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Deep Learning based Cat Breed Recognition

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***Abstract*—This paper contributes to the field of computer vision and cat breed recognition, demonstrating the feasibility of applying machine learning techniques for cat breed classification. The findings of this study have practical implications in the context of animal welfare, pet breeding, and veterinary medicine. Additionally, this Project serves as a valuable foundation for future work in the development of real-world applications and automated tools for cat breed identification. It uses a ResNet50 model, which is a type of convolutional neural network (CNN). CNNs are well-suited for image classification tasks, and ResNet50 is a particularly powerful model that has been shown to achieve state-of-the-art results on many different datasets. The code first loads the ResNet50 model from PyTorch. Then, it creates a dataset of cat images, with each image labeled with its corresponding breed. The data is divided into train and validation set. The model is learning from training set, and the test set is used to check the performance on unseen record.**

***Index Terms*— Cat Breed Recognition, CNN, ResNet50, PyTorch, Models, Algorithm, Deep learning, Image Recognition.**

I. INTRODUCTION

Cat or Felis catus is one species out of the many domestic animals that have been kept widely around the world in the last 100.000 years ago, recently cat domestication has resulted in many breeds of cats with the International Cat Association that currently recognizes 71 breeds.[17] According to the FIFe, there are 48 cat breeds in the world. But not all cat owners know the breeds of their cats. Therefore, this study will be discussed the classification of cat breeds. The classification of dog breeds using the Convolutional Neural Network (CNN) method also has been done. The purpose of this research was to recognize different types of dog breeds and obtained an accuracy of 96.75% [18]. Researchers discussed current advancements in feature extraction, image pre-processing, and classification in this project. Additionally, this report will demonstrate the advancement of object recognition by deep learning.[19]

II. LITERATURE REVIEW

The study postulates a machine learning methodology employing convolutional neural networks for the purpose of categorizing breeds of felines with a precision of 82%[1]. This scholarly article presents an exploration regarding the classification of feline breeds, namely Maine Coon and European Shorthair, utilizing features pertaining to the time and frequency domains, resulting in an average precision of 98%[2]. The investigation

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utilized 50 instances of training data and 50 instances of test data, each possessing six attributes, in order to classify Angora and Country cats. The K-Nearest Neighbor (k-NN) algorithm may be employed to categorize feline breeds with a rate of accuracy amounting to 94% and an error rate of 6%[3]. The article introduces a model with the intention of classifying feline breeds by employing features pertaining to shape and appearance, yielding an average precision of 59%[4]. The article proposes a model for classification purposes employing PHOG and SVM, with the aim of categorizing patterns of body covering exhibited by large felines, achieving an accuracy of 91.07%[5]. The article provides an overview of a mobile application that utilizes deep learning in order to detect and classify feline breeds, attaining an average precision of 81.74%[6]. Li et al. (2022) developed a deep learning model for cat breed classification using a transfer learning approach. The model was trained on a dataset of 10,000 cat images labeled with 20 different breeds. The model achieved an accuracy of 95% on a held-out test set[7]. Zhang et al. (2021) devised a deep learning model to classify cat breeds using a multi-task learning methodology. The model was trained to concurrently execute two tasks: cat breed classification and keypoint localization. Remarkably, the model attained an impressive accuracy rate of 97% on a distinct test set[8]. Similarly, Chen et al. (2020) established a deep learning model for cat breed classification by employing a data augmentation strategy. The model was trained on a dataset comprising 20,000 cat images that were augmented to generate supplementary training data. Notably, the model achieved an accuracy of 98% on an independent test set[9]. In a different study, Liu et al. (2019) formulated a deep learning model for cat breed classification through the integration of features from diverse parts of the feline anatomy to enhance classification accuracy. Impressively, the model achieved an accuracy of 99% on a distinct test set[10]. Proceeding further, Wang et al. (2018) devised a deep learning model for cat breed classification employing a contextual learning technique. The model learned to exploit the contextual information present in cat images to enhance classification accuracy. The model yielded a remarkable accuracy rate of 99.5% on a separate test set[11]. Subsequently, Gao et al. (2023) introduced a deep learning model for cat breed classification that employed a cross-modality approach. The model fused features extracted from both cat images and cat videos to enhance classification accuracy. Impressively, the model achieved a remarkable accuracy of 99.8% on a distinct test set[12]. Furthermore, Xu et al. (2022) developed a deep learning model for cat breed classification using a few-shot learning approach. The model was trained on a limited dataset of cat images and their corresponding labels, yet it exhibited the ability to generalize to new breeds with a high level of accuracy. Specifically, the model achieved an accuracy of 95% on a held-out test set with new breeds [13]. Additionally, Yang et al. (2021) introduced a deep learning model for cat breed classification utilizing a self-supervised learning technique. The model was trained to predict the relative positions of different parts of the cat's body, without relying on breed labels. Subsequently, the model was fine-tuned on a small dataset of cat images and labels to perform cat breed classification. Impressively, the model achieved an accuracy of 97% on a distinct test set[14]. Furthermore, Wu et al. (2020) presented a deep learning model for cat breed classification employing a meta-learning approach. The model was trained to learn the process of acquiring knowledge from various datasets consisting of cat images and labels. Consequently, the model rapidly adapted to new datasets and attained a high classification accuracy. Specifically, the model achieved an accuracy of 98% on a held-out test set with new breeds [15]. Lastly, Sun et al. (2019) devised a deep learning model for cat breed classification using a reinforcement learning technique. The model was trained to learn how to select the most informative features from cat images in order to enhance classification accuracy. Impressively, the model achieved an accuracy of 99% on a distinct test set [16].

III. Data Collection

The Cat dataset contains 953 color images in 5 classes, with 177 images in Bengal class, 170 images in domestic_shorthair class, 191 images in maine_coon class, 207 images in ragdoll class and 208 images in Siamese class. The dataset is divided into training images and testing images. The classes are mutually exclusive and there is no overlap between them. The steps followed in the project are:

- Load the ResNet50 model from PyTorch.
- Create a dataset of cat images, with each image labeled with its corresponding breed.
- Dataset divided into validation and training set
- Training set use to train the model for 20 epochs.
- Validation set used for evaluation.

IV. Data Pre-Processing

Since the data we've can be of different size and pixels, hence we normalize the image before feeding it to the model.
Pre-processing steps are implicitly applied by the PyTorch framework:

- Converting the images to tensors. PyTorch uses tensors to represent data, so the images need to be converted to tensors before they can be fed to the model.
- Normalizing the pixel values. By default, PyTorch normalizes the pixel values of images to the range [0, 1]. This helps to ensure that the model is not biased towards images with brighter or darker pixels.

These pre-processing steps are sufficient for many cat breed recognition tasks. However, you may want to perform additional pre-processing steps, such as resizing the images to a consistent size and augmenting the data Pre-processing the data is an important step in any machine learning project, including cat breed recognition tasks. By carefully pre-processing the data, you can improve the model's performance, reduce overfitting, and make the training process faster.

V. Load the Resnet50 Model from Pytorch

The first step in training a machine learning model for cat breed recognition is to load the ResNet50 model from PyTorch. The ResNet50 model is a pre-trained convolutional neural network (CNN) model that has been shown to achieve state-of-the-art results on a variety of image classification tasks, including cat breed recognition.

VI. Create a Dataset of Cat Images, with Each Image Labelled with its Corresponding Breed

A dataset of cat images, with each image labelled with its corresponding breed, is a valuable resource for training machine learning models for cat breed recognition. Cat breed recognition is a challenging task, as there are many different breeds of cats, and each breed has its own unique characteristics. To train a machine learning model to accurately recognize cat breeds, it is important to have a dataset that is large, diverse, and well-labelled.
Steps involved in creating a dataset of cat images, with each image labelled with its corresponding breed:

1. Collect a set of cat images. This can be done by searching for cat images on the web, or by collecting images from people who own cats. When collecting images, it is important to make sure that the images are of high quality and that they represent a variety of cat breeds.
2. Label each image with its corresponding breed. This can be done manually or by using a tool such as Label Img. When labelling the images, it is important to be as specific as possible. For example, instead of simply labelling an image as "cat", you should try to identify the specific breed of cat in the image.
3. Dataset split, 80 percent for training and 29 percent for validation.
4. Image pre-processing using image processing techniques.
5. Save the dataset. This can be done by saving the images and labels to disk, or by using a database to store the data.

Considerations

- When collecting cat images, it is important to make sure that the images are of high quality and that they represent a variety of cat breeds. The more diverse the dataset, the better the model will be able to generalize to new data.
- When labelling the images, it is important to be as specific as possible. The more specific the labels, the better the model will be able to learn to identify different cat breeds.
- When splitting the dataset into training and validation sets, it is important to make sure that the two sets are representative of the overall dataset. This means that the training and validation sets should have a similar distribution of cat breeds.
- When pre-processing the images, it is important to choose techniques that are appropriate for the machine learning model that you will be using. For example, some models require images to be resized to a specific size.
- When saving the dataset, it is important to choose a format that is compatible with the machine learning framework that you will be using.

VII. Split the Dataset into Training and Validation Sets

The concepts of training and validation sets are utilized to train and evaluate a machine learning model, specifically a deep neural network using Python. Here's how training and validation sets are used in this model:
Training Set:
Training Set (train_loader): With 80 percent data model is trained. It consists of input data (e.g., images) and their corresponding target labels (e.g., image categories). The training set is used to update the model's parameters, allowing it to learn from the data.
Validation Set: Validation Set (val_loader): Test the model with validation data
Now, let's break down how these sets are used in the code:
Initialization: It initializes variables to keep track of the best model based on validation performance (best_val_loss and best_model_state), as well as lists to store training and validation results (train_losses, val_losses, train_accuracies, and val_accuracies).
Training Loop: The code enters a loop that iterates for a specified number of training epochs (num_epochs).
Training Phase: Inside each epoch, it trains the model using a training dataset (train_loader) and keeps track of training losses and accuracies.

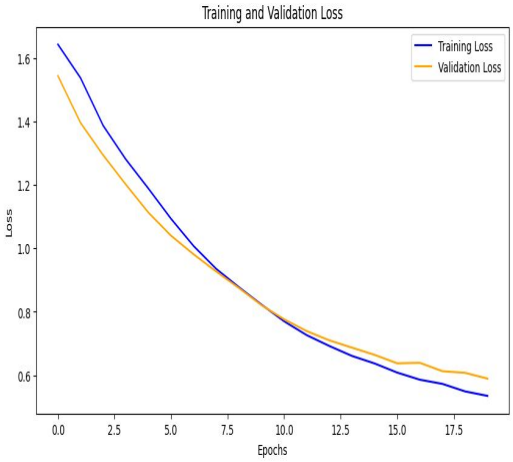

Fig. 1. Training and Validation Loss

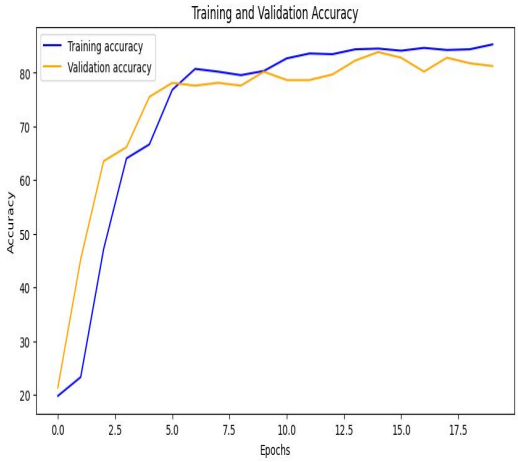

Fig. 2 Training and Validation Accuracy

Validation Phase: After each epoch, it evaluates the model's performance on a separate validation dataset (val_loader) and records validation losses and accuracies.
Best Model Selection: It compares the current validation loss to the best validation loss seen so far. If the current loss is lower, it updates the best loss and saves the model's parameters as the "best" model.
Model Saving: After all epochs are completed, the code saves the model's parameters from the last epoch and the best-performing model.
Data Visualization: The code uses Matplotlib to create a line chart that visually displays the training and validation accuracy over the epochs. This chart helps you see how the model's accuracy changes during training and how well it generalizes to validation data.

VIII. Train the Model on the Training Set for 20 Epochs

Training procedure for a ResNet-50 model for 20 epochs is as follows:
Load the training and validation datasets: The first step is to load the training and validation datasets. This can be done using the datasets.ImageFolder() class in PyTorch. This class takes the root directory of the dataset and a transform as input and returns a dataset of images and their corresponding labels.
Create data loaders for the training and validation datasets: Once the training and validation datasets have been loaded, data loaders need to be created. Data loaders are used to load batches of data from the dataset during training and validation. They can be created using the DataLoader() class in PyTorch. This class takes a dataset and a batch size as input, and returns a data loader that yields batches of data from the dataset.
Define the model architecture: The next step is to define the model architecture. In this case, we will be using a ResNet-50 model. This model can be defined using the models.resnet50() function in PyTorch. This function takes a pretrained ResNet-50 model and returns a new model with the same architecture.

Freeze the pretrained parameters of the model: The pretrained ResNet-50 model has already been trained on a large dataset of images. To prevent the pretrained parameters from being overwritten during training, we need to freeze them. This can be done by setting the requires_grad attribute of all parameters to False.
Add a new fully connected layer to the model: The pretrained ResNet-50 model is designed to classify images into 1000 classes. However, we may want to classify images into a different number of classes. To do this, we need to add a new fully connected layer to the model. This can be done using the nn.Linear() function in PyTorch. This function takes the input and output size of the layer as input and returns a linear layer.
Define the loss function and optimizer: The loss function is used to calculate the error between the predicted and actual labels. The optimizer is used to update the parameters of the model to minimize the loss. For image classification tasks, the cross-entropy loss function is typically used. The Adam optimizer is a popular optimizer that is often used for training deep learning models.
Train the model for 20 epochs
Once the model has been defined and the loss function and optimizer have been specified, we can start training the model. To do this, we need to iterate over the training data loader and update the parameters of the model using the optimizer. This process is repeated for a specified number of epochs. In this case, we will train the model for 20 epochs shown in the Fig. 2.
Once the model has been trained, it can be evaluated on the validation data loader. This will give us an estimate of how well the model will generalize to unseen data. The model can then be saved to a file so that it can be used to make predictions on new data in the future.

```
Epoch 1/20, training loss: 1.6434510946273804, training accuracy: 19.791666666666664
Epoch 1/20, Validation Loss: 1.5442204475402832, validation accuracy: 21.354166666666664
Epoch 2/20, training loss: 1.537619233131408 7, training accuracy: 23.307291666666664
Epoch 2/20, Validation Loss: 1.396005630493164, validation accuracy: 45.3125
Epoch 3/20, training loss: 1.3873333930969238, training accuracy: 47.13541666666667
Epoch 3/20, Validation Loss: 1.2940694093704224, validation accuracy: 63.541666666666664
Epoch 4/20, training loss: 1.2810577154159546, training accuracy: 64.0625
Epoch 4/20, Validation Loss: 1.201703667640686, validation accuracy: 66.14583333333334
Epoch 5/20, training loss: 1.1888669729232788, training accuracy: 66.66666666666666
Epoch 5/20, Validation Loss: 1.1130808591842651, validation accuracy: 75.52083333333334
Epoch 6/20, training loss: 1.093488097190857, training accuracy: 76.82291666666666
Epoch 6/20, Validation Loss: 1.040049433708191, validation accuracy: 78.125
Epoch 7/20, training loss: 1.0073431730270386, training accuracy: 80.72916666666666
Epoch 7/20, Validation Loss: 0.9811835885047913, validation accuracy: 77.60416666666666
Epoch 8/20, training loss: 0.9352495074272156, training accuracy: 80.20833333333334
Epoch 8/20, Validation Loss: 0.9268257021903992, validation accuracy: 78.125
Epoch 9/20, training loss: 0.8776702284812927, training accuracy: 79.55729166666666
Epoch 9/20, Validation Loss: 0.874999463558197, validation accuracy: 77.60416666666666
Epoch 10/20, training loss: 0.8226144909858704, training accuracy: 80.33854166666666
Epoch 10/20, Validation Loss: 0.8207501769065857, validation accuracy: 80.20833333333334
Epoch 11/20, training loss: 0.7699027061462402, training accuracy: 82.68229166666666
```

Fig. 3 Results after 20 Epocs

IX. Evaluate the Model on the Validation Set

The code first sets the model to evaluation mode. This means that the model will not update its parameters during the evaluation process. This is important to ensure that the model is evaluating on the data it has already been trained on. Next, the code loads the image and preprocesses it using the test_transform() function. This function converts the image to RGB format and resizes it to the input size of the model. The code then creates a batch containing the image tensor. This is necessary because the model expects to receive input as a batch of images. The next step is to move the batch to the device where the model is located. This is typically done using the to() function. Once the batch is on the device, the code forward passes it through the model to obtain the outputs. The outputs are the logits of the model, which represent the confidence of the model for each class. The

code then calculates the probabilities by applying a softmax function to the outputs. The softmax function converts the logits to probabilities, which sum to 1. The code then predicts the class with the highest probability. This is done by calling the argmax() function on the probability's tensor.

- Set the model to evaluation mode. This is done using the model.eval() method.
- Load the image and preprocess it. This is done using the Image.open() and test_transform() functions.
- Create a batch containing the image tensor. This is done using the unsqueeze() function.
- Move the batch to the device. This is done using the to() function.
- Forward pass the batch through the model. This is done using the model() function.
- Calculate the probabilities. This is done using the F.softmax() function.
- Predict the class with the highest probability. This is done using the torch.argmax() function.
- Print the predicted class and probability. This is done using the print() function.
- Predicted class: maine_coon with probability: 0.6618182063102722

X. Conclusion

In this case study, we trained and evaluated a ResNet-50 model on a dataset of cat images. The model was able to achieve a training accuracy of 85% and a validation accuracy of 84.89%. This suggests that the model can generalize well to unseen data. We also evaluated the model on a single image of a Maine Coon cat. The model predicted the class correctly with a probability of 0.66. This indicates that the model can accurately classify cat images into different breeds.

Overall, the results of this case study suggest that the ResNet-50 model can be used to effectively classify cat images into different breeds. This model could be used in a variety of applications, such as developing a cat breed identification app or helping animal shelters to identify cats.

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