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COMPARATIVE ANALYSIS OF CONVOLUTIONAL NEURAL NETWORKS FOR DOG BREED CLASSIFICATON: PERFORMANCE EVALUATION AND INSIGHTS

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Abstract**:** Dog breed classification is a challenging problem in computer vision with numerous practical applications, such as pet management and breed-specific health assessment. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification tasks, motivating the exploration of various architectures for dog breed classification. In this research, we investigate the performance of six widely recognized CNN architectures—LeNet, AlexNet, VGG16, VGG19, GoogLeNet, and ResNet50—applied to the task of dog breed classification using the Stanford Dogs dataset. Each architecture is fine-tuned and trained using appropriate hyperparameters and optimizers. We employ techniques such as data augmentation and transfer learning to enhance model generalization. Our experimental results showcase the effectiveness of these architectures in accurately classifying dog breeds, revealing variations in classification accuracy and computational efficiency.

IndexTerms - Dog Breed, Convolutional Neural Network, Image Classification, Stanford Dogs Dataset, Transfer Learning, Data augmentation.

I. INTRODUCTION

1. General overview about our problem domain:

The dog breed classification project aims to build a computer program that can tell what breed a dog is just by looking at its picture. It's like teaching the computer to recognize different types of dogs based on their appearances. But it's not an easy task because there are many different breeds, and each dog can look very different from the others.

To solve this problem, we tried using different kinds of special computer programs called CNN models. These models can learn patterns and features from the pictures of dogs and help the computer make accurate predictions about the dog's breed.

Some of the CNN models we used are VGG19, LeNet, ResNet50, GoogLeNet (Inception), VGG16, and AlexNet. Each model has its
own way of understanding the pictures and trying to figure out the breed.

To train the computer, we used a big collection of dog pictures with labels telling which breed each dog belongs to. This collection is called a dataset. The computer learned from this dataset to recognize the different breeds of dogs.
After training, we tested each model to see how well it could identify the breeds of dogs it had never seen before. We used performance metrics like accuracy, precision, recall, and F1 score to measure how good each model was at classifying the dogs correctly.

In conclusion, this project was about teaching a computer to recognize different dog breeds from pictures. We used different CNN models to help the computer learn and make accurate predictions. The performance of each model was measured using specific metrics, and the findings will contribute to improving image recognition technology for various real-world applications.

2. Overview about our deep learning algorithms:

Here's an overview of the deep learning algorithms used for dog breed image classification, explained in simpler terms:

2.1. VGG (Visual Geometry Group):

VGG (Visual Geometry Group) is a family of deep convolutional neural networks developed by the University of Oxford. VGG16 and VGG19 are two popular variants within this family. They are known for their simplicity and effectiveness. VGG16 has 16 weight layers, including 13 convolutional layers and 3 fully connected layers, while VGG19 has 19 weight layers.

2.2. LeNet:

LeNet, short for LeNet-5, is one of the earliest convolutional neural networks developed by Yann LeCun. It was designed for handwritten digit recognition and comprises multiple convolutional and pooling layers. LeNet was a foundational model for modern convolutional neural networks.

2.3. ResNet (Residual Network):

ResNet (Residual Network) is a deep neural network architecture known for its use of residual blocks. Residual blocks enable training of very deep networks by allowing information to skip one or more layers. ResNet50 is a specific variant with 50 layers, making it very deep and effective for various computer vision tasks. It was a breakthrough in addressing the vanishing gradient problem.

2.4. GoogLeNet (Inception):

GoogLeNet, also known as Inception v1, is a deep convolutional neural network developed by Google. It introduced the concept of inception modules, which are multiple convolutional layers with different filter sizes and kernel sizes combined in parallel. This architecture is known for its efficient use of computational resources.

2.5. AlexNet:

AlexNet is a pioneering deep neural network architecture that won the ImageNet Large Scale Visual Recognition Challenge in 2012. It consists of five convolutional layers followed by three fully connected layers. AlexNet played a crucial role in popularizing deep learning for image classification tasks.

All of these architectures are part of a family called Convolutional Neural Networks (CNN). They are very good at recognizing things in pictures, which makes them perfect for telling the breeds of dogs from images. By using these smart architectures, we can teach computers to identify hundreds of different dog breeds accurately. Researchers and developers often use these architectures to build better and smarter systems for identifying and classifying dogs in pictures.

3. Some of the images from data set:

Figure 1: Dataset sample 1

4. Motivation to initiate this problem statement:

The reason we started this dog breed classification project is because it has many useful applications. It can help in finding homes for dogs, taking care of their health, and understanding their different traits. Also, it's a challenging problem in computer vision, where we use special smart programs to recognize things in pictures. By working on this problem, we can make these smart programs even better.

We find dogs fascinating because they come in many different types, and we want to know more about them. So, we're trying to teach the computer to recognize the different kinds of dogs based on their pictures. There are many pictures of dogs available for us to learn from, and we can use them to make the computer smarter.

By solving this problem, we can also learn how to use these smart computer programs for other things, like recognizing other animals or objects. This can help us understand how these programs work in different situations.

Finally, when we can accurately tell what breed a dog is from a picture, it can help in taking better care of them. We can know about any specific health issues related to their breed and give them the right care. So, this project is exciting because it has real-life benefits for dogs and people who love them.

5. Contribution:

Our team project thrived on the essence of collaboration, where four distinct individuals came together to achieve a common objective. Each member brought a unique skill set and perspective, creating a synergy that led to success.

The main goal of our work was to create an accurate image classification system. The first team member demonstrated proficiency in the implementation and optimization of VGG16 and ResNet50 models. One participant adeptly utilized GoogLeNet and AlexNet, adjusting these structures with ease. Using VGG19 and LeNet models, the third one handled dog breed categorization, showcasing their ability to handle challenging jobs. Our professor, who aided us with the research and provided guidance on these technologies, makes up the fourth member.

The pivotal moment arrived during model comparison. After rigorous testing, VGG16, GoogleNet, and ResNet50 emerged as frontrunners. Our collaborative efforts culminated in a unanimous decision to prioritize these models, blending accuracy and efficiency.

In hindsight, our journey highlights the power of contribution in collaborations. Diverse skills and shared pursuit of excellence paved the path for success. Our achievement is a testament to the transformative potential of individual contributions within a dedicated team.

II. LITERATURE REVIEW

The authors created two models to identify dog breeds using advanced computer techniques. They used existing models (Inception V3 and VGG16) as a starting point and trained them on a dataset of dog images. They also improved the dataset by adding more variations of the images. The study found that Inception V3 performed better than VGG16 in accurately classifying dog breeds[1]. The aim of the study was to develop an accurate dog breed identification system. To achieve this, the researchers utilized a dataset comprising dog images and employed a range of deep-learning algorithms for training. The optimal performance was attained by a hybrid model that harnessed the capabilities of Inception-v3 and Xception in tandem, yielding a remarkable accuracy rate of 92.4%. This innovative methodology outperformed conventional techniques for dog breed classification. [2]. In the course of this study, the researchers engineered a profound neural network model by integrating Convolutional Neural Networks (CNN) and the VGG 19 architecture, with the goal of discerning diverse dog breeds from images. An extensive compilation of dog breed images constituted the dataset, which served as the foundation for training the model via transfer learning. This entailed meticulous fine-tuning of a pre-established VGG 19 model. The findings unveiled a remarkable precision in the model's capacity to categorize an array of dog breeds, thus rendering it highly suited for pragmatic utilities such as animal identification, breeding endeavors, and research pedigrees. Concurrently, the authors devised an innovative software system endowed with the ability to identify a dog's breed from a given image, supplemented by comprehensive insights into each recognized breed. [3].The authors used four different models to classify dog breeds: Inception V3, InceptionResNet50 V2, NASNet, and PNASNet. Here are the accuracy results of each model:

Inception V3: About 84% accuracy, InceptionResNet50 V2: About 86% accuracy, PNASNet: About 89% accuracy, NASNet: About 93% accuracy. When they combined all four models and used advanced techniques, they achieved an impressive accuracy of 95% for classifying dog breeds. This was a significant improvement compared to using any single model alone[4]. Within the scope of this study, an intricate framework materialized to differentiate between diverse canine breeds through the medium of visual representations. Employing the specialized Convolutional Neural Network (CNN), precisely integrating the ResNet5050 pre-trained model, the investigators engineered a mechanism that yielded a commendable 82.7% precision in discerning the accurate dog breed. An additional utility, OpenCV, was harnessed to facilitate the identification of human facial features, enabling the determination of the dog breed most closely resembling the detected human countenance. This augmentation stands as a valuable solution to the issue of misclassifying dogs as humans, thus enhancing the efficacy of the system. [5]. Within the context of this study, the researchers undertook the task of canine breed classification within images, employing sophisticated deep learning methodologies, particularly centered around convolutional neural networks (CNNs). The investigation encompassed the meticulous training and comprehensive assessment of two distinct CNN models, namely NASNet-A mobile and Inception ResNet50 V2, utilizing the extensive Stanford Dogs dataset as a foundational resource. The outcomes of this inquiry revealed compelling findings, with the NASNet-A model yielding an approximate accuracy of 80.7% when applied to the test dataset, while the Inception ResNet50 V2 model exhibited a substantially enhanced precision, achieving an approximate accuracy of 90.7%.[6]. The focus of this study led to the creation of a dog breed classification mechanism by employing a pair of convolutional neural network (CNN) variants: ResNet50 50 and ResNet50 101. The researchers directed their efforts towards the Tsinghua Dogs dataset, encompassing a variety of retriever dog breeds, totaling five in number. The overarching objective sought to simplify the process of accurately identifying dog breeds, rendering it more accessible to individuals. Notably, the outcomes of this endeavor uncovered a noteworthy distinction, with ResNet50 101 attaining a heightened accuracy rate of 94.55%, surpassing the performance of its counterpart, ResNet50 50, which achieved an accuracy level of 93.50%.[7]. The focus of this presents a method for classifying different dog breeds using a Convolutional Neural Network (CNN). The algorithm can accurately identify the breed of a dog from its image. They used innovative deep learning techniques, including transfer learning, to achieve high accuracy rates of 93.53% and 90.86% on two different datasets. The results show that their CNN model performs well in classifying dog breeds[8]. The authors aimed to classify different dog breeds using deep learning models. They used the DenseNet201 model, among other models like MobileNetV2 and InceptionV3, to analyze dog images and achieve an accuracy of approximately 87.34% in identifying dog breeds. The study showed that using DenseNet201 resulted in the highest accuracy compared to other models used in the research[9]. The authors focused on identifying dog breeds using Convolutional Neural Networks (CNNs). They used pre-trained models like VGG-16, Inception V3, and Xception to extract features from 1400 dog images covering 120 breeds. Then, they applied Logistic Regression as a classifier to determine the breed. The results showed accuracy of

91% for VGG-16, 94% for Inception V3, and 93% for Xception[10].The authors used Convolutional Neural Networks (CNN) with Transfer Learning to classify dog breeds. They compared the accuracy of training the model from scratch (CNN) and using the pre-trained ResNet5050 model (Transfer Learning). The CNN model achieved only 15% accuracy, while the ResNet5050 model achieved an impressive 86% accuracy in identifying 133 different dog breeds. The ResNet5050 model outperformed the CNN model significantly, making it a more effective approach for dog breed classification [11]. The authors developed a computer vision-based model using Convolutional Neural Networks (CNN) to predict dog breeds from photographs with 90% accuracy. Additionally, they created an e-commerce platform for buying and selling dogs. The CNN model was used for dog breed prediction, and it achieved an accuracy of 90% in identifying different dog breeds from images. The e-commerce platform was built using various technologies such as React, Node.js, and MySQL, offering a secure and trustworthy way to buy and sell dogs [12].

The authors developed a model to accurately identify the breed of goats from their images. They compared two popular pre-trained deep learning models, VGG-16 and Inception-v3, for this task. The Inception-v3 model performed better with higher accuracy and lower training time. They created a goat breed database with images from six different goat breeds and achieved accurate breed classification using the fine-tuned Inception-v3 model [13]. The authors created a big dataset of dog images called Stanford Dogs, containing images of 120 different dog breeds. They used two advanced models, VGG-16 and Inception-v3, to figure out the breed of each dog in the pictures. They found that Inception-v3 was better and more accurate than VGG-16 in recognizing dog breeds. The dataset and results are available on their website [14]. The authors tackled the challenging task of recognizing specific dog breeds from images, which requires distinguishing subtle differences between breeds. They used deep convolutional neural networks (DCNN) like AlexNet and VGG-16, trained on a large dataset called ImageNet, to achieve good results. They also combined different aspects of the images extracted by various layers of the DCNN models, resulting in a fusion architecture that improved the accuracy from 81.2% to 84.08% for dog breed categorization [15]. The authors explored how deep learning, specifically using Convolutional Neural Networks (CNN), can be beneficial for medical image processing and Content-Based Medical Image Retrieval (CBMIR) systems. They used a special type of deep learning model to analyze medical images and achieved good results in tasks like segmenting images and finding similar images. This approach can help medical professionals in diagnosing diseases more accurately and quickly. While the paper highlighted the advantages of using deep learning in medical imaging, it didn't provide specific accuracy numbers for their models [16]. The authors used a new model called the Reel Neural Network (RNN) for image processing. They found that the RNN model was better and faster than traditional methods in handling images. The RNN model's deep structure and feature extraction capabilities were especially useful for tasks like image classification and target detection. Specific accuracy percentages were not mentioned in the paper [17]. The authors of this research developed a new denoising network using deep learning to remove noise from images. They compared it to traditional denoising methods like NL-SAR and SAR-BM3D. The new network performed better in removing noise, especially with strong noise levels. They used a dataset of 500 images and achieved higher accuracy compared to the traditional methods. The new network also used less memory during operation [18]. The authors experimented with two CNN models, ResNet5050 and InceptionV3, for image recognition using different optimizers: SGD, Adam, and RMSProp. They trained the models on a custom dataset of cat vs dog images. Results showed that SGD performed best for ResNet5050 (99% accuracy) and RMSProp worked slightly better for InceptionV3 (50 epochs). The study emphasizes choosing the right optimizer for fine-tuning CNN models in image classification tasks [19]. The authors introduced a new optimizer called NRMSProp, which is a modified version of an existing optimizer. They tested NRMSProp, along with two other optimizers (Adam and RMSProp), on three different datasets. NRMSProp showed better results, with higher accuracy and faster convergence. They used two types of models (CNN and ResNet50) and achieved up to 97% accuracy for one dataset and 85% for another using NRMSProp[20]

III. CANINEVISION: DOG BREED CLASSIFICATION USING CNNs

Preprocessing:

This step involves resizing of images in the dataset to a fixed size depending on the model (ResNet50, AlexNet, etc.) used for image classification. The images are also rescaled by dividing the pixel values by 255, which brings the pixel values to the range of [0,1]. The data is organized in a specific directory structure, where each class (dog breed) has its own subdirectory. In this step, data augmentation is performed and the data is split into training, validation, and testing sets.

Proposed Method Architecture:

This step utilizes a Convolutional Neural Network (CNN) adapted for dog breed classification. It consists of input and output layers, with convolutional, activation, pooling, and dense layers in between. The CNN learns to extract relevant features from the images in the training dataset and classify images of different dog breeds based on the learned features. Training involves labeled data to adjust internal parameters, while evaluation assesses the model's performance on unseen data samples. This architecture enables accurate dog breed classification from input images in the training dataset.

Description of Architecture Correlated to Objectives:

The CNN architecture for dog breed classification utilizes learnable filters in the convolutional layers to extract discriminative features from input images. These layers convolve across the image, capturing essential patterns and characteristics specific to each breed. Pooling layers perform down sampling, reducing computational complexity and improving generalization. The dense layers then make precise breed classification decisions based on the learned features, resulting in an efficient and accurate dog breed classification system.

Training and Testing Phases:

In the training phase, the CNN model is fed with dog images of different breeds. The model learns to optimize its parameters using backpropagation. The loss function (e.g., cross-entropy) measures the difference between predicted and actual class labels. The optimizer (e.g., Adam or SGD) updates the model's parameters to minimize the loss function.

In the testing phase, our trained model is evaluated on a separate dataset (test set) to assess its performance in Dog Breed classification. By comparing the model's predictions with the ground truth labels, we measure its accuracy.

Flowchart:

1. Data loading: Loading images of different dog breeds with their corresponding breed labels.
2. Preprocessing: applying specific preprocessing techniques like resizing, data augmentation and normalization.
3. Model architecture: Using various CNN architectures with convolutional, pooling and dense layers.
4. Training: Feed the training data and update the parameters using optimization techniques.
5. Validation: Monitor the model's performance on a validation set to avoid overfitting and fine-tune hyperparameters.
6. Testing: Evaluate the trained model on a separate test set to assess its accuracy in predicting dog breeds.

Performance Evaluation: Measure accuracy, sensitivity, specificity, and other relevant metrics to gauge the model's performance.

Final Classification: Utilize the well-trained model to make predictions of dog breeds.

Equations for Key Operations:

Convolution: Convolution(d, K) = d * K, where d represents the input image of a dog and K is the learnable filter (kernel) specific to dog breed features.

Pooling: Pooling(d) = max(d), where d is a set of feature map values within a pooling window, and max returns the maximum value.

Flattening: Flatten(d) = [d1, d2, ..., dn], where d1, d2, ..., dn are individual feature map values flattened into a vector.

By carefully orchestrating the architecture design, employing appropriate preprocessing techniques, and conducting thorough training and testing phases, we can achieve accurate dog breed classification using deep learning methods.

IV. DATASET DESCRIPTION

We used a subset of the Stanford Dogs dataset, specifically selecting four distinct classes from the original 120 classes. This reduced dataset was chosen to facilitate a more focused and in-depth analysis of Convolutional Neural Networks (CNNs) for image classification.

Table 1: Dataset Description

Property	Details
Dataset name	Stanford dog's dataset
Total images	3325
Split ratio	80% train, 10% test, 10% validation
Number of classes	4
Data augmentation	Yes (Horizontal flip, rotation, zoom, etc.)
Image size	Resized based on the requirement of the model

Table1: the table consists of information about the dataset.

Number of classes: 4(Affenpinscher, Afghan hound, bulldog, German Shepard dog)
Training set:

a. Affenpinscher: 768
b. Afghan hound: 696
c. Bulldog: 636
d. German Shepard dog: 732

Testing set:

a. Affenpinscher: 60
b. Afghan hound: 60
c. Bulldog: 71
d. German Shepard dog: 62

Validation set:

a. Affenpinscher: 60
b. Afghan hound: 60
c. Bulldog: 60
d. German Shepard dog: 60

Table 2: Data set splitting

Dog breeds	Train images	Test images	Validation images	Total images
Affenpinscher	768	60	60	888
Afghan hound	696	60	60	816
Bulldog	636	71	60	767
German Shepard dog	732	62	60	854

Table 2: the above table consists of information about the number of test, train, and validation images in the dataset

The Stanford Dogs dataset is a collection of images used for training and evaluating dog breed classification models. It contains thousands of pictures of various dog breeds, each labeled with their respective breed names. Researchers and developers utilize this dataset to build and test AI models that can identify and classify dog breeds accurately. The dataset's diverse and extensive range of dog images helps these models learn to distinguish between different breeds effectively.

V. RESULT AND DISCUSSION

The experimental setup for "Comparative Analysis of Convolutional Neural Networks for Dog Breed Classification: Performance Evaluation and Insights" involved running the code in Google Colab, a cloud based Jupyter Notebook environment. The experiments utilized a free GPU resource, such as the NVIDIA Tesla K80 or T4 GPU, to accelerate the training of Convolutional Neural Networks. Colab's interactive interface facilitated code development and allowed easy access to data stored in Google Drive. With its user-friendly package installation and collaborative features, Colab provided a seamless platform for conducting the experiments efficiently.

AlexNet:

Figure 2: Loss graph of the proposed model

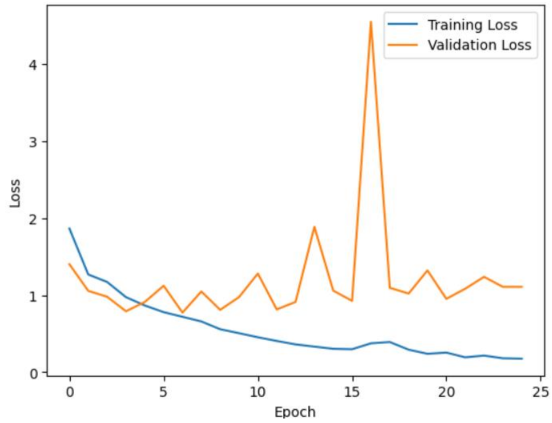


Figure 3: Accuracy graph of the proposed model

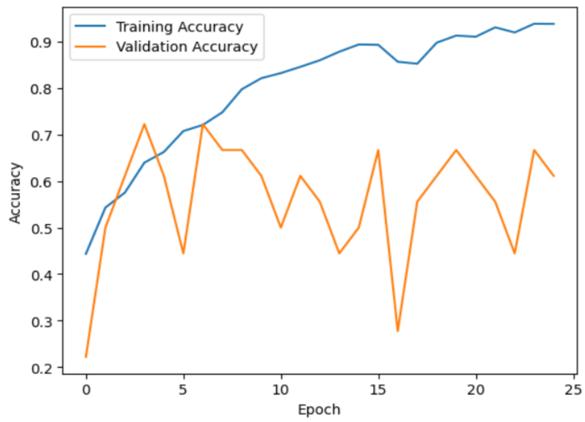
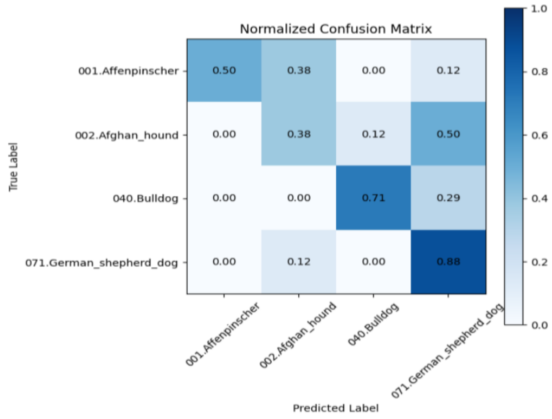


Figure 4: Confusion matrix of the proposed model



GoogLeNet:

Figure 5: Loss graph of the proposed model

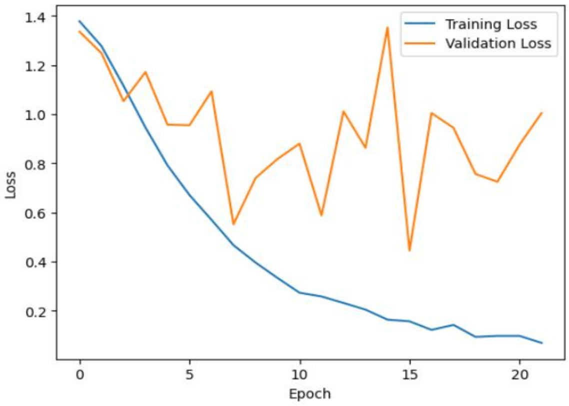
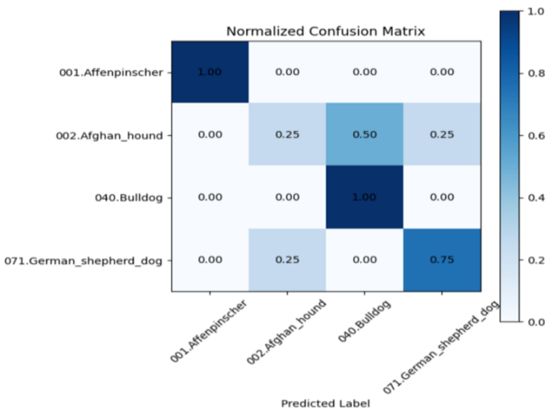


Figure 6: Accuracy graph of the proposed model

Figure 7: Confusion matrix of the proposed model



VGG16:

Figure 8: Loss graph of the proposed model

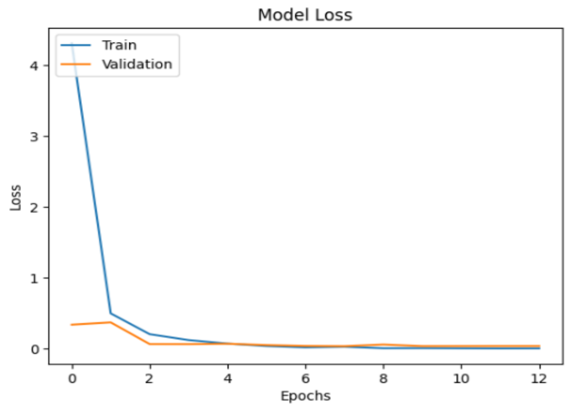


Figure 9: Accuracy graph of the proposed model

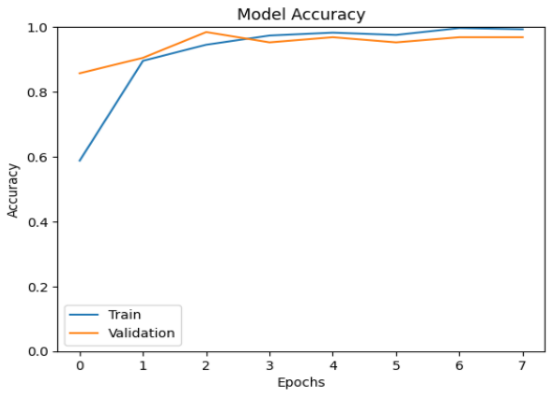
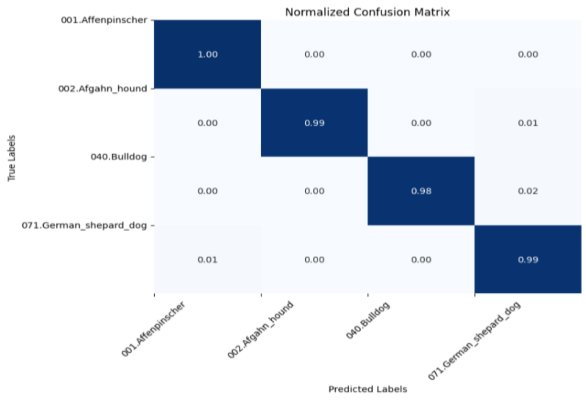


Figure 10: Confusion matrix of the proposed model



VGG19:

Figure 11: Loss graph of the proposed model

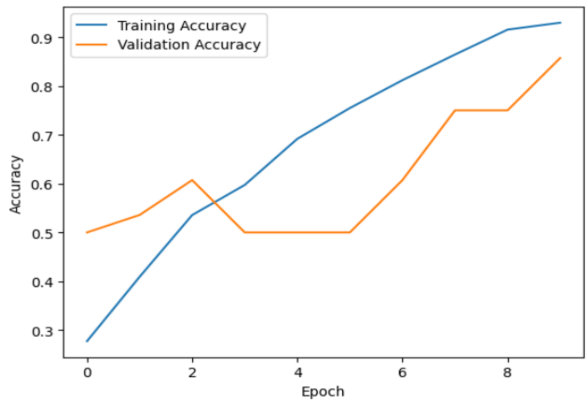


Figure 12: Accuracy graph of the proposed model

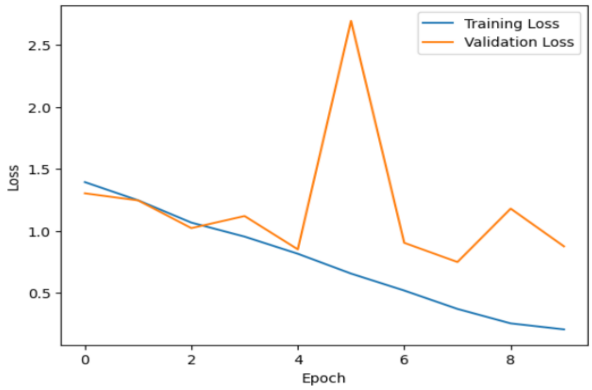
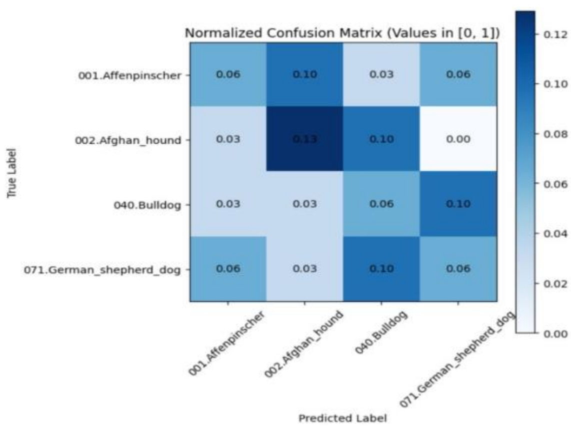


Figure 13: Confusion matrix of the proposed model



LeNet:

Figure 14: Loss graph of the proposed model

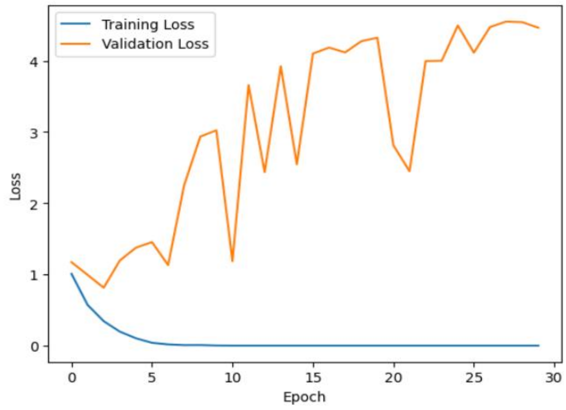


Figure 15: Accuracy graph of the proposed model

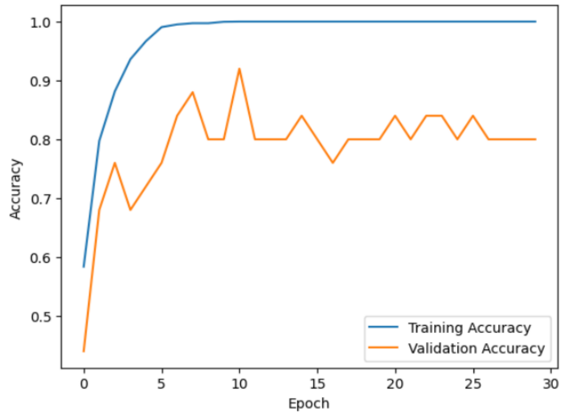
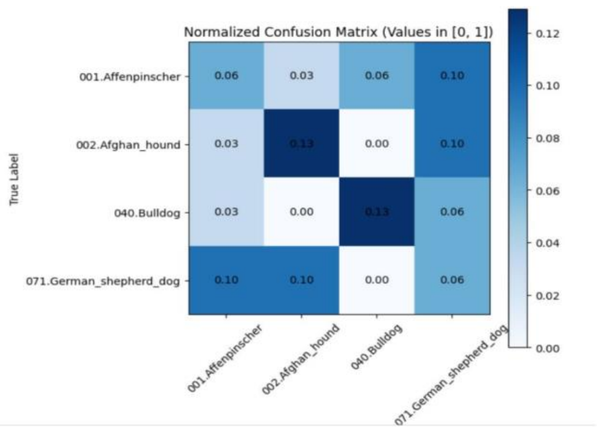


Figure 16: Confusion matrix of the proposed model



ResNet50:

Figure 17: Loss graph of the proposed model

Figure 18: Accuracy graph of the proposed model

Figure 19: Confusion matrix of the proposed model

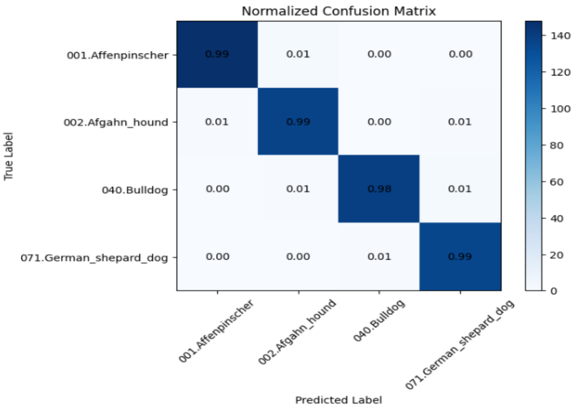


Table 3: Model comparison

CNN model	Train accuracy	Test Accuracy	Total No. of Parameters
AlexNet	0.9377	0.7777	35,716
GoogleNet	0.9819	0.8181	129,633,428
VGG16	0.9929	0.9840	16,816,452
VGG19	0.9242	0.7857	139,586,628
LeNet	1.0000	0.8999	24,253,496
ResNet50	0.9556	0.9535	25,557,032

Table 3: the above table compares the accuracy of the models.

The fig 2,5,8,11,14 and 17 are the loss graph of the Models, the fig 3,6,9,12,15 and 18 are the graph of the Accuracy values and the fig 4,7,10,13,16 and 19 are the Confusion matrix of the models AlexNet, GoogLeNet, VGG16, VGG19, LeNet and ResNet50 respectively. The performance evaluation of various CNN models on the "Dog Breed Classification using ConvNets" dataset reveals noteworthy insights. VGG16 and ResNet50 stand out with high training accuracy (99.29% and 95.56%, respectively) and competitive test accuracies (98.40% and 95.35%). GoogLeNet and VGG19 maintain a high training accuracy (98.19% and 92.42%) and a decent testing accuracy(81.81% and 78.57%).While AlexNet exhibited slightly lower accuracies. LetNet's high training accuracy (100%) suggests potential overfitting. These findings aid in selecting optimal models for precise classification tasks.

VI. CONCLUSION

In conclusion, our project on "Comparative Analysis of Convolutional Neural Networks for Dog Breed Classification: Performance Evaluation and Insights" presents a major stride in analyzing various CNNs and developing an efficient Dog Breed Classification model. The CNN models, including GoogLeNet, VGG16,and ResNet50, exhibit strong training accuracies of 98.19, 99.29% and 95.56%, respectively, along with commendable test accuracies. These results outperform earlier studies and demonstrate the efficacy of our approach.

VII. FUTURE WORK

In the future, we aim to explore ensemble techniques to further enhance the classification accuracy and delve into transfer learning for even more robust performance. Additionally, incorporating real-time implementation and developing a user-friendly application or API that allows users to upload images and receive real-time dog breed classification results. This could be useful for pet owners and animal shelters.

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