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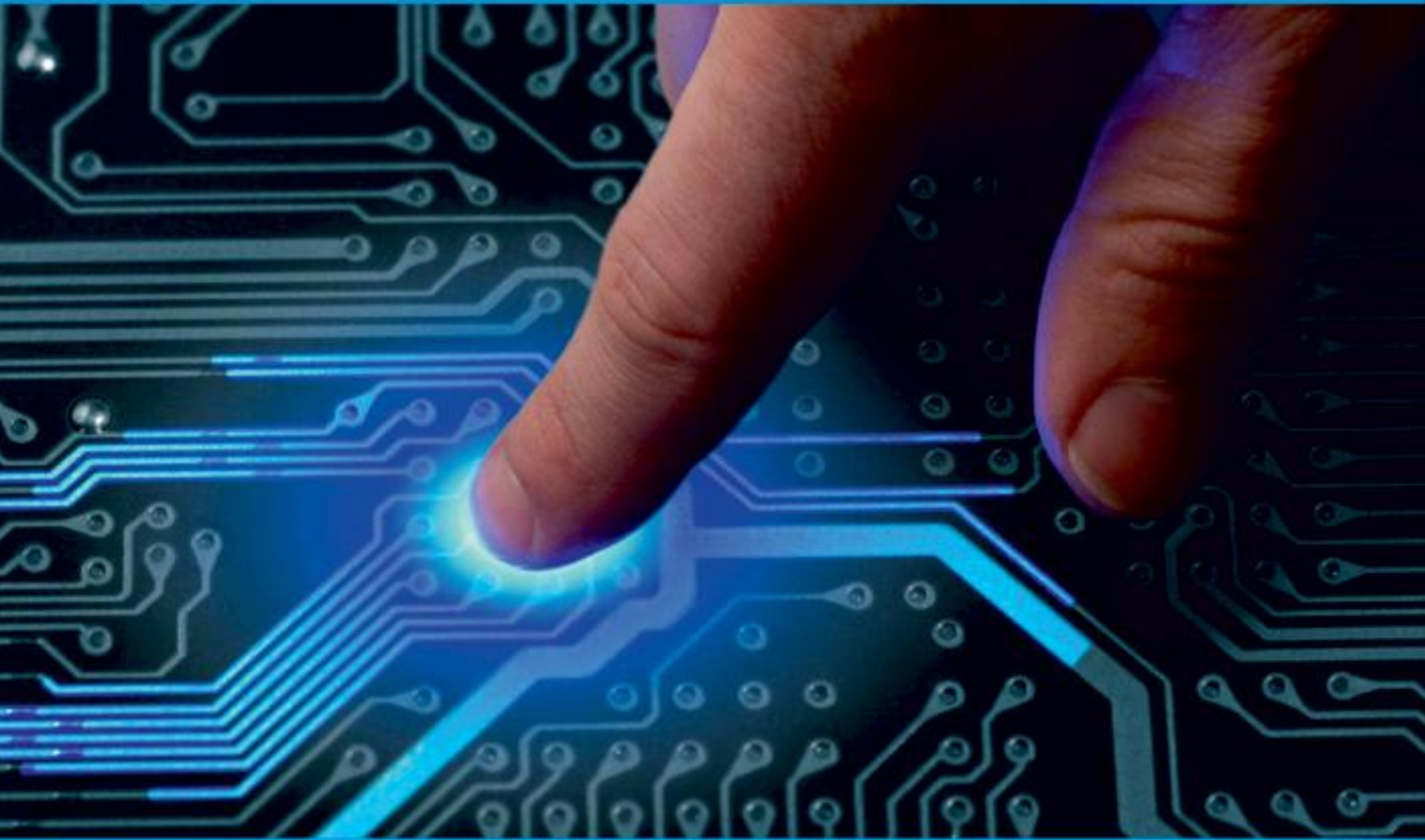

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# Picturegenics: Dog Breed Classifierusing CNN

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**ABSTRACT:** The automatic classification of animal images is an onerous task due to the challenging image conditions, especially when it comes to their breeds. In this project we will build a classifier capable of identifying a dog's breed based on its photo. Considering that on a high level dogs of different breeds can look very similar, it is a challenging task even for humans. To train and evaluate the model the Stanford dataset, containing real world images of dog breeds, was used. A small CNN that was trained from scratch on pre-processed training dataset achieved a testing accuracy rate of 30.42%. To tackle this problem, transfer learning was employed. As a result, the ensemble model obtained achieved a testing accuracy rate of 73.40%.

**KEYWORDS**: Dog Breed, Convolutional Neural Network, Transfer Learning, Resnet50, Classification

## I. INTRODUCTION

Worldwide FCI list recognizes 120+ breeds of dogs. In United States alone the ACK's dog breed list currently includes 120 dog breeds. We often get confused between different dog breeds. A person cannot recognize all the dog breeds.

A lot of work has been done in the field of image recognition over the past few years. In this project a specific object recognition problem was examined. The goal is to build a model capable of identifying to which breed a dog belongs, based only on its photo. This application uses Convolutional Neural Networkand Transfer Learning to identify a dog breed among 20 different breeds. There are 20 different classes used for this work which has train and test images for every class respectively.

## II. RELATED WORK

As it can be shown there are plenty of research papers available in the field of fine-grained classification which is a key concept used in the model, but the model mainly revolved on the concept of dog breed classification for which the references were taken of the following research papers: The Stanford University researchers, namely [3] Whitney, Brian, and Vijay, made a model using deep learning named "Dog Breed Identification" to classify the breed of the dogs. At the end, they were able to achieve 50% of the accuracy working on 133 different breeds of dogs. Also, in 2016 [4] Pratik Devikar researched on the model that uses Transfer Learning as base for the classification of images of various dog breeds. In 2012 [5] Jiongxin, Angjoo, David, and Peter proposed an approach for the dog breed classification using Part Localization. They achieved 67% recognition rate in their research. Dąbrowski and Michalik [6] made a research on "How effective is Transfer Learning method for image classification." In this, they showed that how much Transfer Learning is effective for increasing the accuracy of the model by retraining neural network-based image classification using the approach known as the Transfer Learning.

For making a classifier like what is made, there have to be different techniques implemented together. It was decided to start with the conventional convolutional neural network [7–9] for building a machine which can act as the classifier. But at first, when the process of testing was started with the trained model, the accuracy was pretty low what was not acceptable in the perspective. At last, to have the accuracy of the model up to the mark of the expectations, the implementation of the Transfer Learning [10, 11] concept was used, and it gave 81.578% accuracy. Later, it checks whether if it can predict a dog breed that resembles a human by detecting the human face [12] from the collection of photographs that were provided in the training set. The brief explanation of each of the basic terms used in this model is as follows.

## III. PROPOSED SYSTEM

A. *System Architecture:*

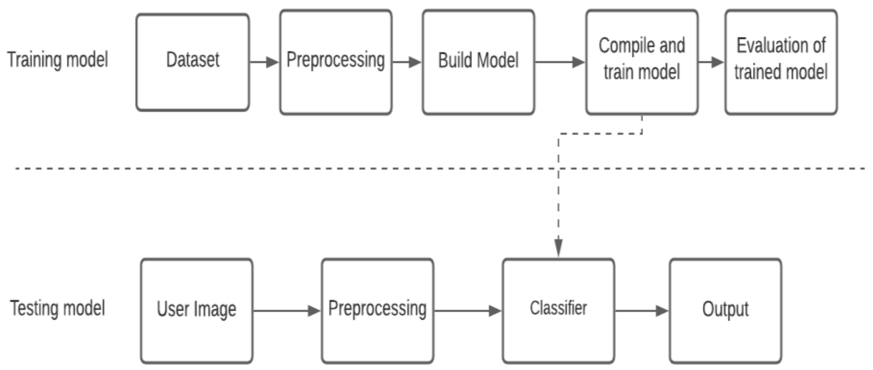


Fig1: Architecture Diagram

The System architecture above consists of a training and a testing model.

Training Model:

i. Images from the dataset are pre-processed where image resizing and normalization of pixels takes place.
ii. The model is built using CNN architecture from scratch. As the accuracy is low, transfer learning is implemented wherein new classifier layer is added to pretrained Resnet50 model to achieve higher accuracy.
iii. The model is evaluated using the validation dataset and accuracy is determined with the help of confusion matrix.

Testing Model:

i. Input image given by the user is resized to 120*120*3 pixels.
ii. The preprocessed image is passed into the trained model.
iii. The output is generated in which the detected dog breed is displayed.

B. *Module Decomposition:*

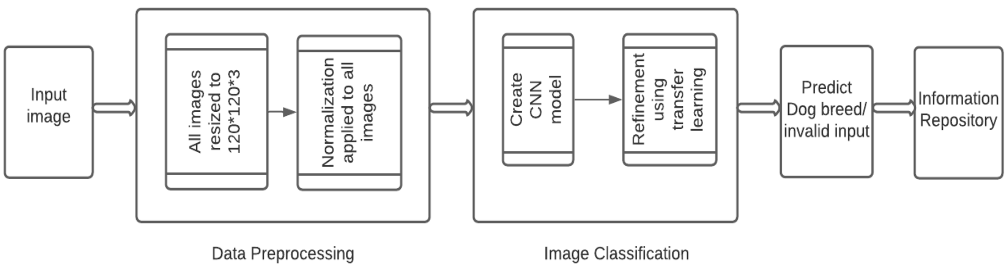


Fig2: Module Decomposition

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1. Data Pre-processing:
   i. The dataset used for this project is Stanford Dog Dataset.
   ii. Each breed of dog is used as one class of the dataset.
   iii. The images are pre-processed by resizing the dimensions to 120*120*3 and then the image is normalized.
2. Classification Model:
   i. Our CNN model is used to predict the dog breed of the given user image.
   ii. This model takes images as input and predicts the dog breed and hence, a CNN architecture has to be built consisting of a number of convoluted layers with few maxpooling and dropout layers in between.
   iii. To increase the accuracy we make use of transfer learning for the model we have created.

3. Information Repository:
   i. Consists of information about the dog breeds supported by our model.
   ii. After predicting the breed, this repository is used to furnish additional details about the breed which includes salient features such as:
      a) Description
      b) Body size
      c) Origin
      d) Life expectancy
      e) Temperament

C. *Algorithm Design:*

Input: Stanford Dogs dataset, Test image

Output: The predicted dog's breed.

Step-1: Pre-process the input image (resize to 120*120*3 and normalize pixel values)

Step-2: Prepare the model for dog breed prediction:
- Add a convolutional layer with 128 filters with Relu activation
- Add a maxpool layer with kernel size 2
- Add a dropout layer with proportion 0.2
- Add a convolutional layer with 256 filters with Relu activation
- Add a maxpool layer with kernel size 2
- Add a dropout layer with proportion 0.2
- Add a flatten layer, dense layer with 1024 nodes
- Add a dense layer with nodes equal to the no. of classes.

Step-3: Run the model for 20 epochs and save the model in json structure.

Step-4: Model refinement using Transfer Learning:
- Here, we use Resnet-50 which is pretrained on ImageNet dataset and add new classification layer for dog breeds classification:
- Run the model for 5 epochs and save the model in json structure.

Step-5: Pre-process the test image to fit the model.

Step-6: Pass the pre-processed image to the dog breed detection model.

Step-7: Display the output obtained to user.

## IV. Results and Discussion

Method 1:

We have not used any prebuilt model and made our model and computed the accuracy. The accuracy is very low about 30. Dataset is very less in comparison to number of breeds and no CUDA enabled graphic card is available so if complex model is build it will halt the whole laptop. CUDA will help the model to train itself parallel on the cores of graphic card. Graphic card contains of about 1000 cores which can make our computation fast.

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Method 2:

We have used Resnet50 prebuilt model and made our model and computed the accuracy. The accuracy is improved to about 75 percent. The accuracy can further be increased by implementing image augmentation and also by training the model with more number of epochs. However, this can be possible only by using graphic cards and GPU's.

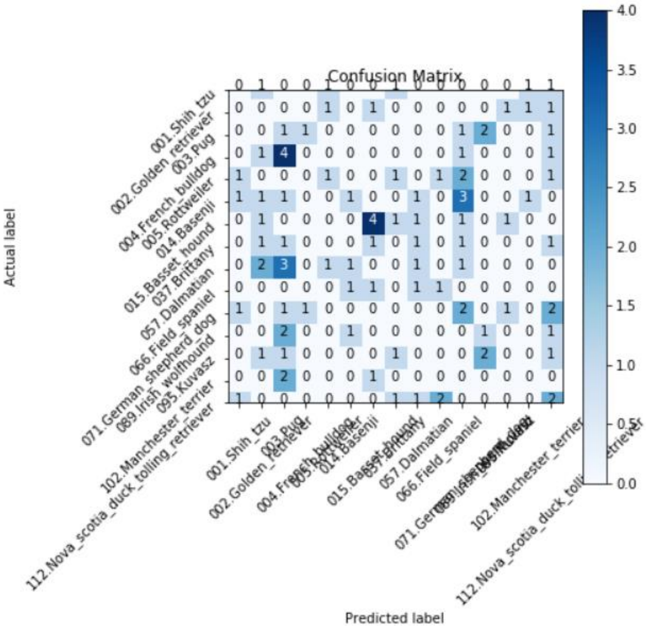


Fig3: Confusion Matrix of Method 1

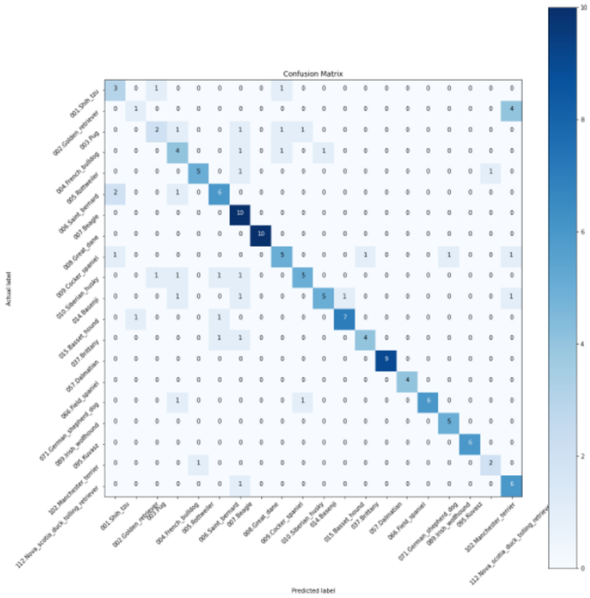

Fig4: Confusion Matrix of Method 2

The below figures are examples of testing where a German Shephard image and an image of a cycle are given as input image.

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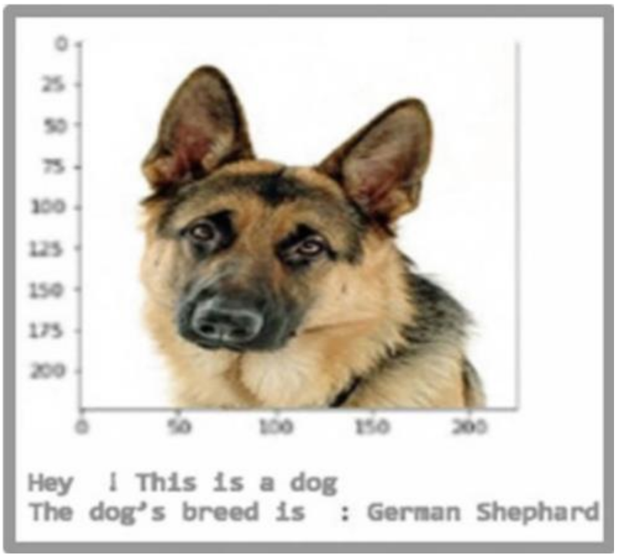


Fig5: Output of German Shephard dog. The image of a dog was collected from the dataset present on the web for testing of the output of themodel.

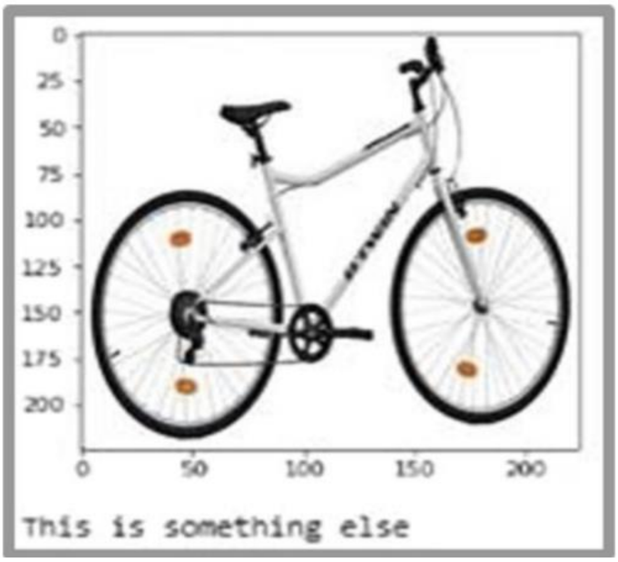


Fig5: Output of invalid image. The image of a cycle was collected from the dataset present on the web for testing of the output of the model.

## V. CONCLUSION AND FUTURE WORK

The research concludes that the Transfer Learning boosted the performance of the classifier model. It gave a significant increase in accuracy from 30% to a remarkable 75%. This research proves that Transfer Learning can be significant in the field of computer vision and machine learning.

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This model can be improved by adding more train and test data and increasing the number of epochs. This model can also be improved by using a different architecture in the process of transfer learning. In future this model can also be used to recognize dog breeds and automatically generate AR lenses or effects in social media applications.

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