A PROPOSED DEEP LEARNING APPROACH FOR INDOOR CACTUS VARIANT DETECTION

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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 "A Proposed Deep Learning Approach for Indoor Cactus Variant Detection", submitted by **Most. Sumi Khatun** 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 16-07-2024.

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DECLARATION

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

Indoor cactus variant detection usually consists in recognizing and categorizing various types of indoor cacti through the application of image analysis and artificial intelligence. This research work introduces a new class of indoor cactus varieties identification technique based on a specific deep learning model called Convolutional Neural Network (CNN). To gather the data, 1200 images of six types of indoor cactus were obtained, and the dataset was expanded to 2620 images to yield higher accuracy. The preprocessed dataset was then fed to the custom CNN architecture designed for identifying cactus variants from the given backgrounds. It can be compared with the other well-known transfer learning models containing Xception, MobileNetV2, DenseNet201 and InceptionV3. The findings highlighted the fact that the proposed custom CNN has the best accuracy compared to the other transfer learning-based models with the recognition accuracy of 99. 62%. This goes to support the effectiveness of the proposed CNN architecture in the accurate differentiation between such visually similar cactus variants.

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CHAPTER 1

Introduction

1.1 Introduction

There is a trend of having indoor gardens, and one of the most sought-after plants is cactus maybe because of its appearance and easy care. There are countless varieties of these tough plants concerning their size, shape, and species they are categorized in. However, the identification of the different types of indoor cacti is a task that can prove to be rather difficult especially for the amateurs and researchers most of whom may not have a background in botany. In the existing approaches to the identification of plants, the general examination of plant specimens and using the professional eye leads to longer and uncertain identification. López-Jiménez et al. [1]. Therefore, when using the power of CNNs, it will be easy to design automated systems for identification of the various variants of the cactus. Such a system can prove to be very useful in supporting plant enthusiasts and botanist and horticulturists working with cactus by providing a credible tool for its identification and management. V. Tiwari et al. [3]. This project involves the development and implementation of a deep learning model to detect the kind of indoor cactus and even their different varieties. The main goal is to create a reliable model that distinguishes six types of indoor cactus using the set of 1200 pictures and apply augmentation techniques to increase the set to 2620 pictures. The proposed methodology includes acquiring new dataset, performing data augmentation and normalization, and the buildup of architecture specific to cactus variant detection. Moreover, it will show the performance comparison of the custom CNN with transfer learning models like Xception, MobileNetV2, DenseNet201, and InceptionV3 A. J. et al [4]. This paper's goal is to propose an accurate detection of cactus variant with the use of custom-designed CNNs and transfer learning. It puts forward a model for implementing our precise cactus recognition framework, which will help increase the rate of plants' proper care and bring beneficial results to both the specific field of cacti and the general scientific study of plant species and their protection.

1.2 Motivation

The reasons for working on this project are linked to the increased demand for indoor gardens and problems related to accurate identification of different cactus types. Owing to general appearance and the relatively low demands towards the conditions in which these plants are placed, enthusiasts and professionals continue to experience problems in differentiating between the many similar cacti species. Conventional identification processes are usually time consuming and can be erroneous, there is, therefore, need to address this issue adequately. Deep learning is used here in the form of convolutional neural networks to build a fast, accurate, and intuitive tool for cactus variant identification. This is not only helpful for people who are inclined to caring about their plants but also helpful to botanical science and plant conservation, making sure that the number of cactus plants is correctly known and can be researched upon.

1.3 Rational of the Study

The following are the reasons for this study: This study intended to solve the problem of inaccurate, time-consuming identification of the cactus variant through technological advancement. As the numbers of cacti kept in interiors increase, the crucial problem is to provide fast and more accurate identification systems different from the comparative approaches that are frequently used and require several days or even weeks. Among the group of related problems, image classification, and specifically object detection, demonstrated great performance when using convolution neural networks (CNNs), thus, this approach is relevant to select for the task. This paper aims at presenting a tool that may help in improving the cactus identification's accuracy and speed by coming up with a strong model that incorporates CNNs and compare it with existing transfer learning models. This holds benefit especially towards plant lovers, plant specialists, and researchers since it enhances plant care, plant preservation, and plant species' analysis.

1.4 Research Questions

1. What is the performance of a custom CNN model in discriminating between six types of indoor cactus from augmented images of plant objects?

2. How do Xception, MobileNetV2, DenseNet201, and InceptionV3 perform in the case of cactus variant detection when transfer learning is being used?

3. In what extent does data augmentation affect both the accuracy and generalization of the cactus variant detection model?

4. What are the proper settings to train the custom CNN model for classifying the cactus variant?

5. How effective is the proposed custom CNN model with regard to changes in indoor lighting as well as the background?

1.5 Expected Output

It is expected that at the end of this study, a very reliable and solid deep learning model shall have been developed and trained in the detection of six distinctive indoor cactus types. This new model which has been trained on the augmented dataset should be one that will yield higher accuracy, precision, recall and F1-score than the initial model. Also, the research objective is to compare the proposed custom CNN architecture to the most frequently used pre-trained transfer learning models (Xception, MobileNetV2, DenseNet201, InceptionV3) and identify their merits and demerits in cactus variant identification. The final deliverable is an application that is easy to use for a user; the user creates a picture of cacti, and the program predicts the correct variant. It is expected that, this tool will go a long way in assisting plant lovers, horticulturists, and researchers in the identification of cacti and their proper care hence proper management of the plants thus help in enhancing research and conservation of the plants.

1.6 Project Management and Finance

Project management of each task will focus on quality and diversification of data through effective acquisition, annotation and preprocessing. On the financial aspect, funds will be needed for computers, data enhancement tools, and possibly, cloud computing for training models. Schedules of important tasks will help to control the growth of the model, settings of hyperparameters, and accurate analysis versus the best benchmarks. Economic efficiency will concentrate on low resource utilization for both scalability and deployment and the effort will be made to obtain a sound deep learning model for viable research and performance results objectives in a timely and cost-effective manner.

Table 1.6: Project Management Table

Work	Time
Data Collection	2 months
Literature Review	1 months
Experimental Setup	1 month
Implementation	2 months
Report Writing	1 months
Total	7 months

1.7 Report layout

The report starts from the introduction of the deep and transfer learning based indoor cactus variant detection and its importance.

Chapter 1: Introduction.

This section gives general information about the purpose, rationale and anticipated benefits of the proposed research work, which aims at designing a deep learning model for distinguishing between indoor cactus variants.

Chapter 2: Background.

Describes the general idea related to the indoor gardens, common trends regarding cacti, difficulties of manual differentiation, and the possibility of using deep learning in image classification.

Chapter 3: Research Methodology

Extremely helpful to outline the approach taken in how data was collected/gathered, how the data was labeled, how image preprocessing was done, how the model was chosen, whether a custom CNN was built from scratch or a transfer learning model was used, how the model was trained, and how the results were evaluated.

Chapter 4: Experimental Results

Provides the results obtained from training and evaluation of deep learning models, such as the accuracy and intention comparison with transfer learning models, and the results of data augmenting.

Chapter 5: The Impact on Society

Assesses the possibility of the improved model providing positive impacts on the members of society to improve their ability in identifying cactus.

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

Concludes the potential of the developed model in the context of the study, offers an outlook on the model's efficiency, and outlines practical implications for the use of deep learning in plant identification and future improvements in the analyzed field of study.

CHAPTER 2
Background

2.1 Preliminaries

In order to discuss deep learning-based indoor cactus variant detection in detail, it is necessary to set prior information and ideas. This section of the work will begin with the definition of terminologies that are commonly associated with deep learning and image classification. The major topics include but are not limited to convolutional neural networks, transferring learning, and dataset formation and enhancement. Knowledge about these preliminaries thus facilitates the grasp of the method adopted in the creation and assessment of the deep learning model on indoor cactus variants. Further, the typical indoor cactus species that can be found, and their morphological differences and their fundamental background, leading to the usage of AI to solve the problem of the identification and maintenance of indoor cacti due to the existing issues with the manual method will be included.

2.2 Related Works

The current literature review also reveals that deep learning contributed to identifying plant species and the subsequent findings produced encouraging outcomes with distinct plant species and climate conditions. For instance, CNN and transfer learning have been deployed in plant identification from images with increased accuracy in various brigadoon situations. Recent improvements show that the application of best solutions can improve the level of accuracy and speed of plant identification and therefore create conditions for the use of similar methods to detect indoor cactus variants.

Now in given below, I am writing some similar type paper review, which are related to my paper and those are help me a lot:

V. Tiwari et al. [3] proposed a deep learning strategy for automatic identification of plant diseases and their type based on the images of the leaves of plants based on Dense CNN from a large dataset of images collected from several countries. When it comes to the problem of dealing with the intricacies of leaf images, dense neural network, proposed here, offer a marvelous solution, work on the average of 99+ cross-validation accuracy. To break it down, the percentage of accuracy was at 58% and an average test accuracy of 99. Around 199% on images which the networks have not seen before, specifically images with complicated backgrounds.

A. J. et al. [4] based exploration of the CNN-based pre-trained models for the efficient detection of plant diseases and higher accuracy, fine-tuning of the hyperparameters of some of the widely used models including DenseNet-121, ResNet-50, VGG-16, and Inception V4. The classification accuracy of DenseNet-121 was recorded to be 99 percent outcoming other models. Successfully detected plant diseases up to 81% thus signifying the possibility of its use in advancing the agricultural field.

S. M. Hassan et al. [5] introduced the novel method for plant disease classification using depth-separable convolution and the number of parameters and computations was decreased. The InceptionV3, InceptionResNetV2, MobileNetV2, and EffcientNetB0 models had overall accuracy percentage in the disease classification, which was much higher than that of the handcrafted and convolutional features. These models also needed less training time and were more profound because they could also run-on portable gadgets.

J. Trivedi et al. [6] introduced a medical model for disease detection and had a combination of two dense layers, sigmoid activation function, followed by four convolutional layers. It achieved an accuracy of 87% when the model was being trained with a dataset of 3663 images comprising of apple and tomato leaves. Nevertheless, overfitting was observed and addressed by adjusting the dropout rate to equal to 0. 2. The methods were tested on a GPU Tesla; parallel processing showed an increase in accuracy and execution time.

A. Sharma et al. [7] upgraded the agricultural yield under adverse temperature and humid conditions by discussing image analysis methods for proper and timely identification of the diseases in plants. The study also demonstrated the applicability of deep learning for enhancing the research outcome in disease detection with better results and accuracy. The study also highlighted the existing issues concerning disease diagnosis and described the possible future studies.

D. Bhise et al. [8] mentioned that deep learning is helpful in agriculture in the following ways, such as automatic learning, feature extraction. The paper presents an evaluation of deep learned and advanced imaging technique for accurate detection and categorization of plant leaf diseases, which will be useful to practitioners and scholars, especially in plant disease probe.

S. P. Mohanty et al. [9] applied deep learning and Smartphone to develop smartphone-based technology for the diagnosis of diseases in crop plants. An end-to-end deep ConvNet was trained for the classification of 14 crop species and 26 diseases with high accuracy parameter of 99%. An 87% on the training set and 35% on a held-out test set using a dataset of 54306 images of diseased and healthy plant leaves. It indicates the possibility of employing the smartphone technology and deep learning approaches for the detection of the crop diseases and stresses the significance of training the studied model on a large and publicly available dataset.

M. Arsenovic et al. [10] introduced a new dataset with 79,265 leaf photos that can be considered as the largest one. The performance of the proposed model was compared in the controlled and real-world situations and had a success rate of 93%. 67% accuracy rate. It was proposed that a two-stage neural network for disease classification that enhanced the basic abilities to detect plant diseases in actual agricultural settings.

K. P. Ferentinos et al. [11] designed CNN models from the photos of the healthy and diseased plant leaves for the detection of diseases. The best performing model was able to correctly determine the combination of the plant and disease or simply a healthy plant by a whopping 99. 53 successful out of 100 transplants mean that it could be used as a sort of early warning device or as an adviser to farmers.

O. Kulkarni et al. [12] applied deep learning for computer vision in diagnosing the state of the leaves so that farmers can recognize diseases in them. They devised a deep learning model that could predict the kind of photos of the leaves and the accuracy that was highest at 99. 45%. It also yielded good disease classification accuracies with the MobileNetV2 model.

S. S. Harakannanavar et al. [13] targeted early symptoms of the diseases in the tomato's leaves. For this purpose, contour tracing, descriptors such as Principal Component Analysis, Discrete Wavelet Transform, Grey Level Co-occurrence Matrix, and machine intelligent methods such as Support Vector Machine (SVM), K-Nearest Neighbor (K-NN), Convolutional Neural Network (CNN) were employed for classification. CNN provided the highest accuracy of 99. 12% for disordered samples of tomato, while cost was at 6%.

S. Anubha Pearline et al. [14] worked on different classifiers and feature extraction techniques to highlight the difference between deep learning techniques and other models suggested for plant species identification. They compared structures of deep learning like VGG 16 and VGG 19 Convolutional Neural Networks (CNNs). The fusion of color channel statistics, LBP, Hu and Haralick features with Random Forest classification provided the overall recognition accuracy of images up to 82.38%.

R. Sujatha et al. [15] have made comparisons of deep learning (DL) and machine learning (ML) algorithms for the identification of diseases afflicting the citrus plant. They only compared models of VGG-16, VGG-19, SVM, RF, SGD, and Inception-v3 among the models they used. The gap between the ML and DL methods was not very significant, with DL models such as the VGG16 and the Inception-v3 being average performers of all the applied models while the Radom Forest possessed the lowest CA of all the models. This work enriches the existing literature for two main areas, namely, the agricultural field which benefits from the understanding of the efficient use of DL techniques in the diagnosis of diseases in citrus plants.

2.3 Comparative Analysis and Summary

The comparative analysis compares the results of the presented custom CNN model with the results of using transfer learning architectures (Xception, MobileNetV2, DenseNet201, InceptionV3) in distinguishing indoor cactus variants. It is evident from the results that although transfer learning models utilize the features of other models efficiently, the proposed custom CNN achieves almost the same performance and even stability. Data augmentation is revealed to have a decisive influence toward optimum classification accuracy in a range of detailed indoor environments according to the research study’s findings. All in all, the completed deep learning model presents a favorable tool for detailed cactus variant identification and its application towards further improvements in plant cultivation and botanical investigation.

Table 2.3: Comparative Analysis of Previous Work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	López-Jiménez, Efren, et al. [1]	CNN	95%.
2.	A. Berka, A. Hafiane, et al.,[2]	CNN	88.73%
3	V. Tiwari, R. C. Joshi,et al., [3]	CNN	99.199%
4	A. J., J. Eunice, et al., [4]	CNN, DenseNet-121, ResNet-50, VGG-16, and Inception V4	DenseNet-121= 99.81%
5	S. M. Hassan, A. K. Maji, et al. [5]	InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0	EfficientNetB0= 99.56%.
6	J. Trivedi, Y. Shamnani, et al. [6]	Deep Learning	87%
7	S. P. Mohanty, D. P. Hughes, et al., [9]	CNN	99.35%
8	K. P. Ferentinos, et al. [11]	CNN	99.53%
9	O. Kulkarni et al. [12]	InceptionV3, MobileNet	InceptionV3= 99.45%,
10	Proposed Model	CNN and Transfer Learning	CNN= 99.62%

2.4 Scope of the Problem

The objectives of this project include proposing a deep learning framework focused on the detection of six typical indoor cactus types. Some of the measures include data gathering and marking, data preparation, and training with designed CNN model and other competitively good transfer models. They called for flexibility in solutions due to the variations in the amount of indoor light, presence of cluttered background, and because the variants of cacti morphologically are quite related. Further, it includes the comparison of the models' performance and the possibility of using the trained model in a simple application that can be used by plant lovers and science researchers for practical purposes. The results will help improve the development of AI for plant identification and promote the proper management and cultivation of indoor cactus varieties.

2.5 Challenges

Many challenges arise when replacing an effective deep learning model for indoor cactus variant detection. First of all, the diversification and quality of the captured data such as lighting conditions, angles, and backgrounds directly affect the accuracy of the trained models. Secondly, identification of differences between look-alike cactus varieties implies the need to hone in on minuscule differences that might be even difficult for an experienced botanist. Thirdly, selection about the precise architecture of a network, as well as whether the intended model should be a custom CNN or those derived from transfer learning, require equal attention to be paid to model intricacy and potential computational requirements. Finally, the trained model indeed needs to be incorporated into the job providing a more convenient and user-friendly identification interface while working out usability and performance problems that can affect the final outcome as seen by the end-users. Solving these issues will be essential for the successful completion of the project's goals and to provide a feasible way of identifying the desired indoor variant of a cactus.

CHAPTER 3
Research Methodology

3.1 Research Subject and Instrumentation

The target of the given research area of the present research work is to design a deep learning model for accurately identifying indoor cactus types. To clarify, the project entails data accrual of images of six indoor cactus plant types, with variations to build model resiliency. Therefore, the instrumentation in this research involves the application of CNNs as the major tool in image classification. More specifically, the proposed research will employ a cactus variant detection CNN model designed and developed for the purpose, as well as comparative testing against the current state of the art transfer learning models including Xception, MobileNetV2, DenseNet201, and InceptionV3. This is possible since CNNs are capable of training from the feed forward architecture, which means that the model can identify and distinguish relative variants in figures based on their features, while the cacti images appear very similar. Thus, the presented research is oriented to the development of the automated plant identification systems and their usage in indoor gardening and botanical science.

3.2 Data Collection Procedure

The procedure of data acquisition includes obtaining a range of samples of indoor cactus types that can be found in people's homes and which are available in 6 different types. Such images are collected from different sources which includes the personal collection as well as botanical gardens and nursery. As a way to improve the general data variety and also to improve the stability of models, the process of image augmentation will be used, which will increase the final dataset number up to 2620 images. Every image will be tagged with the name of the respective cactus variant used for supervised learning in order to accurately teach a deep learning model to identify the cactus variant of interest. Special emphasis is put on the variety of the lighting and positions of the subjects as well as backgrounds to make the dataset as diverse as possible. It is noteworthy that each of these images is properly labeled with the variants of the cactus for the purpose of supervised learning. Quality assurance procedures are applied to check the correctness of labeling and quality of the images. The dataset is then expanded again by using operations such as rotation, flipping, and alterations in colors so that the model occupies a better capacity to predict or generalize on difference. The collection of such data is rigorous and essential to support the training of deep learning model with appropriate proficiency to classify other indoor cactus varieties under varying conditions.

In Given below I am showing some images of datasets in Figure 3.1, 3:2

Figure 3.1: Dataset’s Images

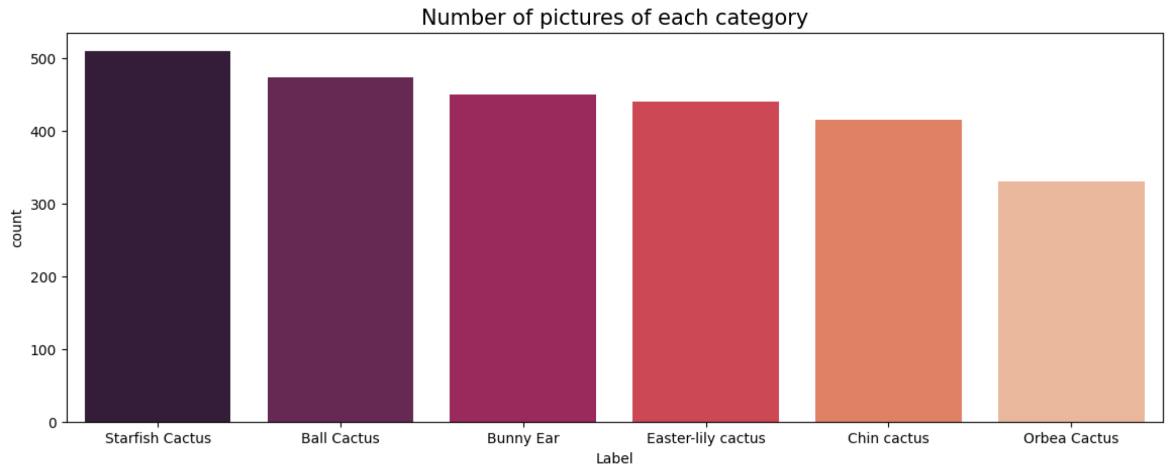

Figure 3.2: Number of categories of Dataset's Images

In Figure 3.2 shown the six target variants. A total of 1200 images will be gathered, distributed among the variants as follows: It has 510 images of Starfish Cactus, 474 images of Ball Cactus, 450 Bunny Ear, 440 Easter-Lily cactuses, 416 Chin cactus and Orbea Cactus with 330 images only.

3.3 Statistical Analysis

Concerning statistical analysis measures in this study, the emphasis will be on assessing the validity of the machine learning models developed for identifying indoors cactus variant. Metrics like accuracy, precision, recall and F1-score that quantify the classification performance of the models will be calculated to reveal the model's performance over the six cactus variants. In this way, confusion matrix that will show how well the instances were classified and where misclassification can occur will be created. Additional statistical tests may also be used to use to compare/custom CNN architecture with the other pre-trained architectures: Xception, MobileNetV2, DenseNet201, InceptionV3. Thus, these analyses will outline potential improvements to the model, what aspects may limit its effectiveness, and enable further refinements of the constituents to make it more precise and usable when applied to realistic situations.

3.4 Proposed Methodology

The following methodology seeks to propose a highly effective deep learning model that can enhance the differentiation of indoor cactus variants, without leaving out any step, from data acquisition to model assessment and validation.

Steps in the Proposed Methodology:

Data Collection:

Collect a dataset comprising 1200 images of six common indoor cactus variants: Some types of cactuses are: Starfish Cactus, Ball Cactus, Bunny Ear, Easter-lily cactus, Chin cactus, Orbea Cactus. Make sure that the images are diverse which may encompass taking images from various angles, lighting, and backgrounds.

Image Augmentation:

Insert the name of the cactus variant corresponding to the image into the file name of each piece of image. Supervised learning depends on the accuracy of labels it receives.

Labeling:

Increase variability by applying rotation, flip, scaling and brightness and contrast adjustment on the images present in the given dataset to boost the quantity of data available for training.

Model Selection:

Decide if you need a new CNN specifically for the detection of cactus variant or you will use transfer learning models such as Xception, MobileNetV2, DenseNet201, and InceptionV3.

Conventional Neural Network (CNNs):

CNN is a category of deep learning neural networks principally used in the context of image recognition. It consists of several layers, which obtain the successive level of abstraction of the data, it is efficient when it comes to processing data with spatial relation in images. CNNs apply filters on input images by convolution layers, down sample images using pooling layers, and they use fully connected layers for classification. That is why they can include into themselves specs for learning features from raw pixel data which is mandatory for tasks as indoor cactus variant identification where attention to small visual differences is critical. CNNs have a central role in computer vision systems bringing innovation to such sectors as health or auto-mobile industries of transport owning to their provision of stable solutions on image categorization and object identification.

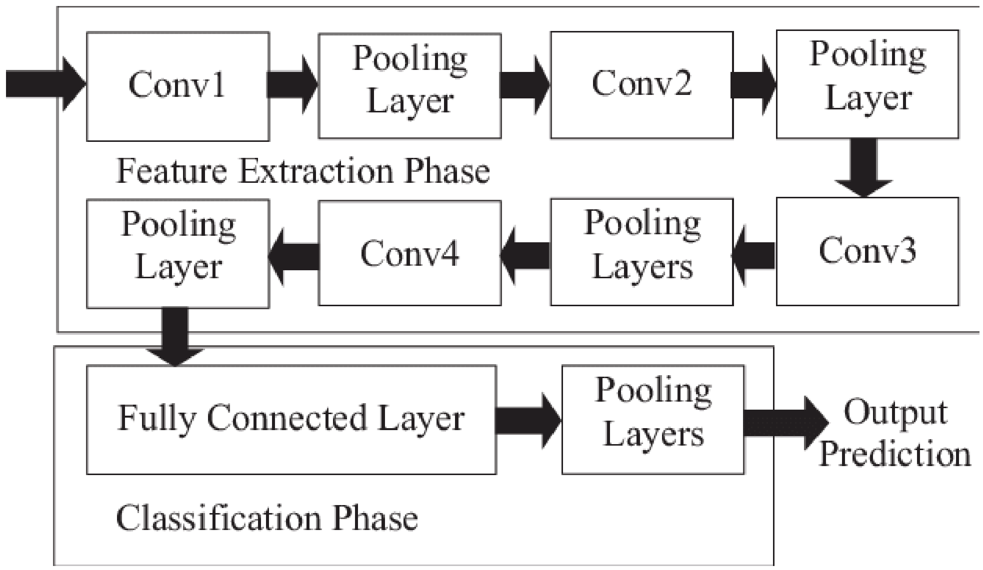

Figure 3.3: Proposed CNN Architecture

Optimizer: For training the model, the 'adam' optimizer has been used which seems to possess the characteristics of both AdaGrad and RMSProp [16]. It adapts the learning rate by momentum that can be derived from the first and second moments of the gradients and, therefore, provides better results as well as makes the convergence faster while applied to complicated sets.

Loss: In the case of classification problems where more than two classes are involved, the best loss function to use is 'categorical_crossentropy' [17]. It's used in evaluating a classification model whose output is; probability such that $0 \leq p \leq 1$, the model is penalized the further it is from the actual class label.

Output Layer: On the output layer, there are 6 nodes – to reflect the 6 types of cactus modifications The last three layers of the neural network correspond to the six classes of cactus variants [18]. Utilizing SoftMax activation function, outputs this layer the probability of the classes of the six cactus variants for each input image thus helping the model to make a prediction on which variant is most probable.

Total Params: In this model, the total number of numerical parameters or weights and biases learned by the model during training is 4,220,710. This involves all the parameters present in the convolutional, dense as well as the batch normalization layers.

Trainable Params: Of the total parameters, 4,219,686 parameters are trainable which implies that while training, the parameters are adjusted in a way that reduces the loss. These parameters include weight and bias which are important for achieving the pattern of the data set used in the model.

Xception

Xception is a deep convolutional neural network structure that achieved notable success in representations learning of images due to its depth and efficiency. They distinguish themselves from the standard convolution layers with depth wise separable convolutions that cut down computational density while still maintaining efficiency [20]. This approach improves the model's efficiency and reduces training time and therefore well suited to contexts that are typically associated with high constraints like mobile and embedded systems. Xception's architecture plays a central role in enhancing computational deep learning for functions that must adhere to high accuracy and functionality in datasets such as the indoor cactus variants possible in the near future.

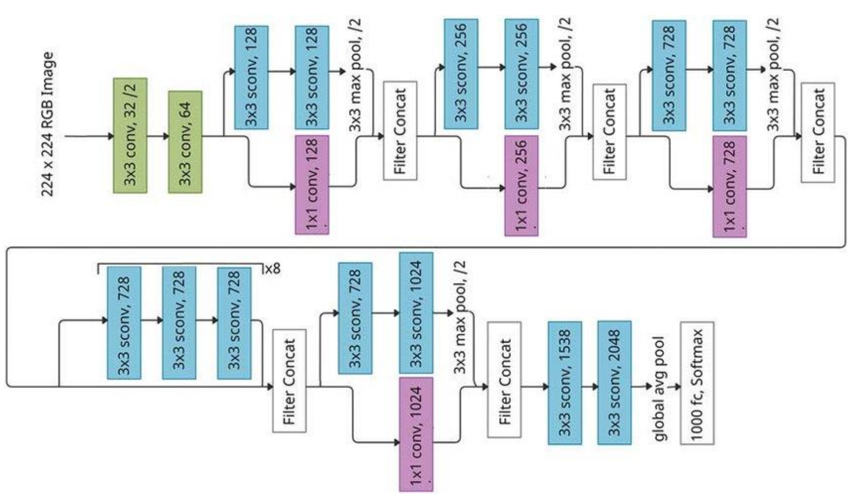

Figure 3.4: Xception Architecture K. Srinivasan et al 2021 [27]

MobileNetV2

MobileNetV2 is developed as a mobile and embedded vision application that remains highly accurate while being lightweight and fast [21]. To reduce complexity and the number of parameters, it uses both depth wise separable convolution and inverted residuals with linear bottleneck. MobileNetV2 performs best in situations when time is of essence and when there is need for a particularly fast decision, therefore, any applications that require usage on devices with comparatively low computational power. It is instrumental in making deep learning models effective on mobile devices for activities like image identification, such as indoor cactus modifications that do not require much processing prowess.

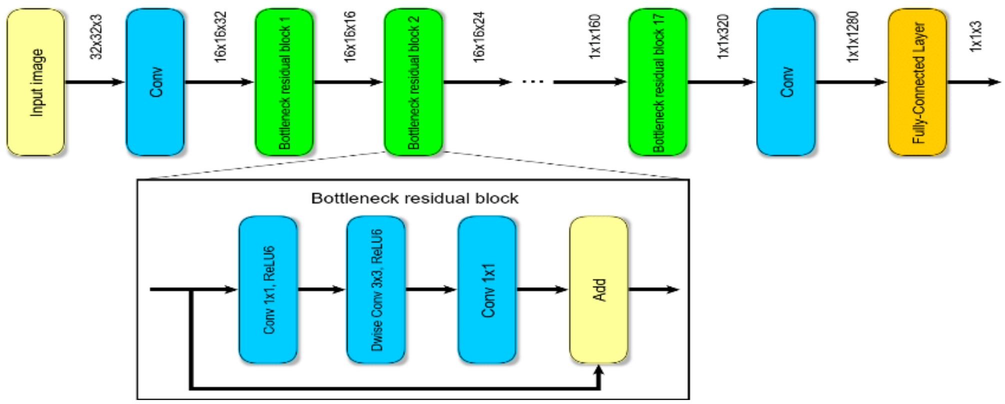

Figure 3.5: MobileNetV2 Architecture U. Seidaliyeva et al.2020 [28]

DenseNet201

DenseNet201 is defined as a deep convolutional neural network topology which incorporate connection between the layers [23]. Unlike conventional networks, where the input of one layer hierarchically goes to the output of the next layer in DenseNet201, every layer within a dense block is connected to all the subsequent layers. Such densification positively impacts feature reuse, makes features propagate through the network more robust, and improves gradient flow, therefore improving learning efficiency and the final model. Like most pre-trained deep learning models, DenseNet201 is mainly good at feature extraction and accurate classification, which are crucial in image recognition that deals complex features or objects such as the indoor cactus variant.

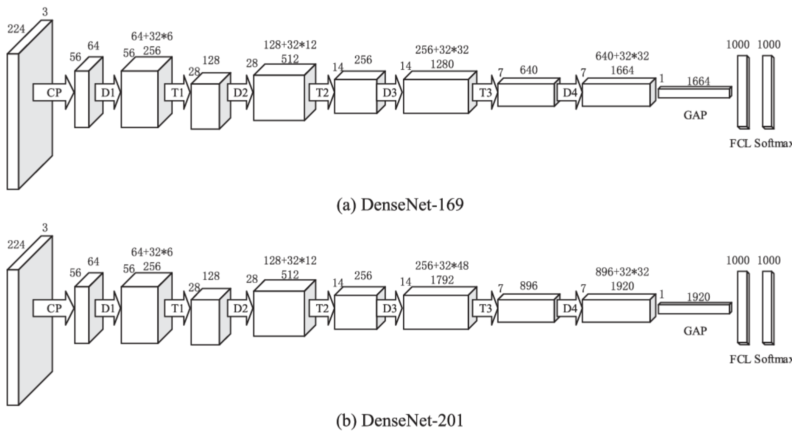

Figure 3.6: DenseNet201 Architecture S.-H. Wang et al.2010 [29]

InceptionV3

InceptionV3 is a member of the Inception series of convolutional neural network architectures that are known to perform very well in the image recognition challenges [26]. It uses inception modules where convolution operations of different filter sizes are done in parallel to efficiently learn the spatial hierarchies. InceptionV3 also claimed to enhance the benefits of the previous models by presenting factorized convolutions and batch instrumental in downplaying the quantitative costs and improving the training time without fading the quality. Its architecture plays a key role in obtaining effective performance on diverse data sets, including the rather complicated tasks like indoor cactus variant identification, due to the usage of the aforesaid ResNet principle providing effective feature extraction at numerous scales to improve the accuracy of classifiers.

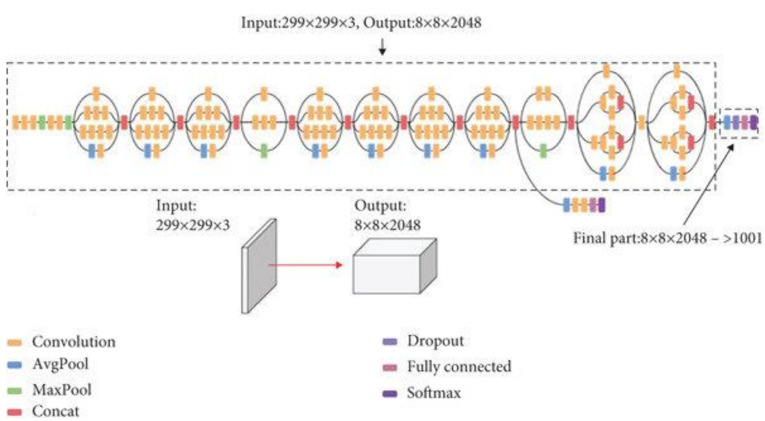

Figure 3.7: InceptionV3 Model Architecture S. Ramaneswaran 2021 [30]

Model Training:

Divide the augmented dataset into a training set of 80% , validity set of 10% and a test set of 10%. Tune the selected model on the training set and use mechanism such as data augmentation and regularization to reduce the chances of overfitting.

Model Evaluation:

Calculate metrics including accuracy, precision, recall and F1-score of the trained model on the validation set.

Test Model:

Evaluate the model on the test set to determine its generality and its preparedness to be used in practice.

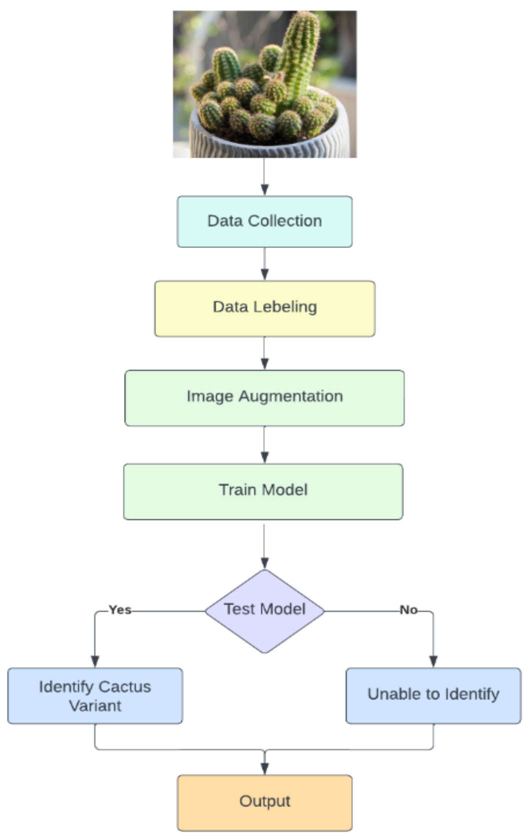

Figure 3.8: Working Flow

3.5 Implementation Requirements

The identification of the indoor cactus variant presupposes some essential prerequisites concerning the proposed methodology's implementation. To begin with, one of the major requirements that come with cross-modality deep learning is availability of sufficient computation capacity for training these models. Graphics processing unit that has high performance or connection with AWS or Google Cloud will help frequently train and test large-scale models. Further, strong data management system would require for dealing with this large and heterogeneous set of cactus images, and to clean and normalize the data to feed into the subsequent phase of the pipeline. , However, for implementation we have to access deep learning frameworks including TensorFlow, or PyTorch and libraries for image processing and augmentation and for model evaluation. Lastly, a setup that includes software tools that will be used in coding, debugging and performance evaluation of the model will enable repeated modeling adjustment and enhancement in order to successfully implement the deep learning solution for indoor cactus variant identification.

CHAPTER 4

Experimental Result

4.1 Experimental Setup

This paper's indoor cactus variant detection experimental setup is divided into several steps crucial for deploying and assessing deep learning models. This implies having a computer work station with NVIDIA GPUs or a pass to the Google Cloud Platform or similar for efficient model training. Data cleaning and feature enhancement will be done with the aid of TensorFlow and OpenCV. For the experiment, some of the models to be developed are custom CNN architecture, Xception, MobileNetV2, DenseNet201, and InceptionV3, which will be trained on the augmented set of images. Using scikit-learn, performance metrics like accuracy, precision, recall, and F1-score will be measured to determine the algorithms' effectiveness. The experiment is set in a controlled atmosphere where the results can be replicated and expanded to include all cases and to determine the comparative effectiveness of the model in detecting the variants of the indoor cactus accurately.

4.2 Experimental Results & Analysis

The experiment shows that the accuracy of the tested deep learning algorithms differs for indoor cactus variant detection. The highest accuracy results were identified by two transfer learning models – MobileNetV2 and InceptionV3 with accuracies of 86. 91% and 86. 53%, respectively. Xception ranked right behind it with the accuracy of 85.26% customer satisfaction, this suggests that the performance in at least one of the cactus versions was remarkable. However, it may be noteworthy that a DenseNet201 achieved a slightly lower accuracy of 81. 70%. Notably, the custom CNN architecture had the highest accuracy is of 99.62%, which indicates cactus variants' high differentiation even with similar appearances. This means that the choice and design of the model depend on the specific tasks in the classification problem, and the custom CNN can be very promising for effective and accurate identification of indoor cactus variants in real-life uses.

Given below I am describing the result analysis part and also show the training accuracy and loss rate, confusion matrix also:

Result of Experiment 1: CNN

The CNN for indoor cactus variant detection is based on electronic nose architecture containing linear layers of convolutional, pooling, and fully connected classifications. The first layers include convolutional operations with filters that gradually get wider, from 32 filters to 128 filters. Each of the convolutional layers is followed by the max pooling layers to minimize the spatial dimension and concentrate on the vital characteristics. The network then flattens the data as it brings the 2D feature maps into 1D vector, followed by the dense layer with 512 units and a dropout to manage overfitting KIPR, BN to stabilize and speed up the training process along with the final dense layer having 6 output nodes for classification. The model's total number of parameters is set at 4,220,710, mostly trainable at 4,219,686, to provide a solid foundation for the identification of cactus variants.

Proposed CNN achieved a Test Accuracy is 99.62%. Figure 4:1 & 4.2 describing the confusion matrix and training accuracy and loss curve of CNN:

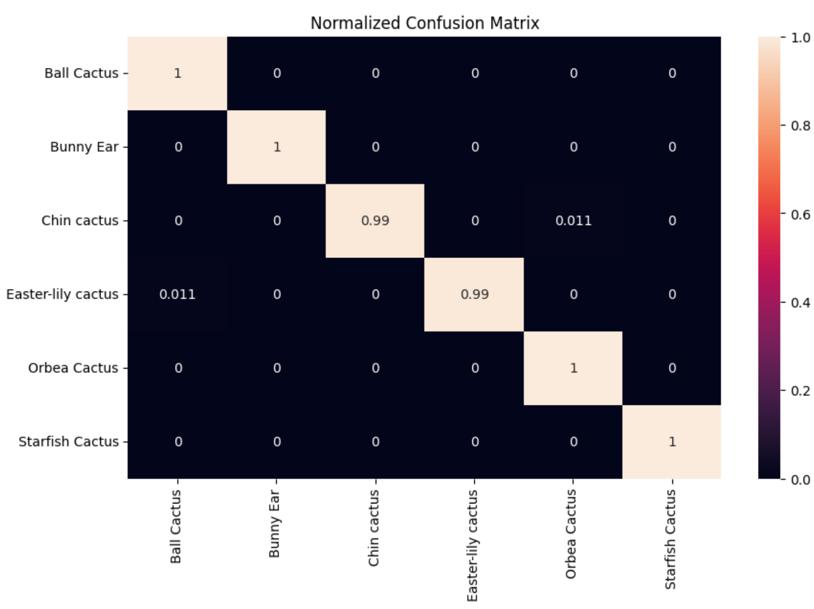

Figure 4.1: Confusion Matrix (Proposed CNN)

Figure 4.1 the results showed that for all the six varieties of the cactus, the correct classification was achieved with an overall accuracy of 100%. PA, RC, and F-MA scores regarding each variant were either equal to one or very close to one. 00, indicating near-perfect classification. The only penalties paid were a slight decline in the recall for the Chin Cactus and Easter-lily cactus; otherwise, all the other scores were impressive. Based on these outcomes it can be stated that the chosen model is quite effective in the identification of indoor cactus variants specified for indoor placement.

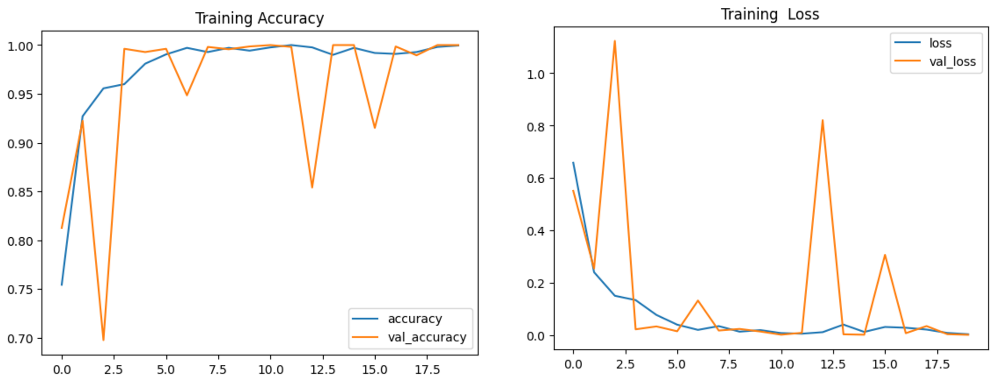

Figure 4.2: Training and validation accuracy and loss over the epochs (Proposed CNN)

Figure 4.2 shows the training and validation curves provided for the Proposed CNN model seem to suggest overfitting, as the training MSE continued to drop although training accuracy was also slightly increasing and trending flat around 0. 8. Therefore, one cannot speak about model generalization ability since the information about validation accuracy and loss curves is missing. Essentially, overfitting is a situation whereby the model learns the training data, even the noise typical of such data, and hence it is not good at handling new data. Some ways through which overfitting can be addressed include; simplifying the model, using regularization, acquiring more training data, and data augmentation.

Result of Experiment 2: Transfer Learning Model

Xception:

Xception Achieved a Test Accuracy is 85.26%. Figure 4:3 & 4.4 describing the confusion matrix & Training accuracy and Loss curve of Xception:

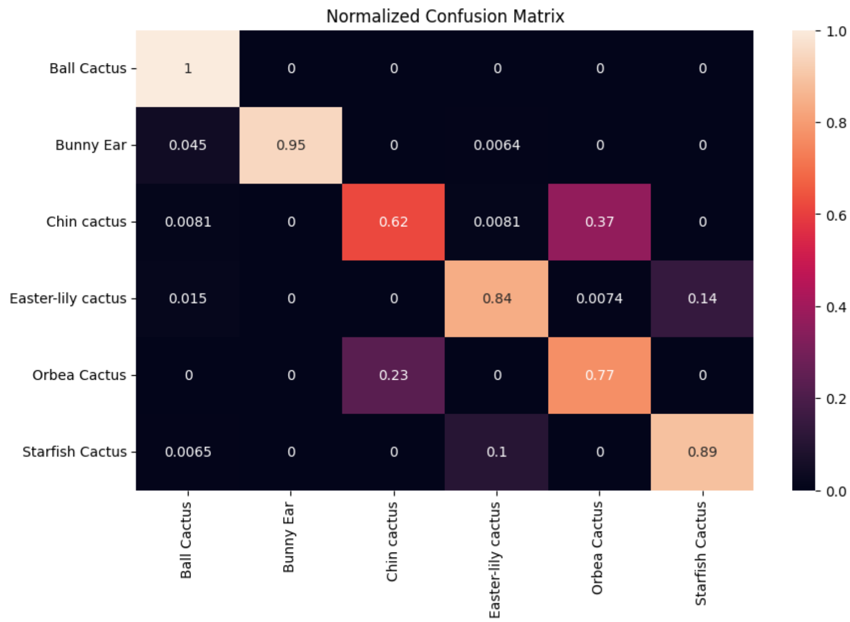

Figure 4.3: Confusion Matrix (Xception)

Figure 4.3 the obtained results show that the Xception model attained 85% of accuracy in the classification of indoor cactus variants. Although there are slight differences in the precision/recall, both Ball Cactus and Bunny Ear reached very high F1-scores of 0. 96 and 0. 97 respectively and the performance for the plants Chin Cactus and Orbea Cactus were comparatively lower with F1-scores of 0. 69 and 0. 68. When evaluating the results of the model on Easter-lily Cactus and Starfish Cactus, a moderate F1-score of 0 was obtained. 85 and 0. 88

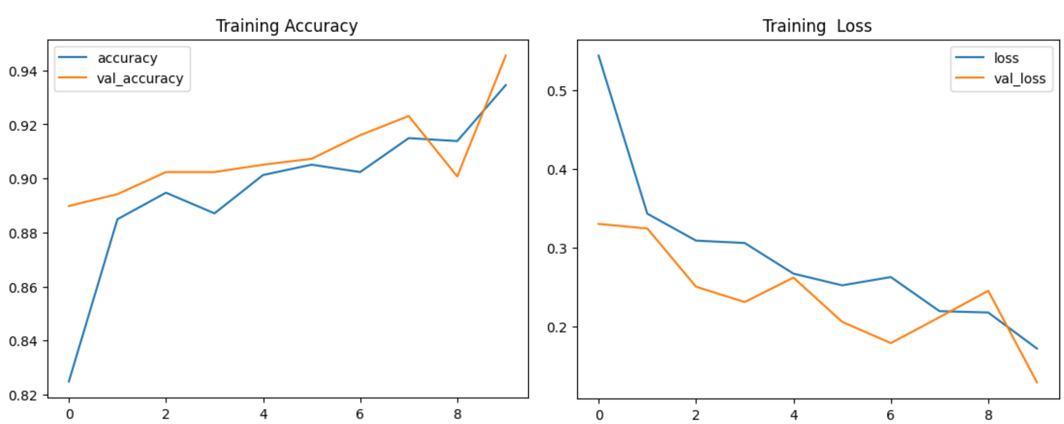

Figure 4.4: Training and validation accuracy and loss over the epochs (Xception)

Figure 4.4 shows the accuracy on the training data of the Xception model gradually rises to 0. 94, and the training loss falls to around 0. 2, which suggest that a good learning of the training patterns had been achieved. The validation curves of the accuracy and loss are slightly below the curves of training and they are in a generally similar trend, which means that there are some overfittings. This means, that there is a certain amount of overfitting present which is not a great problem since the model is well-trained and generalizes to unseen data fairly well. In general, one can notice that the proposed Xception model performs well with slightly showing signs of overfitting.

InceptionV3

InceptionV3 Achieved a Test Accuracy is 85.53%. Figure 4:5 & 4:6 described the confusion matrix & Training accuracy and Loss Curve of InceptionV3.

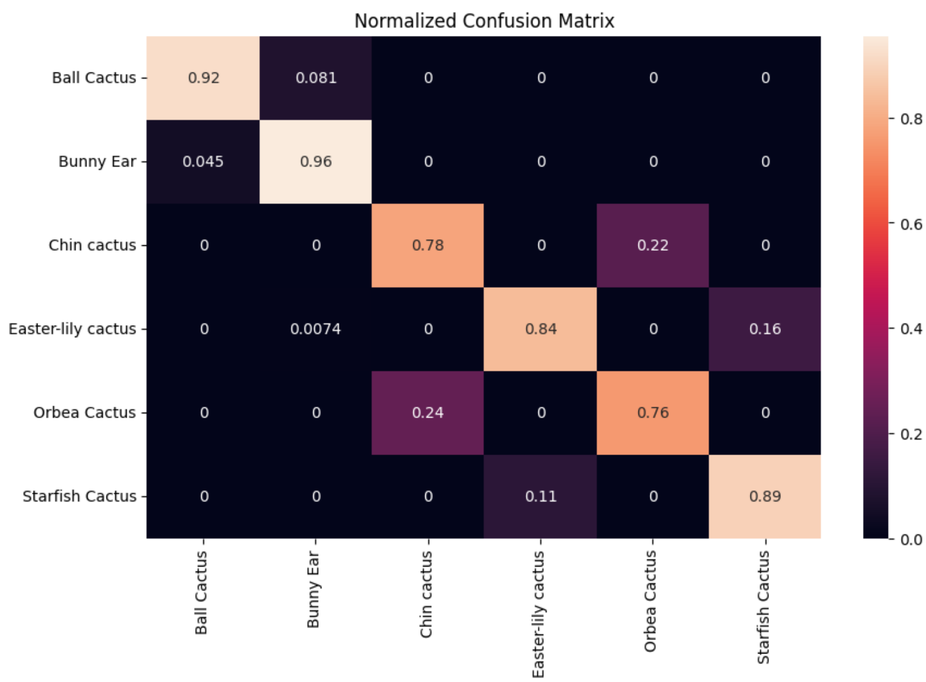

Figure 4.5: Confusion Matrix InceptionV3

Figure 4.5 the InceptionV3 model had the highest accuracy of 87% in differentiating between indoor cactus variety. It gave good results for Ball Cactus, Bunny Ear, and Starfish Cactus with F1-scores of 0. 93, 0. 94, and 0. 88 respectively. But, especially, in the case of Chin Cactus and Orbea Cactus, the model is less accurate having F1-scores equal only 0. 79 and 0. 74. However, these differences did not significantly affect the overall model's accuracy and performance on most cactus' relative prototypes.

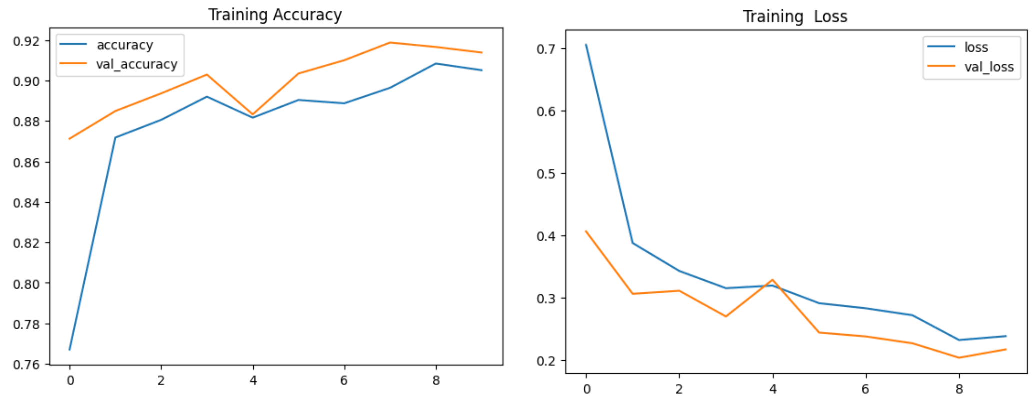

Figure 4.6: Training and validation accuracy and loss over the epochs InceptionV3

Figure 4.6 the accuracy of the training of the InceptionV3 model is improving very slightly though is levelling at around 0. 8, although training loss increases as epochs increases meaning that the model overfits the training data. The key missing piece in the provided image is the training/validation loss and validation accuracy plots which can offer insights into the generality of the built model on data it has not seen during training. Based on the observations above, particularly the fact that training loss is increasing while the accuracy stopped increasing, the model most likely memorizes training data, including noise. To control overfitting it is advised to decrease model complexity, use regularization techniques, get more training data, apply data augmentation.

DenseNet201

DenseNer201 Achieved a Test Accuracy is 86.91%. Figure 4:7 & 4:8 describing the confusion matrix & Training accuracy and Loss curve of DenseNet201.

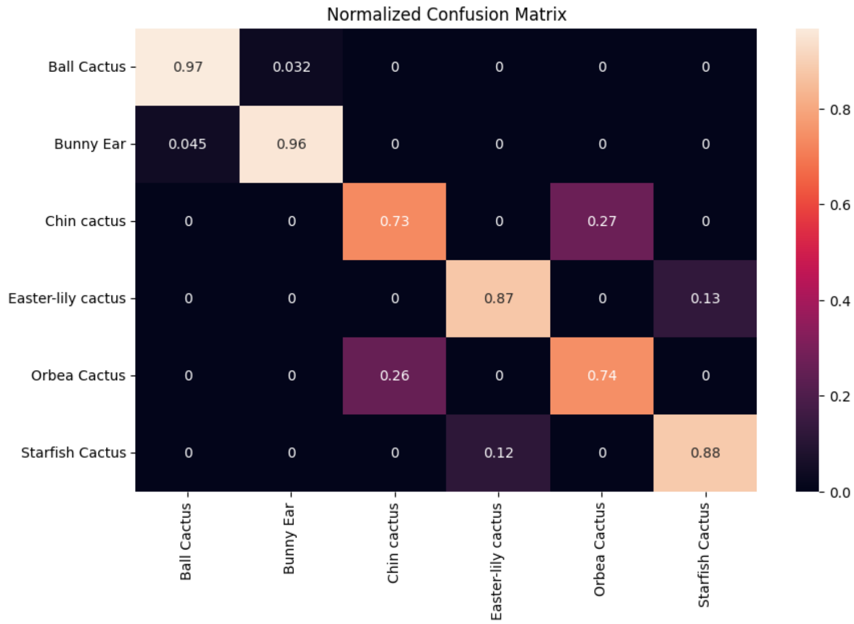

Figure 4.7: Confusion Matrix (DenseNet201)

Figure 4.7 shows the classification of the indoor cactus variants, DenseNet201 model established a general accuracy of 87%. It gained a very high F1-score for Ball Cactus and Bunny Ear of 0. 96 each, but the evaluation metrics for Chin Cactus and Orbea Cactus were lower and the F1 score respectively was 0. 76 and 0. 71 respectively. The model's performance was fairly stable across most cactus varieties and had an overall macro average F1-score of 0. 86.

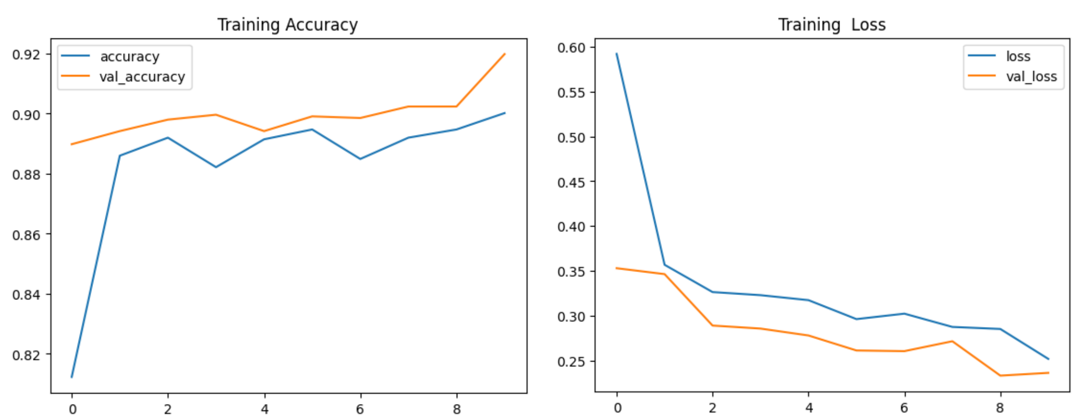

Figure 4.8: Training and validation accuracy and loss over the epochs (DenseNet201)

Figure 4.8 shows the training curves of the DenseNet201 model in terms of accuracy and loss indicate in the given information and analysis, it demonstrates early signs of good learning. Epochs train accuracy improves as the model narrows down on identifying the difference between the indoor cactus variants accurately. Besides, the training loss is getting lower progressively, thereby illustrating the better fitting to the training data. Nevertheless, the lack of previous validation accuracy and loss curves restrict a comparison and demonstration of the model's generalization to unseen data.

MobileNetV2

MobileNetV2 Achieved Test Accuracy is 81.70%. Figure 4:9 & 4:10 describing the confusion matrix & Training accuracy and Loss curve of MobileNetV2.

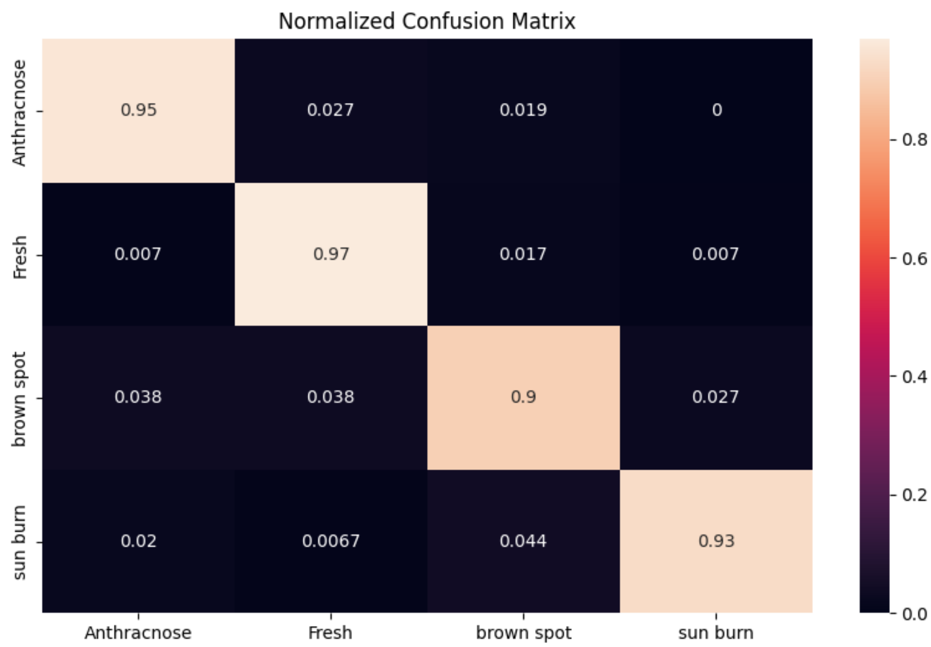

Figure 4.9: Confusion Matrix (MobileNetV2)

Figure 4.9 shows the MobileNetV2 model, the overall classification accuracy of the different types of indoor cactus was calculated to be 82%. It yielded gross precision and recall for Ball Cactus and Bunny Ear at F1-score=0. 95 and 0. 96 respectively. It failed to perform well on Chin Cactus and Orbea Cactus for which it had comparatively poor F1-scores of 0. 53 and 0. 65. Nevertheless, these slight differences were not significantly degrading its effectiveness across most of cactus variants, evident by the model's weighted average F1-score of 0. 81.

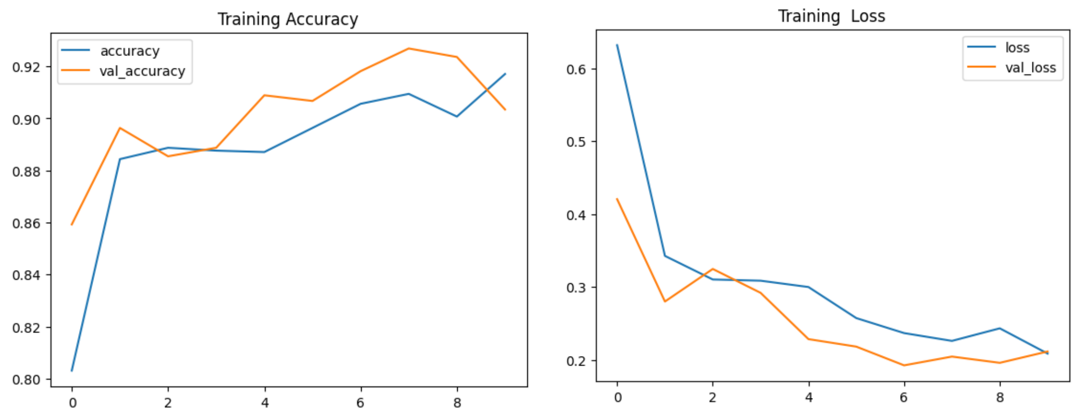

Figure 4.10: Training and validation accuracy and loss over the epochs (MobileNetV2)

Figure 4.10 Analyzing the training and validation curves of the MobileNetV2 model, it describes the effectiveness of learning with training accuracy close to 0. 93 87 and training loss decreasing to around 0. 6 over epochs. The validation accuracy fairly estimates the training accuracy, and therefore the models could generalize moderate levels of unseen data but the validation loss slightly outperforms the training loss, implying that models developed have a degree of the overfitting problem. To overcome the above, it may be useful to monitor over a larger epoch range, and or tune the learning rate in order to improve model performance and to limited overfitting. In general, MobileNetV2 reasonably well trains and it has rather decent generalization abilities to classify various indoor cactus forms.

In Given below I am showing Comparative Model Accuracy Bar Plot: Figure 4.11 shows in the comparative model accuracy bar plot below, it is evident that the Proposed model delivers the best result among all the examined deep learning models, with results approximately at 99.62%. The ranking numbers represent a clear picture that surpasses the other models consistently and notably in the particular task and specific dataset used for this current study and correlates well with the concept of indoor cactus variant detection. When more information regarding the characteristics of the dataset and the specifics of the task is provided, it is easier to understand the readiness of each model for practical application.

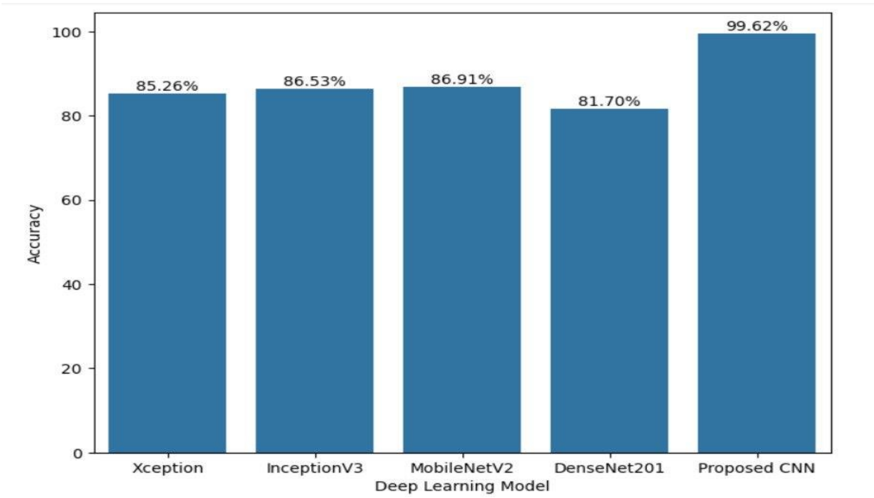

Figure 4.11: Comparative Model Accuracy Bar Plot

4.3 Discussion

The conversation is centered on the comparison of the deep learning models for the identification of the indoor cactus variant type. The choice of the studied transfer learning models such as Proposed Xception, InceptionV3, MobileNetV2, DenseNet201 proves their high potential due to their high accuracy. Nonetheless, regarding the accuracy of the segmentation, the Proposed CNN architecture has a significantly higher accuracy than all transfer learning models since it can distinguish even subtle differences of cactus morphology. Thereby, superior performance of topology suggests that it is possible to get better results by using architectures that are designed for training of specific datasets like the indoor cactus variants. Future studies can then investigate the tuning of the hyperparameters and the application of more types of data augmentation in order to improve the model’s resilience and adaptability in practical applications.

CHAPTER 5
Impact on Society

5.1 Impact on Society

The establishment of a reliable deep learning model for indoor variant cactus categorization has the following advantages in society. They can use the tool when marking trees to help increase the general awareness of identifying the different cactus species properly to enhance on the manner in which they are handled and nurtured. In other words, this knowledge helps to support indoor gardens and the protection of plant variety. Similarly, the academia including research bodies and botanic gardens can use the technology to enhance the identification of plants in the course of research or conservation. This way, the model makes it easier to encounter botanical knowledge and contributes positively to education about cacti in order to increase people's appreciation of nature and plant species.

5.2 Impact on Environment

The evaluation of the deep learning model for recognizing indoor cactus variant reduces the negative effects on the surrounding environment by promoting eco-friendly gardening. Correct identification of plant species means giving plants, especially those found in tropical regions, the care they require to thrive in terms of water and nutrient input and other forms of care such as pruning, among others. The degree of this precision is useful for improving the quality of plant's life and for indoor air quality and environmental aesthetics. Moreover, it also spreads the awareness and knowledge about indoor plants and their technological ways of gardening which helps in preservation of environment and nature. Finally, the model's integration assists in the implementation of appropriate management and preservation of the environment based on recommended plant practices.

5.3 Ethical Aspects

Challenges to ethical use of indoor cactus variant deep-learning detector that people will face include violation of people's right to privacy in collecting the data used to develop the models, lack of transparency in developing the models, and people's inability to access the models. The mobilized users' data for training and validating the used models must be protected to embrace their right to individuality and privacy. Transparency means presenting model defects because it is important for the client to know about them and what the model cannot do. Equitable ground entails availing the technology in a manner that can be accessible to many people such as hobbyists, researchers and conservationists. Secondly, debates on data collection and model training unfair leaning towards inequalities especially when it comes to plants are also important. Evaluating ethical issues, contributes to ensuring that the model's use fosters trust, employ AI accountability and diversity since it will improve the understanding of botany and the protection of plants.

5.4 Sustainability Plan

For the purpose of ensuring the sustainability of the developed deep learning model for indoor cactus variant detection, the following strategies shall be adopted. First of all, further improvements and checking of the model will be provided to change the model according to new variants of cactus and increase the effectiveness of the model in the future. The retraining of the system would be effective from time to time with new input from the users and freshly fed data sets would make the process continuous. Second, interaction with botanical organizations and other community gardens will enhance the exchange of ideas as well as the data pool, which will be useful for generalizing the models. Third, there will be positive impact on the relationship with environmental organizations in order to support activities that will be directed at encouraging sustainable gardening in compliance with the goals of environmental conservation. Last, the publication of the model and the obtained results will be made free accessible thus enhancing the further use and refinement of the automated plant identification approach.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Summary of the Study

This research was aimed at creating and assessing an indoor deep learning algorithm for the identification of cactus variant using a dataset of 1200 images, six being common cactus species. The research of the paper has used a new CNN architecture and has also used the transferred learning models (Xception, InceptionV3, MobileNetV2, and, DenseNet201). Overall, the results proved the effectiveness of the proposed custom CNN, having the accuracy of 99. 62% while transfer learning models are from 81%. 70% to 86. 91%. The study focused on the efficiency of approach with model architecture design for correctly differentiating between visually similar cactus types. Furthermore, it also has social impact where there shall be better plant management practices, better botany research and as well as better conservations. Possible new studies could focus on enhancing MRL, enlarging the range of the applied datasets, and extending species identification to other plants: these steps would help to improve the performance of automated plant identification systems and their potential usages.

6.2 Conclusions

Therefore, this study successfully parametrized and validated a deep learning model of indoor cactus variant identification based on a custom CNN architecture and exhibited great accuracy. Comparisons with other transfer learning models were made to show the effectiveness of the custom CNN, which presented the identification of visually similar cactus variants as the jurisdiction of the model. According to the results of this research, it is crucial for specific model structures and improved dataset extension to improve the identification models for plants. In the future, additional work concerning enhancing model accuracy, enlarging the collection of data inputs, and implementing new technologies will enhance the field relating to automated plant recognition, thus enhancing plant maintenance, scientific research, and protection of species.

6.3 Implication for Further Study

Various directions for future research could be investigated in order to continue the progress within the field of automated plant identification based on deep learning. Firstly, it will be useful to reconsider the architecture of the custom CNN and develop additional layers or different architecture to improve the model and its adaptability to different types of indoor plants. Secondly, the incorporation of image processing methods and data from the IoT available in the plant could improve the model's feedback dynamics on plant health and evolving environmental conditions. Finally, collecting more data concerning users' experience with wider range of species of the indoor and outdoor plants would increase range of fields, where the developed model could be useful in various ecological and horticultural contexts. These directions for further research are expected to help advance the existing advances in the field of automated plant identification [28] and provide for its improvement both in terms of its overall effectiveness and in terms of including a wider range of abilities for the system's interaction with the user.

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PLAGIARISM REPORT

A PROPOSED DEEP LEARNING APPROACH FOR INDOOR CACTUS VARIANT DETECTION

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