Cats Breeds Image Classification

1. Introduction

Image recognition or image processing problem, one of the multiclass classifications, namely determining the breed of a cat in the given picture. This Image processing is getting a lot of attention in machine learning as well as in deep learning. This technique is used to process the image in such a way that the computer understands the features of the image and classifies it. The proposed system involves methods in deep learning, including Convolutional Neural Networks (CNN). CNN is widely used in various situations. It helps to perform different tasks on larger datasets. Cat breed identification is a unique application of Convolutional Neural networks. Since the identification of cat breeds is very difficult because they contain many inter-class similarities and it makes it very hard for a person to identify or classify cats. During the study of Convolutional Neural Networks, I will come across many layers such as Conv2D array, relu, Maxpooling2D, Flatten, Dropout, and Dense which makes a better understanding of the Neural Network architecture layer.

In this project, I will see how to use Keras and TensorFlow to build, train and test a Convolutional Neural Network capable of identifying the breed of a cat in a supplied image. This is a supervised learning problem. Here we have about 14 different cat breeds which consist of 711 images of cats in the dataset. I load these images and convert them into a NumPy array and normalise them. I use 100 epochs and a batch size of 32 to achieve the best accuracy.

2. Related Work

What is their problem and method ? How is your problem and method different? Use 3-4 References.

This problem statement has been extensively studied over the past 5 years by researchers and automotive companies in a bid to create a solution, and all their solutions vary from analysing the cat breed identification using different methods some of the research was as follows.

- The work of K. Mulligan et al [1] and P. Rivas et al [2] in the year 2019, July, conducted cat breed identification with the help of Xception Convolutional Neural Network architecture. This paper is mainly focused on classification tools. The dataset is downloaded from Kaggle. This classification is worked on CNN and Xception with multilayer perceptrons. The methods used for Xception and MLP. Experimented on 120 unique breeds over 10,200 images of dogs. From this project, a confusion matrix was created over training and test sets. Its major drawbacks were generating a diagonal pattern and the values incorrectly predicted. The methods were not passed through cross-validation. Achieved accuracy of 54.80 %. Later with the performance matrix, changing and increasing the number of splits utilised by both LogLoss and balance accuracy. After doing this achieved the correct prediction of describing the image belonging to which type of breed.
- The work performed by Wenting Shi et al [3], Jiaquan Chen et al [4], Muyun Liu et al [5], and Fangyu Liu et al [6] in the year 2019 mostly focused on pattern recognition of which object belongs. This project is based on image or pattern recognition of identifying the dog's breed. Four models were used in this project such as ResNet18, VGG16, DenseNet161, and AlexNet. Data Augmentation was used to increase the number of training data parameters. Conducted some experiments by using Data Augmentation, Transfer Learning, Stochastic Gradient Descent (SGD), Adaptive Moment Estimation (Adam), and parameter tuning. By comparing the four models, Densenet161 gives the best accuracy. Comparing Loss Analysis, and Accuracy Analysis by designing a model using 50 epochs achieved an accuracy of 82.36% from the Densenet161 Model. The major drawback is by using VGG16 overfitting occurs.

- In Y. Liuetet al [7] all research papers, the authors perform domain adaptation, a branch of transfer learning, to adapt the data distributions of source and target so that the classification could be more efficient in a cross-subject scenario.
- In this research paper, Zalan Raduly et al [8], Csaba Sulyok et al [9], Zsolt vadaszi et al [10], and Attila Zoldc et al [11] in the year 2018 implement a fine- grained image recognition problem. Used multiclass classification, Inception ResNetv2, mobile trained model. The dataset is taken from the Stanford cat dataset. The training data is split into train and validation folds. Fine-tuning and 5 – fold cross validation was also used in this project. This project consists of various experiments in CNN architectures, Data Augmentation, Learning and hyperparameters, and Frozen graphs. Accuracy, precision, recall, and confusion matrices were used to predict the accuracy of different methods and take the best one. Used one of the software called “sniff” for the prediction of trained Convolutional neural networks. Two different CNN architectures were used in this project. One is NASNET-A mobile architecture and Inception ResNet v2 deep architecture. By using Inception ResNetv2 we get an accuracy of 90.69%.
- Vijaya Kumar et al [12] and B. Bhavya et al [13] focused on fine-tuning pre- trained models in the year 2019. This project was implemented by using Image classification, Transfer learning, Convolutional Neural Networks, Vgg16, Xception, and Inception V3. Finally, a multi-class classifier named logistic regression was used to identify the breed of the cat. The major drawback is by using CNN we need to have a large amount of dataset and images to reduce this drawback. They used transfer learning to train the model to provide the best solution for this. The results that are produced by transfer learning are better than the results produced by Inception v3. Because a Multinomial linear classifier was applied to pre-train the model in transfer learning. From this project, we can conclude that Convolutional neural networks with transfer learning provides a very better solution for different image classifications. But in this type of project when there is a need to rebuild the project from scratch it is difficult to start because it requires a lot of time and cost by using CNN, so we use transfer learning.

2.1 Inferences From Literature Survey

From the literature survey, Traditional classification makes the classification or identification less effective. To overcome this problem, we need to use pre-trained Convolutional Neural Networks for better efficiency and accuracy. CNN is a class of deep learning and gives good accuracy when there is a large dataset. Convolutional Neural Networks work with different pre-trained models such as Xception, Augmentation, and Transfer Learning, and different layers of CNN such as RESNET18 , MobileNet, VGG16, and DenseNet161 give us better results. From this, I came to know that CNN is the best method for image classification and they are known for their ability to reduce the computational time and adapt to different variations of images.

2.2 Open Problems In The Existing System

Some of the drawbacks or problems with the existing system are:

- By using VGG16 in the model overfitting may occur and gives incorrect predictions.
- While using Convolutional Neural Networks the dataset must be bigger, if not we come across less accuracy.
- By using Data Augmentation, it produces both realistic as well as unrealistic images.
- While using the Xception method for smaller datasets Sometimes the predicted outcomes may become wrong.

2.3 Overall Objective

This project examines how to use Keras and TensorFlow to build, train and test a Convolutional Neural Network capable of identifying the breed of a ca in a supplied image. By using different methods such as MobileNet by predicting the model and finding the accuracy of the model. Later on, building a website with streamlit which will be more user-friendly for the end user to identify the breed of the cat.

3. Materials and Experimental Evaluation

3.0 Materials Or Requirements

Requirements are the basic constraints that are required to develop a system. Requirements are collected while designing the system. The following are the requirements that are to be discussed.

1. Functional requirements
2. Non-Functional requirements
3. Environmental requirements
    A. Hardware requirements
    B. Software requirements

3.0.1 Functional Requirements

The software requirements specification is a technical specification of requirements for the software product. It is the first step in the requirements analysis process. It lists the requirements of a particular software system.

3.0.2 Non-Functional Requirements

Process of functional steps,

1. Problem define
2. Preparing data
3. Evaluating algorithms
4. Improving results
5. Prediction of the result

3.0.3 Environmental Requirements

1. Software Requirements: Operating system: Windows

    Tool: Google Colab, spyder, MS Excel 2013

2. Hardware Requirements:

    A. Internet connection to download and activate.
    B. Minimum 10GB of free disk space
    C. Windows 8.1 or 10 (64-bit version only) is required.
    D. Minimum System Requirements

    To run Office Excel 2013, Computer needs to meet the following minimum hardware requirements:

    - 500-megahertz (MHz)

- 1.5 gigabytes (GB) available space
- 1024x768 or higher resolution monitor

3.1 Problem Statement

Cats are considered to be man’s best friend and they act as the best pet. Now pet industry has increased a lot. Many people were interested to keep a pet like cats in their homes. Some people may not be able to identify the breed of a cat by simply looking at it. So, the only way to find the breed of a cat is to ask the owner or some professionals in the industry. This takes a lot of time and makes a lot of confusion. So, for this purpose, we are going to build a project to identify the breed of a cat.

3.2 Dataset

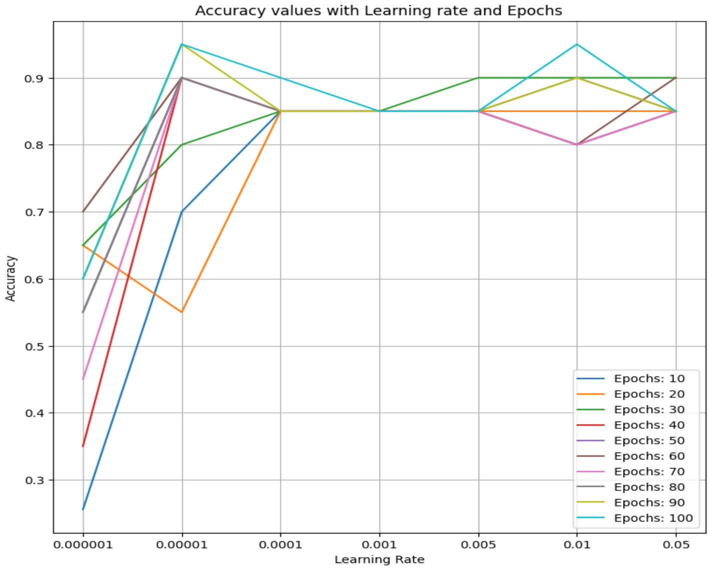
I collected the data from the Kaggle platform. I require dataset cat breeds with images of each cat breed in distinguishing proof just as in picture order. It consists of 14 different types of cat breeds classes and consists of 711 images of cats.

“I used 80% of the data for training and 20% for Validation”

3.3 Methodology

- In this, I imported necessary modules such as NumPy, pandas, Keras, etc.,
- Load images from the dataset and the images are then converted into a NumPy array and finally normalising the array.
- Here I used Convolutional Neural Network architecture for image classification because in recent years it earned much popularity in the image processing field. Here I studied different layers such as the Convolutional layer, Pooling layer, fully connected layer, Dropout, and Activation functions.
- Split the dataset into training and test datasets and create accuracy and value accuracy of the model and plot the accuracy model between them.
- Predicting the accuracy score of the model and I have taken the best one as our model and save it.
  - I used the best model for the prediction of cat breeds.
- By saving the model, creating some HTML files with python code using the flask application, and creating a stream lit application for the

prediction of cat breeds.



3.4 Results

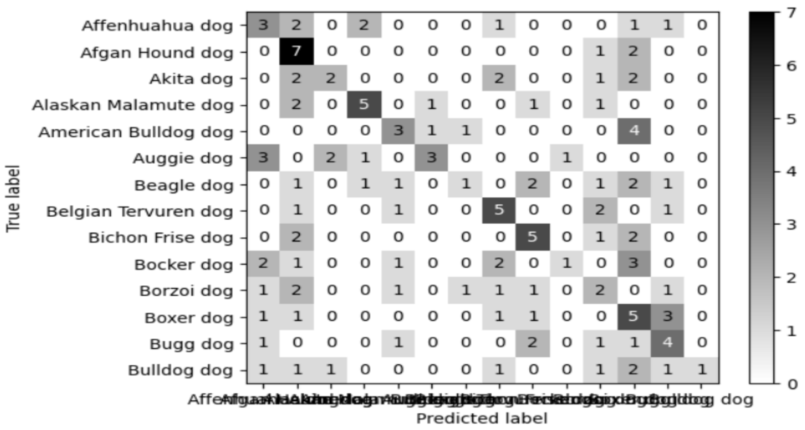
The quality of the model is judged by using different indicators such as accuracy, loss value and recall rate.

Validation Accuracy: [0.11510791629552841, 0.1582733383975029, 0.17985612154006958, 0.22302158176898956, 0.22302158176898956, 0.2374100685119629, 0.2517985701560974, 0.26618704199790955, 0.28776979446411133, 0.3381294906139374]
and

best model accuracy: 0.3381294906139374

From the Validation accuracy the Confusion Matrix was calculated and generated Classification report

The confusion matrix : A confusion matrix provides a detailed breakdown of the classification performance of the model by showing the number of correct and incorrect predictions for each class is illustrated below



Classification Report: A classification report summarises the performance metrics for each class, typically including precision, recall, and F1-score. Here's a format for the classification report:

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Classification Report :
              precision    recall  f1-score   support

           0       0.40      0.20      0.27        10
           1       0.62      1.00      0.77        10
           2       0.50      0.33      0.40         9
           3       0.50      0.30      0.37        10
           4       0.33      0.33      0.33         9
           5       0.40      0.80      0.53        10
           6       0.75      0.30      0.43        10
           7       0.67      0.60      0.63        10
           8       0.60      0.60      0.60        10
           9       0.77      1.00      0.87        10
          10       0.33      0.30      0.32        10
          11       0.47      0.58      0.52        12
          12       0.44      0.40      0.42        10
          13       0.50      0.44      0.47         9

    accuracy                           0.52       139
   macro avg       0.52      0.51      0.50       139
weighted avg       0.52      0.52      0.50       139
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4. Future Work

While the project achieved high classification accuracy, there are opportunities for further improvement. Future work could explore incorporating additional features, such as temporal data from video sequences or integrating other modalities like audio, to enhance the system's capabilities. Additionally, expanding the dataset to include more celebrities and sports disciplines could further improve model performance and applicability.

5. Conclusion

The cat Breeds image classification project demonstrates significant advancements in accurately identifying and categorizing images of cats using modern machine learning techniques. By leveraging convolution neural networks (CNNs) and transfer learning, the system effectively classifies images of cats breeds across various disciplines, achieving high levels of accuracy and robustness. This project highlights the potential of advanced image classification techniques in the cats domain and sets a foundation for future developments in automated cats breeds recognition and management.

6.Reference

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