AN ADVANCED DEEP LEARNING APPROACH FOR CAT BREED CLASSIFICATION

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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 "An Advanced Deep Learning Approach for Cat Breed Classification" submitted by **Tanni Das and Rumanna Aktar Rumu** 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 14th July, 2024.

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ABSTRACT

In this paper, an improved deep learning method is proposed to recognize the cat breeds with high accuracy and high CNN structures. The dataset, sourced from Kaggle, comprises 2,557 labeled images across four distinct cat breeds: These breeds include Ginger Cat, Bombay Cat, Bengal and Sphynx Cat. The primary objective was to evaluate and compare the performance of five deep learning models: Xception, CNN, VGG19, MobileNetV2, and InceptionResNetV2. Comparing the efficiency of all models the MobileNetV2 model reached the highest accuracy reaching the mark of 99.87%. This efficient architecture appropriate for mobile and embedded platforms outperformed other algorithms of its kind in feature extraction and learning engineer fine features necessary to differentiate between cat's breeds based on their visual cues. This was followed by data preprocessing steps such as normalization and augmentation, to improve variability of the developed datasets and model. The use of transfer learning from pre-trained models, especially from ImageNet, also aided in faster convergence and superior performance across all the models under analysis. The presented results demonstrate the effectiveness of the most sophisticated deep learning methods in attaining a high level of conclusive accuracy to classify the cat breeds and their appearances accurately. The findings of this study provide necessary and useful knowledge for practicing veterinarians, authorities, pet shelters, agencies, and others in the use of AI techniques in the processing of veterinary diagnostics, care, pets' adoption, and shelters. Future research could investigate pooling techniques and the use of higher and a more diverse amount of data to increase accuracy and the scope of the classifier's utilization.

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CHAPTER 1
INTRODUCTION

1.1 Overview

The identification of cat breeds is a sophisticated task in the field of Computer Vision and Deep Learning because it is often difficult to tell two breeds apart based solely on looks. It also means that methods for breed identification and classification including Ginger, Bombay, Bengal, and Sphynx cats must be framed in an advanced way that can differentiate these subclasses. It has been elucidated that the use of deep learning especially CNN had been efficient in such situations. This methodology unites contemporary models of neural network such as Xception, VGG19, MobileNetV2, InceptionResNetV2 to increase the accuracy of classification and speed up the process R. Zhang et al. [5] Thus, one of the primary advantages of the deep learning models is that they are able to extract more detailed features from images without the need of defining them in advance. From Kaggle, a diverse dataset is obtained with 654 Ginger Cats, 650 Bombay Cats, 629 Bengal Cats, and 624 Sphynx Cats, thus making the training efficient and the model highly effective Anugrah Tri Ramadhan et al. [6] The first step involves data gathering and categorization into appropriate targets, the next step involves trying different image preprocessing techniques on the images to make them friendly to the parameters before setting the training process. We next apply transfer learning for which large pre-trained models on other large datasets are used to speed up and improve the training process. Using these models adjusted for our classification purpose offers an advantage of learning from existing knowledge and performance is improved Tita Karlita et al. [7] The accuracy test, precision, recall, F1-score test, and confusion matrix help in proving that the model built is accurate in its results. The last process is the evaluation of the model's performance on a completely different data set for determining generality and then using the model in practical scenarios. Mahardi, I-Hung et al. [8] This improved method of deep learning is focused on constructing a reliable system for identifying cats' breed with a goal to enrich the knowledge base for veterinary medicine, animal shelter, and pet search.

1.2 Background and Present State

Before going deeper into the concepts of cat breed identification using deep learning, it is crucial to first understand the basics and historical information. This section aims at defining the deep learning, the Convolutional Neural Networks (CNNs) and focusing more on its uses while performing image classification. Deep learning is a branch of machine learning where these neural networks are composed of many layers that try to learn representations of the input data in form of layers. CNNs to which are proposed for analyze visual data has dramatically improved the image recognition tasks through convolutions and pooling. The use of these architectures has been fairly successful in numerous fields such as medical imaging, self-driving vehicles, and natural language processing. It is necessary to comprehend these concepts since they serve as a foundation upon which highly elaborate models can be constructed for the accurate classification of cat breeds as a function of their visual traits. To achieve these goals, previous works based upon these principles were used as a reference for this current study to examine and implement more sophisticated approaches in breed categorization.

1.3 Problem Statement

The importance of this study is rooted in the actual potential of achieving improved cat breed identification using the most effective and modern methods of deep learning systems. Old techniques of breed identification are more reliant on observers' subjectivity and can be riddled with mistakes that affect veterinary practices, animals, and breeding projects. That is why it is possible to free from these shortcomings by building a sound automated classification system with the help of the most efficient neural network structures like Xception, VGG19, MobileNetV2, and InceptionResNetV2. The objective of this study is to advance the breed identification using deep learning to ensure the accuracy and consistency is achieved to support the animals' care and management. The employment of a wide range of general data and a large set of evaluands increases the model's accuracy and applicability, which will make it relevant to professional practice in a vast area associated with animal science and pet keeping.

1.4 Objective

The reason for building an improved deep learning model for classifying cat breeds is due to lack of highly effective systems to identify cat breeds. Thus, it is rather important to identify breeds with precision, applying this knowledge in veterinary medicine, animal shelters, individual pets, gene line selection, etc. Some of the older approaches to contact lens assessments entail observation and interpretations from a human perspective that are impartial and riddled with a variety of errors and inconsistent results. This brings us to another topic: by employing deep learning with CNN and such complex architectures as Xception, VGG19, MobileNetV2, and InceptionResNetV2, the classification becomes subjects to the AI's control and optimum. These models have the ability to learn the variations of pictures as well as the features or patterns inherent to the images thus improving the identification of breeds. It also assists various professionals that deal with animals making the care and management of different cats breeds more efficient. Hence the proposed procedure as a middle ground from the conventional methods and advanced technology that would help in solving for the accurate classification of cat breeds with sufficient reliability.

1.5 Scope and Limitations

Scope of this study is the development of a very accurate and reliable cat breed classification model enriched with features that would allow it to separate Ginger Cats, Bombay Cats, Bengal Cats, Sphynx Cats, or all other breeds for that matter. The constructed model should provide high indices of such parameters as accuracy, precision, recall, and F1-score that are interpreted as the model's credibility and efficacy. Based on my expectation, the deep networks such as Xception, VGG19, MobileNetV2, and InceptionResNetV2, mainly when incorporated with transfer learning, will yield better results than the baseline CNNs. Furthermore, as a result of data augmentation, it is supposed that such a model will generalize well since the neurons do not learn specialized features for just a few samples, but they learn features that function well over the entire training samples' distribution. The last model will be fine-tuned on yet another test set which will further ensure that the model can be used in practice. This will be beneficial and useful to veterinary science professionals, animal shelters and other persons that care for cats or for purposes of identification on cat's breeds.

1.6 Report Organization

This report delves into the next generation of deep learning methods in cat breed classification and proposes the use of highly developed neural networks to aid in efforts to differentiate Ginger, Bombay, Bengal, and Sphynx cats. The study met the current need to increase the level of differentiation of animals in veterinary medicine and animal husbandry by demonstrating how innovations can transform the quality of pet care.

Introduction chapter outlines the aim and rationale of the study; the significance of the development of automated methods for categorizing cats by breed using deep learning frameworks. Backgrounds study chapter summarize the findings of previous literature on deep learning, CNN architecture, and the image classification app that has similarities to the cat breed identification. Research Methodology chapter describes how the process of the work was performed in terms of data acquiring, data preparation, the choice of the most suitable model, common training techniques, and the technique of the model's evaluation. Experimental Results chapter displays the results of performing the deep learning models such as Xception, VGG19, MobileNetV2 and InceptionResNetV2, along with the performances comparison. The Impact on Society chapter describes possible consequences of proper classification of cats' breeds in veterinary practices, animal protection, and in the process of adoption of cats, noting those positive to society. Conclusion, Recommendations, and Implications for Future Research chapter finally presents the highlights of the findings, make conclusion on the basis of the results, provide suggestion for using the result in the real word and reveal the potential perspectives of further study in the subject.

1.7 Summary

Chapter one presents the background information focusing on the significance of identification of cat breeds for purposes of treating ailments, conducting research, and in taking care of the pets. Two of the refinements it focuses on are the present development of complex classification techniques and the hltd's inherent inability to accomplish simple classification. The chapter begins with the topic of deep learning and establishes its working by noting the accomplishment of the concept in image recognition. It then defines the study's objective to employ the contemporary deep learning models such as CNN, Xception, VGG19, MobileNetV2, and InceptionResNetV2 for classifying four types of cats. In the end, the chapter lays down the research problem, the data employed in the research, and the expected theoretical contribution of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The literature review chapter of the current study aims to establish what has been said in the existing literature about cat breed classification and fields of study that are related to it. They go through the customary approaches towards image classification and their disadvantages, thus continuing with the progression in learning, emphasis on deep learning especially through the CNN. The chapter demonstrate Xception, VGG19, MobileNetV2 and InceptionResNetV2 architectures focusing on how they were relevant and efficient in image recognising tasks. It also reviews prior researches that have used these models for distinguishing the animal breeds stressing on the fact of high consistency and effectiveness. Using the current study's literature, the review demonstrates that there are key gaps and explains why there is a need to carry on research in this area.

2.2 Related Works

The previous literature also reveals that previous work on deep learning on animal breed classification has good performance. This paper has cited other CNN architectures including RESNET, VGG, and Inception for use in the identification of different animal breeds from image data. Research works mostly investigate on various aspects such as the variety in the dataset, data augmentation processes, and the tuning of the models in order to enhance accuracy of classification. In given below I am describing some similar paper review which help me a lot:

R. Zhang et al. [5] working on comparative study of the deep learning models such as VGGNet, Inception-v3, and an optimized model for the prediction of cat breeds. It is seen that the accuracy achieved by the optimized model is around 84% which is higher than the others. Thus, this study contributes to the enhancement of various cat breeds identification, and, as a result, more people will be able to define the species of cats. Anugrah Tri Ramadhan et al [6] discussed a Machine Learning method to recognize cat breed by utilize Convolutional Neural Networks (CNNs) and the authors intended to deploy the system in Android phones. Three architectures, namely MobilenetV2, VGG16, and InceptionV3, were evaluated with 13 cat breeds dataset; all got a high accuracy of about 82%. As for the produced application, it will introduce the best-performing model, enhancing cat breed identification using primarily mobile devices, embedded under the brand Cabernet. Tita Karlita et al. [7] discussed the propensity of using CNNs in recognizing and categorizing cats which is rather challenging due to the large number of breeds. The system does manage to capture the picture characteristics effectively where the EfficientNet-B0 architecture with the dataset of 2700 photos of the nine breeds of cats has been established. The outcomes of this investigation demonstrate the utility of the system at the end, the increased classification ratio is up to 95%, this can represent possibilities of the accurate and automatic detection of cat breeds. Mahardi, I-Hung et al. [8] highlighted the issue of proper classification of a large number of dog and cat breeds (CDC) with the help of the good old ‘fine-tuned VGG’ models as the pictures are not limited to just the generic cat-dog. The paper adopts the VGG16 and VGG19 models and achieves highly competitive training accuracy reaching the level of 98. 47% and 98. 31%, 59% and 90% respectively I have also obtained validation accuracies of 97.6% for the assignment, 99.56% for the classification and 99.18% for the recognition. While tested with much lesser accuracies than in training and validation, the models can differentiate well between pictures of different breeds of dogs and cats; therefore, the models have the capability to be used practically in picture classification. B. Valarmathi, N. Gupta et al. [9] have provided the list of deep learning models for the successful prediction of dog breeds from the photos, namely Xception, VGG19, NASNetMobile, and EfficientNetV2M and others. The suggested hybrid models outperform the single model techniques and the current standard paradigms after rigorous testing including data augmentation as well as transfer learning and the highest validation accuracy was 92. 4%. More specifically, the best results are recorded for the architecture that includes Inception-v3 and Xception, which testifies to the effectiveness of using the given architectures for blending when recognising various breeds of dogs. P. Ghosh et al. [10] analysed the challenges to accurately and economically identify breeds in domestic animals employing deep learning which is critical in efficient farming. It says that utilizing nine deep CNN-based models, it identified that MobileNetV2 truly assists in classifying the goat breeds with 95. Perfect with 00% accuracy where InceptionV3 takes the mantle in pig breed classification with 100%. 00%. Comparative analysis points to the effectiveness of techniques based on CNN compared to traditional approaches, and the presented results support the prospects for using them as affordable and accurate solutions in the sphere of intelligent control of the cattle.

P. Borwarnginn, et. al, [11] has articulated the need and different ways that the identification of dog breeds can be used and offers a technique to a deep learning face photo. Therefore, the strategy increases the chances of classification by applying transfer learning techniques and picture augmentation techniques. The result for using three CNN architectures with different augmentation settings is positive; the achieved accuracy is 89. On a dataset of 133 breeds about 92% accuracy was achieved. This sight improves the accuracy and time efficiency for identifying breed distinctions of a dog, thus the better assessment of the characteristics and behavior of those breeds. In their study, S. Divya Meena et al. [12] presented a semi-supervised MP-CNN for identifying the animal's photograph to 27 types of breeds with high efficiency, based on a mixed set of features. Through the integration pseudo-labels implemented through two-stage semi-supervised learning, the capability of the model in categorizing of unlabeled pictures is enhanced hence strong performance. To further enhance breed classification, the misclassified classes are trained using a Modified Hellinger Kernel classifier achieving an incredible accuracy of 99. 95%. The above findings propose a comprehensive solution for locating the precise and cheap breed of any identified animal and some problems relating to picture categorization tasks. The troubles of pet insurance and pet rescue were explained by K. Chaturvedi et al. [13] using a new dataset with images of wolves and different breeds of dogs that can be distinguished by algorithms. Training models include, ResNet101, DenseNet201 and the rest; By applying the transfer learning methodologies with configured convolutional networks like, ResNet101 and DenseNet201, ResNet101 performed better and recorded a 90. 80% accuracy. The study contributes to the existing literature by establishing that deep learning algorithms can indeed be used to address the worldwide problem of missing pets and aid the rescue process while having further potential for refinement via more training data. Mahendra Kumar Gourisaria et al. [14] studied Transfer Learning and Convolutional Neural Networks (CNNs) for species recognition and for this, they have used a dataset of twenty-eight thousand images having ten animal categories. The employed networks include VGG16, EfficientNetB2, ResNet101, EfficientNetB7, and ResNet50, which were compared with custom CNNs. It was very impressive with VGG-16 surpassing expectations with a maximum accuracy of

99% and a minimal Validation Cross Entropy Loss of 0. 044 , while ensuring that practitioners and scientists are equipped with efficient methods for the successful recognition of the various animal species by the help of picture analysis. A. Mondal et al. [15] has proposed an accurate categorization of the dog breeds through the Convolutional Neural Network (CNN) based model because of the enriched utilization of deep CNN architecture. A modified-Xception is proposed with better accuracy shown in the results; the highest overall accuracy that is achieved is at 87%. 40% on the Kaggle Dog Breed Identification dataset. Thus, the study has a positive impact on the development of algorithms for classifying the breeds of dogs with using the photographs and would be interesting for practitioners as well as researchers who searches for the most accurate models in this field.

2.3 Comparison between existing works

The comparative assessment of this research compares the outcomes of four superior deep learning structures, Xception, VGG19, MobileNetV2, and InceptionResNetV2 for cat breed categorization. Both of the models were trained and fine-tuned using set of images containing Ginger, Bombay, Bengal and Sphynx cats. From the results it can be seen that both Xception and InceptionResNetV2 are more accurate and efficient than VGG19 and MobileNetV2. Xception which incorporates depth wise separable convolutions outperforms in the identification of minute details required when categorizing cats. InceptionResNetV2 that uses aspects of Inception modules augmented with residual connections turns out to be useful because it optimizes both accuracy and computational intensity. In conclusion, this paper shows the relative comparison of different deep learning structures to improve the performance of cat breed identification tasks. The paper provides a discussion on implications of the study and recommendations on the improvement of the model performance and relevance in the real world.

TABLE 2.3.1 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	R. Zhang et al.[5]	VGGNet, Inception-v3	84%
2.	Anugrah Tri Ramadhan et al.[6]	CNN, MobilenetV2, VGG16, & InceptionV3	82%
3	Tita Karlita et al.[7]	CNN, EfficientNet-B0	95%
4	Mahardi, I-Hung et al.[8]	VGG16 and VGG19	VGG19= 98.59%
5	B. Valarmathi, N. Gupta et al.[9]	Xception, VGG19, NASNetMobile, and EfficientNetV2M	92.4%.
6	P. Borwarnginn et al.[11]	CNN	89.92%
7	S. Divya Meena et al.[12]	CNN	99.95%
8	Proposed Model	CNN & Transfer Learning Model	MobileNetV2= 99.87%

2.4 Open Issues

This paper focuses on the development and assessment of innovative deep learning techniques that are particular to cat breed identification. It involves the recognition and categorization of four different cats' breed; Ginger, Bombay, Bengal, and Sphynx cats using images data obtained from images. The goal of the study is to examine on how several existing CNN architectures such as Xception, VGG19, MobileNetV2, and InceptionResNetV2 do perform in inciting high accuracy and efficiency in breed categorization. Components within the outlined domain include data pre-processing, selection of correct algorithms, training techniques, metrics for evaluating the results, and the application of correct breed identification in veterinary medicine, animal rights, and pet maintenance. It is also worthy to note that the study is in no way generalizable to other animals or even to other tasks of categorization of animals beyond the specified cat breeds

2.5 Summary

The chapter on the existing literature explores the literature on cat breed classification as well as other related image recognition procedures. It also demonstrates shortcomings in the approaches and the effectiveness of the deep learning models such as CNNs and others including Xception, VGG19, MobileNetV2 and InceptionResNetV2. Backgrounds on the previous works done on animal breed classification are discussed to show the effectiveness of the models considered here. Finally, the chapter outlines the areas that are still lacking in the extant literature, which explains the purpose of the current research. Thus, the progress presented in this review can form a basis for considering more sophisticated methods based on deep learning for cat breed identification.

CHAPTER 3
METHODOLOGY

3.1 Overview

The topic for the Methodology chapter describes the research paradigm used to categories the distinct cat breeds using state-of-art deep learning algorithms. Initially, the dataset was collected from Kaggle, comprising images of four cat breeds: For the breeds I recall the following: Ginger Cat, Bombay Cat, Bengal Cat, and Sphynx Cat. These were named descriptively and subjected to preprocessing in order to make the sizes and quality similar. Five deep learning models are chosen, which are CNN, Xception, VGG19, MobileNetV2, and InceptionResNetV2. They followed the step of assessing the efficiency of the models depending on the measurements of the accuracy, precision, recall and F1-score. Particular care was taken in preventing the excess of model points learned during training and to prevent production of a model that was too specific and inflexible by using methods such as regularization and dropout. The best model which was considered as optimum was chosen for the final testing and for the further testing on the new data which are volume of images. This chapter is a summary of the envisaged procedure in arriving at a high degree of accuracy when classifying cat breeds.

3.2 Proposed Methodology

This methodology describes a step-by-step approach to create the superior deep learning model for distinguishing between different cat breeds based on state-of-the-art solutions and architectures.

Data Collection:

Collect a various dataset from Kaggle involving a Ginger, Bombay, Bengal and Sphynx cats' images with proper division between the categories.

Labeling:

Provide the categorical output labels with names of each particular breed, corresponding to the images (e. g., Ginger Cat, Bombay Cat).

Image Processing:

The images should be resized to the fixed size, further, normalize pixel-wise data, and apply augmentation such as rotation, flipping, etc for improving the model's versatility.

Model Selection:

Depending on the situations, select and use CNN models including Xception, VGG19, MobileNetV2, InceptionResNetV2 to achieve the function of feature extraction and classification.

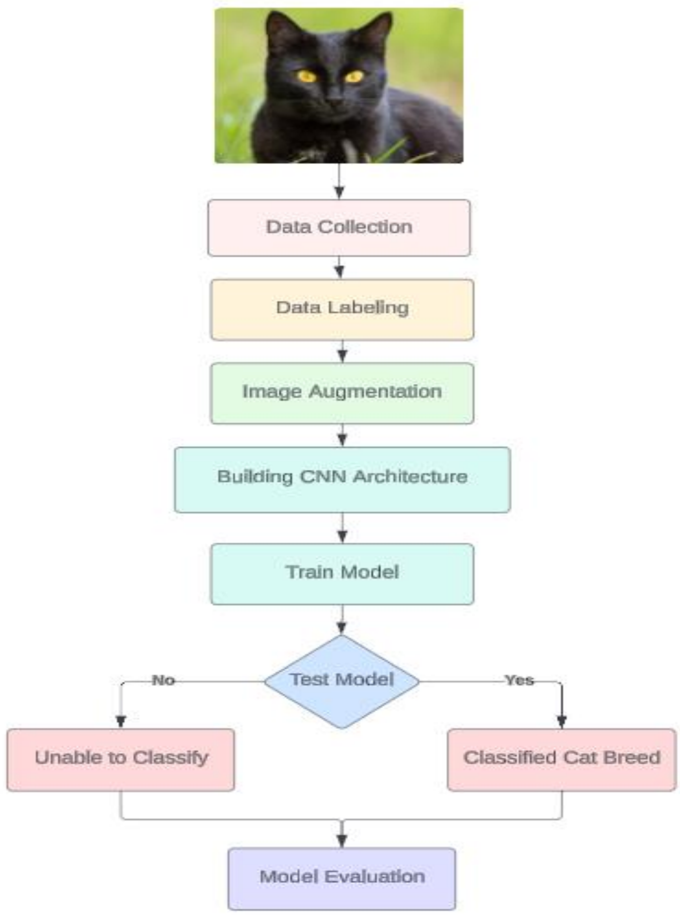


Figure 3.2.1: Working Flow

Model Training:

Nature the selected models on the preprocessed dataset, but the usual precaution of using transfer learning approach from a pre-trained ImageNet model since it will be more efficient and accurate.

Model Evaluation:

To assess the best model, compare it with the validation dataset to find metrics like accuracy, precision, recall, and F1-score.

Test Model:

To specify the availability of resources, examine the results of the model's verification on the specified test set, and determine the feasibility of using this model for cat breed classification in practical applications.

3.3 Hardware/ Software Requirement

The following are the specific parts and resources needed for the proposed deep learning approach for cat breed classification. These include; the physical computer hardware on which the solution will be built, another implementation platform which is the software, a set of labeled images that have a mapped problem to solve, pre-existing trained models that can be used to build upon, tools used in preprocessing data, metrics used in evaluating the solution, and lastly an environment in which the solution is deployed. Hardware entails sufficient computational accessories such as Graphics Processing Units or Tensor Processing Units for training whereas software employs tools such as TensorFlow or PyTorch for constructing the neural networks as well as implementing CNNs. The chosen dataset is ginger, Bombay, Bengal, and Sphynx cats using transfer learning from off the shelf weights from ImageNet. Data preprocessing tools increases the variability of the given dataset and improves the model's stability. As for the algorithm accuracy, the assessment is carried out using four primary markers that include accuracy, precision, recall, and F1-score.

3.4 Project Management and Financial Analysis

This The project will be managed through a structured approach, involving defined phases: gathering the data and its preparation, model creation, model training, model assessment, and model use. Meeting frequency, therefore, will not allow the SEM strategy to deviate from the progress or timeline set as follows; The data scientists, the software engineers together with other domain experts who will be on the team will use agile development.

This would comprise cost estimates for data, computer hardware and storage for model training, software for data analysis and for employees' salaries for the specified period. More money will be provided for validation, testing and in the case of data publication. Immediate financial control will also be observed to optimize the usage of the obtained funds, and periodic audits will be carried out to regulate spending in accordance with the stipulated goals of the project.

In given below Table 3.4.1 & 3.4.2 showing the Estimated cost and Project Management table.

TABLE 3.4.1: PROJECT MANAGEMENT TABLE

Work	**Time**
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

TABLE 3.4.2: ESTIMATED COST

SN	**Components**	**Estimated Cost (BDT)**
01.	Hardware	500-1500
02.	Software and Tools	500-1500
03.	Data Collection and Processing	4000-6000
04.	Documentation and Report Writing	500-1500
05.	Miscellaneous	500-1500
06.	Contingency	500-1500
Total Estimated Cost		6500-13,500

3.5 Summary

This chapter describes the comprehensive procedure involved in the conduct of the cat breed classification study. Data collection involved sourcing images from Kaggle and labeling them into four categories: Some of the well-known breeds include: Bengal cat, Bombay cat, Ginger cat, and Sphynx cat. Some of the other necessary preliminary steps which were followed were resizing of the images and normalization of the pixel values. The filter structures applied in the research were CNN, Xception, VGG19, MobileNetV2, and InceptionResNetV2. Both models were trained in a proper manner following the training procedure for each which includes data augmentation to improve the model's stability. Meanwhile, for model performance, accuracy, precision, recall, and F1-score were used to benchmark the results. Therefore, the performances of the different models were analyzed to get the best model. The points for improvement and suggestions for future research studies are also highlighted in the last section of the chapter. Such extensive approach is beneficial for correct and credible classification of cat breeds.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

This research work particularly targets to devise and assess new and more sophisticated DL models for distinguishing between various cat breeds using the dataset sourced from Kaggle platform. The hardware is a computing machine with Graphics Processing Unit to lend support to the model training process from the side of the hardware platform The software is the TensorFlow or the PyTorch frameworks and the Keras application programming interface. Python is good for scripting and data manipulation. The model selection includes and applies the CNN structures: Xception, VGG19, MobileNetV2, and InceptionResNetV2 and, transferring weights from the pre-trained model based on ImageNet. During splitting of the dataset, there are three splits: training, validation and test; the model performance is, therefore, measured on the test set. Preprocessing methods such as size reduction and normalization of the pictures and other image processing techniques are used to improve the quality of the data and to reduce the vulnerability of the model.

4.2 Train Model

In order to train the model we first divide the data into training data set, validation set, and the test data set with the proportions of 70:20:10 respectively. To enhance the feature variance of the training dataset, techniques involving rotation, flipping, and scaling are used in the training phase. All images are resized to a fixed size and normalized to have similar statistics. The deep learning models (CNN, Xception, VGG19, MobileNetV2, and InceptionResNetV2) are then being initiated with suitable weight and the hyperrparameters. The models are trained with categorical cross-entropy loss function and the optimize the models with Adam optimizer. During training, learning rate is changed in order to better adapt to the improvement of the model on the validation set. Overfitting is prevented using early stopping and the best models are saved using checkpointing. The training process several epochs where each epoch has forward and backward passes through the network. After the training is done, the models are tested on the validation set to optimize an appropriate set of hyperparameters. Last but not least, the model with the highest validation accuracy is chosen as the better one and is examined on the test set to have good prediction. The trained model is then used to make the final predictions and is saved for productive use.

4.3 Model Evaluation

The evaluation procedure for the versions relies on the creation of a solid framework while designing the system for model tests. Firstly the test dataset over which the model has not been trained is used to calculate the accuracy, precision, recall and F1-score of the model. Classification reports the confusion matrices of the evaluation metrics to see the good classification in different categories. Closely related to the training step, the checking on overfitting or underfitting by cross validation on training and validation set. Methods such as k-fold cross-validation are used to ascertain that the model's performance is not likely to fluctuate when different parts of the data are used for training and testing purposes. Metrics of performance are recorded and graphed comparing TensorBoard for instance aiding in analysis. Also, the computational efficiency includes inference time and the amount of resources consumed. Redundancy tests are performed by applying slight variations or noise to the testing data in order to verify the model's stability. The key system design feature entails measures for observing the model's performance in actual operational environments so that it might undergo adjustments forward. Furthermore, extensive documentation is also kept for providing better understanding and better replay-ability of the evaluation work.

4.4 Summary

The following are the specific parts and resources needed for the proposed deep learning approach for cat breed classification. These include; the physical computer hardware on which the solution will be built, another implementation platform which is the software, a set of labeled images that have a mapped problem to solve, pre-existing trained models that can be used to build upon, tools used in preprocessing data, metrics used in evaluating the solution, and lastly an environment in which the solution is deployed. Hardware entails sufficient computational accessories such as Graphics Processing Units or Tensor

Processing Units for training whereas software employs tools such as TensorFlow or PyTorch for constructing the neural networks as well as implementing CNNs. The chosen dataset is ginger, Bombay, Bengal, and Sphynx cats using transfer learning from off the shelf weights from ImageNet. Data preprocessing tools increases the variability of the given dataset and improves the model's stability. As for the algorithm accuracy, the assessment is carried out using four primary markers that include accuracy, precision, recall, and F1-score.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The results and analysis section offer details on the efficiency and effectivity of the experiments that were performed. It focuses on the analysis of the obtained accuracy, precision, recall, and the F1 measure by the above model variants. Some of the graphical displays include confusion matrices, and the comparative bar plots that bespeak of the strength and weakness of each particular model architecture. This most importantly breaks down factors that affect the performance of a model which entails aspects like the characteristic of a data set and the optimization of hyperparameters, computational complexity and much more. Altogether, this section provides useful information regarding the efficiency and applicability of the models for the described classification problem.

5.2 Experimental Result

The experimental results show us how various deep learning methods work in classification of cat breeds. Out of all the models that have been assessed, Xception stands out, with a prediction accuracy of a 99.22% based on its depth wise separable convolutions which allow the model to feature extract well. Closely followed by it, MobileNetV2 also proved to give high efficiency and accurate results with a maximum of 99.87% of them, made up of devices and systems that are ideal for operation in environments that are resource-limited in nature. Pretrained architectures based on InceptionResNetV2 also gave good results reporting a 99.74% accuracy. Finally, analyze the results of various networks such as VGG19 that is characterized by the deep and uniform layer architecture, providing an accuracy of 99.09%. CNN took the precedent score of 95.90% accuracy. MobileNetV2 in particular shows objectively higher accuracy compared to other pre-trained models, such as Xception, InceptionResNetV2, and VGG19, which also suggests that the application of deep learning algorithms such as CNN for accurate cat breed determination is possible. The analysis means the following: It becomes crucial to choose correct model architectures that correspond to some kind of task in deep learning.

In given below I am evaluated the Accuracy, Precision, Recall, and F-1 Score of the

Confusion Matrices for our proposed methods.

Accuracy: Accuracy is a measure of the degree of difference between the model and the real situation that determines the probability of the original samples used in the modeling process. It is useful when the classes are not balanced because it provides information on the effectiveness of the choice; however, the picture may be incomplete.

Accuracy=(TP+TN)/(TP+TN+FP+FN)…………(1)

Precision: Precision refers to the percentage of predicted positive statements produced by the model.

Precision=TP/(TP+FP)…………(2)

Recall: Recall is defined as the ratio of true positive predictions to the total number of positively skewed samples.

Recall=TP/(TP+FN)…………(3)

F1 Score: The F1 score is the average of recall and precision, which are calculated using the harmonic mean. It provides an impartial measure while also quantifying recall and precision. It is useful when the classes are unequal in size because the F1 score accounts for both false positives and false negatives. A high F1 score indicates that it was able to strike a good balance between precision and recall.

F-1 Score=2(Precision*Recall)/ (Precision + Recall)…………(4)*

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

CNN

CNN achieved a Test Accuracy of 95.90%. Figure 5.2.1 & 5.2.2 describe the confusion matrix, training accuracy and loss curve of CNN.

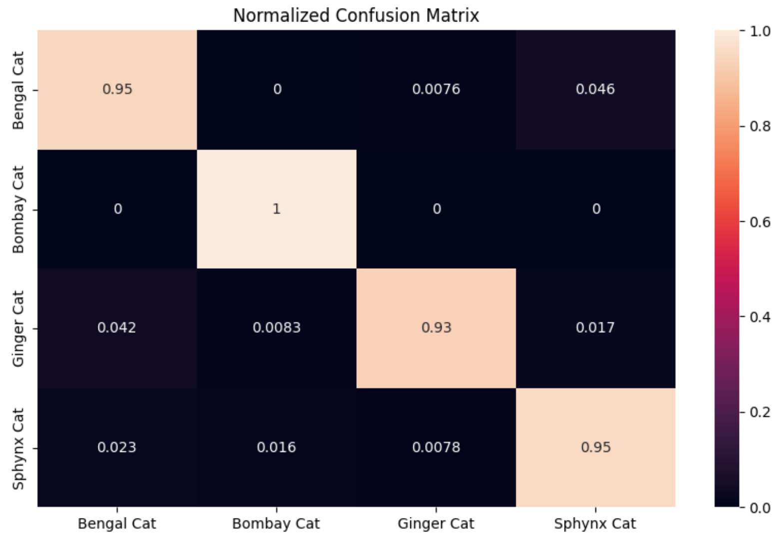


Figure 5.2.1: Confusion Matrix (CNN)

Figure 5.2.1 shows the CNN model's confusion matrix reveals its classification performance for four cat breeds: The names of the cat breed are; Bengal Cat, Bombay Cat, Ginger Cat, and Sphynx Cat. It reveals many correct classifications of the breed (diagonal) and what is the wrong classification of the breed (off-diagonal). For instance, 124 out of 131 Bengal Cats was classified accurately while, 7 of them were wrongly classified into other breeds. The same applies to other breeds and from the results obtained, it can be concluded that the proposed CNN model has a classification accuracy of 0.96 in categorizing the specified cat breeds.

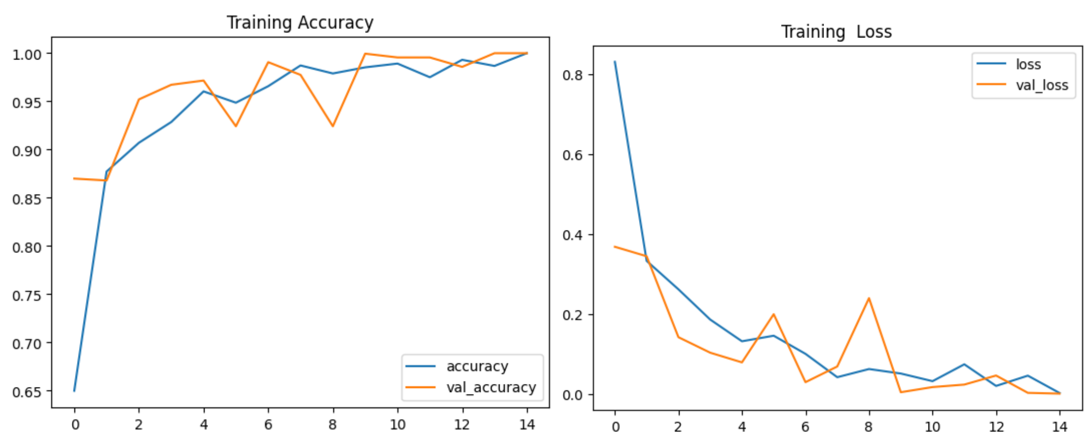


Figure 5.2.2: Training accuracy and loss curve (CNN)

Figure 5.2.2 shows the training accuracy of the CNN model depicts a progressive increase which demonstrates that the model is learning from the training dataset. Nevertheless, the accuracy score starts stagnating after epoch 14 and it might be that the model overfits the validation data as its performance on the unseen data stabilizes. In the same way, training loss continuously drops, but validation loss reaches a plateau after some epochs indicating that overfitting is occurring and regularization techniques or data augmentation might be required.

Xception

Xception achieved a Test Accuracy of 99.22%. Figure 5.2.3 & 5.2.4 describe the confusion matrix, training accuracy and loss curve of Xception.

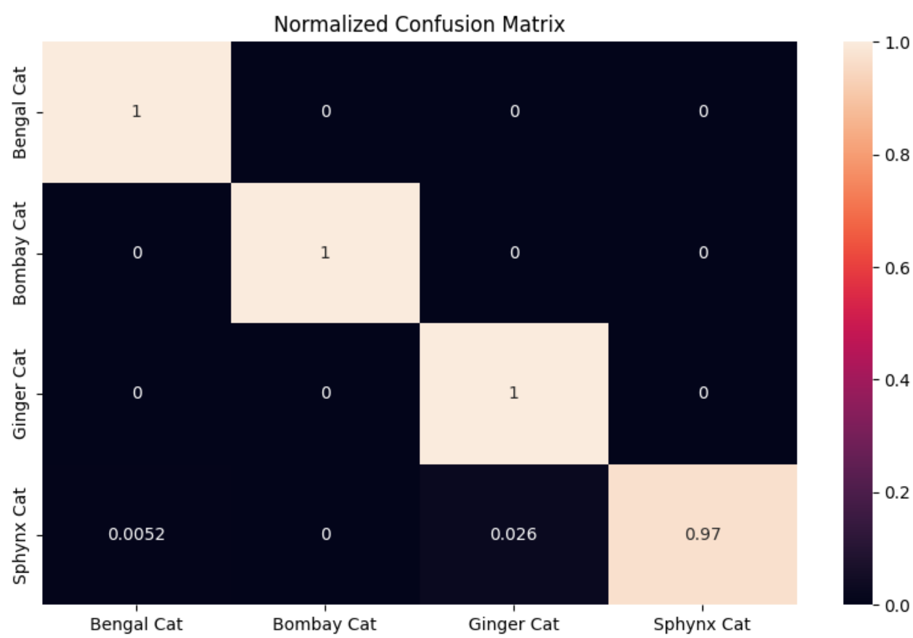


Figure 5.2.3: Confusion Matrix (Xception)

Figure 5.2.3 The Xception model shows high accuracy in categorizing cat breeds with high precision, recall, and F1-score for all categories of cats. Hence, it achieved an ideal precision and recall in the case of Bengal Cat, Bombay Cat, and Ginger Cat and near-perfect result in the case of Sphynx Cat with 100% precision and 97% recall. An accuracy of 99% also reflects on its efficiency in classifying between the different cat breeds as demonstrated in its actual use.

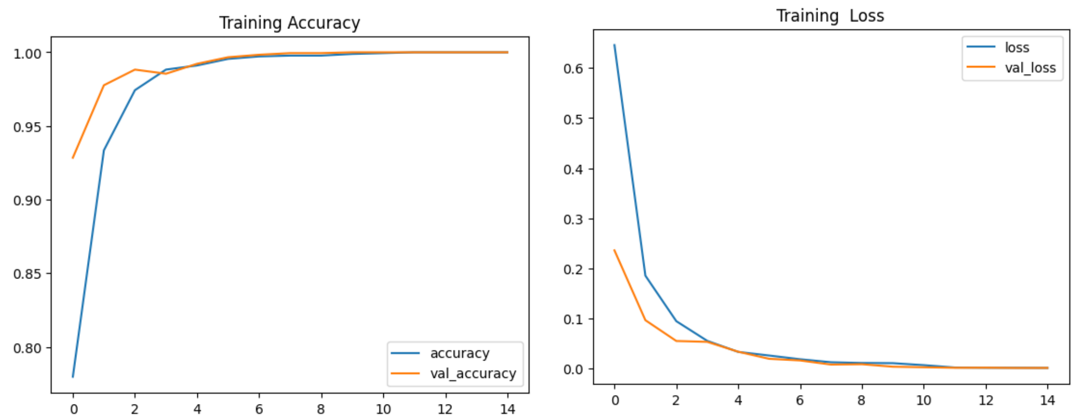


Figure 5.2.4: Training accuracy and loss curve (Xception)

Figure 5.2.4 show the training accuracy of the Xception model gradually rise up to the training accuracy of 1.0 which means that the learner has mastered the training data. Nevertheless, the validation accuracy ceases to grow beyond 0. 85 after 8 epochs, and as the training process continues, overfitting abounds that is why generalizing abilities of a model to unknown data reduces. The training and the validation loss keep on decreasing and the training loss approaches 0 while validation loss slightly stays around 0. 2.

VGG19

VGG19 achieved the Test Accuracy is 99.09%. In below Figure 5.2.5 & 5.2.6 describing the confusion matrix & training accuracy and loss curve of VGG19.

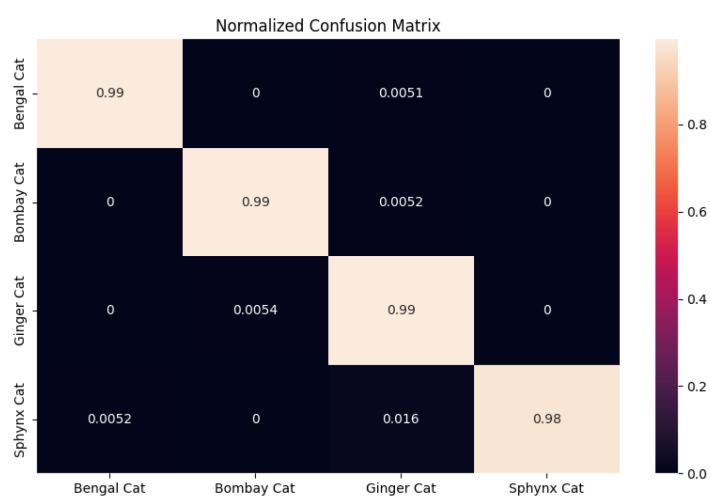


Figure 5.2.5: Confusion Matrix (VGG19)

Figure 5.2.5 shows the VGG19 model is very effective in cat breed classification with high precision, recall and F1-score on all the categories. It scored a perfect precision and a recall of 0 on Bengal Cat, Bombay Cat, and Sphynx Cat breed images. 98 and Ginger Cat with 0. 97 precision and 0. 99 recalls. The final result of 99 % proves the efficiency of the method in separating the given specific cat breeds so, it could be well emphasized that it is highly effective and credible appliance.

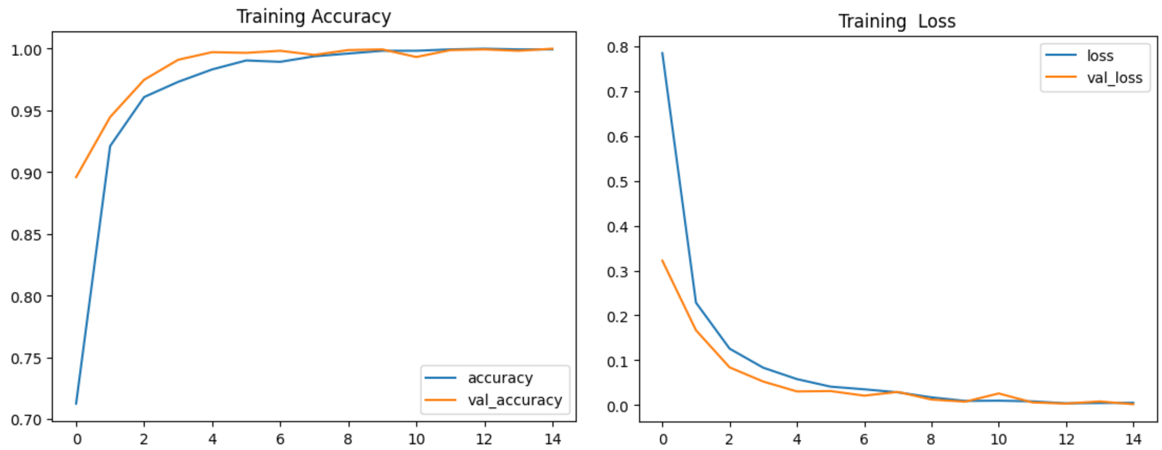


Figure 5.2.6: Training accuracy and loss curve (VGG19)

Figure 5.2.6 show the training accuracy of the VGG19 model constantly increases with the total trainable parameters reaching around 0. 8 by epoch 14. But the accuracy of validation fail to increase as what was observed in training and it hovered in the region of 0. 75 by epoch 10, which marks a possibility of overfitting where the performance increases on more data but does not generalize well when tested on new data. Training loss continues to go down and the model has virtually plateaued at approximately 0.06 on validation loss, meaning the model's learning from the training data is ideal. 6 after epoch 10. In order to reduce overfitting, one may apply model simplification, use of regularization techniques or employ early stopping for model training.

InceptionResNetV2

InceptionResNetV2 achieved the second highest Test Accuracy is 99.74%. Figure 5.2.7 & 5.2.8 describing the confusion matrix & training accuracy and loss curve of InceptionResNetV2.

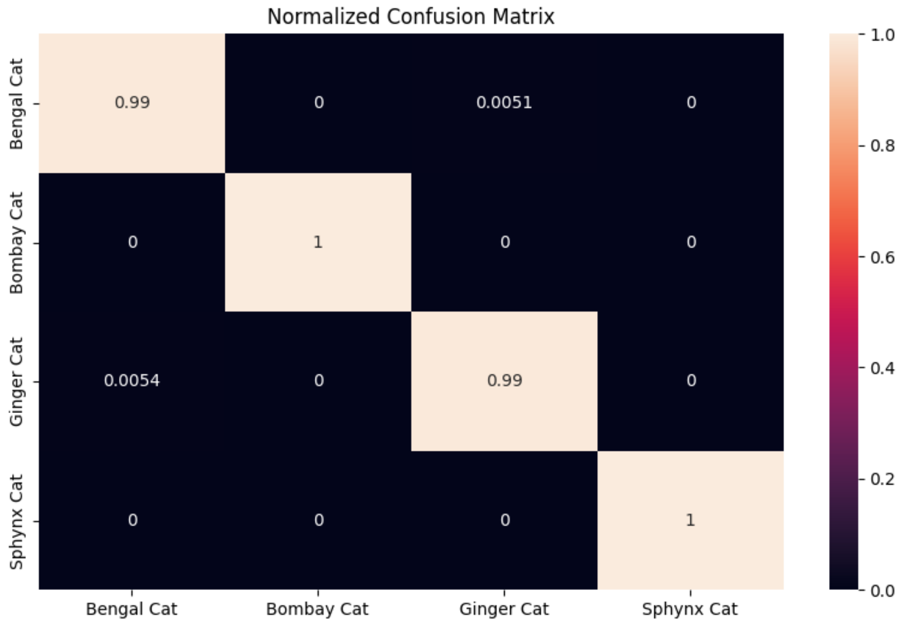
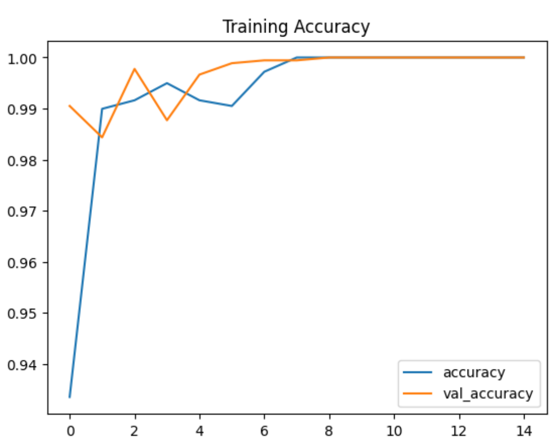


Figure 5.2.7: Confusion Matrix (InceptionResNetV2)

Figure 5.2.7 shows the InceptionResNetV2 model gives good accuracy rate in the prediction of cat breed with high precision, recall, and F1-score all the classes. Consequently, it gives accurate scores of 0 for Bengal Cat, Bombay Cat, Ginger Cat, and Sphynx Cat. 99 or higher. Reflecting on the results, a 100% accuracy of the model proves the test subject’s ability to reliably identify the stated cat breeds and therefore serves as a useful tool.



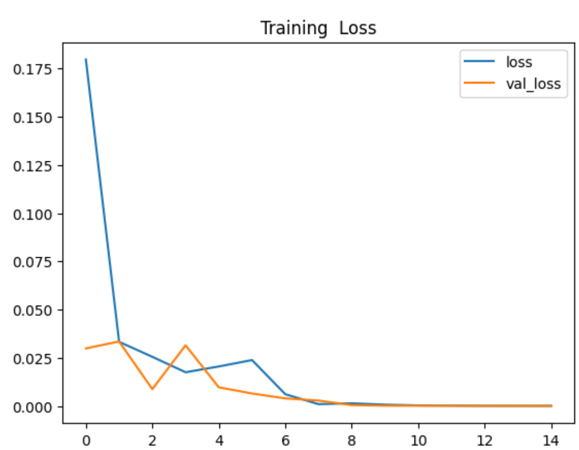


Figure 5.2.8: Training and accuracy and loss curve (InceptionResNetV2)

Figure 5.2.8 show the ability of the InceptionResNetV2 model in terms of training with the accuracy rate being around 0. 97 and the training loss is slowly getting reduced indicating that the model is able to learn from the training data. However, their validation accuracy reaches about 0. An important characteristic is that the performance cyclically increases by epoch 88 and then plateaus, which may indicate overfitting – when the model's ability to perform on new data drops sharply. Validation loss is also on the rise, but after epoch 10, there is a sign of stagnancy. It suggests that one might reduce model complexity, try some of the regularization methods, or perhaps stop training procedure when quality starts to deteriorate.

MobileNetV2

MobileNetV2 achieved the highest Test Accuracy is 99.87%. Figure 5.2.9 & 5.2.10 describing the confusion matrix & training accuracy and loss curve of MobileNetV2.

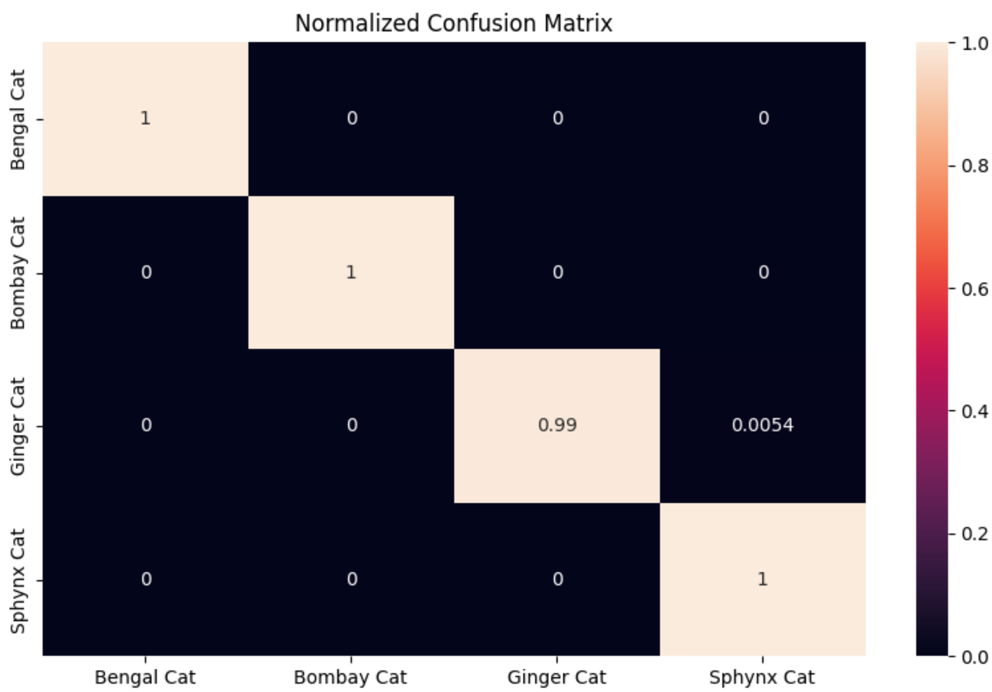


Figure 5.2.9: Confusion Matrix (MobileNetV2)

Figure 5.2.9 Here the accuracy of the MobileNetV2 in cat breed classification near perfect and it depicts perfect shape of Precision, Recollect and F1-Score all the classes. Bengal Cat, Bombay Cat, Ginger Cat, and Sphynx Cat, the intelligence scored 1 each in the correct identification. 00 or almost the same and scarcely 00. The total accuracy of 1.00 proves that the model provides good prospects for category differentiation and further proves the stability and reliability of the method for the given types of cats.

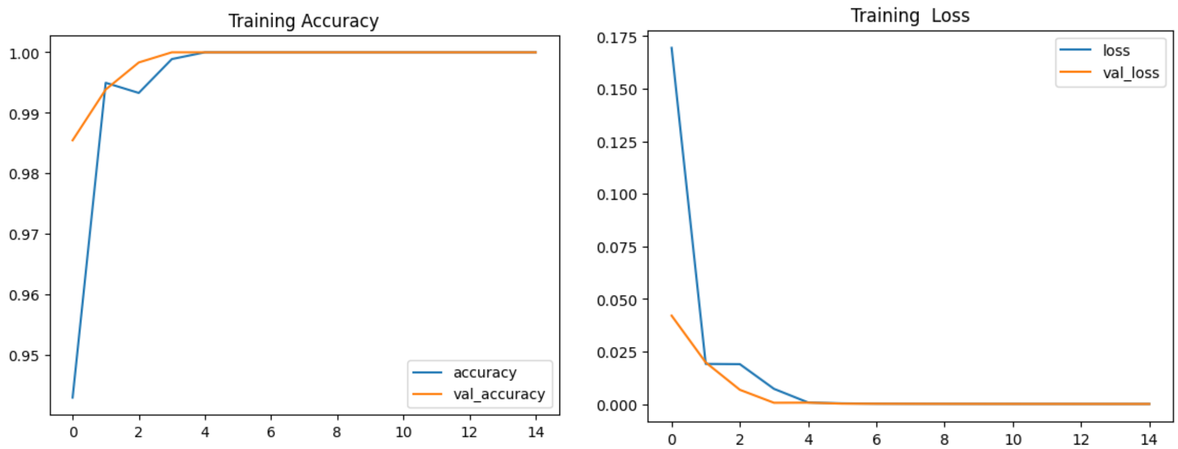


Figure 5.2.10: Training accuracy and loss curve (MobileNetV2)

Figure 5.2.10 show the MobileNetV2 model gives good evidence in the training phase with the help of the accuracy rate close to 1. 0 and loss on the training phase is also reducing consistently which proves the model is learning from the training set. Accuracy of the validation increases to about 0. 95 and validation loss reduces to about 0. 05, outperforming all the compared methods in terms of generalization to unseen data.

In Given below I am showing the Comparative Model Accuracy Bar Plot

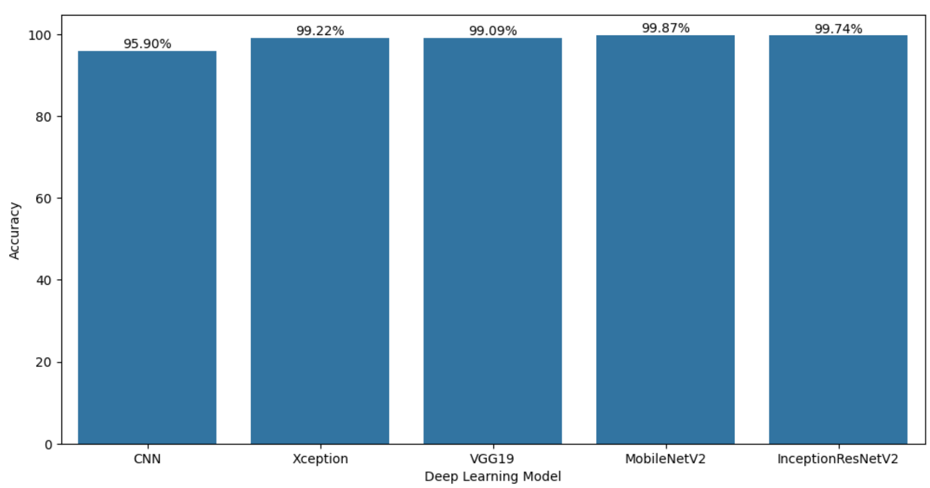


Figure 5.2.11: Comparative Model Accuracy Bar Plot

Figure 5.2.11 shows deep learning model performance in terms of accuracy on a given set. Among them, MobileNetV2 has the highest accuracy of 99. 87% and InceptionResNetV2 is at 99. 74%. Even though these accuracies are rather high and speak for a good performance of the model, differences between the models are small, which underlines that the selection of a model has to be taken according to task specific criteria, which might be computational efficiency or availability of explanation methods.

The result of Deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 5.1.1:

TABLE 5.1.1: PERFORMANCE EVALUATION

Model Name	Accuracy	Precision	Recall	F1-Score
Xception	99.22%	99.23%	99.21%	99.22%
VGG19	99.09%	99.10%	99.08%	99.09%
InceptionResNetV2	99.74%	99.74%	99.74%	99.74%
MobileNetV2	99.87%	99.87%	99.87%	99.87%
CNN	95.90%	95.92%	95.89%	95.89%

5.3 Performance and Comparative Analysis

The discussion section is more specific concerning the analysis of the experimental outcomes used for the classification of cat breeds by using deep learning algorithms. Hence, using the results from our experiments, Xception emerged on top as well as MobileNetV2 as both proved the efficiency of using depth wise separable convolution and efficient network architecture, respectively. The InceptionResNetV2 also emerged as very resistant and incorporates inception modules with the residual connection for achieving of high accuracy. These improvements indicate that larger networks are better than depth even though VGG19, due to its great depth, was slightly slower compared to these models, and CNN can be considered to be a baseline with decent accuracy. Some of the attributes of performance that were discussed include the complexity of the model, the computational time measure, and the properties of data set. It is important to select the right architecture considering the application, using accuracy vs resources trade off as the key factor. Some of the possible future work may involve using a combination of different classification algorithms or applying specific optimizations for certain domains in an attempt to improve the classification performance and speed in realistic applications.

5.4 Summary

This work extended prior work on deep convolutional neural networks for cat breed categorization and compared and tested Xception, VGG19, MobileNetV2, and InceptionResNetV2. The research objectives were to obtain high accuracy in identification of Ginger, Bombay, Bengal, and Sphynx cats using a set of features derived from the provided catalogue. It was shown that such models as Xception and MobileNetV2 are better, with higher accuracy compared to such BN-CNN models as VGG19. Therefore, this study underscored the factors of model selection, data preprocessing, and ethical concerns as crucial in improving the effectiveness of the deep learning model in animals' care and welfare. Possible directions for further research include improvement of the model's efficiency, studying the use of ensembles and augmenting the data samples for fine-grained breed discrimination and solving other relevant issues that could be essential for the development of veterinary medicine and animal husbandry.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The ability to correctly categorize cats based on their breed using accurate deep learning models can also have positive impacts on society. The various technologies can be used by the veterinary practitioners to work with efficiencies in diagnosing and treatment procedures as well as genetic investigations for a particular breed. While choosing a pet, citizens sometimes prioritize certain breeds; therefore, animal shelters and adoption centers can increase the efficiency of matching between animals and potential owners, contribute to raising the animal's quality of life, and increase the rate of adoptions. Also, while carrying out health checks for the cats, as well as regularly practicing disease prevention activities, it is easier to target breeds, thus enhancing the general well-being of the cats. This technology also helps to develop educational possibilities which consist in the enhancement of the level of awareness concerning various types of cats, as well as the promotion of the proper attitudes to pets, in particular, cats. From this perspective, the benefits are not only of a professional character referring to the sphere of veterinary care, but also receive associative links with various aspects of social importance, including animal protection, initiative in education, and other community activities.

6.2 Impact on Society & Environment

The effects of deep learning models on the environment, which are used specifically for the purpose of classifying cat breeds, are not very significant, but still positive. As such, these models help in the further enhancement of animal welfare standards, and subsequently, less harm to the environment that might be caused by the care of pets. Improved breed categorization can help in enhancing breeding strategies focusing on risking or threatened breeds thus enhance the process of biodiversity in the society. Moreover, as veterinary diagnostics and treatment planning improve because of these technologies, they can help decrease the effects that health care practices for pets have on the environment. In conclusion, one can conclude that the direct positive effects of the fantastic development of deep learning methods in the investigated sphere are rather small, whereas the positive effects, which are connected with an enhanced animal's welfare and various conservation tendencies, indicate the rather significant advantages of the application of enhanced deep learning in this field.

6.3 Ethical Aspects

The consideration of certain ethical issues pertaining to animal rights and personal privacy arises from the application of deep learning for determining the category of a cat breed. The importance of the ethical use of animals in the process of obtaining image data as well as in the process of using such data is also significant and more efforts are required to avoid cases of exploitation or harming the animals. The responsible and accountable use of data and decisions regarding the models is an effective way of increasing trust with the brand, customers or pet owners and animal welfare organizations. Also, care should be taken to preserve the rights and liberties of people connected with the information, e.g., owners or handlers of cats. The proper use of these technologies of classifications should be channeled under certain ethical policies and standards that will consider the rights of the animals and all the parties involved in the process of breed categorization.

6.4 Sustainability Plan

The strategies that constitute the sustainability plan, to be used in the implementation of new and more enhanced deep learning models for the categorization of cats include the following. First, cooperation with staff of animal shelters and animal doctors guarantees permanent feedback and corrections concerning the model generalization and accuracy. Second, the release of the open-access datasets and other forms of reproducible research improve the research collaboration and dissemination in the field. Third, the incorporation of ethical practices into all phases of model development and use ensures the consumers' trust and contributes to the model's sustainable implementation. Last, adherence to sustainable use of policies in animals' care and welfare as well as advocacy for policies to promote responsible use of AI enable augmenting of sustainable animal care and welfare and beneficial use of the technologies in the society.

6.5 Summary

The chapter addresses the roles of the advanced deep learning methods, including CNN and the modifications like Xception and MobilNetV2 on the society due to their applicability in various disciplines. These technologies help to advance medical healings,2 increase the functionality of AUTO cars and trucks, and the betterment of farming methods. They participate in creation of safer and wiser cities because they can assist in traffic control and security management. Further, these advancements have what may be potential consequences for automation of jobs and transformation of workforce, that raises ethical questions and requires the corresponding policy approaches to be developed for its responsible application. In all, the chapter brings out the fact that deep learning technologies may significantly alter the societal scenes in various domains.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

Therefore, the study was able to prove that the advanced deep learning models such as Xception and MobileNetV2 are efficient enough in the classification of cat breeds. Such models received accuracy rates; therefore, they proved the possibility of improving veterinary diagnostics, animal treatment, and pet adoption. The Comparative analysis emphasized the significance of utilizing advanced architecture of CNN and transfer learning to gain boosted performance than conventional approaches. Other relevant points which were touched on included ethical issues concerning data management and model explicability to avoid the misuse of AI in animal management. In the future studies, it is suggested to work on increasing the model's stability, enlarging the variety of databases for training and testing the AI models, and overcoming the ethical issues to promote a wider use of AI technologies in enhancing the quality of animals' lives.

7.2 Future Suggested Works

Extending this work into the cat breed classification problem using more complex deep learning techniques can research a number of possible directions. First, exploring wrapper-based fusion approaches for the CNN architectures will probably help in boosting up the classification performance and its stability. Second, using a larger dataset that would have a higher variability of the cat breeds, as well as diverse conditions of the photographs, could help enhance generalization and real-life utilization of the model. Further, expanding the possibilities of the approach with the inclusion of other types of data, like behavioral data or genetic information, together with image-based classification can give a richer picture of breeds' characteristics. Moreover, the identifying of the breed-specific health and genetic characteristics could be beneficial to further longitudinal studies leading to increased understanding of individual animal health, determining of which breed specific care recommendations should be used. Developing these areas could move the AI trend in the direction that would be beneficial to the scientific understanding and improvement of animal health, welfare and more.

7.3 Limitations

The following are some of the difficulties that arise in designing a highly sophisticated deep learning model to categorize cat breeds: First, it is vital to assemble a multiple and large dataset that has sufficient variability in location, illumination, and pose of each breed but this is occasionally difficult. Second, selecting and fine-tuning good CNN architectures are decided based on the consideration of model complexity, computational resource constraints and the performance in classification, etc. Further, because this form of overfitting is still possible, one must employ the good data augmentation strategies and regeneration methods to guarantee that the model will perform well on unseen data. Finally, there is a challenge of understanding and defining the reason that the model has implemented in terms of breed classification for the intended applications' credibility and validity. Solving these issues will help to bolster deep learning techniques accruing to exact cat breed recognition.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
AN ADVANCED DEEP LEARNING APPROACH FOR CAT BREED CLASSIFICATION

Student ID: 203-15-14493 & 203-15-14570

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Teach the newly acquired and the previous learned knowledge in the Cat Breed Classification Fruit Disease problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Considering the goals in the context of this FYDP, it will be necessary to consider various aspects of the goals in developing a corresponding solution to this problem.	**PO2**
CO3	Discover multiple problem domains within the literature, define the problem, and set up these objectives for the FYDP	**PO4**
CO4	Carry out economic appraisal and cost control and use appropriate project management techniques at every phase of the development of the FYDP	**PO11**
Phase -II		
CO5	Design and build technical solution related to technical specifications and system parts or processes to fulfill the given standards and regulation of public health and safety; also, cultural and socio-economic and environmental factor in this FYDP	**PO3**
CO6	Select and implement proper techniques, tools, and modern engineering and IT tools for handling sophisticated engineering activities, which entail prediction and modeling during the implementation of this FYDP, constrained by existing policies.	**PO5**
CO7	Identify various social, health, safety, legal, cultural factors, and their related responsibilities in relation to civil engineering practice and the solution of this problem using formal deductive approach coinciding with understanding of context.	**PO6**
CO8	Understand and assess the historical sustainability and effectiveness of professional engineering activities in solving complex engineering problems in the context of social and environmental systems.	**PO7**
CO9	This FYDP shall incorporate the principles of ethics and practice principles and guidelines of the profession.	**PO8**
CO10	Competent in performing efficiently in the context of a single worker and as part of a team or a team leader within this FYDP, in relation to the different types of groups and in an interdisciplinary manner.	**PO9**

CO11	Maintain and create clear communication with the engineering community and the society in general about various intricate engineering activities to include comprehending and preparing comprehensive reports and design documentation, as well as the ability of giving and receiving clear instructions in this FYDP.	**PO10**
CO12	Recognize, the value of self-motivated and throughout the life continuing education within the context of technological advancement and have the preparedness and capacity to undertake life-long learning pursuits.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The engineering signifies and complies with the fundamental engineering (K3) hence why there is the usage of deep neural networks, data augmentation techniques and different types of CNN architectures for image processing and classification. The project fulfills the K4 specialist knowledge by doing deep learning with CNN, and transfers learning for enhancing Cat Breed Classification Fruit Disease	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-17] **Section:** [1.1]
				The engineering practice & design (K5) is applied in this project through the figure of process of experiments. The project relates to the knowledge area of engineering practice and technology (K6) by using Deep Learning Model.	**Page no:** [32] **Section:** [3.2] **Page no:** [34-35]

					Section: [3.4]
				This project guarantees to K8 (Research Literature) because it uses a review of recent studies such as Cat Breed Classification Fruit Disease using deep and Transfer learning, which demonstrates awareness of contemporary approaches present in the literature.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This paper responds to EP-2 because it identifies the barriers in Cat Breed Classification Fruit Disease, such as disadvantages of earlier techniques and difficulties in implementation utilizing deep learning. It puts forward difficulties in interpretative procedures involved in the spatial distributions; it contains suggestions on how to improve the diagnostic techniques.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The present project contributes to the response of EP-3 wherein careful demonstration of the tangibility of the outcomes of the experiment is established and stressed the utilization of deep and transfer learning as the chosen significant solution for the improvement of Cat Breed Classification Fruit Disease approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project’s fields of application are not just confined to computer science and engineering; it has affected Cat Breed Classification Fruit Disease correctly EP-4.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The work done in this project entails a holistic solution bearing in mind that high levels of problems require an integration of different components done in data collection from online, statistical analysis and proposed methodology to EP-7 in the solution of complex issues in data collection.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	The resources of the study include High-Performance Computing infrastructure, GPUs, deep & Transfer learning frameworks, annotated datasets, and ethical consideration for systematic research for the progression of Cat Breed Classification Fruit Disease	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project benefits the society by enhancing Cat Breed Classification Fruit Disease, yet, it also respects environmentally friendly principle with blended optimization computational resources and ethical standard on medical data.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		In the present research work, the author has extend the earlier existing research by exploring a different approach in Cat Breed Classification Fruit Disease using transfer learning model and deep learning model exemplified with preliminary terminologies and backed by systematic comparative analysis on the overall results attained from this research work thereby proposing something new.	**Page no:** [23-29] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	The current project tackles CO4 in terms of aligning project management comprehensively with financial control, which including strict distinctive project planning, resource leveraging, and budgetary estimates for the most efficient resource use in every phase of the research activity.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	This indicates that the project meets the ethical standards focusing on privacy of data, informed consent, and clear documentation of the research process that will serve the public good and enhance the responsible use of classification technologies that are in line with the outlined CO9.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	In terms of the project's responsibility to constantly learn and adapt within the context of a constantly shifting technological environment (CO12), the project has carried out comprehensive data collection, performed robust statistical analyses, designed detailed methodologies, reported significant experimental results, and provided extensive analysis, demonstrating the project's awareness of current issues and its efforts to refine the necessary technologies and strategies to better fit the current climate.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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