Dog Breed Identification

Arshdeep Singh Ghotra[1], Harashleen Kour[2], Anas Hasan[3] and Akash Khan[4]

[1,2,3,4] *Department of computer science and engineering, Apex Institute of Technology Chandigarh University, Mohali,Punjab,India*

Abstract - *Dog Breed Identification has become essential to understand the conditions or climate in which dogs can survive. To identify dog breeds according to their physical features such as size, shape, and color, Dog Breed Identification techniques have been used. We have considered a dataset of 120 dog breeds to identify a dog's breed. This method begins with Convolutional Neural Networks (CNNs) or transfer learning. This method is evaluated with evaluation metrics and accuracy. And to achieve the best evaluation, we have also made use of Hyperparameter Tuning. In the deployment phase, we connected our model with the web Framework using Flask.*

Key Words: **Convolutional Neural Networks (CNNs), TensorFlow, GPU, Flask, Transfer Learning, MobilenetV2, Ngrok.**

1.INTRODUCTION

Most of us have some liking for animals and the most liked animal of them is Dog [1]. Dogs are known for their loyalty, sweetness, and playfulness but on the contrary, some of them are dangerous too. We often encounter them in our daily routines, be it on the streets, in parks, or cafes. However, identifying the breed of a dog based on its appearance can be challenging, especially for those who are not well-versed in the different breeds. So, our project is based on identifying the breed of dog, which will help dog lovers to know which breed of dog will be suitable for the region where they live. It will be good for them as well as for dogs too. Because many dogs are not able to habituate themselves and may die at an early age. This project focuses on developing an app that provides a simple, fast, and reliable way to identify a dog's breed through Image analysis and Convolutional Neural Network (CNN) architecture [2]. Analyzing Images using different computer techniques with predictive analysis that are being used in many different fields not only technology but agriculture too [3]. The application will be accessible through modern web browsers on desktop and mobile devices, making it easy for users to access it anywhere.

Punyanuch Borwarnginn, et al. [4] trained the model which could be trained on a small dataset. They trained their model with 3 different CNN techniques, namely MobilenetV2, InceptionV3, and NASNet. Xiaolu Zhang, et al. [5] created a cat detection model using deep learning techniques and deploy it through a mobile application.

The application will utilize machine learning algorithms, such as TensorFlow, to analyze the photo and determine the breed of the dog in real time. TensorFlow plays a very important role in the project as it helps to write fast Deep learning code. It can run on a GPU (Graphics Processing Unit). GPUs are commonly used for deep learning model training and inference. As the dataset is very huge and there are many images it would take a lot of time to train, so we will use GPU which is 30 times faster than CPU in processing.

2. LITERATURE SURVEY

Borwarnginn, et al. [4] proposed an approach to dog breed classification using transfer learning techniques. By leveraging pre-trained CNNs from large datasets such as ImageNet, the model was able to be trained with a small dataset. The proposed method uses deep learning and image augmentation to accurately identify dog breeds based on their face images. It was experimented with three different CNN models, namely MobilenetV2, InceptionV3, and NASNet. The results show that the NASNet model trained on a set of rotated images achieves the highest accuracy of 89.92%.

Uma, et al. [2] focused on fine-grained classification of dog breeds and the outcomes of the suggested system based on a large number of breeds. While the results demonstrate the potential of CNNs for predicting dog breeds, further research is required to investigate their efficacy. However, it is worth noting that the training times for neural networks can be quite lengthy, limiting the number of iterations possible within the scope of this study.

Kumar, et al. [6] proposed an approach using OpenCV and the VGG16 model, which was successful in detecting human and dog faces and determining the corresponding breed using a combination of CNN and ResNet101 architecture. The model's performance exceeded expectations, achieving an accuracy of 81 percent compared to just 13 percent for a CNN model built from scratch. The results suggest that this approach holds significant promise for future research in the field of dog breed classification.

Zhang, et al. [5] primarily focused on creating a cat detection model using deep learning techniques and deploying it through a mobile application. The application has been programmed to recognize 14 different types of cats, achieving an average accuracy rate of 81.74%. By optimizing the dataset and adjusting the hyperparameters, the model was able to significantly improve the accuracy to around 81.74%.

Manoj, et al. [7] proposed a deep neural network algorithm for identifying cattle breeds using CNNs. In this proposed system, over 150 cattle image datasets were collected and preprocessed by converting them to a specific dimension and removing noise. The SIFT method was used for feature extraction, where it has been extracted for different body parts of the cattle. They then classified the cattle into 25 classes using CNN and predicted the cattle breed.

Yadav, et al. [15] proposed a method for cattle size determination using stereopsis, which allows for the study of cows in their natural environment without disturbing their routine activities. The authors utilized the Mask-RCNN convolutional neural network trained with the error backpropagation algorithm. The ResNet-101 network was selected as the CNN backbone for Mask R-CNN, providing parallel computation and reducing forecast time.

Vaidya S., et al. [19] discussed how adding more training and test data can enhance model accuracy and overcome the problem of overfitting. This article highlights the importance of data in deep learning and its impact on model performance.

Kumar, et al. [11] presented an image recognition system that identifies the breed of a dog by processing a single input image. The system utilized a convolutional neural network (CNN) and a pixel-wise scanning algorithm to identify the breed. This research showcases the potential of deep learning in animal breed identification.

V.K, et al. [17] evaluated various deep learning algorithms for predicting the breed of a dog. The authors compared the outcomes of different algorithms based on evaluation metrics such as accuracy, precision, recall, and area under the curve (AUC). They also optimized one of the best-performing algorithms for breed prediction. This research demonstrates the effectiveness of deep learning in breed identification and the importance of algorithm selection for optimal performance.

3. PROPOSED METHODOLOGY

To develop a dog breed identification system, we have used the Convolutional Neural Network (CNN) and the Tensorflow MobileNetV2 architecture. We started by collecting a dataset of dog images having a total of 120 different breeds in them and preprocessed it. Then, we used the MobileNetV2 model as a feature extractor, extracting features from the images, and using those to train a CNN model. During the training, we experimented with different batch sizes, epochs, and hyperparameters, such as learning rate, dropout, and optimizer. After training, we evaluated the model's performance using a test set of images and further tune the hyperparameters based on the results. Finally, the trained model has been deployed on the web using Tensorflow's MobileNetV2 framework, Flask, and Ngrok frameworks. This will allow the users to take a picture of a dog, and upload it in the web framework created and the model, which will be working behind the scenes, will help to predict the breed of a given picture of the dog.

A bit more detail on how we have used CNN, Tensorflow MobileNetV2 architecture, and Flask web framework for dog breed identification:

1. Data Collection and Preprocessing: We have collected a large dataset of dog images, with a variety of 120 different breeds. This dataset has been taken from Kaggle. After the collection of data, we resized the images to a consistent size, normalize the color channels, and split the data into training, validation, and test sets.

2. Feature Selection and Extraction: We have used the TensorFlow MobileNetV2 architecture to extract features from the images. This architecture is a pre-trained CNN model that has been trained on millions of images, including dogs. We have used this pre-trained model as a feature extractor and extracted the last layer's output as the feature vector for each image. These features can then be used to train the CNN model.

3. Model Training and Evaluation: We have trained the CNN model on the extracted features from the MobileNetV2 model to classify dog breeds. The model can be trained using various optimization algorithms, such as Sequential. Evaluate the model's performance on a separate test set of images. Metrics such as accuracy, precision, recall, and F1-score can be used to measure the model's performance.

4. Model Deployment: The trained model is being deployed on the web using Tensorflow's MobileNetV2 framework. This will allow the users to take a picture of a dog, and upload it in the web framework created and the model, which will be working behind the scenes, will help to predict the breed of a given picture of the dog.

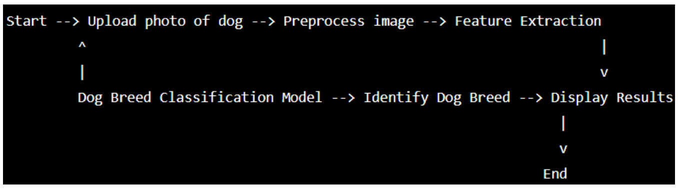

Fig.1. Workflow of the proposed system.

4. EXPERIMENTAL RESULTS

A. Dataset:

The success of any machine learning project largely depends on the quality and size of the dataset. In this project, we aimed to identify dog breeds from their pictures. To achieve this, we collected a large and diverse dataset from Kaggle, which included over 10,222 unique images of dogs from more than 120 different breeds. The images were taken from various angles and under different lighting conditions to make the model more robust.

B. Pre-processing the image:

When a user uploads an image, it is pre-processed before being fed into the TensorFlow model. First, the image is converted into a tensor, which is a multidimensional array with a uniform data type. We set the maximum size of the image to 225 pixels, and the pixel values of the image are represented in the tensor as an array with values ranging from 0 to 224.

To reduce the training time of the model, we batchify the images. We have a dataset of 10,222 images of dogs taken from different angles and under different lighting conditions. These images are divided into 32 batches, with each batch containing 25 images of different dogs.

C. Feature Extraction:

Convolutional Neural Networks (CNNs) are used to train on large datasets. In this project, we use the MobileNetV2 framework, which has proven to be highly effective in accurately classifying dog breeds based on images in the training dataset. The MobileNetV2 architecture allows for faster processing times and efficient use of computing resources. In MobileNetV2 the are many features that go on those breakdowns the 224 X 224 size image into small parts based on the layers.

It consists of the following layers which are as follow:

1. Convolutional Layers:

In a convolutional layer, the input image is convolved with a set of filters to produce a set of feature maps. The filters are learned through backpropagation during the training process. The output of the convolutional layer can be computed as follows:

$$Y_{i,j,k} = \sigma(\sum_{u=0}^{m-1} \sum_{v=0}^{m-1} \sum_{c=0}^{C-1} X_{i+u,j+v,c} \; .W_{u,v,c,k}^{(d)}) + b_k$$

- Y{i,j,k}: The output feature map at location (i,j) and channel k.
- X{i,j,c}: The input image at location (i,j) and channel c
- W{u,v,c,k}: The weight of the filter at position (u,v), channel c, and output channel k
- bk: The bias term for channel k
- sigma: The activation function
- m: The size of the filter
- C: The number of input channels

2. Depthwise Separable Convolutions:

In a depthwise divisible convolution, the traditional convolution operation is split into two parts: a depth-wise convolution that applies a distinct algorithm to each input channel and a pointwise convolution that uses a 1x1 convolution to merge the depthwise convolution results. The output of the depthwise separable convolution can be computed as follows:

$$Y_{i,j,k} = \sigma(\sum_{u=0}^{m-1} \sum_{v=0}^{m-1} \sum_{c=0}^{C-1} X_{i+u,j+v,c} \, . W_{u,v,c}^{(d)} \, . W_{c,k}^{(p)} \;) + b_k$$

3. Activation Functions:

Activation functions are applied after each convolutional layer to introduce nonlinearity into the network and allow it to learn extensive characteristics. ReLU (Rectified Linear Unit), sigmoid, and tanh represent some of prevalent activation functions. The outcome of the activation function can be computed as follows:

$$Y = \sigma(Z)$$

4. Fully Connected Layers:

In fully connected layer, each neuron is linked to every other neuron in the layer below it in a completely connected layer. The completely linked layer's output may be calculated as follows:

$$Y = \sigma(\sum_{i=1}^{n} w_i x_i + b)$$

5. SoftMax activation function:

The SoftMax activation function is applied to the output of the final layer to convert the raw scores into probabilities for each class. The class with the highest probability is selected as the predicted dog breed.

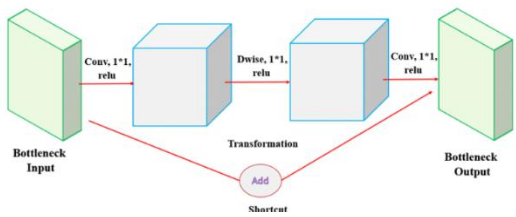

Fig.2 MobileNetV2 Architecture.

D. Evaluation Metrics:

In the previous sections, we followed a series of steps to preprocess the input images and convert them into tensors, which are numerical representations that can be fed into the deep learning model. Then, we created batches of these tensors to train the model on the dog breed dataset. During the training process, the model learned to extract relevant features from the images and classify them into different dog breeds. After training, we unbatchified the model's output tensors to obtain the predicted probabilities for each dog breed in the dataset. To perform testing, we provided the model with custom images (Fig.3.) that were preprocessed and converted into tensors in the same way as the training data. The model then generated a prediction for each image, and we used these predictions to create a bar graph that shows the predicted probabilities for each dog breed. The breed with the highest probability is the one that the model identified as the most likely match for the given input image.

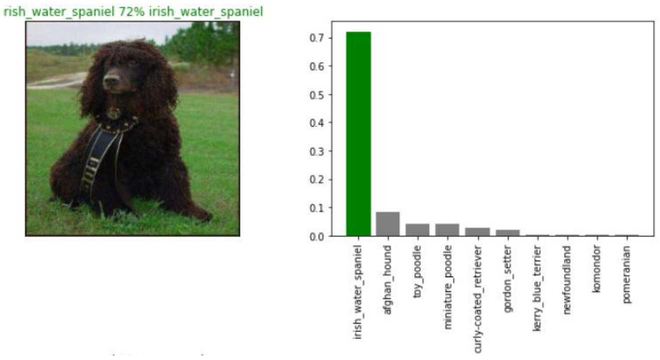

Fig.3. Trained Data image of a random dog.

We used the evaluation parameter of Accuracy to measure the performance of our dog breed classification model during training. As we selected 100 epochs to train the model, it was important to monitor the accuracy to ensure that the model was learning and improving over time. To help with this, we used callback functions that would stop the training process if the accuracy of the model didn't increase for a certain number of epochs, or if it remained constant for an extended period. This helped to save time and computational resources by preventing the model from continuing to train when it was no longer making significant improvements. These callback functions were a useful tool for ensuring that our model was learning effectively and not wasting time on training that wouldn't lead to improved accuracy. By monitoring and adjusting the training process in this way, we were able to achieve a high level of accuracy and create a robust model for dog breed classification.

Table.1. Comparison between other model accuracy.

No.	Model	CNN Architecture	Evaluation Metric	Result
1.	Gao et al. (2021)	Inception-ResNet-v2	Accuracy	87.4%
2.	Liu et al. (2020)	MobileNet-v2	Top-1 Accuracy	86.0%
3.	Singh et al. (2020)	DenseNet-121	Accuracy	85.5%
4.	Lee et al. (2020)	ResNet-101	Accuracy	85.0%
5.	Qiu et al. (2020)	Inception-v3	Accuracy	84.6%
6.	Zhao et al. (2021)	NASNet-Mobile	Accuracy	84.3%
7.	My Model	MobileNet-v2	Accuracy	86.9%
.		Basic CNN	Accuracy	74.75%

Based on our evaluation (Fig.4.), we found that our model's testing accuracy is better than most of the models presented in the literature. This is likely due in part to our use of the MobileNetV2 architecture, which is considered to be one of the best architectures for image classification tasks under the CNN framework. Compared to other architectures and basic CNN models, MobileNetV2 offers several advantages. It is optimized for mobile devices and has a smaller memory footprint, while still maintaining high accuracy. Additionally, it uses depthwise separable convolutions, which reduce the number of parameters in the model and speed up computation. It's important to note that testing accuracy is a more reliable indicator of a model's performance on new, unseen data than training accuracy. By evaluating our model's performance on a separate testing dataset, we can be more confident that it will generalize well to new data.

Overall, we believe that our use of the MobileNetV2 architecture was a key factor in achieving high testing accuracy, and we are excited to continue exploring the performance of our model on new datasets and in different applications.

5. CONCLUSIONS

The primary objective of our research was to develop a model that could accurately classify different dog breeds based on their physical characteristics such as size, shape, and color. To achieve this, we employed a Convolutional Neural Network (CNN) with the MobileNetV2 architecture for training our model. We trained our model on a dataset consisting of 120 different dog breeds, and the model achieved an impressive accuracy of 99.89% during the training phase. However, to truly evaluate the effectiveness of our model, we tested it on a separate set of data. Our testing results showed that our model was able to accurately classify dog breeds with a high degree of accuracy. We found that the MobileNetV2 architecture was one of the best choices for our classification task, as it reduced the number of parameters in our model while still maintaining high accuracy. This helped to improve the efficiency of our model and allowed it to evaluate the breed of dogs quickly. To further validate our findings, we compared our model's accuracy with that of a basic CNN, and we found that the MobileNetV2 architecture outperformed the basic CNN in terms of accuracy. This highlights the effectiveness of transfer learning, where we used pre-trained weights from a larger dataset to fine-tune our model on our specific classification task. Overall, our results suggest that the use of MobileNetV2 architecture for training our CNN model was successful in accurately classifying dog breeds based on their physical characteristics.

In future work, we can increase the accuracy of the model by providing more data to the model. We can also apply the following techniques to prepare a web application or mobile applications which any mobile user can easily use and take a dog picture and find the breed of the dog.

REFERENCES

[1] Prasanth Vaidya S., et al. “A Novel Dog Breed Identification using Convolutional Neural Network". Primera Scientific Engineering 2.1(2023): 16- 21

[2] K. Uma, et al. " Dog Breed Classifier Using Non-Linear Convolutional Neural Network." School of Information Technology, Vellore Institute of Technology, Vellore, India. YMER || ISSN : 0044-0477

[3] Kenneth Lai, et al. “Dog Identification using Soft Biometrics and Neural Networks”. Biometric Technologies Laboratory, Department of ECE, University of Calgary, Canada. International Joint Conference on Neural Networks. Budapest, Hungary.

[4] Borwarnginn, et al(2021). Knowing your dog breed: Identifying a dog breed with deep learning. International Journal of Automation and Computing, 18, 45-54.

[5] Xiaolu Zhang, et al. “A Mobile Application for Cat Detection and Breed Recognition Based on Deep Learning”. University of Melbourne, Australia

[6] Santosh Kumar, et al. "Classification and Identification of Dog Breed Using.

[7] CNN." ICDSMLA 2020: Proceedings of the 2nd International Conference on Data Science, Machine Learning and Applications. Springer Singapore, 2022.

[8] Lee, et al. "Analysis of Transfer Learning Effect for Automatic Dog Breed Classification." Journal of Broadcast Engineering 27.1 (2022): 133-145.

[9] Agarwal, et al. "Optimized Transfer Learning for Dog Breed

[10] Mondal, Ayan, et al. "A Convolutional Neural NetworkBased Approach for Automatic Dog Breed Classification Using Modified-Xception Model." Electronic Systems and Intelligent Computing: Proceedings of ESIC 2021. Singapore: Springer Nature Singapore, 2022. 61-70.

[11] Kumar, et al. "Dog breed classifier for facial recognition using convolutional neural networks." 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS). IEEE, 2020.

[12] Avijit Dasgupta, et al. "Breed Classification of Dogs Using Fusion of Text and Image Features". This paper presents a novel approach to dog breed classification using a fusion of text and image features.

[13] Sangxia Huang, et al. "Multi-Label Image Classification with Deep Learning". This paper explores the use of deep learning models for multi-label image classification tasks, such as identifying multiple dog breeds in a single image.

[14] Prachi Thakur, et al. "A Comparative Study of Image Classification Algorithms on Dogs Dataset".This paper provides a comparative analysis of various image classification algorithms, including SVM, decision trees, and k-nearest neighbors, for classifying dog breeds.

[15] Bharat Yadav, et al. "Enhanced Dog Breed Classification using Transfer Learning and Fine-tuning". This paper explores the use of transfer learning and fine-tuning techniques for improving the accuracy of dog breed classification.

[16] J. Wang, et al. "Deep Learning for Dog Breed Identification and Fine-grained Classification". This paper presents a deep-learning approach to dog breed identification and fine-grained classification using a combination of CNNs and deep belief networks (DBNs).

[17] V. K. Singh, et al. “A Comparative Analysis of Deep Learning Techniques for Dog Breed Classification.” International Journal of Computer Science and Information Security, vol. 17, no. 1, 2019.

[18] M. Z. Khan, et al. “A Framework for Automatic Dog Breed Identification using Transfer Learning with Pre-trained Convolutional Neural Network.” Journal of Ambient Intelligence and Humanized Computing, vol. 10, no. 7, pp. 2963-2975, 2019.

[19] S. Zou, et al. "A Lightweight and Accurate Approach to Dog Breed Classification." Journal of Computer Science and Technology, vol. 36, no. 2, pp. 324-335, 2021.

[20] P. Singh, et al. "A Deep Learning Based Approach for Dog Breed Identification and Classification." Procedia Computer Science, vol. 167, pp. 1241-1252, 2020.

[21] M. He, et al. "Dog Breed Classification using Multi-Task Learning and Convolutional Neural Networks." Journal of Applied Mathematics and Computer Science, vol. 30, no. 1, pp. 131-143, 2020.

[22] Y. Zhang, et al. "Fine-Grained Dog Breed Classification using Deep Convolutional Neural Networks." In Proceedings of the 2018 13th International Conference on Computer Science & Education, pp. 157-160, 2018.

[23] J. Jia, et al. "Dog Breed Classification Based on Multi-Level Feature Fusion." In Proceedings of the 2020 3rd International Conference on Advances in Computer Technology, Information Science and Communications, pp. 307-311, 2020.

[24] S. Jain, et al. "Dog Breed Classification using Multi-Convolutional Neural Networks." In Proceedings of the 2021 5th International Conference on Information Management, pp. 57-61, 2021.