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ORIGINAL ARTICLE

Advancing automatic plant classification system in Saudi Arabia: introducing a novel dataset and ensemble deep learning approach

Emna Amri[1] · Yonis Gulzar[2] · Ashfak Yeafi[3] · Siwar Jendoubi[4] · Faten Dhawi[5] · Mohammad Shuaib Mir[2]

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Abstract

Automated plant detection plays a pivotal role in various domains, including agriculture, environmental monitoring, and biodiversity conservation. In this paper presents a novel deep learning model specifically designed for classifying the diverse flora of Saudi Arabia. To accomplish this task, a novel dataset was created, named SaudiArabiaFlora Dataset, comprising samples from ten distinct types of plants found across various regions of Saudi Arabia. Our novel database provides an extensive range of plant species. The proposed model, named MIV-PlantNet, leverages the strengths of three well-established architectures: MobileNet, Inception, and VGG. By combining their unique characteristics, the model aims to achieve superior performance in terms of classification accuracy, precision, and F1-score. Extensive experiments were conducted to evaluate the model's efficacy, and comparisons were made with state-of-the-art models such as MobileNet, Inception, and VGG. The results demonstrate that the MIV-PlantNet deep learning model achieved an outstanding accuracy of 99%. Moreover, it demonstrates remarkable precision at 96% and an outstanding F1-score of 98%, underscoring its robustness and reliability. To gain insights into the model decision-making process, we utilized visual explainable AI approaches, specifically SHAP (SHapley Additive exPlanations). This analysis reveals the essential elements contributing to model predictions, enhancing our understanding of the classification process and model behavior. The findings of this study have substantial implications, accurate plant classification in Saudi Arabia has significant implications for biodiversity preservation and ecological studies. Our Dataset and MIV-PlantNet model offers exceptional resources and valuable insights for automated plant detection in various fields.

Keywords Deep learning · Plant species classification · Plant dataset · Flora Saudi Arabia · Image classification · Automated classification

✉ Yonis Gulzar
Ygulzar@kfu.edu.sa

✉ Siwar Jendoubi
siwar.jendoubi@upskills.ai
http://www.upskills.com

Emna Amri
amri.emna.90@gmail.com

Ashfak Yeafi
yeafiashfak@gmail.com

Faten Dhawi
Falmuhanna@kfu.edu.sa

Mohammad Shuaib Mir
mmir@kfu.edu.sa

[1] Research Team on Intelligent Systems in Imaging and Artificial Vision (SIIVA), LR16ES06 Laboratoire de Recherche en Informatique, Modélisation et Traitement de l'Information et de la Connaissance (LIMTIC), Institut Supérieur d'Informatique, University of Tunis El Manar, 2080 Ariana, Tunisia

[2] Department of Management Information Systems, College of Business Administration, King Faisal University, 31982 Al-Ahsa, Saudi Arabia

[3] Department of Electrical and Electronic Engineering (EEE), Khulna University of Engineering and Technology (KUET), Khulna, 9203 Khulna, Bangladesh

[4] UpSkills R&D, 16 Rue Marc Sangnier, 94600 Choisy-Le-Roi, France

[5] Agricultural Biotechnology Department, College of Agricultural and Food Sciences, King Faisal University, 31982 Al-Ahsa, Saudi Arabia

Introduction

Plants play an enormous role in our daily lives, providing us with essential materials and contributing to our well-being in a variety of ways. Plants are the primary course of food, medicine as well as materials for housing and clothing. Plants also contribute to environmental sustainability by lowering air pollution, mitigating climate change through carbon sequestration, and preserving ecological balance through the support of various habitats. Plants play a vital role for human survival. They do not only provide food, medicine, shelter but also provide fuel as well as play an important role in keeping the ecosystem running (Cumo 2015). The classification of different types of plants is extremely important in biology and beyond. Plant categorization helps us comprehend their relationships, properties, and ecological responsibilities by grouping them into various categories based on shared criteria. Simpson (Simpson 2019) emphasizes that "classification provides a framework for organizing and understanding the diversity of plants and their relationships with other organisms." Scientists, botanists, and researchers can more successfully identify and analyze plant species through classification, allowing for breakthroughs in disciplines such as agriculture, medicine, ecology, and conservation. Furthermore, classification aids in plant identification, allowing farmers to make informed crop selection and cultivation decisions, as well as conservationists in identifying and safeguarding endangered plant species.

In recent years, advances in deep learning have significantly improved image classification, providing promising ways to automate this task. Deep learning has been used in different domains to improve the accuracy such as Computer Vision (Krizhevsky et al. 2012), Object Detection and Recognition (Pathak et al. 2018; Emna et al. 2020), Image Segmentation (Minaee et al. 2021; Benoit et al. 2021), Environment (Saint-fleur et al. 2023; Mosaffaei et al. 2020; Zamri et al. 2023), Healthcare (Alam et al. 2022; Thanmai et al. 2023), e-commerce (Gulzar et al. 2023), Autonomous Systems (Qurashi et al. 2023), Education (Sghir et al. 2023; Ouyang et al. 2022), Natural Language Processing (NLP) (Lauriola et al. 2022). With its unique characteristics, deep learning has significantly contributed to the field of agriculture, particularly in plant classification and taxonomy. Traditionally, plant classification relies on manual observation and expertise, which is considered as timing-consuming and subjective. The existence of numerous similarities among various species demands a significant level of knowledge and experience to ensure precise and accurate identification. Conventional identification methods are not only time-consuming but frustrating, and often require familiarity with technical terminology. This complexity hinders beginners from acquiring proficiency in differentiating plant species. All these factors make it difficult for a common person to become familiar with the different types of plants. Therefore, there is a need to develop a computer vision-based automatic plant identification system that can facilitate and speed up the identification process. Having automated plant detection (APD) holds significant value for multiple reasons. Firstly, it aids in monitoring and preserving plant diversity within natural ecosystems. Secondly, APD facilitates the identification of unique plant varieties that possess desirable traits, contributing to enhanced agricultural productivity. Furthermore, APD serves as an effective tool for identifying and managing invasive plant species that can have detrimental effects on both the environment and agriculture. Consequently, APD enables environmental monitoring and control of plant communities, ensuring sustainable practices.

In addition to their practical applications, APDs offer significant potential for advancing ecological and botanical research. By streamlining plant identification processes, scientists can efficiently gather extensive datasets pertaining to plant communities and their environmental interactions. The versatility of APDs extends to diverse areas such as biodiversity preservation, agricultural practices, environmental surveillance, and scientific investigations. It offers invaluable insights into plant variety and plays a pivotal role in promoting environmental sustainability. Consequently, it proves indispensable for researchers, farmers, and advocates of ecological well-being. There have been many attempts made by the researcher to develop a computer vision-based system for the classification of plants. For instance, Mohanty et al. (2016) proposed a deep learning model for detection of diseases found in plants. This study was conducted for 14 different plants, which had 26 different types of diseases. Their proposed model has achieved 99.35% of accuracy. Yalcin and Razavi (2016) proposed a CNN model for classification of plants. The dataset they have used contained around 1200 images of 16 different plants such as tangerine, sunflower, apricot, tomato, grapes and many more. Their model has achieved around 97.47% accuracy. Pound et al. (2017) developed a new dataset containing the images of wheat spikes and spikelets. They proposed a CNN model which achieved 95.91% for spikes and 99.66% spikelets. Duong-Trung et al. (2019) proposed a deep learning model, leveraging the transfer learning for herb classification. They trained their proposed model based on a self-collected dataset and claim that it has achieved 98.7% accuracy. They have also compared their model with state-of-the-art (SOTA) models and their proposed model has outperformed the SOTA models.

Mamani Diaz et al. (2019) presented a deep learning model for plant classification. They have used a public dataset “Plant Seedlings Dataset”, containing 980 images of 12 different plants. Their model has achieved 86.21% accuracy. They have further compared their model with InceptionV3, VGG16 and Xception and claim that their model has outperformed these pretrained models. A deep learning model, based on VGG16 (Ariunzaya et al. 2023; Yang et al. 2021) was proposed for classification of seeds, containing 14 different classes. The proposed model achieved 99% accuracy in identifying different types of seeds. In 2021 a comparative study was conducted by Sai Kumar et al. (2021) in which they trained the SOTA model on the Rural Medicinal Plant (RMP) dataset, containing 8 different classes. The results show that MobileNet has outperformed Dense121, InceptionV3, VGG16, Xception, and VGG19. Alsaedi et al. (2022) proposed a deep learning model for dessert plant classification. They created a dataset of having 5 different classes and each class contains around 332 images. Their results claim that their model was able to identify different types of plants with 99.8% accuracy. There are other studies which have been using deep learning for classifying different types of fruits (Alsaedi et al. 2022; Abu-Jamie et al. 2022). In Hossain et al. (2018) the author proposed a deep learning model for industrial fruit classification. Their models achieved up to 99.75% accuracy using different databases. Whereas in (Abu-Jamie 2026), a deep learning-based fruit classification framework was introduced, featuring two distinct architectures: a six-layer convolutional neural network and a finely-tuned pretrained Visual Geometry Group-16 (VGG-16) model. Remarkably, the second model achieved outstanding accuracy rates of 99.75% on clear fruit images and 96.75% on challenging ones. Batchuluun et al. (2022) proposed a model for classifying plant and crop diseases using thermal images. They collected a new dataset containing 4,720 various images of flowers and leaves. The proposed CNN based model has achieved 98.55% accuracy while identifying plant and crop diseases.

In this research work, a novel deep learning model, MIV-PlantNet, is proposed for classification of varied flora of Saudi Arabia. This work contributes to discipline in several important ways. Following are the contributions of this research article.

- Comprehensive novel dataset creation: This research work contributes to the field by collecting samples from 10 different plant species that can be found throughout Saudi Arabia's varied areas. This novel dataset, available upon request, is specifically designed to address Saudi Arabia's distinctive flora, which was previously missing from other databases. Researchers may now develop and test deep learning models for precise plant classification in the area thanks to the creation of this dataset.
- Hybrid model leveraging established architectures: the study offers the MIV-PlantNet deep learning model, which combines the strengths of these three well-known architectures. The model seeks to obtain improved performance in terms of classification accuracy by utilizing the distinct features of MobileNet, Inception, and VGG architectures. This contribution demonstrates the effectiveness of combining established techniques to tackle complex classification tasks in specific domains.
- Significant classification performance: Extensive experiments were conducted to evaluate the efficacy of the MIV-PlantNet model and compare it with state-of-the-art models like MobileNet, Inception, and VGG. The results underscore the remarkable performance of the MIV-PlantNet model, boasting an impressive 99% accuracy and an F1-score of 0.98, all achieved within a swift inference time of just 0.4 s.
- Implications for environmental conservation and botany research: The accurate classification of plant species in Saudi Arabia has substantial implications for various domains, including environmental conservation and botany research. By facilitating the preservation of biodiversity and aiding in ecological studies, the proposed deep learning model contributes to efforts aimed at understanding and protecting the unique plant life in Saudi Arabia. It provides researchers with a valuable tool to study and identify plant species in the region accurately. This contribution extends beyond academic research, empowering a broader community to contribute to plant identification, environmental monitoring, and other related activities in the region.

The paper is organized into four distinct sections, each contributing essential elements to the study. Firstly, the experimental data and evaluation metrics are presented, laying the foundation for the subsequent analysis, and proposing a new Flora dataset. The second section introduces both the tested and proposed methods, while outlining the experimental setup utilized for evaluation. Moving forward, the third section scrutinizes the obtained results and assesses the performance of the models under examination. Lastly, the fourth section offers a comprehensive discussion covering the strengths, limitations, and noteworthy observations. In conclusion, key findings are summarized, and promising avenues for future research are suggested.

Experimental data and evaluation metrics

SaudiArabiaFlora dataset and preprocessing

Our novel dataset, called SaudiArabiaFlora, offers a valuable resource for plant recognition tasks, encompassing RGB images of 10 distinct plant families prevalent in Saudi Arabia. With a collection of over 1050 images, the dataset provides a substantial volume of samples for training and

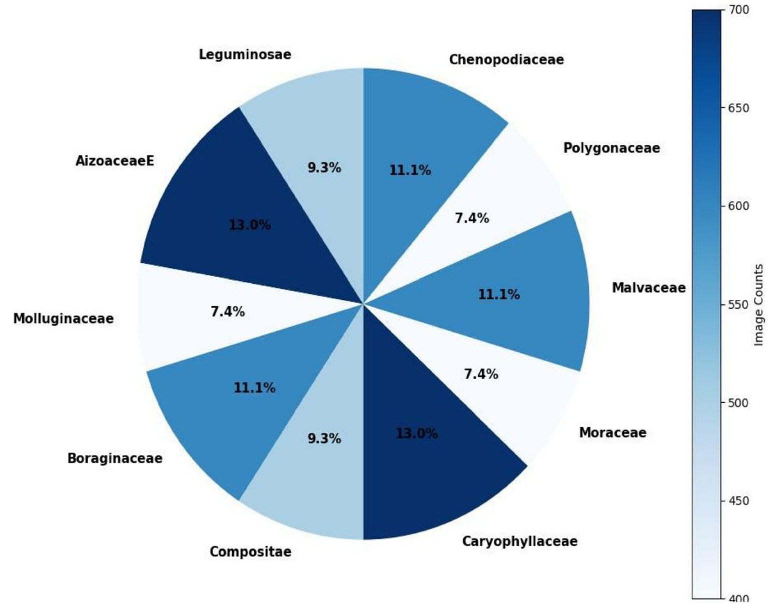


Fig. 1 Distribution of images per class among the SaudiArabiaFlora dataset

Fig. 2 Samples of each class of plant species in the SaudiArabiaFlora dataset

evaluation purposes. The images were meticulously captured using a Nikon D5100 16.2MP DSLR camera paired with an 18-55 mm VR lens, ensuring high-quality image acquisition. The resulting images have a resolution of 3679×5439 pixels, facilitating a detailed analysis of plant features. Figure 1 shows the Pie chart depicting the distribution of images across the 10 main plant classes in the dataset. Each class is represented by a slice in the chart, reflecting the relative proportion of images. The intensity of color in each slice corresponds to the number of images, with darker shades indicating higher image counts. Figure 2 exhibits a selection of photographed images from the 10 plant species. The figure provides a glimpse into the variety and characteristics of the different plant classes encompassed by the dataset.

Our dataset for plant recognition originates from natural environments, presenting a multitude of obstacles and diverse characteristics. These challenges, visually represented in Fig. 3 encompass variations in background, size, season, angle of view, and lighting conditions. Background elements may include hands, roads, or the ground itself. Shots taken from different positions can lead to discrepancies

Fig. 3 Images of dataset with significant variations in background and zoom levels

in plant size. The images were captured across various seasons, causing variations in leaf color, flower appearance, size, and other attributes. Varying angles of view expose distinct plant features, such as leaf patterns. Additionally, lighting conditions differ depending on the time of day when the images were taken, leading to subtle variations in plant colors due to sunlight. The images demonstrate the range of environmental contexts and magnification settings encountered within the dataset, capturing the inherent variability in background scenery and the degree of visual focus on the plant subjects.

To prepare a data set that can be used to train a deep learning model, we performed two preparation strategies. The first is to minimize data preparation methods, and the second is to apply more advanced preparation processes. For the first, we applied scaling and normalization as suggested for using images in deep learning applications. Therefore, we scaled the image to the input dimension of the network (512 pixels). In addition, we normalized the red, green, and blue color channels separately to a mean value of 0 and standard. For heavy processing, we made several data enhancements to increase the richness of the dataset. We randomly divide the dataset into specified proportions. 80% of the data will be assigned to the training subset, while the remaining 20% will be assigned to the testing subset. The split is conducted while ensuring that the class distribution is preserved in both the training and testing subsets. Figure 4 shows the split of the main dataset into a training and test set.

Evaluation metrics

Conventional metrics

To quantify the performance of our proposed model, a set of metrics has been used such as accuracy, precision, recall, F1 score and the confusion matrix. The formula of each metric is detailed in the following. Regarding recall, it was calculated by the ratio between the number of true positive classes and the total number of positive classes. In order to get a complete comparison of the different facets of performance, we use precision as a common measure. Besides, we use the F1 score, a harmonic mean combining precision and recall, to provide a better overview of performance. We have also evaluated our performances across each class using the confusion matrix.

Visual explanation metrics

Deep learning models evaluation often relies on performance metrics, but interpreting their predictions, especially for complex deep neural networks, can pose challenges. Explainable Artificial Intelligence (XAI) has gained significance in understanding algorithmic decision-making processes, given the growing acceptance and integration of artificial intelligence (Szegedy et al. 2016). XAI, introduced by Sujatha et al. (2021), refers to a system's ability to explain AI-based predictions. In this study, we focus on perturbation-based explanation methods, specifically SHapley Additive exPlanation (SHAP) (Sculley et al. 2018). SHAP quantifies feature importance for individual predictions by computing Shapley values using game theory concepts. KernelSHAP and DeepSHAP are some methods proposed for estimating SHAP values, outperforming other techniques such as LRP and LIME (Linardatos et al. 2021; Van et al. 2004). SHAP also provides insights into feature importance and their impact on network decisions (Lundberg et al. 2017; Knapič et al. 2021; Amri et al. 2022).

Proposed methods

Adapted deep learning models

As highlighted in the literature, the impressive performance of deep learning approaches outperforms conventional object detection approaches. The availability of a collection of RGB images with a rich variability and various plants allows us to consider such deep models

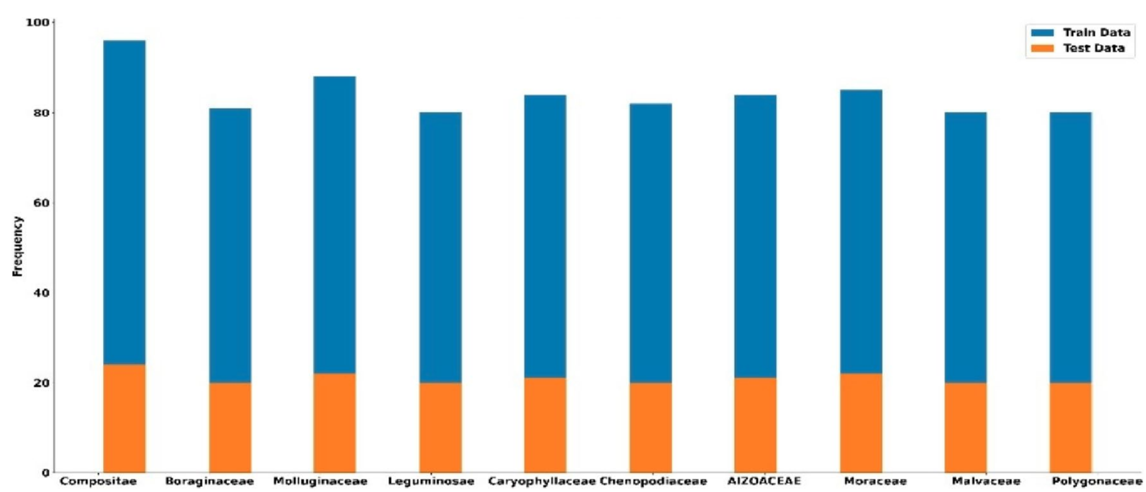


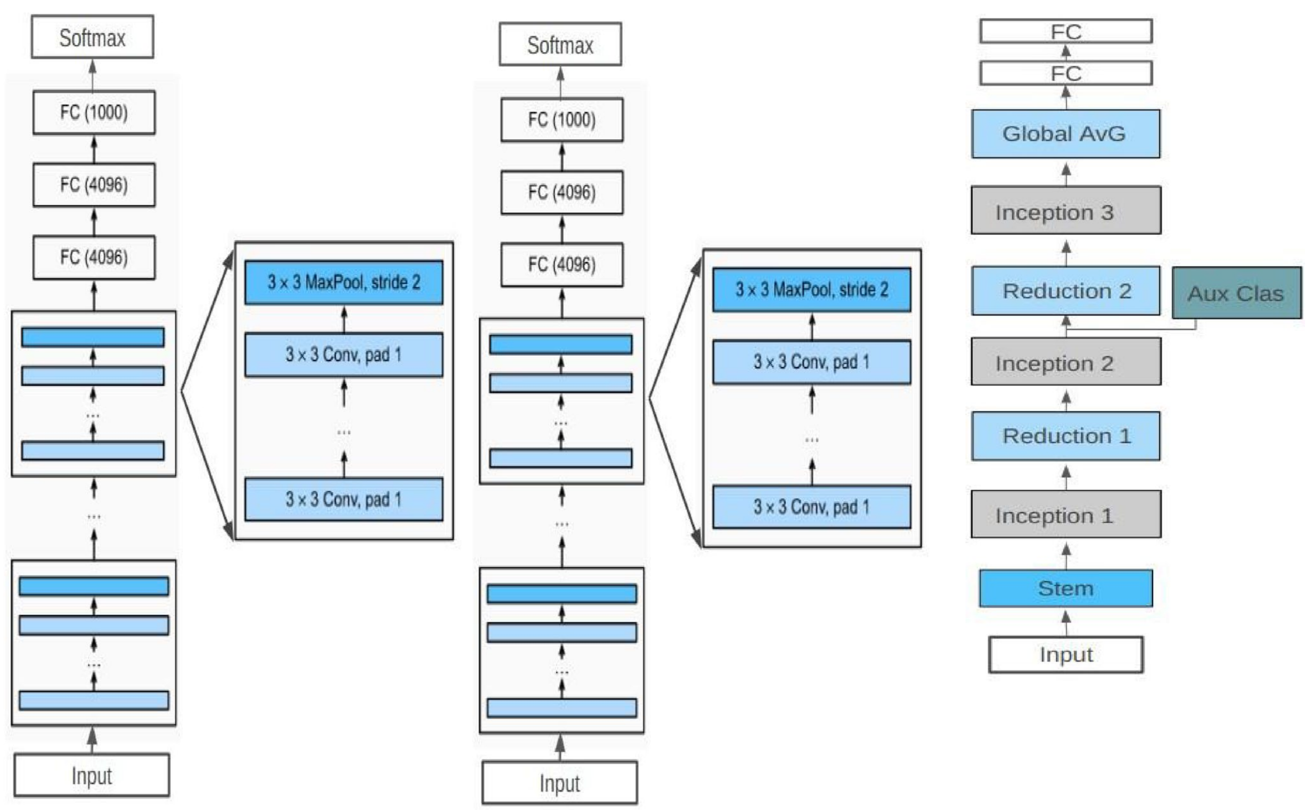
Fig. 4 Visualization of Data Distribution by Class in the Training and Validation Sets, with 20 samples reserved for the Test Set in each class

in a supervised learning approach. When it comes to the classification of plants, selecting the appropriate deep learning models is crucial for achieving accurate and reliable results. In this regard, Three popular choices in this domain are VGG19 (Abu-Jamie et al. 2022), MobileNetV2 (Batchuluun et al. 2022), and InceptionV3 (Simonyan and Zisserman 2014). These models have gained prominence due to their unique architectures and exceptional performance in image classification tasks.

VGG19 (Abu-Jamie et al. 2022): VGG19 is known for its deep structure, enabling it to capture intricate features and patterns in plant images. This architecture comprises multiple convolutional layers with small receptive fields, followed by fully connected layers, as depicted in Fig. 5(a). We specifically selected the VGG-19 version, which includes 16 convolutional layers and three fully connected layers. Its additional layers enable the model to learn intricate image patterns effectively. Compared to other architectures like AlexNet or GoogLeNet, VGG-19 offers a more compact size, resulting in faster computation without compromising accuracy and robustness in plant detection tasks where detailed feature representation is crucial (Sandler et al. 2018).

MobileNetV2 (Batchuluun et al. 2022): MobileNetV2 is a convolutional neural network architecture designed for mobile and embedded devices, which aims to achieve high accuracy while maintaining low latency. It consists of lightweight depth wise convolutions that reduce the number of parameters in the model without compromising its performance. Furthermore, MobileNetV2 improves its efficiency by incorporating inverted residual connections and linear bottleneck layers, as shown in the architecture Fig. 5(b). This design approach effectively reduces the computational effort required by a standard convolution network while maintaining high accuracy. In addition, MobileNetV2 uses linear bottlenecks with shortcut connections between bottleneck layers to promote efficient information transfer within the network. This approach enables training deeper models while keeping computational costs under control. Overall, MobileNetV2 offers an attractive combination of efficiency, speed, and accuracy, making it a good choice for crop detection applications, especially in resource-constrained environments and mobile devices.

Inception V3 (Simonyan and Zisserman 2014): This architecture is built upon the idea of using multiple filters of different sizes within a single layer. The architecture is depicted in Fig. 5(c). InceptionV3 utilizes a combination of



(a) VGG-19 (b) MobileNetV2 (c) Inception V3

Fig. 5 Overview of the VGG-19, MobileNetV2 and Inception V3 architecture

Stem blocks, Inception blocks, and an auxiliary classification block. The Stem block extracts low-level features as a basic backbone. The Inception blocks capture multi-scale contextual information, leading to more robust representations. InceptionNet employs a combination of 1×1, 3×3, and 5×5 convolutional filters alongside max pooling operations to extract features at different levels of abstraction. Regarding the auxiliary classification block aids in training. This architecture enables InceptionV3 to achieve strong performance in image classification tasks.

Proposed model: MIV-PlantNet

In this research work, we have proposed a novel model called MIV-PlantNet, that leverages the collaborative strength of ensemble modeling with late fusion. MIV-PlantNet involves loading multiple models, each with its own unique characteristics, and integrating them into a cohesive ensemble.

Drawing inspiration from the concept of ensemble modeling, which has proven effective in various domains, our proposed model embraces the collective intelligence of the state-of-art models to achieve enhanced performance. Through a fusion process, we aggregate the predictions of these (VGG19, MobileNetv2, InceptionV3) individual models to create a unified and more robust output that incorporates the collective knowledge of the ensemble. Several tests have been performed to find the best combination of the model, Table 1 shows the combination tested, including the proposed models MIV-PlantNet, which stands for Mobile Inception VGG PlantNet which combines the three models. Using the late fusion technique enables us to effectively combine the predictions of individual models at a later stage, resulting in a more comprehensive and reliable output.

Figure 6 illustrates the architecture of our proposed model, incorporating three deep learning models for plant detection.

To improve the performance of plant detection, a novel approach, MIV-PlantNet, was employed by combining the predictions of the three compared deep learning models: MobileNetV2, InceptionV3, and VGG16. By leveraging the strengths of each individual model, this combination technique aimed to enhance the accuracy and robustness of the overall plant detection system. The choice of employing ensemble learning for the plant detection classifier was motivated by several advantages it offers. Firstly, ensemble

Table 1 List of model combinations tested

Combined models
MobileNetV2 + Inception V3
VGG19 + InceptionV3
VGG19 + MobileNetV2
MIV-PlantNet

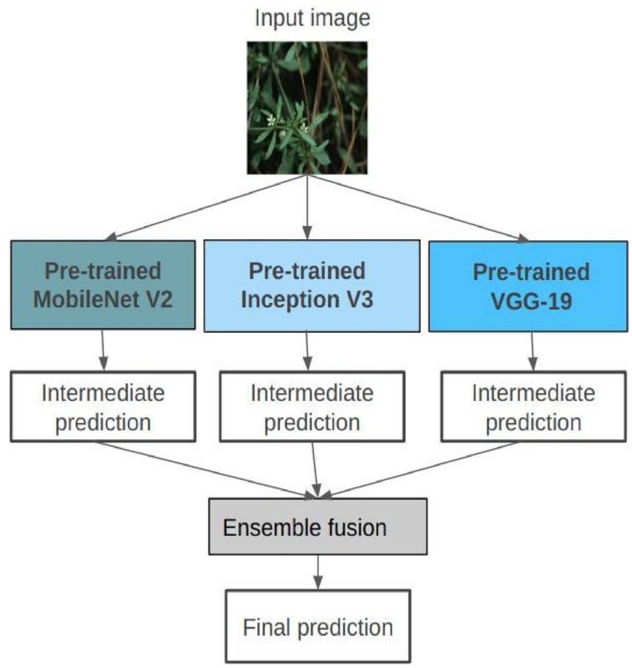


Fig. 6 Proposed model for plant detection

learning enhances the accuracy of the classifier by combining predictions from multiple models, minimizing the likelihood of errors and misclassifications. Secondly, it improves the classifier robustness by leveraging the diversity of individual models, enabling it to effectively handle variations in plant appearance caused by factors such as backgrounds, lighting conditions, seasons, and viewpoints. Ensemble learning also mitigates overfitting by leveraging the collective wisdom of different models, thereby enhancing generalization performance on unseen data. Furthermore, it addresses the challenge of class imbalance by providing a balanced perspective and improving classification results across all plant classes. By leveraging models such as MobileNetV2, InceptionV3, and VGG16, each with their unique strengths, the ensemble approach aims to create a more powerful and comprehensive plant detection classifier.

Experimental settings

This research aims to propose an optimal model which identifies and classifies different types of plants. The proposed model was implemented using Python 3.10 on the Linux operating system, using an *i7* processor and 15 GB RAM and an NVIDIA GeForce GTX 1060 Mobile 6 GB GPU. We also provided a detailed description of the experimental setup employed in our study, ensuring transparency and reproducibility of our results. We discussed the dataset used for training evaluation, the selection of deep learning models, and the evaluation metrics employed.

This comprehensive overview enables researchers to validate and build upon our work effectively. We followed the above systematic workflow consisting of several essential steps:

Data pre-processing: In this stage, we resized and normalized the pixels of the images to ensure consistency and facilitate further analysis. Besides, we explored data augmentation techniques, however, after careful evaluation, we found that implementing these techniques did not significantly improve the performance of our model. Therefore, we made the decision to exclude these techniques from our experimentation phase. Despite not utilizing data augmentation, our model demonstrated satisfactory and stable performance, indicating that it could effectively detect plants without relying on these additional methods.

Model training: In the model training stage, each classifier undergoes pre-training on the ImageNet dataset before being trained on our specific training set for plant detection. This approach, known as transfer learning, reduces the need for large amounts of data and accelerates training time. By leveraging the pre-learned features, the model initializes with a solid foundation and adapts its representations to the unique requirements of plant detection. Hyperparameters like learning rate, batch size, and regularization techniques (dropout, early stopping) are meticulously tuned to ensure fair comparisons between classifiers. The widely used Adam optimizer is employed as the optimization algorithm, with a learning rate of 1e-3 controlling the weight update step size. For the loss function, categorical cross entropy is chosen due to its suitability for multi-class classification tasks.

Performance assessments: To ensure reliable and robust performance estimation, our model underwent K-Fold cross-validation during the training phase. This technique enhances the trustworthiness and generalizability of the models by dividing the dataset into K subsets. Through iterative training and evaluation on different subsets, we obtained a comprehensive understanding of the models' performance. This approach effectively addressed concerns of overfitting and provided valuable insights into the consistency and stability of the models in plant detection across diverse subsets. The integration of K-Fold cross-validation in our study ensured a rigorous evaluation process, boosting confidence in models' ability to generalize to unseen plant images. Moving forward, the evaluation of model performance during the testing stage will involve considering multiple metrics. These include confusion matrix, accuracy, precision, recall, and F1-score. To conduct a more thorough performance evaluation and gain a deeper understanding of how our deep learning model makes decisions, we have incorporated the use of visual explainable artificial intelligence, specifically employing SHAP explanation.

Comparative analysis: We establish a comparative study of the classifiers' performance on a test set separate from the training and validation sets in the comparative study. We aim to evaluate the performance and computational effectiveness of the classifiers. We hope to gain insight into how the classifiers work in real-life circumstances.

Results

Comparative study

The performance of three deep learning models, namely MobileNetV2, InceptionV3, VGG16, was evaluated for the task of plant detection using a dataset comprising 10 plant classes. The training loss and accuracy for the three models were analyzed and plotted together in Fig. 7. The figure offers a comprehensive visualization of the training dynamics and comparative analysis of the models learning behavior. One important aspect of this study is the consistent training setup employed for all three models: MobileNetV2, InceptionV3, and VGG16. These models were trained using the same dataset and evaluated on an identical test set. Each model was trained using the same configuration and utilized pretraining weights from the ImageNet dataset, offering the advantage of leveraging learned feature representations, minimizing the need for extensive labeled plant data during training. By adopting this consistent methodology, a fair and unbiased comparison of the models' performances were ensured. Consequently, this approach allowed for a reliable assessment of the model capabilities in plant detection, as any observed differences could be attributed to their inherent qualities rather than variations in training procedures. Figure 7 illustrates the remarkable trend in both training and validation accuracy, reaching nearly 100% by the conclusion of the training process. Simultaneously, the training and validation loss consistently decrease, approaching zero as the training progresses. The plotted figures provide valuable insights into the training progress and performance of the models. The training loss curve illustrates the convergence of models' learning process, demonstrating the gradual reduction in error as training progresses (near 0 around 12 iterations). On the other hand, the accuracy curve shows how well the models were able to correctly classify plant images during training. It starts clearly from the fourth iteration and reaches its highest value around the twelfth iteration. By examining the training loss and accuracy curves for all three models together, it is clearly illustrated that their patterns are quite similar (Fig. 7). It is particularly relevant to consider the relationship between these metrics and the specific nature of the plant detection task.

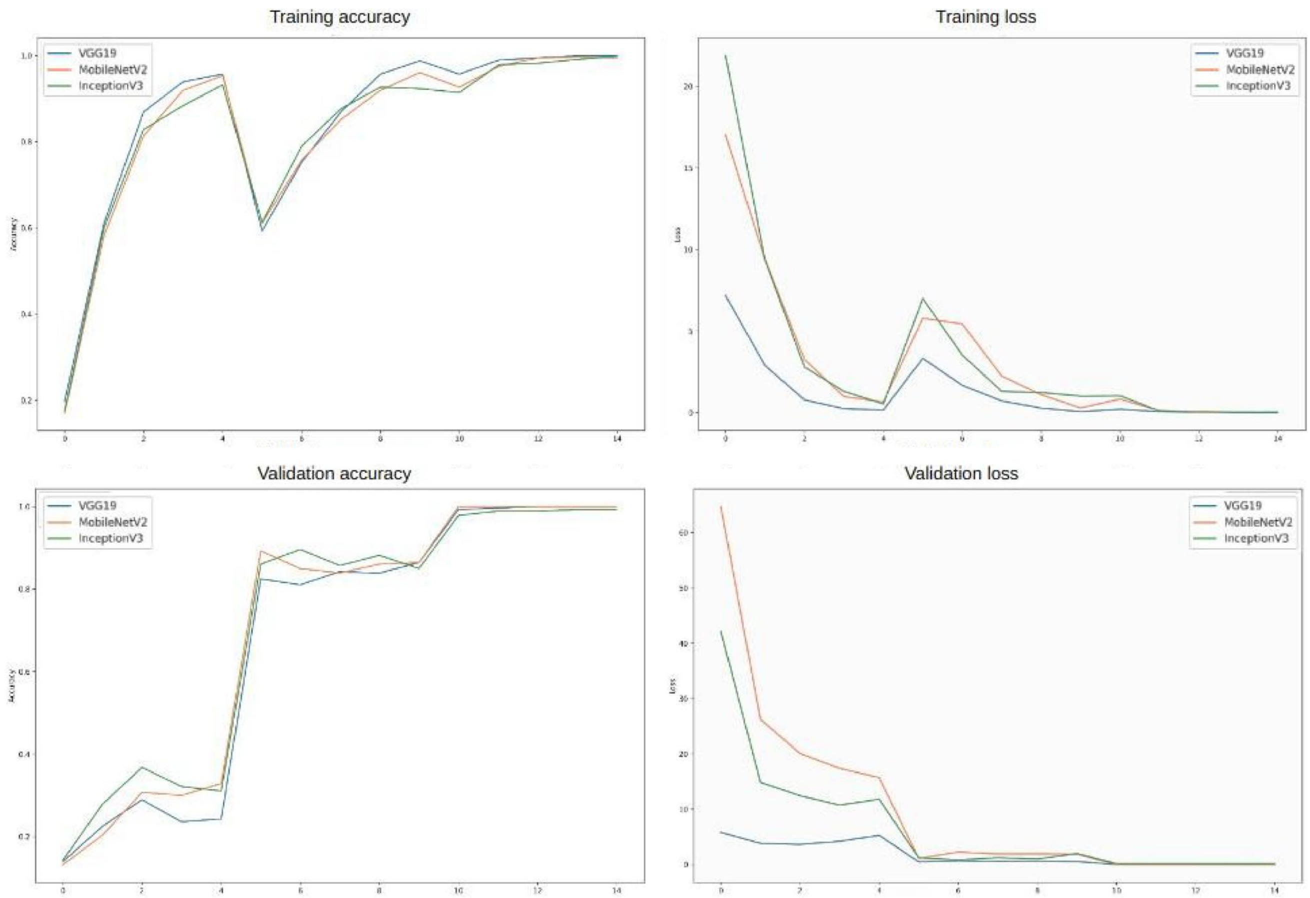


Fig. 7 Training accuracy and loss of VGG19, MobileNetV2 and InceptionV3

As the models are trained on data specifically related to plants, a decreasing training loss indicates that the models are effectively learning (the loss curves tending towards 0 around the last epochs) and adapting to the unique characteristics of plant images. Moreover, an upward trend in accuracy signifies improved model performance and their ability to accurately differentiate between different plant classes (the accuracy curves tending towards 1 around the last epochs). The challenge of our dataset with its specificity, namely variations in backgrounds, seasonal changes, and diverse viewpoints, can have an impact on the model's learning process. Therefore, the training loss and accuracy curves serve as important indicators of the models' capability to handle such data specificity and refine their predictions accordingly. The classification accuracy, precision, recall, and F1 score were computed for each model as presented in Table 2. The test set consisted of around 20 samples for each class. One can note that the best obtained performance is achieved by the MIV-PlantNet model.

Table 2 Accuracy, precision, recall and F1-score of different models on a test set of 210 images

Model name	Precision	Recall	F1-score	Accuracy
MobileNetV2	0.85	0.85	0.85	0.85
InceptionV3	0.86	0.87	0.85	0.85
VGG19	0.87	0.86	0.86	0.87
MobileNetV2 + InceptionV3	0.96	0.96	0.96	0.96
VGG19 + MobileNetV2	0.94	0.94	0.94	0.95
VGG19 + InceptionV3	0.94	0.93	0.94	0.94
MIV-PlantNet	**0.98**	**0.98**	**0.98**	**0.99**

Bold values indicate the significance of the proposed model: MIV-PlantNet

Figure 8 illustrates the confusion matrix obtained during testing of MobileNetV2, InceptionV3, VGG19 and MIV-PlantNet. The test set contained the 20 samples of each class. From the figure it can be inferred that the proposed model, MIV-PlantNet has achieved the highest accuracy by predicting all the classes correctly, except Aizoaceae, Caryophyllaceae, and Mavaceae, which got one instance wrong. Whereas VGG16 was the second-best model in predicting the correct instances during testing. InceptionV3 and MobileNetV2 were having the highest

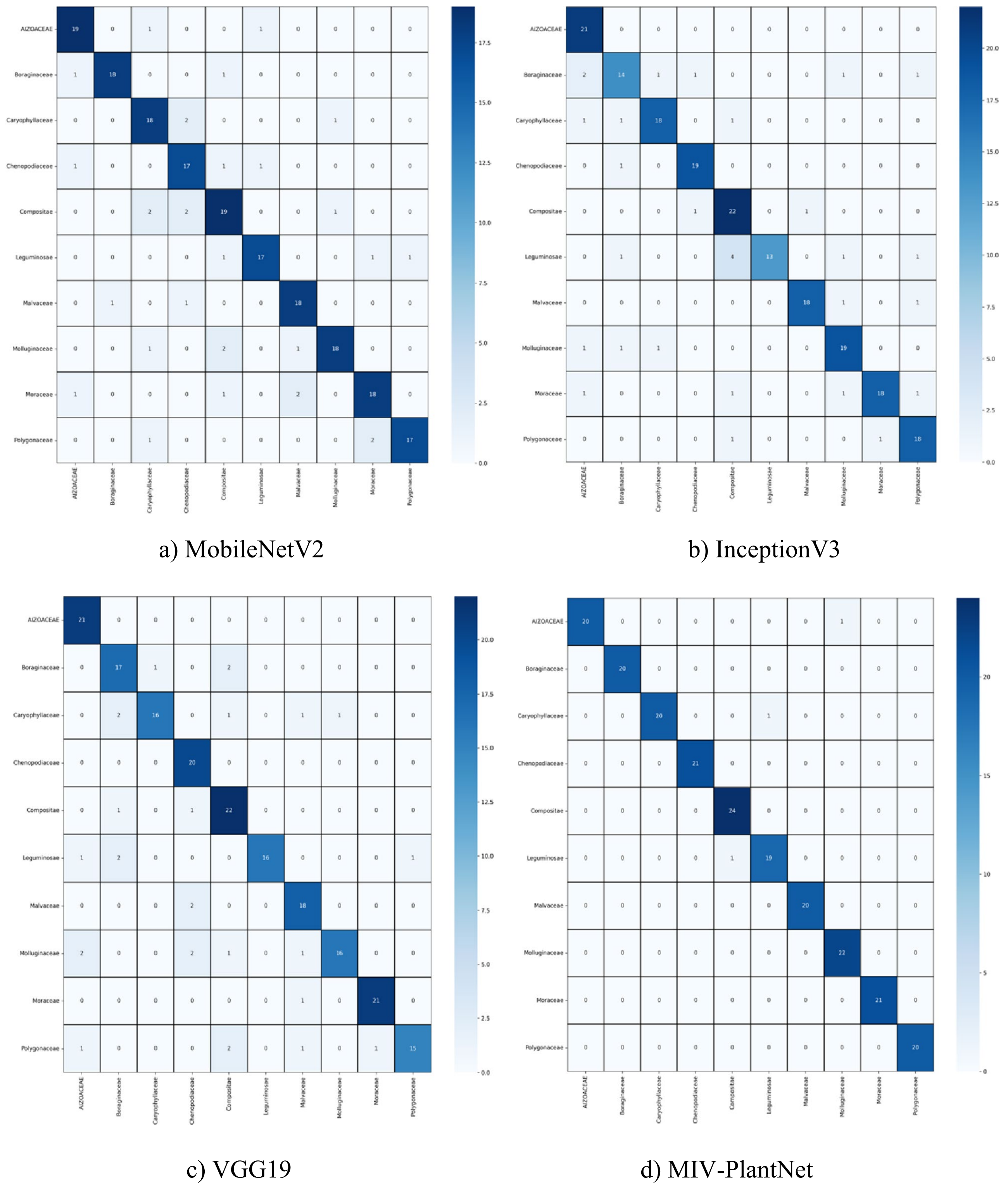


Fig. 8 Confusion matrix of all three models MobileNetV2, InceptionV3, VGG19 and MIV-PlantNet

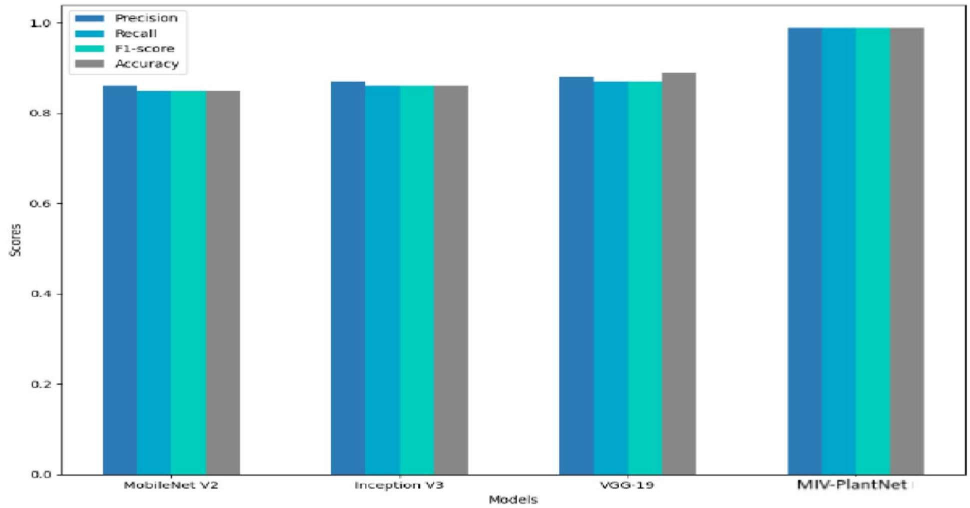


Fig. 9 Classification report for the tested models Vs MIV-PlantNet

	precision	recall	f1-score	support
AIZOACEAE	1.00	0.95	0.98	21
Boraginaceae	1.00	1.00	1.00	20
Caryophyllaceae	1.00	0.95	0.98	21
Chenopodiaceae	1.00	1.00	1.00	21
Compositae	0.96	1.00	0.98	24
Leguminosae	0.95	0.95	0.95	20
Malvaceae	1.00	1.00	1.00	20
Molluginaceae	0.96	1.00	0.98	22
Moraceae	1.00	1.00	1.00	21
Polygonaceae	1.00	1.00	1.00	20
accuracy			0.99	210
macro avg	0.99	0.99	0.99	210
weighted avg	0.99	0.99	0.99	210

Fig. 10 MIV-PlantNet Model metrics report, class-wise evaluation

number of wrong predictions during the plant classification. Furthermore, Fig. 9 showcases the Precision, recall, F1-score, and accuracy of the compared models. It is evident from the results that the proposed model outperforms all the other models.

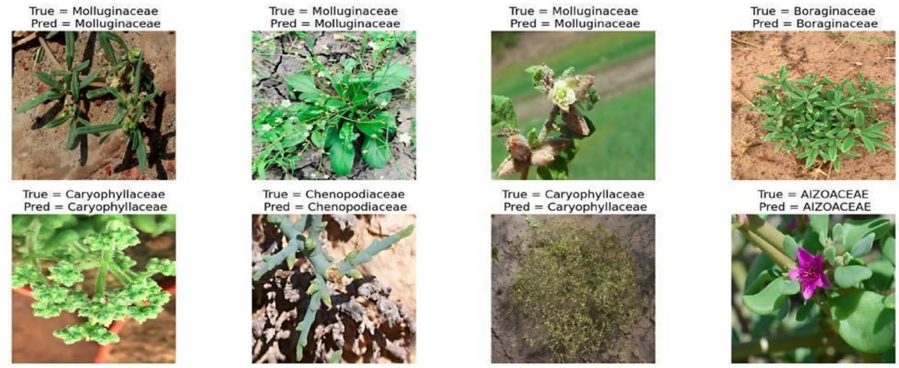
Going further, we present an analysis of the best outcomes achieved by MIV-PlantNet, with more detailed metrics illustrated in Fig. 10. The evaluation metrics are displayed through a Class-wise Evaluation, providing insights into each class's performance in the test set, including the number of samples (support column), precision, recall, and F1-score. For instance, taking the class as an example, we observe that classes like "Chenopodiaceae", "Boraginaceae","Malvaceae", "Maraceae," and "Polygonaceae" show precision, recall, and F1-scores of 1. Additionally, an overall perspective of the prediction across all classes is provided through the macro-average and weighted average accuracy, achieving an impressive accuracy of 0.99.

Correct prediction analysis

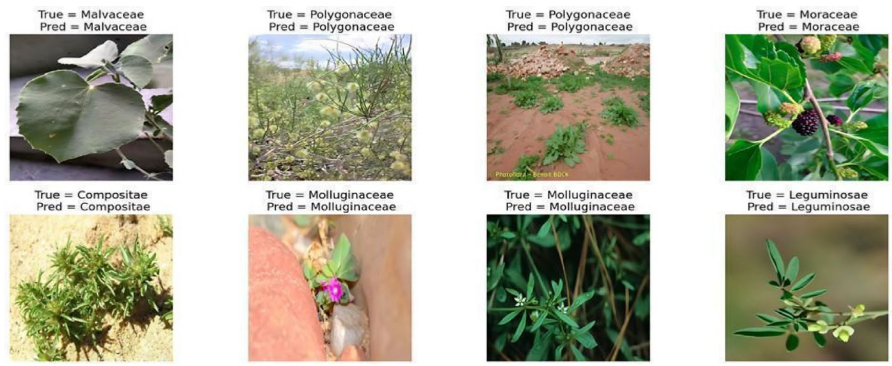
To demonstrate the performance of the plant detection models, namely MobileNetV2, InceptionV3, VGG19, and MIV-PlantNet a series of sample predictions were gathered from the test set. The results are visually depicted in Fig. 11. These illustrations offer a glimpse into the models' proficiency in accurately classifying various plant images, thus highlighting their efficacy in plant detection tasks.

One can notes that the prediction from the MobileNetV2 model (Fig. 11a) involved the successful identification of an image belonging to the Leguminosae class, demonstrating the model effectiveness in detecting specific plant families. Similarly, the InceptionV3 model (Fig. 11b) exhibited precise classification by accurately assigning an image to the Chenopodiaceae class, indicating its ability to differentiate between different plant categories. Likewise, the VGG16 model (Fig. 11c) made an accurate prediction by correctly categorizing an image as part of the Compositea class, showcasing its competence in recognizing complex plant structures. Furthermore, the models demonstrated robust performance in classifying images that presented challenges such as variations in backgrounds, seasonal changes, and diverse viewpoints. For instance, the MobileNetV2 model successfully classified an image captured in a dense forest environment, highlighting its resilience in handling different background conditions. In another scenario, the InceptionV3 model effectively identified an image taken during winter, showcasing its adaptability to seasonal variations. Similarly, the VGG16 model demonstrated its capability to handle varying viewpoints by accurately recognizing an image captured from a low-angle perspective. These sample predictions collectively exemplify the models' ability to accurately

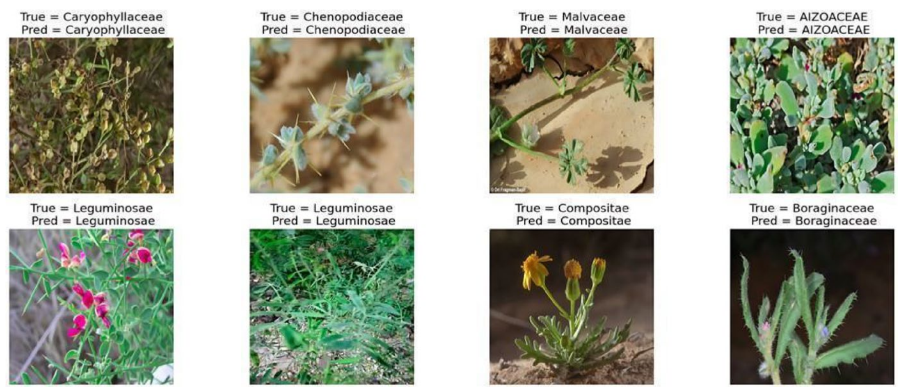
Fig. 11 Plant detection results across various models



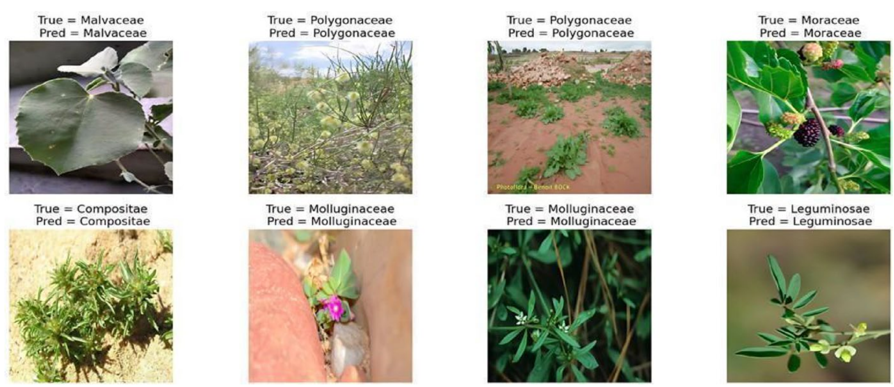
a) MobileNetV2



b) InceptionV3



c) VGG 19



d) MIV-PlantNet

classify plants across various classes and challenging conditions. They provide concrete evidence of the models' robustness, adaptability, and sensitivity to the specific characteristics exhibited by plant images. Figure 11d showcases the combined performance of the three aforementioned models, highlighting the superior performance achieved.

Wrong prediction analysis

The wrong prediction of different models is visually depicted in Fig. 12 for the different models. The disparity between the true class and the model predicted class emphasizes the occurrence of misclassifications in the plant detection process.

Plant species within the same family or even across different families can share certain visual traits, such as leaf shape, flower color, or growth pattern. This makes it challenging for a deep learning classifier to accurately distinguish between closely related species or those with similar visual features. In addition to the inherent visual similarities between plant species, another factor that can contribute to wrong detection is the variation in the image composition and contextual information. The test set includes images that are zoomed in on specific parts of the plant without providing much contextual information, while others are zoomed out, encompassing a wider view that includes other surrounding elements or phenomena as shown in Fig. 12. When images are zoomed in on specific plant parts, the task of distinguishing between similar-looking species becomes more challenging. Without the broader contextual information, the classifier relies on limited visual cues within the zoomed-in region, which can result in misclassifications, particularly when species share similar characteristics in that area. On the contrary, when images are zoomed out to include a larger portion of the plant and its surroundings, the classification task becomes more complex. The presence of diverse visual features, such as different plant structures, background objects, or environmental factors, adds intricacy to the classification process. This complexity makes it harder for the classifier to focus solely on the distinguishing characteristics of the target species, increasing the likelihood of classification errors. In its entirety, studies show that deep learning models are advantageous for plant detecting tasks. VGG16 stands out for its overall accuracy, although InceptionV3 and MobileNetV2 deliver competitive results with distinct strengths in specific classes.

Visual explanation of models classifications

To shed light on the decision-making process of our proposed model MIV-PlantNet, we employ SHAP explanations. This visual explanation technique allows us to delve into the factors that influence the model predictions. Identifying the key areas that have a significant impact on the model decision yields valuable insights into the model's inner workings. An interpretation of the plant prediction realized by the MIV-PlantNet model can be observed in Fig. 13. The model demonstrates a particular strong SHAP values on various distinguishing areas in the images such as leaf patterns, the fruits, and flowers to make its decision about the plant species. The SHAP explanation helps interpret the underlying features that contribute to the model decision, enhancing our understanding of how the model perceives and distinguishes different plant attributes. The analysis, depicted in Fig. 14, offers a sample of visual explanations to deepen our understanding of the factors influencing the model's incorrect predictions (as shown in Fig. 12d). It revealed that the model assigned considerable importance to the background of the images, as indicated by the regions with positive SHAP values highlighted in red. One can note the sand region and rock elements in the images shown in Fig. 14. Interestingly, these regions were predominantly found along the borders of the images, where the background is present. This finding suggests that the model's incorrect predictions may be influenced by the presence of the background, which it mistakenly associated with certain plant species. The model's attention to the background highlights the potential challenges in distinguishing between the foreground (plant) and background elements, especially when the images contain zoomed-in or cropped views. Additionally, it focused on the flowers and leaves of the detected plants, potentially causing confusion when distinguishing between different species. The SHAP explanation revealed that the model attributed significant importance to the background, as seeing the positive SHAP values highlighted in red are found mostly in the areas of the borders of the images where there is the background. By leveraging the SHAP explanation, we can identify areas for potential enhancement, ultimately improving the reliability of the plant detection model.

Discussion

The proposed model MIV-PlantNet demonstrated excellent precision across most classes, with a precision score of 1.0, indicating minimal misclassifications. Notably, in the confusion matrix presented in Fig. 10 for the Compositea, Leguminosae, and Molluginaceae classes, the precision score hovered around 0.95, showcasing our proposed model capability to accurately classify plants across a wide range of classes, with only a slight variation for specific classes. The outstanding performance of the MIV-PlantNet model highlights the strength of combining multiple deep learning models. By aggregating the predictions from MobileNetV2, InceptionV3, and VGG16, the MIV-PlantNet model effectively mitigated the limitations of individual models

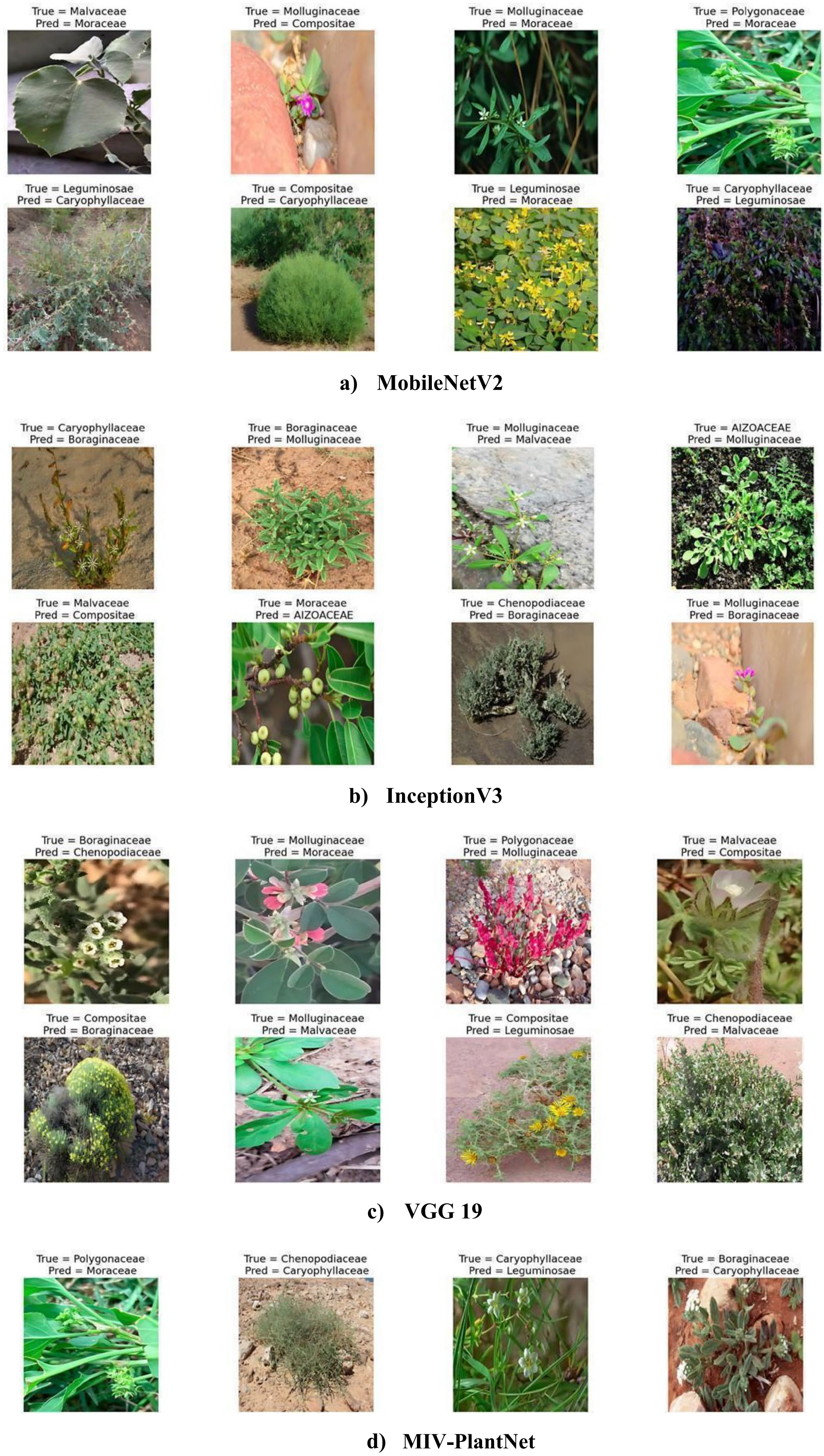


Fig. 12 Wrong predictions made by different models

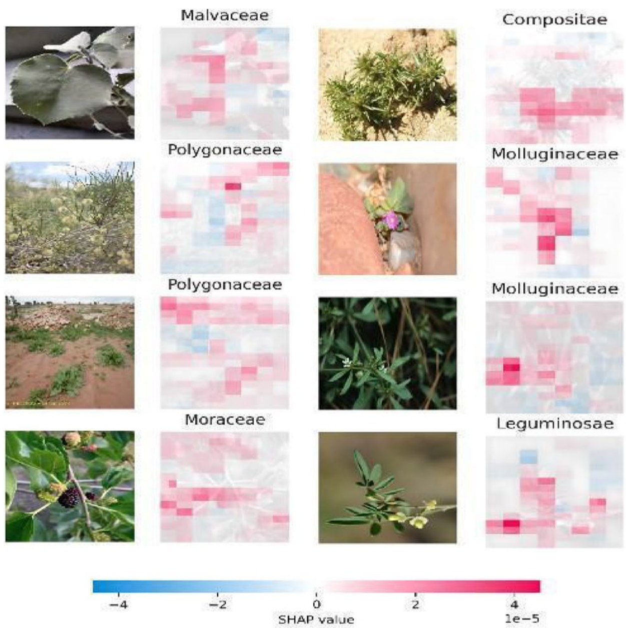


Fig. 13 SHAP explains MIV-PlantNet model's correct predictions using colored regions. Deep red or blue = high feature importance; lighter colors = lower importance

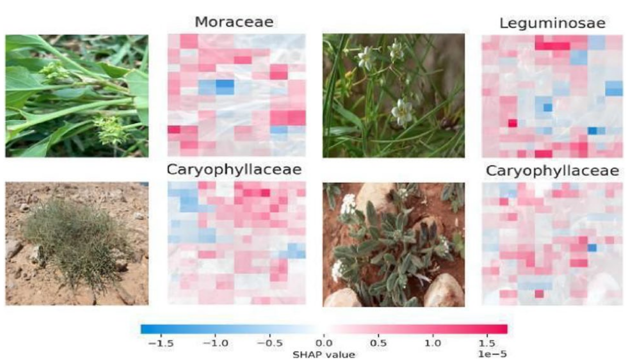


Fig. 14 SHAP explains MIV-PlantNet model's wrong predictions using colored regions, same legend as Fig. 13

and capitalized on their collective strengths, resulting in significantly improved accuracy and precision. The MIV-PlantNet model's ability to handle the challenges posed by the dataset, including variations in backgrounds, seasons, viewpoints, and zoom levels, further emphasizes its robustness and adaptability. Such versatility makes the model suitable for real-world applications where environmental factors can introduce significant variations in plant appearance. Another interesting aspect to consider is the comparison of inference times for all the tested models vs our proposed model. Table 3 presents the inference times of different models used in plant detection. Notably, Inception V3, VGG-19, and MobileNet V2 achieved inference times of 0.4295, 0.4157, and 0.4180 s, respectively. Interestingly, ensemble

Table 3 Inference time comparison for individual models and our proposed model

Model	Inference time (s)
InceptionV3	0.4295
VGG-19	0.4157
MobileNet V2	0.4180
MobileNet + Inception	0.4519
MobileNet + VGG	0.4428
MIV-PlantNet	0.4621

models, such as MobileNet + Inception, MobileNet + VGG, and MIV-PlantNet demonstrated similar inference times to their individual counterparts while yielding better results. This implies that the ensemble models offer improved accuracy without significantly increasing the inference time. Therefore, these ensemble models are valuable for real-time plant detection applications. The findings of our study reveal an interesting discovery regarding the application of data augmentation techniques in the field of plant detection using deep learning. Through extensive experimentation and analysis, we have observed that employing sophisticated data augmentation methods does not yield significant improvements in the performance of plant detection models.

This discovery challenges the prevailing belief that data augmentation universally enhances the accuracy and robustness of deep learning models across various computer vision tasks. The intricate structures, diverse species, and complex backgrounds of plant images pose challenges in generating meaningful variations through augmentation without compromising crucial features. Additionally, the natural variations in lighting conditions and occlusions commonly encountered in plant images further restrict the efficacy of augmentation techniques. Consequently, we conclude that, in the specific domain of plant detection, advanced data augmentation methods may not be imperative for achieving satisfactory performance.

Conclusion

In summary, in our research endeavor, we set out on a thorough exploration of plant detection, placing a particular spotlight on the intriguing and seldom-seen plant species flourishing in the landscapes of Saudi Arabia. What truly sets our study apart is the introduction of an innovative dataset meticulously tailored to zero in on these less-frequented plant categories, effectively bridging a substantial gap in the realm of plant classification research. This dataset encompasses diverse backgrounds, seasonal variations, and multiple viewpoints, mirroring the real-world challenges faced in the field of plant detection. This dataset has been used to study the potential of deep learning models, conducting a comprehensive analysis of plant detection using three distinct deep learning models: MobileNetV2, InceptionV3, and VGG16. Furthermore, a proposed model MIV-PlantNet based on ensemble technique was proposed, combining the predictions of all three models. The ensemble approach yielded exceptional outcomes, achieving an impressive accuracy of 99% and consistently high precision across most classes. The results obtained from extensive experimentation and evaluation demonstrate the effectiveness of these models in accurately classifying plant images across a diverse range of ten plant classes. Evaluation metrics such as accuracy, precision, recall, and F1 score were utilized to provide a thorough assessment of the model's performance. The evaluation process was conducted on a comprehensive test set consisting of 210 samples, with 20 samples per class, thereby simulating real-world scenarios and accounting for the challenges encountered in plant detection tasks. The dataset encompassed diverse backgrounds, seasonal variations, and various viewpoints, ensuring a rigorous assessment of the models' capabilities. The individual models showcased promising results, with VGG16 achieving the highest accuracy of 86%, closely followed by MobileNetV2 and InceptionV3, both attaining an accuracy of 85%. The highest performance is achieved by the proposed MIV-PlantNet model. Our findings underscore the significance of combining the strengths of proposed modeling and late fusion techniques in enhancing the accuracy and robustness of plant detection classifiers. By leveraging the diverse predictions of multiple models, the ensemble approach achieved superior overall performance. These research findings contribute valuable insights to the field of plant detection and pave the way for future advancements in leveraging ensemble techniques to augment the accuracy and reliability of plant classification systems. Considering the study findings and achievement, several perspectives can be considered for further advancements in the field of plant detection. Firstly, expanding the dataset to include the subclasses. Including the subclasses and samples would allow for a more thorough assessment of the classifier performance across a broader range of plant types and variations. Additionally, exploring more sophisticated ensemble techniques could lead to even greater improvements in classification performance. Another key perspective of this work is to address the challenges associated with wrong classifications in deep learning models for plant species. This can be achieved by carefully considering image composition during training and evaluation, including a balanced mix of zoomed-in and zoomed-out images.

In conclusion, the outcomes of this study highlight the potential of deep learning models, both individually and in combination, to achieve high accuracy in plant detection tasks. These findings have substantial implications for researchers, practitioners, and stakeholders in various domains such as agriculture, ecology, and biodiversity monitoring, where precise plant detection is pivotal for effective species understanding and management.

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Data availability The dataset is available upon request. Due to the proprietary nature of the dataset, it is subject to certain restrictions and usage agreements. Interested researchers can contact the corresponding author to obtain access to the dataset. The availability of this dataset aims to promote transparency, reproducibility, and collaboration in the field of plant detection research.

Declarations

Conflict of interest The Authors declares that there is no conflict of interest associated with this research.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

Consent to publish All individual participants consent to publish this article.

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