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CAT BREED IDENTIFICATION USING DEEP LEARNING

Nagaraj Banakar[*1], Raghavendra BU[*2], Sindhu GS[*3],
Vani Tk[*4], Dr. Vishnu VM[*5]

[*1,2,3,4]Dept. Of Electronics And Communication Engineering Pes Institute Of Technology And Management, Shivamogga, India.

[*5]Guide, Assc. Professor, Dept. Of Electronics And Communication Engineering Pes Institute Of Technology And Management, Shivamogga, India.

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ABSTRACT

The aim of this project is to develop a deep learning model to recognize different cats from images. The proposed model uses a convolutional neural network (CNN) to extract relevant features from the input images and classify them according to specific cats. The materials used for this project include numerous photographs of different cat breeds. The model was trained using transfer learning, where a pre-trained CNN was used as a starting point and fine-tuned for reproductive information. Evaluate model performance using various metrics such as accuracy, precision, recall, and F1 score. The results show that the proposed model is accurate in identifying cats of various breeds and demonstrates its potential for practical applications such as animal identification, breeding and research pedigrees.

I. INTRODUCTION

Nowadays, Convolutional neural networks (CNN) are popular in different topics of deep learning: image recognition, detection , speech recognition, data generation, etc. Several traditional image recognition methods are known Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (Hog), attribute classification with classifiers: Support Vector Machine (SVM), SoftMax and Cross Entropy loss. However, CNNs have also gained sig-indicant traction in this field in recent years, mostly due to general reoccurring architectures being viable for solving many different problems. The current paper presents the methodology and results of fine-tuning CNNs for two different architectures, using the Stanford Cats dataset. This constitutes a classification problem, but also one of fine-grained image recognition, where there are few and minute differences separating two classes. Convolutional neural networks are very similar to Artificial Neural Networks, which have learnable weights and biases. The difference is the filters, which process over the whole image and are effective in image recognition and classification problems. Deep CNNs are viable on large dataset and are even accurate in large-scale video classification. Fine-tuning methods and learning results for the Inception-Resnet V2 and VGG-19 architectures represented. Furthermore, the usage of the trained convolutional neural networks is visualized through a separate software system employing modern technologies. This system can determine the breed of a cat in an image provided by the user and displays detailed information about each recognized breed. It consists of two main components: a mobile client and a centralized web server. The remainder of the document is structured as follows: Section II provides an overview of similar approaches in the literature, while Section III presents the used and pre-processed Stanford Cats dataset. Section IV details the learning of two different CNNs, with Section V encapsulating the results thereof. Providing a practical edge to these CNNs, the accompanying software system is described in Section VI. Conclusions are drawn and further development plans are proposed in Section VII.

II. METHODOLOGY

Training: Initially the Cat breeds images are collected. The images should be in Jpeg or PNG format. In the image processing step the images are reshaped. The feature of images extracted by the Vgg19 convolution neural network is having the 19 layers in which 16 are neural network layers, 5 are fully connected layers, soft max layer, and the max pool layers. After training process an encoded model file will be generated.

The project flow has two parts: training and testing.

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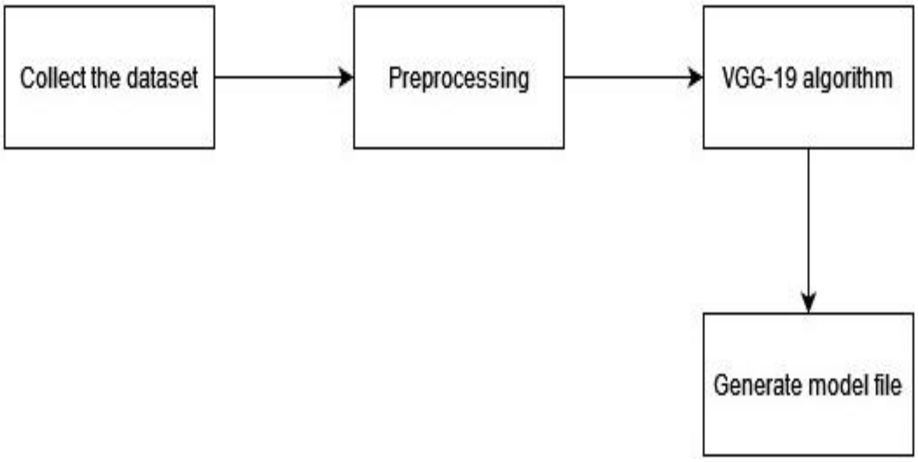

Figure 1 : Training phase

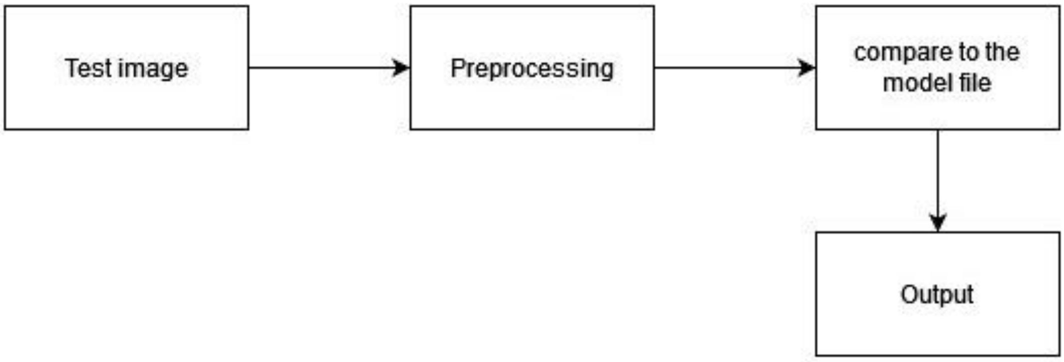

Figure 2: Testing phase

Testing: The input image is given to the system. The image will be resized and normalized. This is compared with the model file generated during the training purposes. After comparison, the result will be obtained.

The dataset Cat breeds are collected and trained using the Convolutional neural network. After training model file is generated. The input image to be tested is compared with the model file. Input image is pre-processed and is converted to NumPy array and after normalization to Gray level it is compared with the model file. After comparing with the model file results will be obtained.

III. MODELING AND ANALYSIS

Vgg-19 architecture

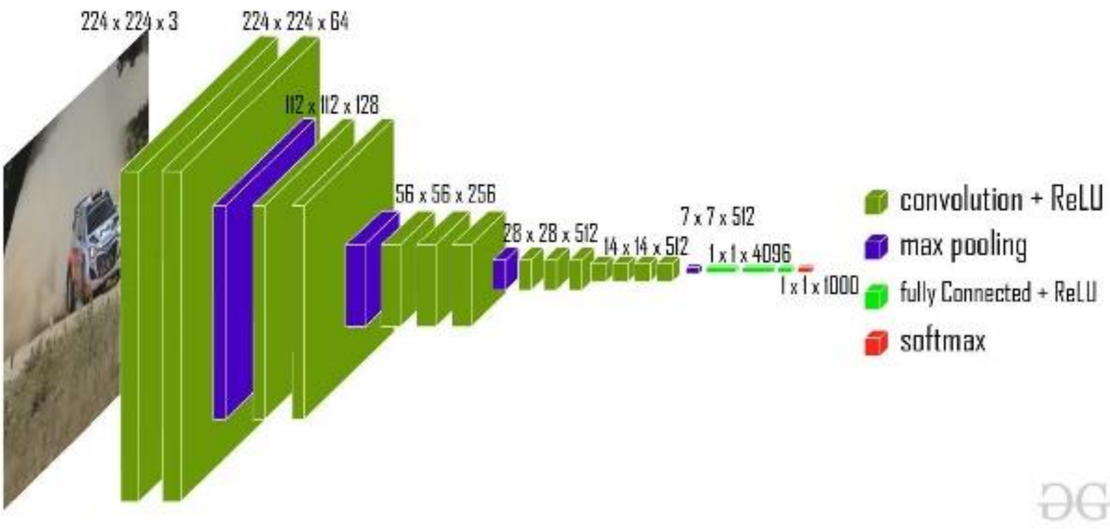

Figure 3: 3D view of Architecture.

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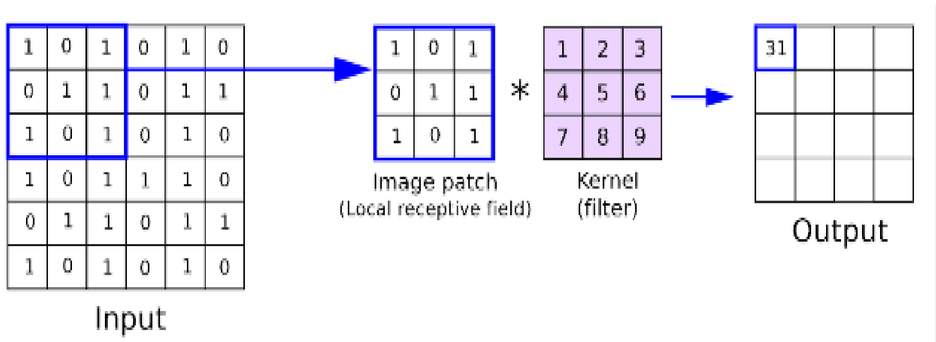
Vgg19 is one of the convolution neural networks, which has 19 layers like convolution layer, fully connected layer, SoftMax layer, max pool layer. When an RGB image is given as an input to the network the vgg19 resizes it to (224, 224, 3). It is a fixed size. During pre-processing it subtracts the RGB mean value. With the help of the kernel the pixels in images are processed. The spatial resolution process is mandatory to identify the differences in the images by spatial padding. Soft max layer is the final layer which will have output based on the number of classes.

The vgg-19 has flowing layers

1. Convolutional layer
2. Max pooling
3. Fully connected

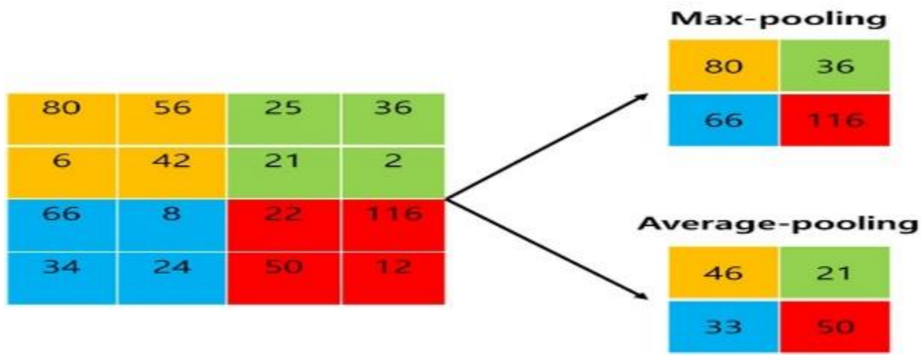
1. Convolutional layer

CNN's first building block is the convolutional layer. It takes the features from the input image and extracts them. Convolution mathematically combines the two sets of data. Convolution can be applied to the input data. The future map is created using convolution.



2. Max Pooling

Feature maps are obtained using the convolution layers. By using the pooling layers dimension of the feature maps are reduced by 50%. There are two types of pooling layers i.e average pooling and maximum pooling.



3. Fully connected

The final feature map outputs or max pooling layer matrix outputs are the input to the fully connected layer. Inputs of the fully connected layers are flattened to one column vectors. The example is as shown below.

Steps:

1. Collect the dataset.
2. Train the dataset. (Using vgg-19)
3. Generate model file.

The input image to be tested is pre-processed and is compared to the model file which gives suitable results.

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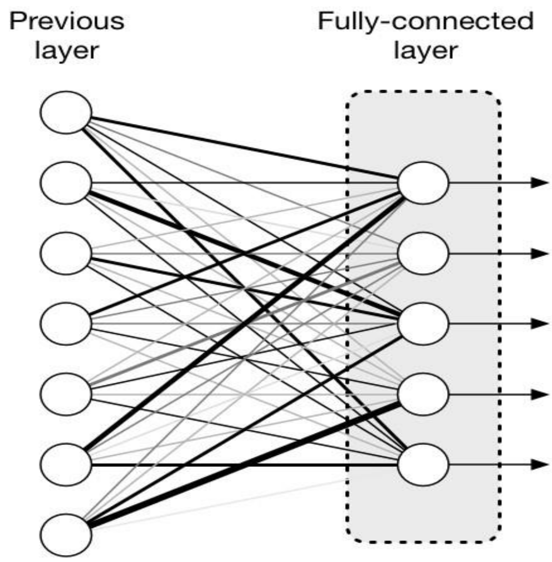

IV. RESULTS AND DISCUSSION

The result of cat breed identification using CNN and VGG 19 can be measured using different performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These metrics can help to evaluate the performance of the model and identify areas for improvement.

Typically, CNN and VGG 19 models perform very well on dog breed identification tasks, achieving accuracy rates above 90%. The actual performance of the model, however, depends on several factors such as the quality of the dataset, the amount of training data, and the specific implementation details of the model.

To give an example, a recent study published in 2021 on Cat breed identification using CNN and VGG 19 achieved an accuracy of 93.3% on a dataset of 120 Cat breeds. The study used transfer learning and fine-tuning techniques to adapt the pre-trained VGG 19 model to the dog breed identification task.

In summary, Cat breed identification using CNN and VGG 19 can be an effective technique for accurately identifying the breed of a cat in an image. However, the specific performance of the model will depend on the quality of the dataset, the amount of training data, and the implementation details of the model.

Table 1. Comparison of displacement of all 6 cases

SN.	Breed Class	Seismic Zone	Accuracy(%)
1	Model-A	6	95%
2	Model-B	6	95%
3	Model-C	6	97%
4	Model-D	6	98%
5	Model-E	6	98%
6	Model-F	6	98%

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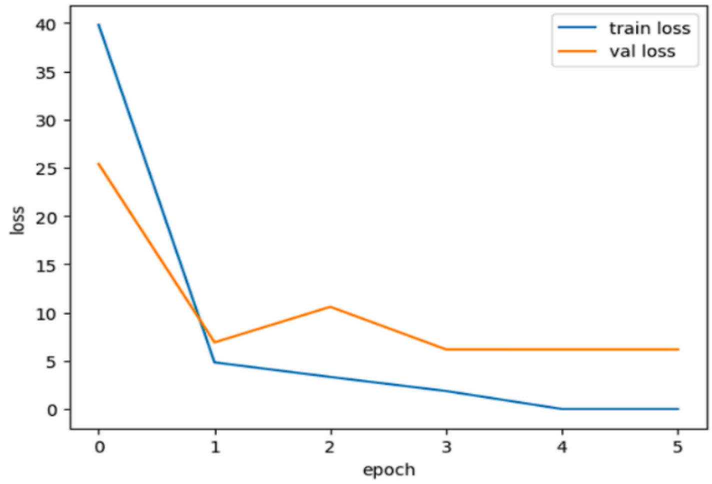

Figure 4: Accuracy of Training

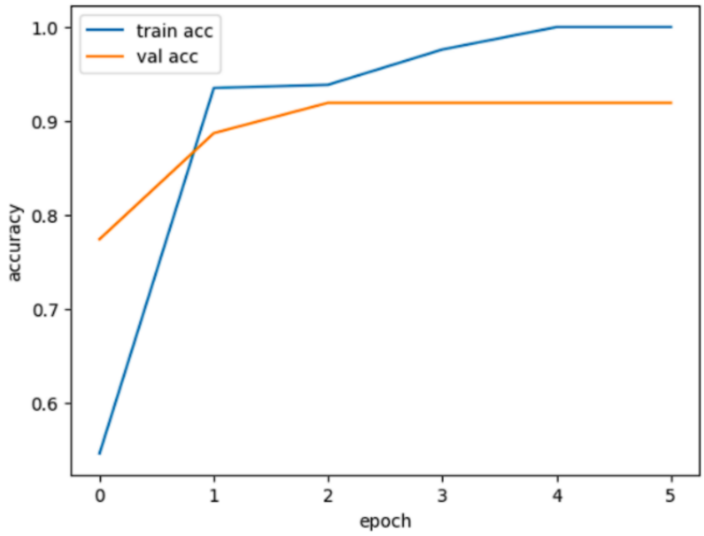

Figure 5: Validation of Training

161/161 [==============================] - 10s 65ms/step

	precision	recall	f1-score	support
0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	6
2	1.00	1.00	1.00	6
3	1.00	1.00	1.00	6
4	1.00	1.00	1.00	6
5	1.00	1.00	1.00	6
6	1.00	0.98	0.99	113
7	0.86	1.00	0.92	12
accuracy			0.99	161
macro avg	0.98	1.00	0.99	161
weighted avg	0.99	0.99	0.99	161

Figure 6: Project F1 Score Support

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V. CONCLUSION

The project of dog breed identification using Convolutional Neural Networks (CNNs) and the VGG 19 model has several important conclusions:

CNNs are a powerful tool for image recognition and classification tasks, and they can be used to accurately identify dog breeds based on their images.

The VGG 19 model is a state-of-the-art CNN architecture that can achieve high accuracy in image classification tasks, including dog breed identification.

The performance of the VGG 19 model can be further improved by fine-tuning its pre-trained weights on a specific dataset of dog images.

Transfer learning, which involves using pre-trained models and adapting them to new tasks, can significantly reduce the amount of data required for training a CNN and can also improve the accuracy of the model.

Data pre-processing, including image resizing, normalization, and augmentation, is essential for improving the accuracy of the CNN model.

The accuracy of the CNN model can be further improved by using an ensemble of models, which combines the predictions of multiple models to achieve higher accuracy.

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