INDOOR PLANT CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Indoor Plant Classification Using Deep Learning Techniques" submitted by **Riajul Kahem** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 16th July, 2024.

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I hereby declare that this project has been done by us under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The plants interior spaces are used to improve the quality of indoor air and looks; however, identification of specific plant species is a complex process. This paper discusses an attempt towards categorization of indoor plants using deep learning methodologies. To compile the dataset, 3000 images of 10 different plant species were taken from local nurseries and personal gardens. Every image was marked according to the plant species mentioned above, such as Heartleaf-philodendrons, Aglaonemas, Ball-Cactus, and others. Data augmentation strategies were employed in order to expand the number of data instances and improve model robustness. The dataset was also used for training and testing a variety of deep and transfer learning models that include VGG19, EfficientNetB4, EfficientNetB6, ResNet152 and custom CNN. The results of the experiments indicated that VGG19 provided the highest accuracy which was 99. 58% which proves that it is useful for indoor plant classification. The findings of this study suggest that deep learning strategies could be effectively applied to optimize indoor plant management practices and promote higher levels of environmental responsibility. It will be beneficial to conduct future studies to identify more features and circumstances to increase the accuracy of the classification models and use them in other fields.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Indoor plants have also become an essential accessory in most homes, offices, and other living facilities to enhance the interior beauty of the environment as well as upgrading the quality of air and mental health. With the increase in the adoption of indoor gardening, there is likewise a growing need to identify specific species of plants. Correct identification is necessary for providing adequate care such as watering, sunlight exposure and pest control for the well-being and survival of the plants. Plant identification through identification books or with the help of specialists or by comparing plants with identification books also has its drawbacks – it takes a lot of time. Hence, there is a great demand for the development of automated systems for the reliable identification of indoor plants M. Fathi Kazerouni et al. [1].

Deep learning approaches have now emerged as a way of solving the image classification problem through the development of highly accurate models that can be trained to recognize a vast category of objects including plant species. Specifically, Convolutional Neural Networks have shown impressive results for identifying complex patterns regarding features in images, which is quite useful in plant identification. With the help of these methods, it is possible to create a solid data model for indoor plant classification which will be helpful for beginner and advanced gardeners which will help them identify their plants correctly Liu, Yu, et al. [2].

In-depth classification of the type of plants appropriate for an indoor environment is the key interest in this line of research. The methodology encompasses several critical steps: data gathering, enhancement of the images, data annotation, choosing the right model, training the obtained model, model assessment, and validation. The data collection process focuses on collecting a wide range of images from local nurseries and other personal gardens to obtain a representative dataset. Usually, image augmentation is applied to increase the size of the dataset artificially and enforce new data variety to improve the model’s performance. Every image is carefully marked with the species of the plant they contain and it makes up the ground for supervised learning. There are four architectures of deep learning that are considered more effective in the present study: VGG19, EfficientNetB4, EfficientNetB6, ResNet152. To take advantage of these more sophisticated models Transfer Learning is used where models pre-trained on large datasets are fine-tuned on the indoor plant dataset. This training process optimizes the hyperparameters and prevent overfitting through the employment of various techniques in machine learning. The efficiency of the model is checked using a validation set and the generality of model is tested by a test set A. Ojha and V. Kumar et al. [3].

This classification of indoor plants is developed based on an observed need for the determination of an organized roadmap that can be effectively used by both amateur growers as well as plant specialists to determine the right type of plant for an indoor setting and how to properly attend to the plant species. This study can improve the effectiveness of plant classification by adopting deep learning methods based on this system, leading to improved plant management and practices.

1.2 Motivation

The idea of creating the indoor plant classification system by employing deep learning methods derives from the rising trend of indoor gardening and the importance of a reliable plant identification. Homing plants are used not only as ornaments, but they also enhance the quality of inhale air, and improve psychological states of individuals. But such care on these plants needs proper identification of the particular plant and this is a hard thing for so many people. Currently, identification methods take a lot of time, and the results are far from the actual picture, mostly relying on knowledge from experience. With the improvement of deep learning especially in image classification, there is the opportunity to develop a solid and effective solution for helping plant lovers and specialists. This system is designed to minimize the identification process due to delivery of proper care to the plant, thereby achieving healthier living space and enhanced experience in plant’s growth.

1.3 Rational of the study

The justification for this study revolves around the difficulties experienced in the identification of indoor plants, which is essential in their management. Identification is critical so that plants are watered, placed in the right location regarding light requirement, and controlled for pests that can harm the plants. Documentary identification methods tend to be slow and inaccurate for most people who do not have the background knowledge of botany. As one of the concerned targets of this work, the efficiency and robustness of the chosen deep learning techniques will help this study design an effective method for the classification of indoor plants. With the help of this system, even those who have little experience in gardening or even the professionals could easily identify the plants and give them the right care they need. Also, the progress made with image classification, applied in deep learning allow for the development of high variability and complexity models of plant species. In conclusion, this research aims at improving indoor plant care, making successful gardening practices possible and improving the knowledge about plant species through technology.

1.4 Research Questions

1. To what extent can the generated deep learning models help in the classification of various species of the indoor plants?

2. How does the use of data augmentation affect the performance of plant classification models?

3. In this case, which architecture of deep learning, VGG19, EfficientNetB4, EfficientNetB6, or ResNet152, is the most suitable for indoor plant classification?

4. What strategies can be adopted in transfer learning to enhance plant classification models' accuracy?

5. How might I adjust my code to ensure that a deep learning model is trained on an indoor plant dataset to its fullest potential?

6. To what extent are the trained models capable of discerning proper associations with new images of indoor plants?

7. What are the features used by deep learning models to distinguish the various species of indoor plants?

1.5 Expected Output

The expected output of this study is to yield a correct, accurate as well as efficient indoor plant classification model that is based on deep learning. It will be possible to accurately recognize 10 types of indoor plants using the specified models, including VGG19, EfficientNetB4, EfficientNetB6, ResNet152. Further, it will also give information regarding how various deep learning architectures work and how data augmentation affects the model. It also assumes the final model to perform well on unseen images meaning that it shall perform well in the real world. In this way, the implemented system of plant species recognition will help to approach the correct care for plants at the level of an amateur gardener and an experienced horticulturist. It is designed to advance the current status of indoor gardening, improve the overall health of plants and illustrate the use of state-of-the-art image classification methods in daily life.

1.6 Project Management and Finance

There goes the realization that without efficient management of the project and sustainable and efficient financial planning, the given study cannot be implemented. The project will be managed in phases: data gather and clean, select model, train, test, and finally use the model. Every phase will have defined deliverables and working checklists, which will help guide the manner in which the work will be accomplished. The team would consist of data scientists, software engineers and domain specialists in botany and there would be communication meetings scheduled frequently to report and discuss on the encountered issues. For financial implications, the project will entail the cost of data collection, computer processing and analysis tools. Budgeting will determine where to get high-quality images for the models, cloud facilities for training models, and software costs. Some extra money will be needed in the event of hiring consultants or experts on the project and for such purposes like publication and dissemination of the findings. Resource budget management and priorities shall also be put into place so as to uphold the expenses of the project without compromising the goals it is set to meet.

Table 1.6: Estimated Cost

Components	Estimated Cost (BDT)
Hardware	1000-1500
Software and Tools	1500-1500
Data Collection and Processing	5000-6000
Documentation and Report Writing	500-1500
Miscellaneous	500-1500
Contingency	500-1500
Total Estimated Cost	9000-13,500

1.7 Report layout

The following report explains the usage of deep learning methods for the classification of indoor plants. Each of them is divided into several sections and all of them are devoted to the analysis of different aspects of the study.

Chapter 1: Introduction.

This chapter defines the purpose of the study by describing the importance of classifying indoor plants while also identifying the rationale for engaging deep learning approaches.

Chapter 2: Background.

In this section, the context on the general Information on indoor gardening, different classification method for plants and the earlier form of deep learning called as Image classification.

Chapter 3: Research Methodology

This chapter describes how data has been collected, preprocessed, and analyzed to identify the model, how the training process has been done and how the results have been evaluated for the roadmap of the study.

Chapter 4: Experimental Results

As a part of the experiments, specific results typical for the deep learning models alongside comparison between the architectures are presented in this chapter.

Chapter 5: The Impact on Society

There are several implications of accurate classification of indoor plants for the society as discussed below with reference its benefits from indoor plant enthusiasts and professionals.

Chapter Six: Summary, Conclusion, Recommendations, and Implications for Future Research

This is the final chapter of the book where the author captures and discusses the major findings, presents conclusions, indicates the potential real-life application of the results obtained and points out the possible further developments of the field.

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

This report begins by developing the preliminary knowledge about the context of the research including the definitions and concepts used in classifying indoor plants and applying deep learning. This section briefly explains the existing methods of indoor gardening, the importance of plant identification and the concept of deep learning, CNN and transfer learning. Getting acquainted with these ideas will help readers understand the motivation for the proposed research, the way it was carried out and what could be the potential impact of the methods for classifying indoor plants based on the deployed deep learning approaches discussed in the further chapters. Furthermore, the brief description of the format of the report is presented in order to assist the audience in finding their way through further sections and parts of the work easily.

2.2 Related Works

The literature review aims at reviewing research done on classification of indoor plants with emphasis on the methods used which include deep learning. Previous research has examined several forms of classifying plants such as using conventional machine learning techniques and the image analysis techniques. Although these methods were quite useful in the past, new developments in deep learning have attracted significant attention to plant identification as a powerful technique. Prior studies have explored the usage of deep learning structures like CNNs as well as transfer learning for plant categorizations. This literature review will provide a synthesis of various works on indoor plant classification with the view of establishing areas that need further investigation with the help of deep learning approaches.

As given below, I am writing a similar paper review, which will help me more:

M. Fathi Kazerouni, et al. [1] presented a Convolutional neural network (CNN) that is capable of identifying four different species of plants in un-moderated outdoor environments. With an astounding 99.5% accuracy rate of the plant recognition, it highlights the capability of deep learning to revolutionize the future. The CNN is especially efficient and has the potential to expand the recognition sphere to a range of outside conditions, for example, farms and forests. In addition, the developed system is real-time, which makes it possible to apply immediately in plant identification tasks.

Liu, Yu, et al. [2] discussed early identification of anomalies in vertical plant wall systems through machine learning for indoor climate maintenance enhancing results. In cases of points and contexts, pattern recognition as well as the prediction approach are employed. The specific models of the analyzed neural network, autoencoders and LSTM-ED showed a better ability to identify the corresponding ones, which could mean that they could be used in industrial conditions. The practical implementation of the prediction-based methods is shown in cloud architectures, and a new data cleaning technique is proposed. In general, the study provides focus on possibilities of using machine learning and IoT to advance building environment research solutions.

A. Ojha and V. Kumar et al. [3] employed the machine learning approach to tackle the issue of identifying ornamental plants from their leaves. For analysis, the dataset containing 5608 RGB images of leaves belonging to 25 classes was obtained. For classification, various techniques of machine classifiers MLP, LR, NB, SVM, DT and KNN were applied. The comparison study unveiled that MLP excelled other algorithms regarding the maximum achievable accuracies, which was 93%. 90%. Confusion matrix also provided an overall and detailed picture of MLP's performance from one class to another.

Munirah Hayati Hamidon et al. [4] introduced a one-stage object detector-based automated method to detect a tip-burn lettuce utilizing a deep-learning algorithm. As samples of LED light sources, this study used white, red and blue LED lights; for the range of indoor background conditions and lighting. After the image augmentation process, three separate one-stage detectors, namely CenterNet, YOLO v4, and YOLO v5, were exposed to 2333 images. All the models' per-image mean average precision (mAP) were above 80%, save for YOLOv4. Nevertheless, concerning the detection of tip-burns, YOLOv5 gained the highest mAP score of 82. 8%. Our experiments showed that an indoor farm light environment affects the algorithms and thus proved that YOLOv5 performs better than CenterNet and YOLOv4. Thus, the employment of deep-learning algorithms facilitates the early detection of tip-burn on lettuce irrespective of the lighting conditions so as to enhance the growth of the indoor plants.

D. Radočaj, I. Rapčan, et al. [5] compared and analyzed how RF and XGB approaches perform when estimating SPAD values in the indoor plant leaves against the DNN models. It employs multispectral and soil electro-conductivity sensors which are relatively cheaper and used nondestructively. When RVA is applied to the multicollinearity data set, DNN takes better performance in comparison with RF and XGB from the view point of R square, RMSE and MAE. Specifically, for external validation, DNN achieved R2 of 0. 589, RMSE of 11. 68, and an MAE of 9.52 with filtered data and 0.826 with all input covariates Regarding the R-squared, STAT-IN produced R2 of 0. 476, RMSE of 12. 88 and MAE was 9. 94. Even with such differences, DNN results offer better performances compared to the traditional machine learning algorithm when it comes to estimating SPAD values in indoor plants.

M. H. Hamidon et al. [6] Utilizing deep learning algorithms, this study aimed to design an intelligent system capable of identifying defective lettuce seedlings in indoor environments. Popular pictures of seedlings captured in diverse and different lighting indoors such as white, blue, and red-light illuminations were analyzed using the fast R-CNN algorithms which include CenterNet and YOLOv5 and YOLOv7. Hence, when it was a question of deciding whether out of the seedlings grown, some were defective or not, YOLOv7 was the most accurate of all, achieving the highest mAP of 97. 2%. In addition to this, there was seamless output of improved detection rates by YOLOv7 across different types of lightning.

Dyrmann, Mads, et al. [7] proposed a pioneering approach to achieve a plant species identification system based on color image using CNN. The deep learning model is trained and tested on a large dataset of 10,413 photos which consist of 22 weed and crop species taken in their young stage. These photos were sourced from six sets of images: Range of conditions sets include pictures taken in controlled planter boxes and directly from a mobile phone on field, with variations in lighting, resolution, and types of soil. Achieving an 86.2% classification accuracy in its training phase, the DNN became a potent tool for B2M classification in total for all those 22 species, so it proves how efficient CNN can be when it comes to plant recognition from photographs.

B. G. Martini et al. [8] describe Indoor Plant, a computational model for indoor agriculture that has as its purpose to offer smart services according to context understanding. We have evaluated Indoor Plant in three different settings enabled by the seven months of data recorded from hydroponic plant cultivation. The results demonstrate the ability of the Indoor Plant system to predict workload as well as identify and propose solutions for issues with the cultivation process. Consequently, Indoor Plant was capable of assessing cultivation times of radicchio, lettuce, and arugula with low RMSEC as well as RMSECV scores and high R2 values by employing partial least squares regression. Additionally, a questionnaire using Technology Acceptance Model to assess user satisfaction in the case of Indoor Plant reveals a very high level of satisfaction because farmers approved the product 92% for relevance or usefulness and 98% for ease of use.

V. Durairajah, S. Gobee et al. [9] proposed an automatic vision system for classification which employs SVM and DNN classifiers in recognizing the Malaysian herbs. During training, the system achieved overall accurate recognition as per SVM and DNN of 86.63%, while, in the real-world testing, it was only 74.98% and 93%. The result demonstrated good recognition, even in wet, dried or deformed leaves, making the system accuracy at 52.50% with a dataset of 1000 leaves in the training and testing sets. When it came to the efficiency and the recognition rate, it was clearly seen that the suggested system provided nearly 98% more recognition than any other similar system currently in use. Aravind, Krishnaswamy Rangarajan, et al. [10] applied and evaluated the suitability of the SqueezeNet framework for disease prediction using the PlantVillage dataset to illuminate its prospects in the domain. Moreover, the paper shows the detailed description of the deep learning architecture and describes elements that are critical to the understanding of the discussed subject. In this experiment, original color images have been used with SqueezeNet that gave a remarkably high classification accuracy of 98. 49%. It considers conditions concerning feature learning and is a discussion about misclassification in certain classes. Finally, suggestions for future investigations are given for enhancing the real-time diagnosis classification systems.

Oishi, Yu, et al. [11] presented an automatic system that employs deep learning models and a handheld video camera to recognize atypical potato plants. Thus making a clear distinction between Montana potato leaves, which are strange to some extent, some parts which are strange as compared to the other plants or an abnormally developing plant at any stage. Thus, the average precision derived for this case is about 78. 2% accuracy for detection and about 90% in classifying the unhealthy and healthy potato plants which is sufficiently effective.

Shoaib, Muhammad, et al. [12] utilized the InceptionNet model which is a deep convolutional neural network for classifying the diseases in the tomato plant from the plant leaves image data. The overall performance achieved through this method for disease detection and segmentation is high and higher than that of the U-net and Modified U-net of 99%. 0% for model validation while the accuracy was 98. 12% for six-level classification.

In their study, M. O. Ojo et al. [13] systematically collected and evaluated the presence and performance of deep learning approaches in CEA structures, with special emphasis on greenhouses. This study identified that CNNs reign supreme as the model of choice for CEA production and the Adam optimizer reigns supreme when it comes to optimizers of choice. The review also looked at standard DL models, where it measures performance, and evaluators and optimizers.

A. Musa, M. Hassan, et al. [14] proposed an innovative approach to plant disease diagnosis that increases efficiency with more accuracy while consuming low power. This approach means that they cut at least 50 parameters, and all of which is accomplished by utilizing distillation techniques to derive information from a deep model to a shallow neural network. This reduction goes a long way in eliminating power usage and the overall number crunching that will be needed with hardware.

Huang, Cheng-Cheng et al. [15] also designed an elaborate cultivation and management environment for interior tea seedlings through artificial intelligence of things (A-IoT). They also include recognition of characteristics and diseases of tea trees such as brown blight, white scab diseases and algal spot disease, this is done with the help of image processing algorithm and deep learning technique. It is an advanced precautionary notification that provides timely information on infections and a real-time data acquisition system utilizing a mobile app interface to cut down on infections, increase efficiency and yield key data valuable to the producers of tea factories in setting up smart plant factories.

2.3 Comparative Analysis and Summary

The comparison showed that accuracy rates of different deep learning models were dissimilar with regard to classification of indoor plants. From the results, it was revealed that VGG19 has the highest accuracy of 99.58% while other models EfficientNetB4 and EfficientNetB6 have achieved the accuracies of 53.17% and 64.33%, respectively. From the tables above, it is also possible to see that ResNet152 performed relatively well with an accuracy of 89.83% and a custom CNN accomplished the accuracy of 98%. Altogether, it can be stated that the implementation of the VGG19 served as the key to achieving the most favorable results in terms of identifying the species of Indoor plants. This summary underscores the choice of proper deep learning architectures for plant classification and emphasizes the prospective of the deep learning solutions for the improvement of the indoor plant management and the further enhancement of the environmental protocols.

Table 2.3. Comparative analysis with previous work

References	Algorithms	Best Accuracy
M. Fathi Kazerouni, et al. [1]	CNN	99.5%
A. Ojha and V. Kumar [3]	Machine Learning Model	MLP=93.30%
Munirah Hayati Hamidon et al.,[4]	Deep Learning Model	82.8%
Dyrmann, Mads, et al. [7]	CNN	86.2%
B. G. Martini et al.,[8]	CNN	98%
V. Durairajah, S. Gobee et al. [9]	SVM, DNN	DNN= 98%
Proposed Model	CNN & Transfer Learning Model	VGG19= 99.58%

2.4 Scope of the Problem

The problem area lies in the identification of indoor plant species using deep learning methods in order to classify the species correctly. This means solving issues like variation in the appearance of plants, many folds in the leaves of the foliage, and several variations of lighting conditions encountered in the natural environment. This research aims at designing a proper classification model that is able to distinguish a vast array of kinds of indoor plants efficiently. The cost-efficient approach is to explore how to integrate the available deep learning architectures, data augmentation techniques, and transfer learning methods that can improve the model's performance. Moreover, the possibility of the applicability of the given classification system is discussed in regard to indoor gardening, horticulture, and botanical sciences. In managing these challenges and arriving at the ideal solution, the study should be beneficial to indoor plant care practices and distinguishing indoor plant species.

2.5 Challenges

Some of the issues in categorizing indoor plants by the proposed deep learning approaches include the differences in the appearance of plants that belong to different species but share many attributes. Further, the structures of the indoor plants are very elaborative with great distinction in the textures of the leaves, which hampers the process of feature extraction. Big differences in color/sample lighting like natural daylight and fluorescent light also pose a huge challenge during classification. Another challenge is that data for indoor plant species are scarce, and acquiring data labeled as such is even more challenging, making this procedure a laborious one that needs to be repeated due to limited data availability. Moreover, it is also likely that deep learning models can be overfitted just because of the fact, the dataset is not so big. The over-parametrization of models often leads to solving an easier problem instead of the given one and increases computational cost. To solve the above challenges, new strategies for data acquisition, utilizing sophisticated methods of data preprocessing, model selection with focusing on the training methodology, and the consideration of the real-life utilization of the classification system are introduced.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The focus of this research lies in the application of deep learning for the classification of indoor plants. The concept of the study is composed of the establishment of an effective and efficient classification system that would be used in the identification of numerous species of indoor plants. To this end, some of the most advanced deep learning frameworks namely; VGG19, EfficientNetB4, EfficientNetB6, ResNet152 are employed. Standard techniques of data augmentation are used with the objective of rotation, flipping, zooming and brightness of the images are some of the common techniques used to make the variety and resilience in the images used. The process of transfer learning is used to utilize the existing models and adjust their parameters on the indoor plant dataset. The accuracy, precision, recall, and F1-score are used to measures the degree of success of the classification system. Numbers are produced employing a range of experiments on a validation set and an independent test set in order to determine the model's effectiveness in unseen cases. The topic of the research area seeks to make a positive impact on the development of optimum practices regarding indoor plants and also enhance the application of deep learning strategies in horticulture and botany field.

3.2 Data Collection Procedure

The dataset for indoor plant classification was collected methodically based on data acquisition process while maintaining data integrity. First, they had photographs of plants from a local nursery and a personal garden, which allowed for the representation of a broad assortment of indoor plants. Digital photographs were taken to capture eating visual features of each plant to make proper identification and classification.

Following the capture of raw imagery, augmentation procedures were used to expand the set of data and enhance the model's ability to generalize. This included simple image transformations such as random rotation, flipping, zooming as well as the image brightness values. The increased dataset consists of 3000 pictures, while there are images of 10 main attributes – each of them has 300 pictures. The target attributes and their values are Heartleaf Philodendron, Aglaonema, Yellow Kewda Plants, Ball Cactus, Yellow Corn, N-Joy Pothos, Butterfly Lily Plants, Rhaphidophora, ZZ Plant and Pink Prayer Plants containing 300 images in each target attribute. The set of images was obtained as the result of accurate collection and enlargement of the dataset required for the training and testing of the indoor plant classification. In given below there are some images of datasets in Figure 3.1:

Figure 3.1: Dataset Images

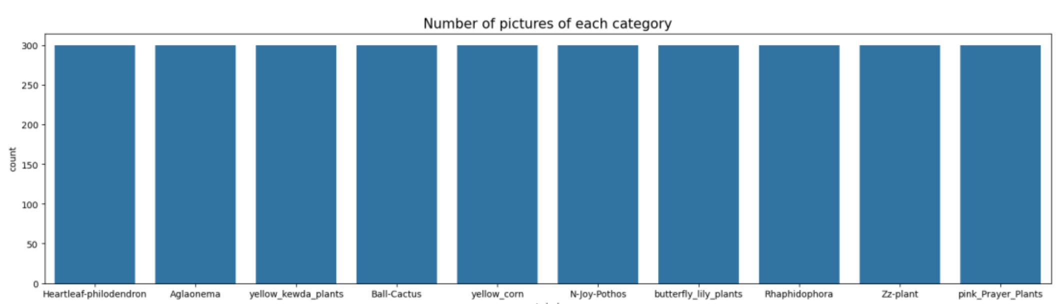

Figure 3.2: Number of categories of Dataset's Images

In Figure 3.3 shown the specified attributes and their values are as follows: the Heartleaf

Philodendron, Aglaonema, Yellow Kewda Plants, Ball Cactus, Yellow Corn, N-Joy Pothos, Butterfly Lily Plants, Rhaphidophora, ZZ Plant, and Pink Prayer Plants; each has 300 images.

3.3 Statistical Analysis

The preprocessing of the indoor plant classification dataset includes Exploratory Data Analysis using descriptive statistics to understand the distribution and nature of samples. Mean, median, standard deviation and range are calculated on the quantitative attributes like size of the image and intensity of the pixel. Moreover, class distribution analysis shows the detail information regarding the equality or inequality of the distribution of plant species in the dataset. These may involve we correlation analysis in order to find out the relationship between the features of the images obtained and the plant species. In addition, in order to make decisions regarding the significance of observed differences or trends, inferential statistics for hypothesis testing or confidence interval estimation can be performed. The statistical description provides the key knowledge on the characteristics of the dataset, which is useful in the decisions of the preprocessing the data and in the building and assessing the proposed indoor plant classification model.

3.4 Proposed Methodology

The working methodology contains a step-by-step approach to the classification of indoor plants with the help of deep learning. This indeed forms a broad research approach that consists of several significant stages such as data accumulation, model validation, and assessment. Every step is taken deliberately in order to achieve the synergy of the correct and rigid classification of indoor plants. Thus, the proposed methodology is targeting the variability of plant appearance, scarcity of labeled data, and generalization of the model. The detailed method used in the paper involves data augmentation, transfer learning, and proper validation of the model in order to yield the best results. By following a systematic process, we seek to contribute our findings to the body of knowledge regarding the classification of indoor plants and give useful recommendations for those interested in indoor gardening. Steps in the Proposed Methodology:

Data Collection:

The data collection process involves identifying and selecting images of indoor plants from various sources which include local gardens, own galleries, and online databases. Pictures are taken with digital cameras or a smartphone with a good camera when there is sufficient variation in the types of plants, the lighting conditions, and the positions.

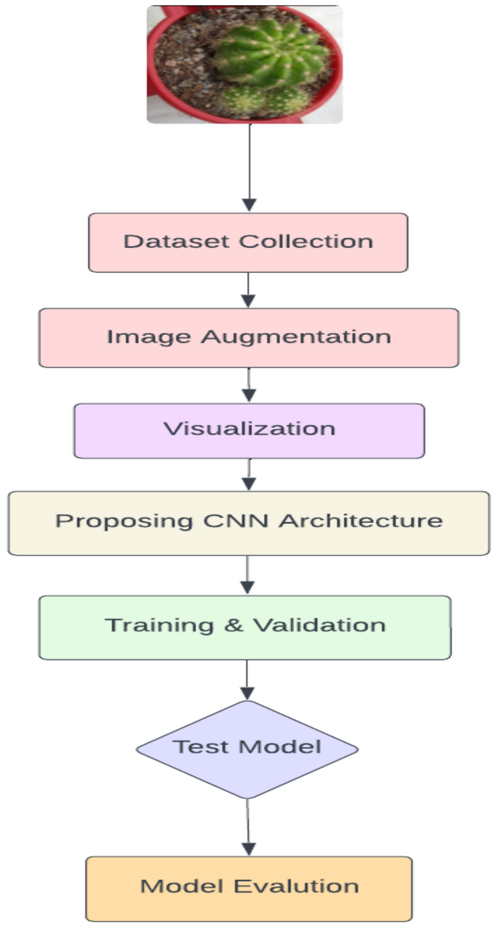

Figure 3.3: Work Flow

Image Augmentation:

Data augmentation strategies are used to expand the variety and correctness of the dataset. These include, rotation, flipping, zooming, brightness, among others which are associated with transformations on the images. Augmentation comes in handy when trying to train for real-world variations and to avoid cases of overfitting.

Labeling:

All the images in the dataset are carefully annotated regarding the identified plant variety or species. In supervised labeling, the classes are well defined and labeling is done to ensure that during the model training process the model is able to relate images with their different classes.

Model Selection:

The work compares several deep learning architectures like VGG19, EfficientNetB4, ResNet152, and select the best model for the indoor plant classification.

Conventional Neural Network (CNNs):

CNN is one of the categories of deep learning models that increases in the sophistication of modeling for image recognition and classifications. They are very efficient in automatically and dynamically learning the hierarchy of features in the input images, which makes them effective tools for the analysis of the nature of visual data. Hence, this thesis employs CNNs in the classifications of indoor plants because of their effectiveness in capturing and distinguishing subtle features such as shapes, textures, and color patterns on the leaves of the plants. CNNs enable the establishment of a causative and effective plant identification system that can analyze different and unpredictable picture data. Hence, by applying the work of CNN, it is also possible to increase the indicators of accuracy and reliability in indoor plant identification, which will positively impact indoor gardening and environmental sustainability.

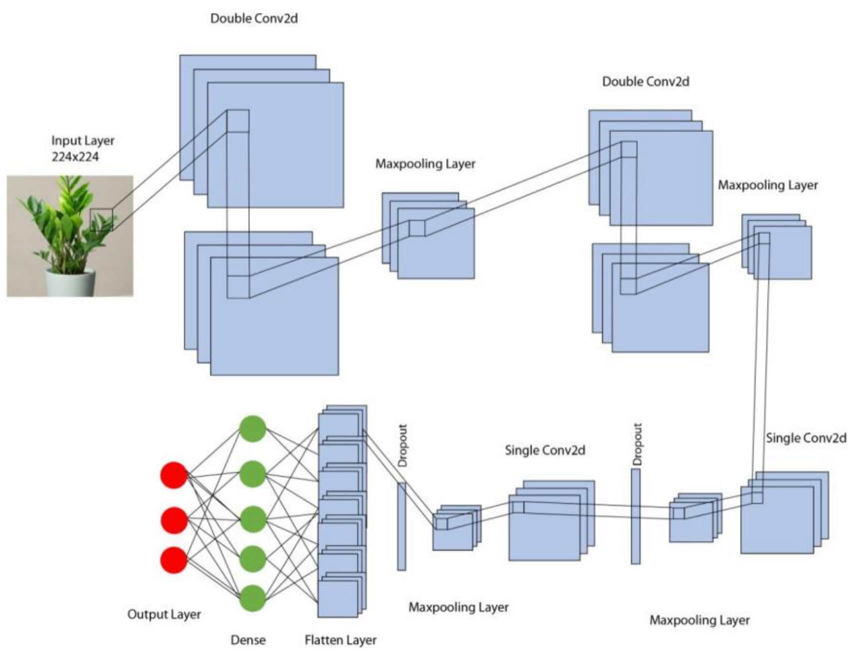

Figure 3.4: Proposed CNN Architecture.

VGG19

VGG19 is a convolutional neural network architecture that is infamous for its simplicity and high performance always seen in it when it comes to image classification. It contains 19 different layers, such as convolutional and fully connected where the former enables the identification of multiple features from the input images. More specifically, VGG19 is of particular relevance in this thesis since it was established that it exhibits high functionality in categorizing different visual datasets. It has a deep structure that allows features required to separate similar kinds of close indoor plant species to be extracted. An efficiency of 99% is accomplished by VGG19 with an accuracy of higher order. This percentage reckoned in this study establishes its efficiency in dealing with the complex changes of the plant images; therefore, highly valued in the system of classifying the indoor plants. Thus, using VGG19, this research has the purpose of providing reliable identification results for plants to improve the quality of indoor gardening and promote sustainability.

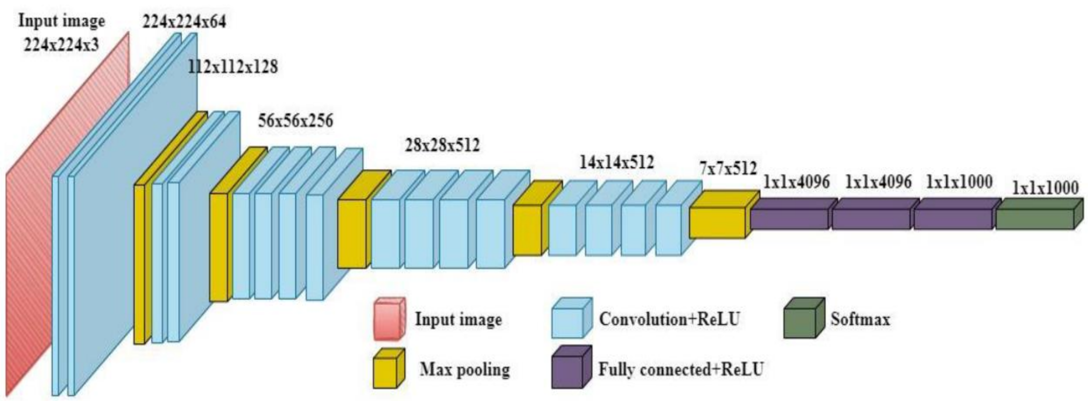

Figure 3.5: VGG19 Architecture T.-H. Nguyen 2022 [27]

EfficientNetB4

EfficientNetB4 is one of the most advanced deep learning architectures used to solve image classification tasks that accurately reduces the computational complexity via the sparse convolution method by uniformly scaling depth, width, and resolution. Especially when it comes to the EfficientNetB4 architecture which is important in this thesis since it offers a high performance while at the same time having comparatively fewer parameters and requiring less computational resources. In this study were obtained Through optimizing architecture design, EfficientNetB4 is useful in situations where resource constraints are a major concern while targeting high efficiency. Since the outlier points by definition are not representative of the dataset distribution, the architecture is particularly effective for constructing scalable and efficient indoor plant classification systems that can be implemented on devices with limited computational capabilities. While leveraging EfficientNetB4, this work aims to pave the way for the development of more efficient and cost-effective approaches for indoors plants identification that can in turn enhance the practical usage and availability of indoor plant and environmental care resources in such areas as gardening and sustainability.

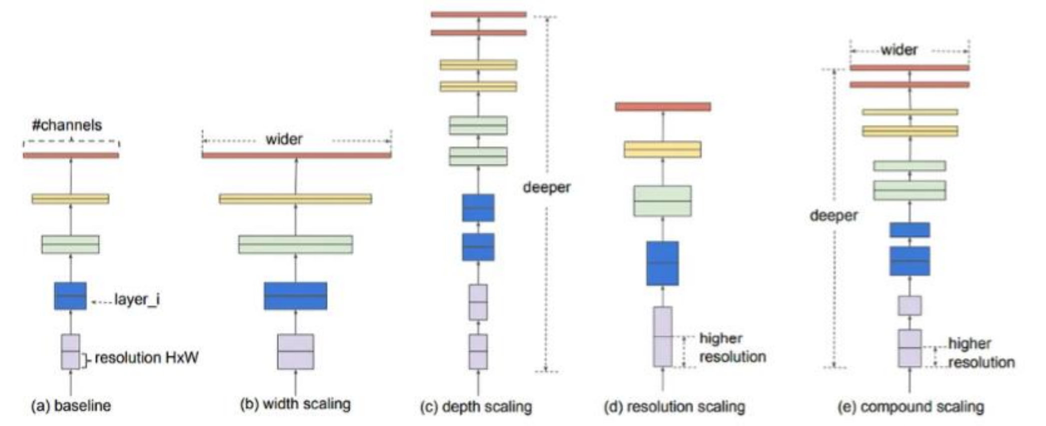

Figure 3.6: EfficientNetB4 Architecture V. Agarwal, 2020 [28]

EfficientNetB6

EfficientNetB6 is an advanced deep learning model that extends the EfficientNet architecture by further scaling its depth, width, and resolution, enabling it to capture more complex features from high-resolution images. In this thesis, EfficientNetB6 is significant due to its potential for achieving high accuracy with efficient use of computational resources. Although it achieved an accuracy of 64.33%, its sophisticated scaling approach ensures that it can handle detailed and varied indoor plant images more effectively than simpler models. EfficientNetB6's ability to balance performance and efficiency makes it an important consideration for developing robust indoor plant classification systems. By leveraging EfficientNetB6, this research aims to explore the upper bounds of model accuracy while maintaining computational feasibility, contributing to the development of advanced, scalable solutions for accurate indoor plant identification and enhancing indoor gardening practices.

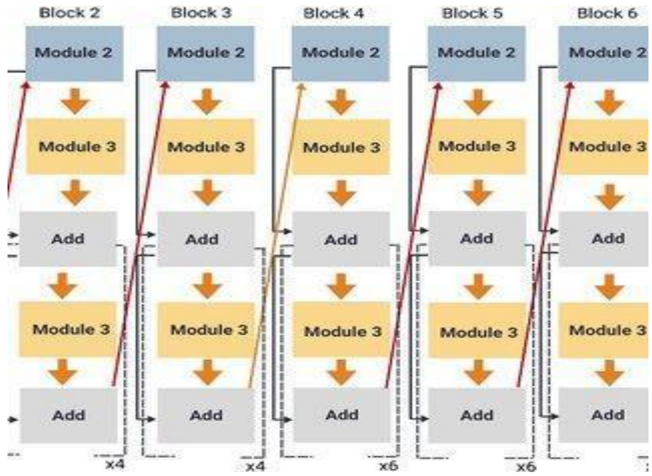

Figure 3.7: EfficientNetB6 Architecture Anis-Ul-Islam Rafid 2023 [29]

ResNet152

ResNet152 is the depth architecture of convolutional neural networks to train very deep networks without facing the problems of vanishing gradient mainly due to the residual connections. ResNet152 is relevant in this thesis because of its success in undertaking intricate objective image recognition tasks with an accuracy of 89.70% for outdoor plant classification. Thus, its depth and ability to continue learning from residuals allow it to better capture fine details of plants and variations between similar types of plants. Thus, by applying ResNet152 in this work, it is expected to increase the stability and efficiency of the devised plant classification system and ensure the correct identification of plants in challenging conditions. The presence of ResNet152 shows the ability of a deep learning approach to transforming standards of indoor plant management and assist in developments of horticulture and environmentalism.

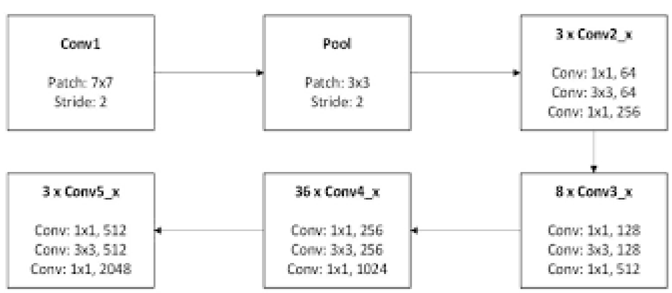

Figure 3.8: ResNet152 Architecture L. A. Leonidas 2021 [30]

Model Training:

In the following stage, the selected model is trained on the labeled dataset using techniques related to transfer learning. The downloaded models are retrained on the indoor plant data set to capitalize on learned attributes and provide early convergence. It achieves high training efficiency and model performance; hyperparameters are constantly tweaked to improve these metrics.

Model Evaluation:

After the training of the model is done the model is tested on a validation set where some performance metrics like accuracy, precision, recall, and F1-score are computed. This evaluation stage plays an important role in the fine-tuning process of the model and to determine what aspects must be worked upon.

Test Model:

And lastly, the trained model is tested on an independent test set in order to evaluate its ability to generalize. This step helps guarantee that the model handles practical use efficiently and furnishes accurate predictions for various indoor plant classification challenges.

3.5 Implementation Requirements

The successful implementation of the proposed methodology for indoor plant classification using deep learning techniques requires several key resources and tools: Computing resources: GPUs or TPUs are required for fine-tuning and inference of such models High-performance computing resources, including GPUs or TPUs, are crucial for efficient model training and inference. ML libraries based on deep learning architectures such as TensorFlow or PyTorch are required to construct, train, and assess the classification models. Furthermore, other mathematical and data processing libraries, such as OpenCV for basic image processing, can be employed for data preprocessing. It is also important to have a diverse and well-labeled dataset with images of indoor plants with no overlapping of subjects for training and testing. The dataset should feature diverse plants and the different aspects of variations in lighting conditions. In some cases, there is a need to increase the competency of the data set, which has been made possible by the presence of image augmentation libraries like Keras, Image Data Generator or Augmentations. Google

Colab and other text processing tools are used to report implementation process, progress, and results in order to provide effective communication of the project outcomes.

CHAPTER 4
EXPERIMENTAL RESULT

4.1 Experimental Setup

The experimental setup for indoor plant classification involves configuring the deep learning environment, preparing the dataset, and defining the training and evaluation procedures. A workstation equipped with high-performance GPUs is utilized for model training. The dataset, consisting of labeled images of indoor plants, is divided into training, validation, and test sets. The images in the dataset are then divided into 80% and 20% training and test sets, respectively while maintaining the set distribution across the ten plant images. Data augmentation strategies are employed to the training images so as to promote model's resistance. Random data generators for training, validation, and testing are established with the purpose of providing efficient procedures of batching. The training data is augmented and used to train the model, and a separate validation set is used to check the model performances.

After training, the performance and the generalization ability of the model are test using the unseen test data set. This procedure helps to build a more relevant properly tuned model that could work in practice when making prediction. The approach of data augmentation is used to enrich the dataset. The selected deep learning architecture like VGG19 or ResNet152 is developed in TensorFlow or PyTorch, respectively. Transfer learning is applied here where the models are first trained on the indoor plant dataset. A process of model training is performed within the training set, and model performance is then tested on the validation set. Last but not, the least is the evaluation of the generalization ability of the trained model on the unseen test data to confirm its use in real life situations.

4.2 Experimental Results & Analysis

Specifically, various deep learning and transfer learning models were trained and tested to classify the indoor plant types using a validation dataset and the results were then compared with the model accuracy. In regard to the model assessment, the proposed VGG19 model topped the scores with an accuracy of 99. 58% proving the efficient feedback as a means of classifying the species of the indoor plants. Thus, EfficientNetB4 and EfficientNetB6 had accuracies of 53.17% and 64.33%. combined, they had moderate performance assessing respectively. It can be seen from the results that ResNet152 achieved high accuracy of 89. 83% which normally demonstrates the effectiveness of the random forest in solving of complex classification problems. The custom CNN was found to achieve an overall accuracy of 98% thus can be said to be competitive. These findings underpin the need for specifying an accurate deep learning structure for the classification of indoor plants based on the learning performance, where VGG19 turned out to be the best model in this research. Additional assessments of misclassified samples and the stability of created models could be made for future modifications and uses. In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Result of Experiment 1: CNN

The CNN architecture for the indoor plant classification is shared and has several convolutional and pooling layers and dense layers. It starts with two convolution layers (32 filters each), one pooling layer, two convolution layers (64 filters each), and another pooling layer. This pattern is maintained with 128 filters proceeding to the next convolutional layers with intermediate dropout layers for combating overfitting. The model following the last max pooling layer includes the flatten layer and then a dense layer with 512 neurons and a dense layer of 10 neurons being the output layer for classification. The model has a whopping number of trainable parameters amounting to 8,222,506 which means that this model can effectively capture high level features of images of indoor plants.

Achieving Test Accuracy of CNN is 98.00%. In below Figure 4:1 describing the confusion matrix of CNN. Figure 4.1 shows the custom CNN model utilization resulted in improved performance on all classes and an overall accuracy of 98%. All the plant species including Aglaonema, Rhaphidophora, and pink- Prayer Plant identified perfect precision, recall and F1 scores. Zz-plant and Heartleaf-philodendron had minor misclassification with comparatively lower recall values. On the whole, the model exhibited a satisfactory or even adequate distinction of different indoor plant species.

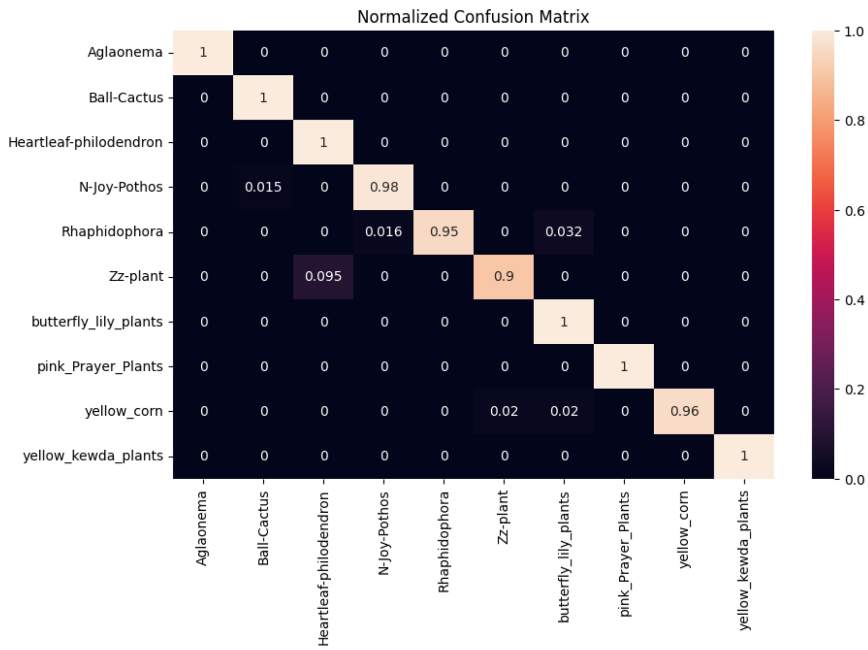

Figure 4.1: Confusion Matrix (CNN)

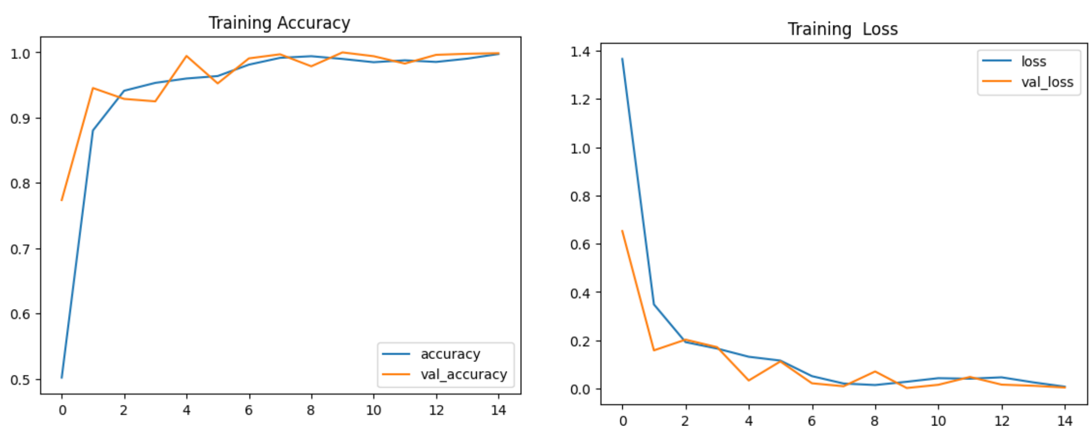

Figure 4.2: Training and validation accuracy and loss over the epochs (CNN)

Figure 4.2 shows the test accuracy of the CNN model is defined as 0 during the beginning of the training. 5 and is close to 1 respectively. 0 by epoch 14 with a training loss drops from 1. 2 to nearly 0. D, which implies that the model’s learning rate from the training data was effective at zero. The validity rises from 0 to 1 as we can see in the following table listing down the validation accuracy of the given model. 6 to around 0. 8 to 0.941, and test loss decreases from 1. 0 to 0. 4, which indicates moderate generalization to the unseen data. Training and validation curves generally move in the same direction, which means that the model is not overfitting and has sufficient learning capability. Specifically, when the curves are closely located to each other then it will imply that the model is performing well.

Result of Experiment 2: Transfer Learning Model

Transfer learning, one of the machine learning approaches, aims at enhancing productivity and performance by utilizing the data experienced through large informational datasets for enhanced classification of more localized indoor plants' structures. This technique is quite useful and can be applied mostly in areas where resources are limited. Four transfer learning models are used in this study: These include the VGG19, EfficientNetB4, EfficientNetB6, ResNet152. VGG19 becomes deeply designed to improve the classification metrics' precision. EfficientNetB4 gives both the high accuracy and low float-point operations per second while EfficientNetB6 boosts the accuracy by uniformly scaling the depth, width, and resolution of the network. ResNet152 preserves residual connections to train networks with depths efficiently, make the gradient of the error backpropagation process not vanish, and capture the most minute details of the training images.

ResNet152:

Achieving Test Accuracy of Resnet152 is 89.83%. In below Figure 4:3 describing the confusion matrix of ResNet152.

Figure 4.3 shows the ResNet152 model managed to provide a test accuracy of 90% in the classification of indoor plant species. About this classification, high precision and recall were measured for Ball-Cactus and yellow_kewda_plants with F1-scores close to ideal level of 1.00. Certainly, species like Heart-leaf philodendron and Aglaonema pointed lower recall values of 0.62 and 0.78 respectively, which means that there are occasional mistakes. However, these variances do not significantly affect the model's performance but the overall, as the proposed solution, which was checked on 10 classes, achieved a good, nearly balanced weighted average F1 score of 0.90.

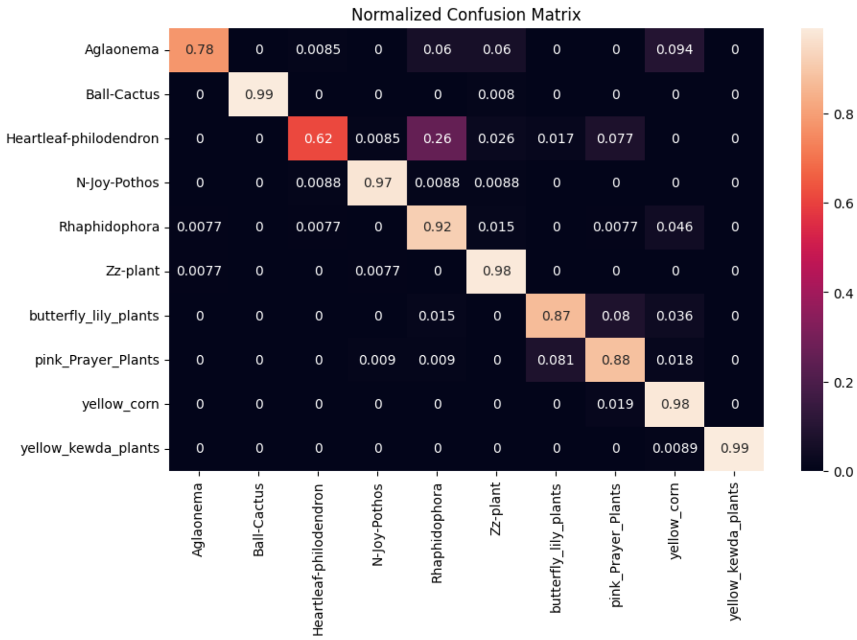

Figure 4.3: Confusion Matrix (ResNet152)

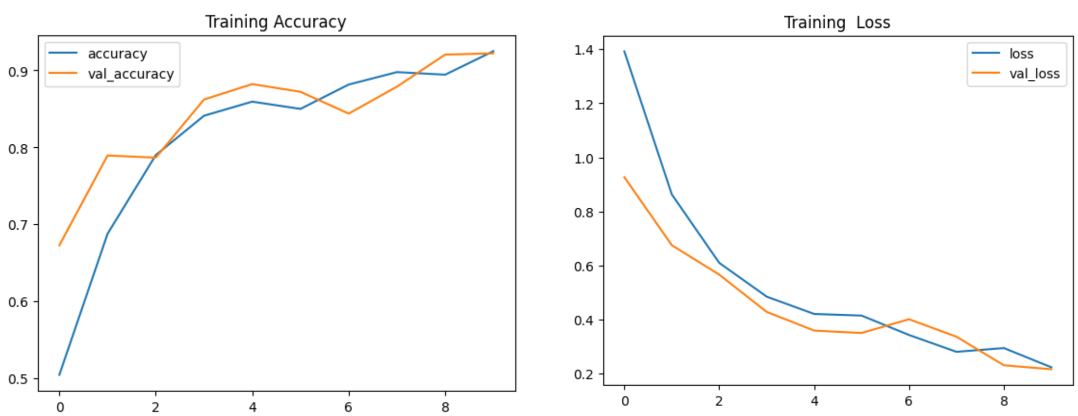

Figure 4.4: Training and validation accuracy and loss over the epochs (ResNet152)

Figure 4.4 shows the training accuracy of the ResNet152 model rises relatively high of 0.6 and that of the last element is nearly 0 and that happens through stages reaching 7 and decreasing to nearly 0.9 by epoch 8 since the training loss was reduced from 1. 4 to nearly 0.2 which reflects effective learning from the training data set. However, the validation accuracy curve starts lower, at 0.5 and rises up to approximately 0.7 by epoch 8, having the validation loss drop from 1.2 to around 0. The number of epochs is 8, it could be seen that there is some overfitting as the training accuracy increases, while the validation accuracy slightly worsens after around 4 epochs.

EfficientNetB4

Achieving Test Accuracy of EfficientNetB4 is 53.17%. In below Figure 4:5 describing the confusion matrix of EfficientNetB4. The overall accuracy of the EfficientNetB4 was 53% in the identification of the indoor plant species. In the matter of Ball-Cactus and N-Joy-Pothos, it demonstrated fair precision and an acceptable recall value that gave an F1-score of 0.91 and 0. 1, respectively. That said, performance was rather poor in other classes due to lower precisions and recalls achieved for Rhaphidophora, Zz-plant, and pink Prayer Plants.

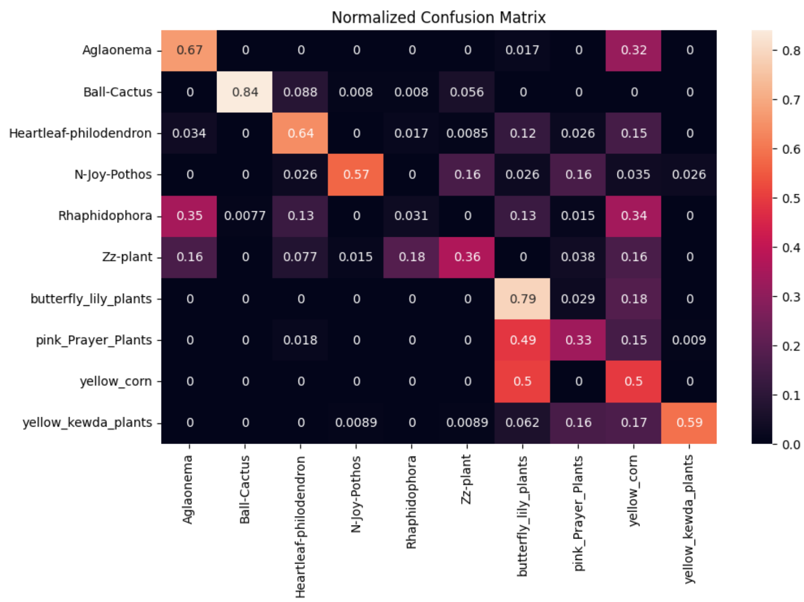

Figure 4.5: Confusion Matrix (EfficientNetB4)

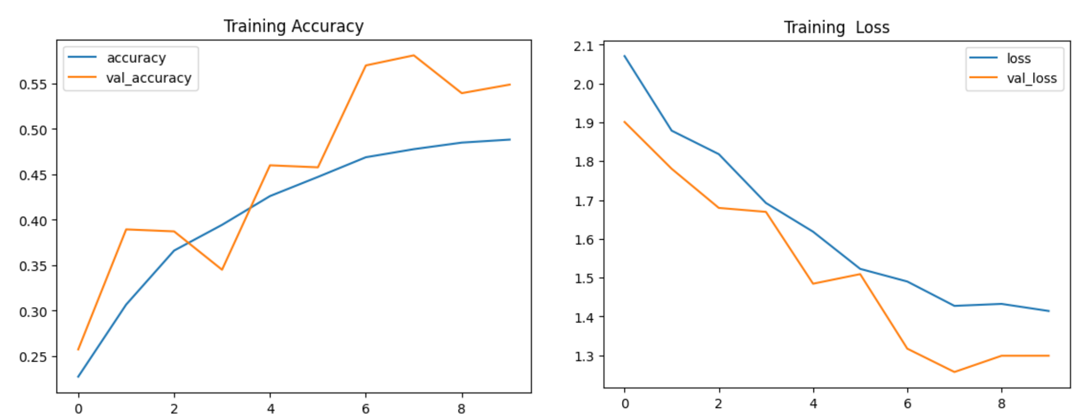

Figure 4.6: Training and validation accuracy and loss over the epochs (EfficientNetB4)

Figure 4.6 shows that the training accuracy of the EfficientNetB4 model is initially 0. It ranges from 35 and approaches 0 as the number of patients increases. 55 at epoch 8, with the training loss initially starting at the value of 2.1 to around 1.3, this means learning from the training data or in other words supervising the feature learning. However, the validation accuracy curve starts lower starting at 0.30 and drops to around 0.50 by epoch 8, with the validation loss dropping down from 2.0 to around 1.6, it indicated that there could be over fitting because there was gap between the training accuracy and the validation accuracy.

EfficientNetB6

Achieving Test Accuracy of EfficientNetB6 is 64.33%. In below Figure 4:7 describing the confusion matrix of EfficientNetB6

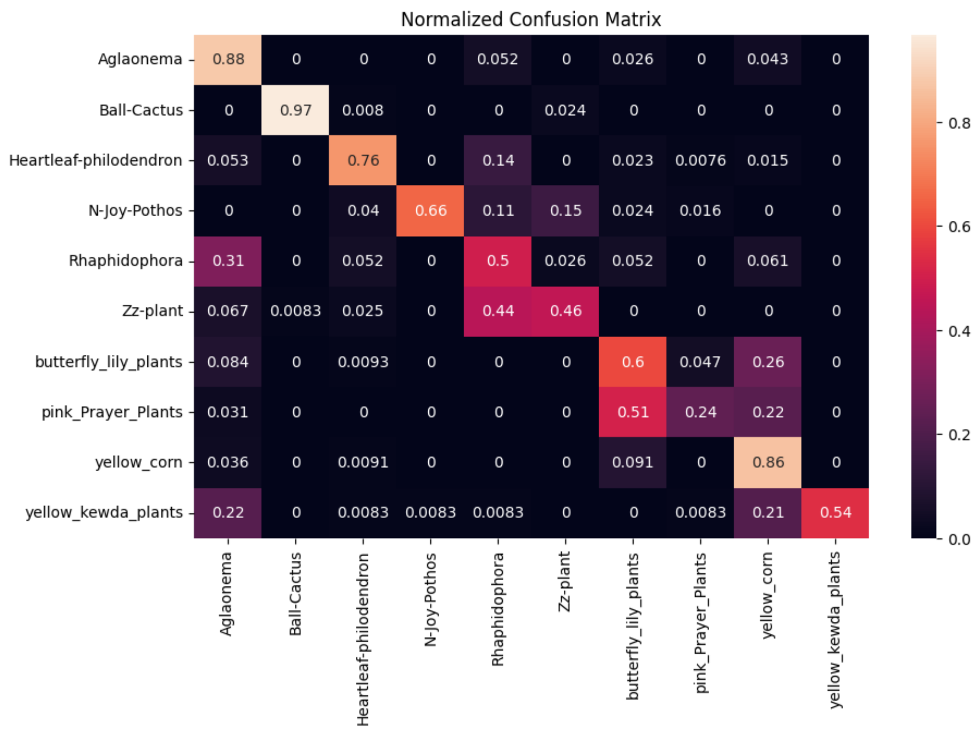

Figure 4.7: Confusion Matrix (EfficientNetB6)

Figure 4.7 shows the EfficientNetB6 model performed at a 64% level of accuracy when predicting indoor plant species. According to the results, the proposed technique achieved high precision and recall on Ball-Cactus, with an F1-score of 0. 98, indicating excellent performance. Although, there is a general improvement in the results, there are lesser precision and recall values to other classes such as Rhaphidophora, Zz-plant, and butterfly_lily_plants. Altogether, the model's classification performance was moderate and, out of all the possible classes, some of them had a higher classification performance.

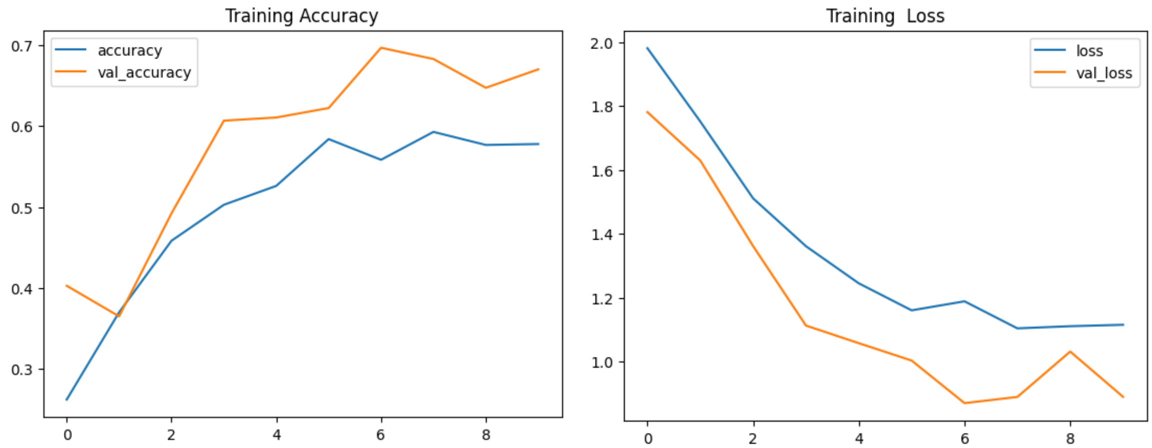

Figure 4.8: Training and validation accuracy and loss over the epochs (EfficientNetB6)

Figure 4.8 shows the training accuracy of the considered EfficientNetB6 model is initiated from 0. 4 and rises to virtually 0. 7 by epoch 8, and although the training loss is small and started from value 1. 8 to around 1. Ideally it should be 0, meaning that it has learned from the training data. However, the validation accuracy curve starts lower at 0 though it increases almost linearly with the number of epochs until it ca seize to rise beyond a certain point, a point which is 4 in this case. 3 and it gradually rises up to 0. Increased from 3 by epoch 8, with the validation loss reducing from 1. 6 to around 1. 4, which might mean overfitting as it is seen by the split between the training and the validation accuracy.

VGG19

Achieving Test Accuracy of VGG19 is 99.58%. In below Figure 4:9 describing the confusion matrix of VGG19. Figure 4.9 shows the VGG19 model has given the overall accuracy of hundred percent to distinguishing between the indoor plant species. Here the given classifier shows the exact result in precision, the recall rate and F1 score of most of the classes and due to this we can define it as a perfect classifier. The model yielded high classification accuracy and remained fairly stable in all the plant species; thus, would be more suitable for classifying indoor plants. For such a striking outcome’s credibility, it may be advisable to engage in additional research and calculations.

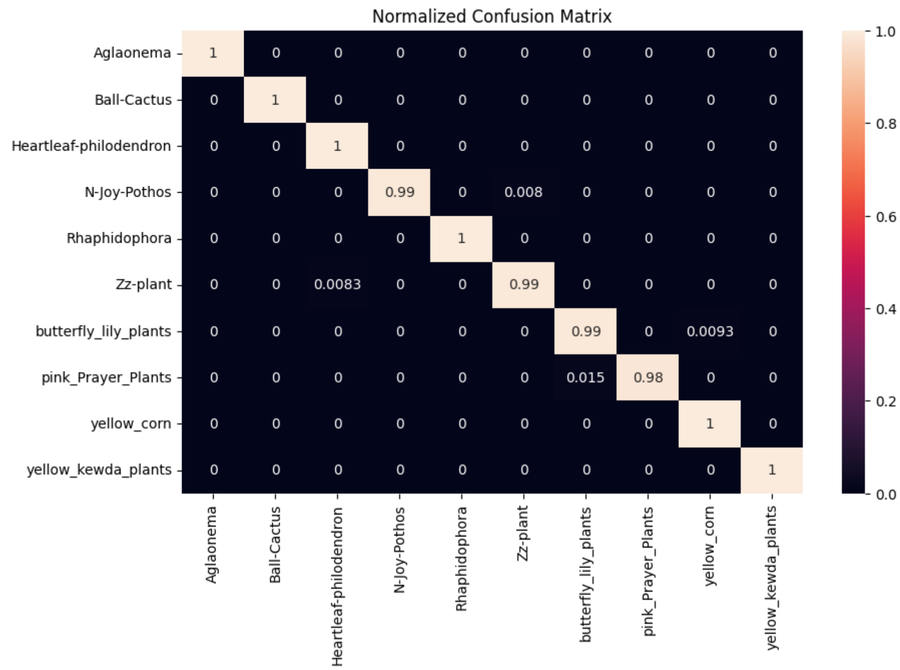

Figure 4.9: Confusion Matrix (VGG19)

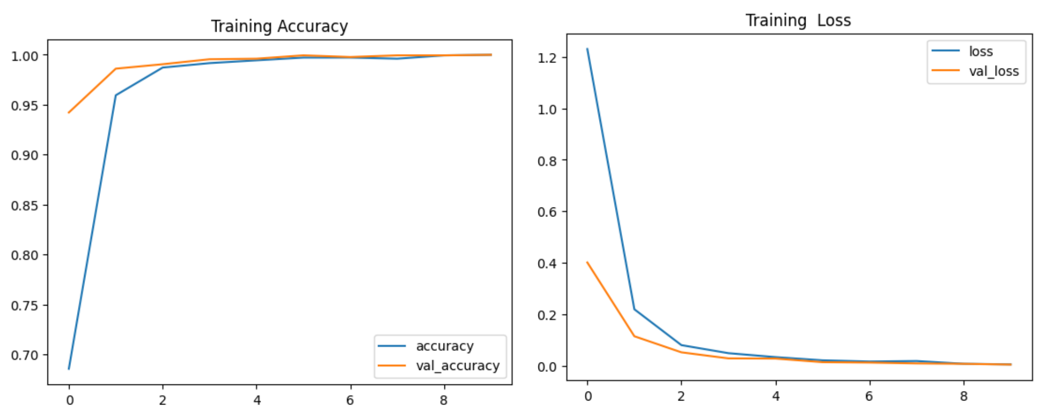

Figure 4.10: Training and validation accuracy and loss over the epochs (VGG19)

Figure 4.10 shows the training accuracy they got from the VGG19 model is almost 0 at the beginning. 7 and then rising to nearly 1. Training loss is decreasing by epoch 8 and is equal to 0 afterwards: As there is no discussion on how participants were excluded or removed from the studies, it created an impression that participants were not a consideration at all in the analysis. 2 to nearly 0. The regularized term of the model is 0, showing that the model is learning well from the training data. However, the validation accuracy curve that starts slightly lower at about 0. 6 and rises to about 0. 8 by epoch 8, while the validation loss goes down from 1. 0 to around 0. 4, which might be suspected to overfit as is evidenced by the difference in the patterns of the training and validation accuracy. Basing on this however, the model shows excellent learning capacity and the ability to work on new data not used before. More fine-tuning can thus be made in order to fine-tune its functionality for practical use cases.

Table 4.1: Model Performance Evaluation

Model Name	**Accuracy**	**Precision**	**Recall**	**F1 Score**
VGG19	99.58%	99%	99%	99%
EfficientNetB4	53.17%	58%	53%	53%
EfficientNetB6	64.33%	72%	64%	64%
ResNet152	89.83%	90%	90%	90%
CNN	98.00%	98%	98%	98%

In given below I am showing Comparative Model Accuracy Bar Plot:

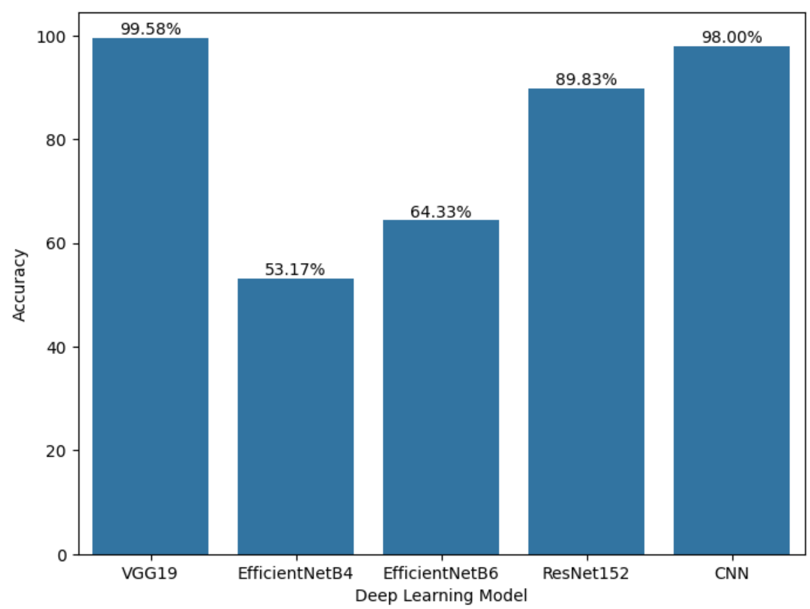

Figure 4.11: Comparative Model Accuracy Bar Plot

Figure 4.11 shows a comparative model accuracy bar plot of five deep learning models: : The deep learning model includes VGG19, EfficientNetB4, EfficientNetB6, ResNet152. It is a relative measure obtained on a percentage basis from 20% to 100%. This shows that VGG19 model is the most accurate model among the four networks proposed, the second best being EfficientNetB4. It is clear from the results depicted in the tables that the other three models have much lower accuracies than the specified model. The results are a set of axes depending on the dataset used to train and test models, the selection parameters for each of them, and the complexity. For such models the chance of over fitting rises high which means that while the models could perform very well on the training data they would not perform so well on the actual data.

4.3 Discussion

Experiment analysis shows that, VGG19 model performs better to the deep leaning mode and transfer learning mode for the indoor plant classification and has the accuracy of 99. 58%. This underscore VGG19's capability in extracting fine attributes of indoor plants from its architecture. EfficientNetB4 and EfficientNetB6 have a moderate accuracy and ResNet152 has proven its worth again in terms of classification. The custom CNN performs well and indicates that optimal architectures can be reached through 'learning by building'. The specific analysis of the bases for the differences in the performance of the models, as well as the future research on the question of the interpretability of the models, can contribute to the improvement of the classification systems for indoor plants. Moreover, the future studies can be also dedicated to the increase of the variety of datasets, optimization of the models' structures, and identification of possible practical utilization of the indoor plant classification in horticulture and botanical science.

CHAPTER 5
IMPACT ON SOCIETY

5.1 Impact on Society

Improved deep learning approaches toward accurate indoor plant classification has imply potential to transform society in numerous ways. Since, people will be provided with a credible solution for differentiating indoor plant species, this technology can help the ordinary and professional gardeners to grow and take care of the plants more efficiently. Enhanced identification of plants can enhance quality air indoors and thus improve wellbeing of persons indoors and productivity of any firm. In addition, the improvement of the indoor plants categorization system opens up new horizons of improvised cultivation techniques, contributes to environmental awareness, and cultivates an increased awareness of nature within the residents of the central cities. In sum, the extensive application of such technologies can help in the process of developing healthier and more vital indoor environments and improving living experience of people and society.

5.2 Impact on Environment

Deep learning for classification of indoor plants has brought about positive changes to the environment in as much as encouraging indoor gardening. Exploiting the above facts, people can identify and choose vegetation which will be appropriate in their enclosed surroundings and hence minimize water, fertilize and pesticide use. Moreover, the plants bring the interior quality of the air and enhance the amount of fresh oxygen and the low level of unhealthy airborne material. Thus, through enhancing the growth of indoor plants, this particular technology helps people to feel that they are attuned to nature, and possibly, inspire them to take better care of the environment. Moreover, it can be concluded that the introduction of indoor plant classification systems can also exert positive impacts on green building design and development of urban environment as it will provide certain effectiveness to classify the plants in order to fulfil the health benefits of human beings along with creating eco-friendly environment. In conclusion, this technology helps the endeavor of reducing the extent of environmental pollution as well as enhancing the quality of the environment indoors.

5.3 Ethical Aspects

The identification of indoor plants utilizing deep learning comes with significant ethical issues, such as data privacy, and ecological impact. When it comes to the event of collecting and utilizing pictures of plants, there should be respect of the people's rights and their privacy as well. Further, it would be advisable to reduce any negative impacts of indoor gardening on the environment as much as is possible. Moreover, the shortcomings of using classification models and possible sources of bias should also be disclosed to prevent users from getting wrong or incomplete information. In conclusion, ethical issues should be incorporated into all development and application phases of indoor plant classification systems to promote fairness and the best use of technology for the welfare of society and nature.

5.4 Sustainability Plan

Therefore, for the proper establishment and sustenance of indoor plant classification technology, it is crucial to have a clear long-term development strategy. This includes encouraging stewardship for the environmental through practices such as use of environmentally friendly items in the garden and the avoidance of wastage of water. Furthermore, more research related to the topic is required to advance the creation of better classification models that are precise, efficient in the use of resources, and environmentally friendly. Engaging in partnership with botanical gardens, environmental non-governmental organizations, and university and college can support knowledge exchange and enhance best practices. In addition, raising public awareness can help people learn about the uses of the interior plants and saving the species of fauna and flora. For this purpose, it is possible to speak about the need to adopt the principles of sustainability for the creation and application of classification of indoor plants using the opportunities of the technology that would help to create a healthy and friendly climate for future generations.

CHAPTER 6
CONCLUSION AND FUTURE WORKS

6.1 Conclusions

Therefore, this research shows that it is possible and efficient to classify indoor plants with deep learning approaches. By means of the numerous experiments, it is revealed that VGG19 performs better than the other deep learning models with the accuracy ranging from 99. 58%. The findings stress the importance of proper identification of the plant to support the practice of healthy indoor plant and improve indoor environment and health. Also, other issues that need to be taken into consideration are ethical issues for instance the privacy of data collected and the effects of the plant classification systems on the environment. Consequently, future studies and developmental processes should aim at improving on the classification models, on the variety and source of data sets for classification, and on real world issues in order to get the greatest utility of this technology on society and the environment as much as possible.

6.2 Further Works

This study points to the following topics for further research in the context of indoor plant classification utilizing deep learning approaches: Further research could consider the use of more characteristic description of the object's image or use data from other sensors in order to increase the classification rate and stability. Furthermore, studying the effect of environmental factors like humidity and temperature on the specified aspects related to the plants could be beneficial for the application of the classification. Also, plant growth and health monitoring studies would improve the knowledge we have on plant behavior and improve the dynamic classification models. Moreover, it is also possible to actualize the further application of indoor plant classification technology in other industries including agriculture, forestry, and conservation biology in order to reveal more advantageous and efficient utilization of this technology in more extensive areas concerning society and environment.

REFERENCES

[1] M. Fathi Kazerouni, N. T. Mohammed Saeed, and K.-D. Kuhnert, “Fully-automatic natural plant recognition system using deep neural network for dynamic outdoor environments,” SN Applied Sciences, vol. 1, no. 7, Jun. 2019, doi: https://doi.org/10.1007/s42452-019-0785-9.

[2] Y. Liu, Z. Pang, M. Karlsson, and S. Gong, “Anomaly detection based on machine learning in IoT-based vertical plant wall for indoor climate control,” Building and Environment, vol. 183, p. 107212, Oct. 2020, doi: https://doi.org/10.1016/j.buildenv.2020.107212.

[3] A. Ojha and V. Kumar, “Image Classification of Ornamental Plants Leaf using Machine Learning Algorithms,” 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), Sep. 2022, doi: https://doi.org/10.1109/icirca54612.2022.9985604.

[4] Munirah Hayati Hamidon and T. Ahamed, “Detection of Tip-Burn Stress on Lettuce Grown in an Indoor Environment Using Deep Learning Algorithms,” vol. 22, no. 19, pp. 7251–7251, Sep. 2022, doi: https://doi.org/10.3390/s22197251.

[5] D. Radočaj, I. Rapčan, and M. Jurišić, “Indoor Plant Soil-Plant Analysis Development (SPAD) Prediction Based on Multispectral Indices and Soil Electroconductivity: A Deep Learning Approach,” Horticulturae, vol. 9, no. 12, p. 1290, Dec. 2023, doi: https://doi.org/10.3390/horticulturae9121290.

[6] M. H. Hamidon and T. Ahamed, “Detection of Defective Lettuce Seedlings Grown in an Indoor Environment under Different Lighting Conditions Using Deep Learning Algorithms,” Sensors, vol. 23, no. 13, p. 5790, Jan. 2023, doi: https://doi.org/10.3390/s23135790.

[7] M. Dyrmann, H. Karstoft, and H. S. Midtiby, “Plant species classification using deep convolutional neural network,” Biosystems Engineering, vol. 151, pp. 72–80, Nov. 2016, doi: https://doi.org/10.1016/j.biosystemseng.2016.08.024.

[8] B. G. Martini et al., “IndoorPlant: A Model for Intelligent Services in Indoor Agriculture Based on Context Histories,” Sensors, vol. 21, no. 5, p. 1631, Jan. 2021, doi: https://doi.org/10.3390/s21051631.

[9] Vickneswari Durairajah, Suresh Gobee, and Amgad Muneer, “Automatic Vision Based Classification System Using DNN and SVM Classifiers,” Sep. 2018, doi: https://doi.org/10.1109/crc.2018.00011.

[10] K. Rangarajan Aravind, P. Maheswari, P. Raja, and C. Szczepański, “Crop disease classification using deep learning approach: an overview and a case study,” Deep Learning for Data Analytics, pp. 173–195, 2020, doi: https://doi.org/10.1016/b978-0-12-819764-6.00010-7.

[11] Y. Oishi et al., “Automated abnormal potato plant detection system using deep learning models and portable video cameras,” International Journal of Applied Earth Observation and Geoinformation, vol. 104, p. 102509, Dec. 2021, doi: https://doi.org/10.1016/j.jag.2021.102509.

[12] M. Shoaib et al., “Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease,” Frontiers in Plant Science, vol. 13, Oct. 2022, doi: https://doi.org/10.3389/fpls.2022.1031748.

[13] M. O. Ojo and A. Zahid, “Deep Learning in Controlled Environment Agriculture: A Review of Recent Advancements, Challenges and Prospects,” Sensors, vol. 22, no. 20, p. 7965, Oct. 2022, doi: https://doi.org/10.3390/s22207965.

[14] A. Musa, M. Hassan, M. Hamada, and F. Aliyu, “Low-Power Deep Learning Model for Plant Disease Detection for Smart-Hydroponics Using Knowledge Distillation Techniques,” Journal of Low Power Electronics and Applications, vol. 12, no. 2, p. 24, Apr. 2022, doi: https://doi.org/10.3390/jlpea12020024.

[15] S. Giraddi, S. Seeri, P. S. Hiremath, and J. G.N, “Flower Classification using Deep Learning models,” IEEE

Xplore, Oct. 01, 2020. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9277041 (accessed Jan. 08, 2023).

[16] S. Kosankar and Dr. V. Khan, “Flower Classification using MobileNet: An Optimized Deep Learning Model,” IJARCCE, vol. 8, no. 2, pp. 186–192, Feb. 2019, doi: https://doi.org/10.17148/ijarcce.2019.8233.

[17] N. M. Ibrahim, D. G. I. Gabr, A. Rahman, S. Dash, and A. Nayyar, “A deep learning approach to intelligent fruit identification and family classification,” Multimedia Tools and Applications, Mar. 2022, doi: https://doi.org/10.1007/s11042-022-12942-9.

[18] S. Jumaboev, D. Jurakuziev, and M. Lee, “Photovoltaics Plant Fault Detection Using Deep Learning Techniques,” Remote Sensing, vol. 14, no. 15, p. 3728, Aug. 2022, doi: https://doi.org/10.3390/rs14153728.

[19] R. Ramin Shamshiri et al., “Advances in greenhouse automation and controlled environment agriculture: A transition to plant factories and urban agriculture,” International Journal of Agricultural and Biological Engineering, vol. 11, no. 1, pp. 1–22, 2018, doi: https://doi.org/10.25165/j.ijabe.20181101.3210.

[20] S. Prasad, K Umme Haniya, Syeda Zeenathunnisa, M. Tahir, and M. Sulaiman, “Deep learning based Automatic Indoor Plant Management System using Arduino,” Oct. 2023, doi: https://doi.org/10.1109/gcat59970.2023.10353399.

[21] E. Buss, T. Aust, M. Wahby, Tim-Lucas Rabbel, Serge Kernbach, and H. Hamann, “Stimulus classification with electrical potential and impedance of living plants: comparing discriminant analysis and deep-learning methods,” Bioinspiration & biomimetics, vol. 18, no. 2, pp. 025003–025003, Mar. 2023, doi: https://doi.org/10.1088/1748-3190/acbad2.

[22] Y. Sun, X. Guo, and H. Yang, “Win-Former: Window-Based Transformer for Maize Plant Point Cloud Semantic Segmentation,” Agronomy, vol. 13, no. 11, pp. 2723–2723, Oct. 2023, doi: https://doi.org/10.3390/agronomy13112723.

[23] K. Turgut, H. Dutagaci, G. Galopin, and D. Rousseau, “Segmentation of structural parts of rosebush plants with 3D point-based deep learning methods,” Plant Methods, vol. 18, no. 1, Feb. 2022, doi: https://doi.org/10.1186/s13007-022-00857-3.

[24] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 12, pp. 2481–2495, Dec. 2017.

[25] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, “A comparative study of fine-tuning deep learning models for plant disease identification,” Computers and Electronics in Agriculture, vol. 161, Mar. 2018, doi: https://doi.org/10.1016/j.compag.2018.03.032.

[26] V. Maeda-Gutiérrez et al., “Comparison of Convolutional Neural Network Architectures for Classification of Tomato Plant Diseases,” Applied Sciences, vol. 10, no. 4, p. 1245, Jan. 2020, doi: https://doi.org/10.3390/app10041245.

[27] T.-H. Nguyen, T.-N. Nguyen, and B.-V. Ngo, “A VGG-19 Model with Transfer Learning and Image Segmentation for Classification of Tomato Leaf Disease,” AgriEngineering, vol. 4, no. 4, pp. 871–887, Dec. 2022, doi: https://doi.org/10.3390/agriengineering4040056.

[28] P. Kaur et al., “Recognition of Leaf Disease Using Hybrid Convolutional Neural Network by Applying Feature Reduction,” Sensors, vol. 22, no. 2, p. 575, Jan. 2022, doi: https://doi.org/10.3390/s22020575.

[29] Anis-Ul-Islam Rafid, S. Sanjana, Muhaimin Bin Munir, and Nusrat Sharmin, “An early-stage diagnosis of diabetic retinopathy based on ensemble framework,” Signal, image and video processing, vol. 18, no. 1, pp. 735–749, Oct. 2023, doi: https://doi.org/10.1007/s11760-023-02796-5.

[30] L. A. Leonidas and Y. Jie, “Ship Classification Based on Improved Convolutional Neural Network Architecture

for Intelligent Transport Systems,” Information, vol. 12, no. 8, p. 302, Jul. 2021, doi: https://doi.org/10.3390/info12080302.

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