solution proposed in Hessane et al.[22] and 1,05 % over the approach proposed in Hessane et al.[18]. These significant accuracy gains demonstrate the effectiveness of the proposed approach and underscore the suitability of pre-trained MobileNet for feature extraction and stage-wise classification of WSD.[34]

Table 4. References

Reference	Approach / Model	Performance
Feature extraction using GLCM and HSV features, and SVM Classifier.	98,29 %	
VGG16 for feature extraction and a fine tunned FCNN for classification.	98,06 %	
Proposed solution	Transfer learning based MobileNet model.	99,09 %

CONCLUSION AND PERSPECTIVES

Transfer learning has emerged as a groundbreaking technique for accurately detecting and classifying the various stages of White Spot Disease (WSD) in date palm trees. Our comprehensive evaluation of six pre-trained convolutional neural networks (CNNs) unveiled the remarkable performance of the MobileNet model across diverse metrics, including sensitivity to training data volume and inference time. This study holds immense potential for the agriculture industry and crop management practices, offering a reliable tool for early disease detection and effective management strategies. The conducted experiments conclusively demonstrate the promise of this approach, paving the way for advancements in date palm crop management and protection. The accurate classification of the disease infestation degree enables more precise pesticide usage, ultimately enhancing crop quality and yield.

To further enhance the effectiveness of date palm diseases detection and classification, future research should explore the applicability of transfer learning to other diseases and pests, investigate alternative deep learning models and techniques, and curate larger and more diverse datasets. Additionally, developing user-friendly tools and interfaces, implementing advanced disease monitoring systems, and expanding the scope of data used to train and evaluate deep learning models can help ensure the health and vitality of agricultural ecosystems.

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