

**PIGEON BREED CLASSIFICATION WITH CONVOLUTIONAL NEURAL
NETWORK USING SUPERVISED LEARNING METHOD**

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Degree of Bachelor of Science in Computer Science and Engineering

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DAFFODIL INTERNATIONAL UNIVERSITY

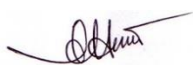
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APPROVAL

This Project/internship titled “**Pigeon Breed Classification with Convolutional Neural Network using Supervised Learning Method**”, submitted by Maksudur Rahman and Sakeef Ameer Prodhan, ID No: 162-15-7955 and 163-15-8304 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 7 October, 2020.

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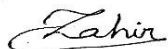


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We hereby declare that, this project has been done by us under the supervision of **Mr. Md. Tarek Habib, Assistant Professor** and **Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

“Pigeon Breed Classification with Convolutional Neural Network using Supervised Learning Method” is a research project based on the fundamentals of Computer Vision and Deep Learning field of Computer Science. This project has been inspired by the novel research works done by renowned scholars who are working to solve different image classification problems. The system we propose is a Deep Learning model that has been trained on a large dataset of different pigeon breed images. This system can identify the pigeon breeds when images of those breeds are shown to it. It then classifies those images and gives the name of the breeds as result. This system we created can be scaled to small systems such as smartphones and large systems such as Computer Vision models on cloud. Thus, both the end users like pigeon buyers and the researchers conducting state of the art research works can use this system to fulfill their purposes. Moreover, this system can be used as a baseline threshold in classification tasks and so future works on such image classification problems can be compared with the performance of this system. We have studied hard and applied different research methods and knowledge to bring this project to life.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Our project is a research project inspired by the recent novel research works in the field of Computer Science. In order to complete our project with good efficiency, we studied Machine Learning, Deep Learning and Computer Vision with our best effort. As our project is based on images, we mainly focused on learning about Convolutional Neural Networks which has been very popular for producing best results in Computer Vision tasks. Then we created our dataset both by taking images using camera and by scraping images from copyright free sources and finally combined them. Next, we followed transfer learning method by using state-of-the-art neural network architectures and trained them on our dataset. We also designed a custom neural network of our own and trained it on the dataset. At the final stage we chose the model or architecture that produced the best result and finalized it as our pigeon classifier and recognizer model.

1.2 Motivation

Pigeon farming is a very popular business and hobby in Bangladesh. People of different ages make farms in their homes and raise pigeons with great care. From the commercial perspective, selling adult pigeons and their eggs is a good source of income. It can be a great way of defeating poverty. But newcomers in pigeon farming and sometimes even experienced persons fall victim to buying low priced breeds at very high prices. This happens because some breeds of pigeons look similar in human eyes though they are very much different. So, recognizing a specific breed of pigeon can be a challenging task. To solve this problem, we want to help pigeon farmers to identify pigeon breeds easily using technology.

1.3 Rationale of the study

The two facts we kept in mind before starting the project are that:

- there is no state-of-the-art dataset of pigeon images available publicly so we propose a dataset that consists of different pigeon breeds (taken from different angles and lighting)
- No deep learning architecture have been trained on pigeon breed images. This is why we propose a deep learning architecture that is trained on our dataset which can classify pigeon breeds from images.

1.4 Research Questions

- How much necessary a pigeon recognition system is in our country's perspective?
- Is it possible to create a refined dataset of pigeon images?
- How effective would the convolutional neural networks be to classify pigeon images?
- Can we use the proposed system on real world images?

1.5 Expected Output

The expected outcomes of our project are:

- A large dataset consisting of different pigeon breed images taken from different angles and lighting.
- An in-depth investigation of appropriacy of different state of the art machine learning techniques.
- A variety of existing machine learning techniques for pigeon breed recognition.
- Publication of one or more articles in international conference and/or journal.

1.6 Project Management and Finance

The resources we needed to conduct our research project are given below:

- Camera device to capture images: We have used the camera on smartphones to capture images in our dataset.
- Coding Environment with flexible computational resource: For this purpose, we have used the Google cloud services and their free resources of GPU support has been enough for our work.
- Deploying platform: We have used the local server in a computer to test and deploy our system.

So, the expense behind our project has been mostly the use of intellectual property of our research-oriented minds and the processing powers provided by open-source service.

1.7 Report Layout

Chapter 1: Introduction

This section consists of motivation behind our project, objectives, description and expected outcome of our project.

Chapter 2: Background

In this section we briefly discussed about reviewing of literatures, comparison between works and extent of our project.

Chapter 3: Research Methodology

This section embodies the specification of all requirements and the analysis on how to achieve them.

Chapter 4: Experimental Results and Discussion

This section contains brief analysis of the complete design of our project.

Chapter 5: Impact on Society, Environment and Sustainability

In this section, we implemented our project and tested it to face practical environment.

Chapter 6: Summary, Conclusion, Recommendation and Implication for Future

Research

This section embodies the conclusion and future scope of our project.

CHAPTER 2

BACKGROUND

2.1 Terminologies

The terminologies we have used in this report are short forms of many research works on the topics related to our project. Table 2.1 provides the list of the terminologies and their respective full forms.

TABLE 2.1: USED TERMINOLOGIES AND THEIR FULL FORMS

Terminology	Full Form
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CV	Computer Vision
NN	Neural Network
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
sota	State-of-the-Art

2.2 Related Works

Since the beginning of the current century, a significant number of novel research studies have been conducted in the field of Machine Learning (ML), Deep Learning (DL) and Computer Vision (CV) which are the domains of our project. Remotely sensed image data of multiple types of crops were classified using the state-of-the-art (sota) ML algorithm classifier Support Vector Machine (SVM) by Foody et al. (2004) [1]. They also compared their result with the performance of other novel classifying algorithms such as

Discriminant Analysis (DA), Decision Tree (DT) and feed forward Neural Network (NN) where SVM was the best performing algorithm. A brief overview of such comparison is stated in Table 2.2.

TABLE 2.2: COMPARISON BETWEEN PERFORMANCE ACCURACY OF DIFFERENT CLASSIFIERS BY FOODY ET AL (2004).

Performance Metric	Classifiers			
	DA	DT	NN	SVM
Overall Accuracy	90.00 %	90.31 %	91.88 %	93.75 %

Bosch et al. (2007) [2] focused on the task of image classification from the perspective of Region of Interest (ROI) which is a method of working on the regions of an image where the important features are present. They did this significant analysis using the novel classifiers Random Forest (RF) and Random Ferns (RF) [3]. We have been inspired by the semi-supervised approach of Guillaumin et al. (2010) [4] which is basically training classifiers on labeled image data and testing them on unlabeled data.

With the publication of many sota image datasets in the recent years, the quantity of training data required for ML algorithms has significantly increased. This phenomenon has enabled neural networks to outperform traditional ML algorithms in recent time though the concept of neural networks was first introduced in the 1940's. At present Convolutional Neural Networks (CNN) are the most popular form of neural networks for performing best on image data. Krizhevsky et al. (2012) [5] proposed an eight-layer CNN where five layers were convolutional and the rest three layers were fully connected dense layers. Their research work revolutionized the field of Computer Vision as it showed the true capacity of neural network architectures at classifying large quantity of image data. The authors participated in the ImageNet [6] challenge which has been a benchmark competition for testing novel ML and DL algorithms and outperformed other classifiers by producing sota result in the year 2012.

Many research works targeted to solve the problem of classification of animal breeds have been done after that. Authors of paper [7] proposed the categorization of different dog breeds using position and size of identifiable local parts of dog breeds as target features. They used the Principle Component Analysis (PCA) to achieve faster processing time than conventional methods. Wang et al. (2014) [8] approached the classification problem of dog breeds from a unique point-of-view where they found that one dog breed could be discriminated from any other breed using landmarks as features. They extracted such features from dog images using Grassmann Manifold (GM) [9] and compared their geometrical traits as distinctive components. This approach produced sota result in that period of time. Branson et al. (2014) [10] Studied the effects of pose normalization on fine-grained classification of bird species from images. They evaluated functions such as geometric warping of bird poses in images and also a graph-based clustering algorithm for classifying bird images. Simonyan et al. (2014) [11] of Visual Geometry Group (VGG) at Oxford University presented VGG, a deep neural network structure that has been a sota model in image recognition tasks. Their proposed model achieved lowest error in the ILSVRC challenge [6] and the score comparison can be learned from Table 2.3.

TABLE 2.3: COMPARISON BETWEEN TOP-5 ERRORS OF VGG AND OTHER MODELS.

Proposed model / method	Top-5 validation error	Top-5 test error
VGG (Simonyan et al. 2014)) [11]	26.9 %	25.3 %
GoogLeNet (Szegedy et al. (2014)) [12]	-	26.7 %
Overfeat (Sermanet et al. (2013)) [13]	30.0 %	29.9 %
Krizhevsky et al. (2012) [5]	-	34.2 %

We have also followed transfer learning strategy in our project. Transfer learning has been largely popular and impactful in DL community. This method allows sota neural network architectures trained on large dataset to be transferred to use in different datasets. Many research works have been done on this method. Such as Zoph et al. (2018) [14] whose key contribution was that they proposed a new search space named NASNet (Neural Architecture Search Network). This search space allowed them to search for the best convolutional layer in a neural network under a controller Recurrent Neural Network (RNN) and then transfer it to use on a different neural network. Their work contributed to the improvement of the scalability of transfer learning in image recognition and other vision tasks. Their method overview is presented in Figure 2.1 [14].

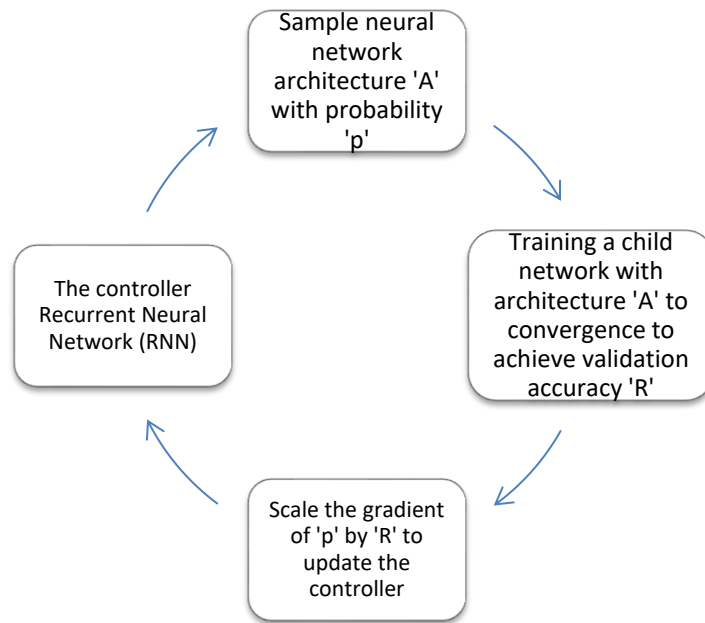


Figure 2.1: Overview of NASNet architecture.

Ráduly et al (2018) [15] adopted transfer learning by fine tuning different sota neural network models on the Stanford Dogs [16] dataset and proposed a scalable system to solve dog breed classification problem. Their research work greatly inspired us to solve the pigeon breed recognition problem.

2.3 Comparative Analysis and Summary

The main target of our project is that we want to solve the problem of recognition of pigeon breeds from images. There are many image classification research works but none of them have been targeted to recognize different bird species or breeds. From this point of view our project is unique and novel.

2.4 Scope of the Problem

In our project, we want to work on images of different pigeon breeds. There are no datasets publicly available that consist of such images. This is why our primary goal has been to construct a novel dataset of pigeon breed images. Moreover, we want to achieve sota accuracy and precision in classifying pigeon breeds. As Convolutional Neural Networks (CNNs) perform very well on vision-based tasks, we choose novel CNN architectures as our base classifiers. After training classifiers and gaining good results, our final target is to deploy the trained model in real world scenario.

2.5 Challenges

The challenges in our project are: -

- **Data scarcity:** Most pigeon farmers in the urban areas keep just a single breed of pigeon. Thus, it is hard to collect images of different breeds of pigeons because there are no variations in those farms.
- **Color variation in gender:** Male and female pigeons of the same breed tend to have different body color and texture. So, it is often difficult to identify a breed even using the eyes of an expert pigeon farmer. This is a challenge to the image classification task of our project.
- **Model overfitting:** Deep Learning models often get overfitted on the training data due to the distribution of dataset. As a result, they perform poorly on real life data.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Machine Learning

Machine Learning (ML) is a sub-field of Artificial Intelligence domain of Computer Science. ML is the way of providing machines the ability to learn a task and improving their performance on the task automatically. This field is mainly dependent on data. Different types of data are fed into ML algorithms for different purposes. These data can be numerical, text, image, video or sequence data. ML algorithms then learn the patterns in these data and try to predict on unseen data. If the accuracy is not sufficient, the algorithms then improve their learning patterns or equations and repeat the prediction part. The capabilities of ML do not just include prediction but also consist of classification or clustering, regression etc. ML is poles apart from traditional computing. The functionality of ML does not need any human assistance as the algorithms learn on their own. On the other hand, in traditional computing everything is provided and supervised by humans. More significantly, in ML computing, machines or computers are fed data with outputs related to data and computers give programs or models as result. Contrarily, traditional computing requires data and programs written as codes to the computer and it gives outputs of related data. Here programs are mainly instructions written in the form of code by humans. Figure 3.1 provides a graphical view of the difference between ML and traditional computing.

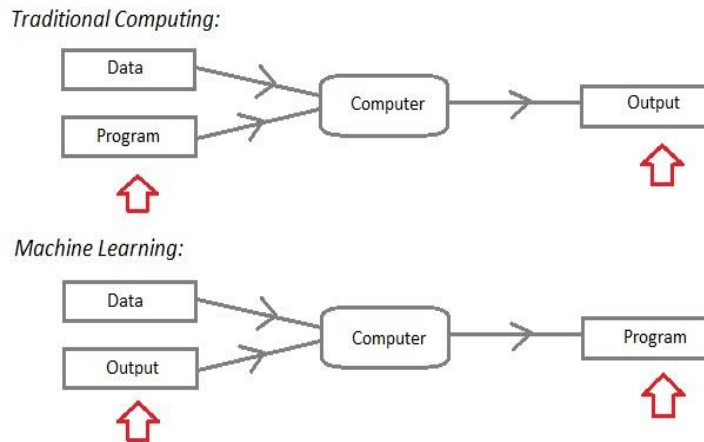


Figure 3.1: Difference between Machine Learning and traditional computing.

The learning method in ML is divided into two major categories. They are:

A. **Supervised Learning:** In this method the computer is given both data and output or label. So, it knows what kind of label to predict. Supervised learning consists of two types of algorithms. They are:

a. *Classification:*

- i. Support Vector Machine
- ii. Discriminant Analysis
- iii. Logistic Regression
- iv. Naive Bayes
- v. Nearest Neighbor

b. *Regression:*

- i. Linear Regression
- ii. Decision Tree
- iii. Ensemble Methods

B. **Unsupervised Learning:** In this method, the computer is only given data. It is not instructed what to do. So, the algorithms learn on their own what to do with the data. This method has clustering-based algorithms:

a. *Clustering:*

- i. K-means

- ii. Principle Component Analysis
- iii. Hidden Markov Model

Deep Learning

Deep Learning (DL) is the sub-field of Machine Learning (ML) and it is the study of deep structures of Artificial Neural Networks (ANNs). Figure 3.2 shows us how ML, DL and AI is related to each other.

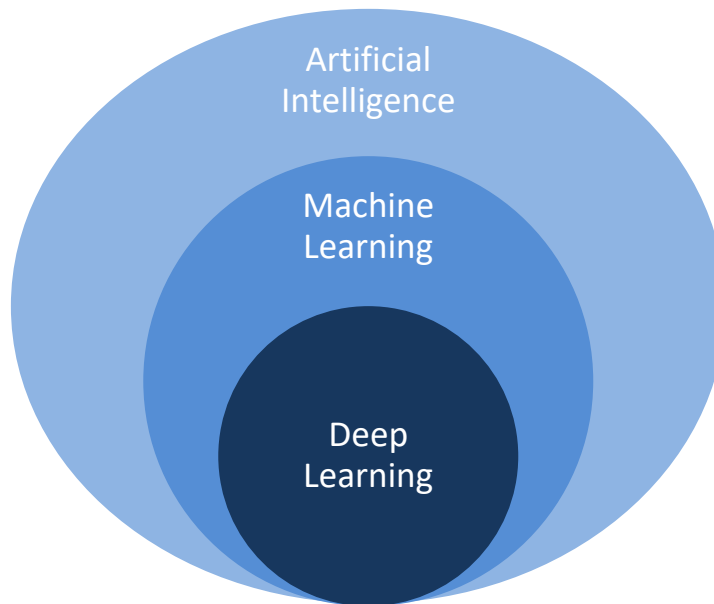


Figure 3.2: Relational Venn-diagram of AI, ML and DL.

As ANNs were designed after biological neural networks of animals, they are significantly similar from the perspective of structure and activity. Similar to neurons of animal brains, ‘perceptron’ is the fundamental unit of ANN and it is actually a single layer of neural network. So, if we connect multiple perceptron in proper way, we get multi-layer neural networks. We can observe a visualization of perceptron in figure 3.3 [17].

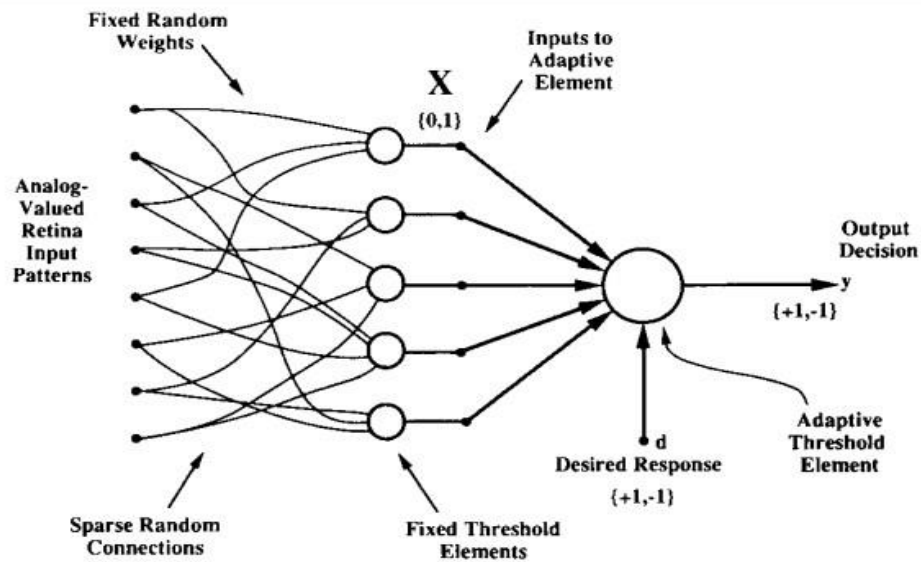


Figure 3.3: Rosenblatt's α -Perceptron.

The mathematical calculations behind ANNs can be divided into three phases. They are: -

- a) **Forward Propagation:** As every neuron in any neural network is interconnected with every other neuron, they pass the data to the neurons in the front by propagating. The equation that is used to calculate the output from the input between neurons is: -

$$Y = w \times X + b \quad (1)$$

In this equation, Y is the output neurons value. So if we multiply input (x) with corresponding weight (w) and add bias (b) with it, we get the value of Y.

We can understand this process from figure 3.4.

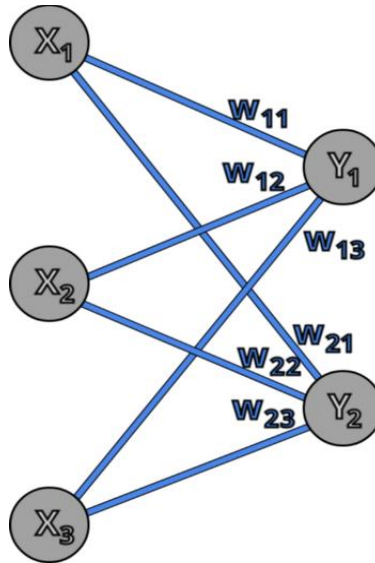


Figure 3.4: Forward propagation in a neural network.

So using equation (1) we derive the output values of neurons Y_1 and Y_2 in figure 3.1.4 where the calculation that take place is shown in figure 3.5.

$$Y_1 = W_{11} \times X_1 + W_{12} \times X_2 + W_{13} \times X_3$$

$$Y_2 = W_{21} \times X_1 + W_{22} \times X_2 + W_{23} \times X_3$$

Figure 3.5: Mathematical calculation in forward propagation.

So this kind of calculation takes place in every neuron in a neural network when it is actively doing any forward propagation to deliver data.

- b) **Backward Propagation:** Neural networks learn from their mistakes or errors during the forward propagation and their neurons of one layer pass the error value to the neurons of previous layer. This is the backward propagation process.

$$E_{n-1} = W_n^T \times E_n \quad (2)$$

Equation (2) is the mentioned process where the error value of previous layer (n-1-th layer) is being updated by the multiplication between the transposed weight and the error value of the current activated layer (n-th layer).

- c) **Weight Update:** This is an important step where neural networks solve their previously done mistakes by updating weights to the best value. Here the best value would be what gives the best result.

$$W_n = W_n - Lr \times \frac{\delta E_{n+1}}{\delta W_n} \quad (3)$$

Equation (3) is the weight update equation where the new term Lr is the learning rate at which the neurons are learning.

The rise of DL in the current decade happened because of two main reasons. They are:

- Larger datasets
- Faster computational speed

The sizes of new labeled datasets increased by million times compared to older datasets. So, it has been possible for neural networks to learn and adapt on millions of parameters. ML algorithms significantly fail to compute such huge number of parameters. Moreover, new technologies have enabled super-fast computers to be accessible to computer scientists. As a result, they have been able to train hundreds and thousands of layered neural networks easily. Thus, DL have been largely popular in recent time.

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are similar to regular Artificial Neural Networks (ANNs). CNNs are made of neurons or specifically perceptrons which perform non-linear calculations. The key component that separates CNNs from regular ANNs is the convolutional layer. The convolutional layer can have one or more convolution filters of user defined sizes such as 5x5x3 (height x width x depth). Here the depth of the filter is actually for three channels of colors (RGB-RedGreenBlue) of any colored image. A filter moves across an input image and creates dot products of its own values and nearby pixel

values of the image. These dot products are stored as weights for the calculation of the next layer of the CNN. Now the purpose of this filtering process is that it helps to detect important features in an image. A convolution filter calculates a large weight if the target pixel holds any feature such as an edge. Then only this weight shows large value in the feature map and thus the feature extraction takes place in the convolutional layer. This process is described in figure 3.6 [18].

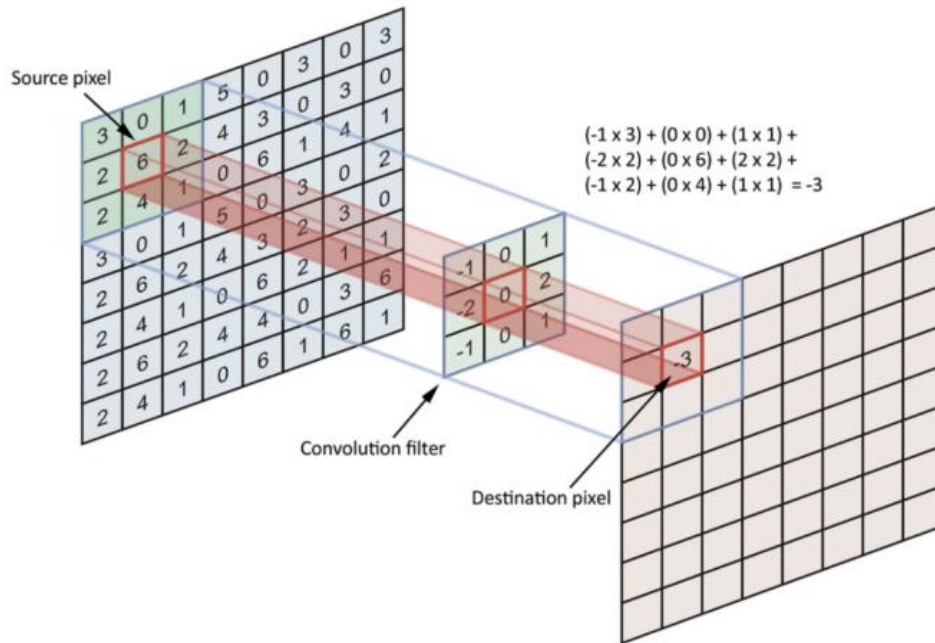


Figure 3.6: The convolutional operation of a random 3x3 filter on an image.

3.2 Data Collection Procedure

To collect data for our dataset, we have followed two procedures: -

- Capturing image using device: We have collected some images of pigeons by visiting some local pigeon farms and then capturing them using camera devices. The images were taken in daylight and from different perspectives.
- Scraping image from web: As the data collected using the previous method was not sufficient, we used Python scraping method to collect data. This method

allowed us to add more images of pigeon breeds to our dataset using search engines.

Figure 3.7 shows a portion of our dataset of pigeon images in the local storage.



Figure 3.7: Sample of Rock Dove pigeon images in the dataset.

3.3 Statistical Analysis

We have divided the dataset into three folders which are train, validation and test. The purpose of this split is that we can easily load the data and use the train folder's images to train models and the validation folder's images to validate the model's performance. The last split which is the test data is for using as real-world test images that the models have not seen during training or validation. Figure 3.8 shows a statistical analysis that compares the number of images in each split of the dataset.

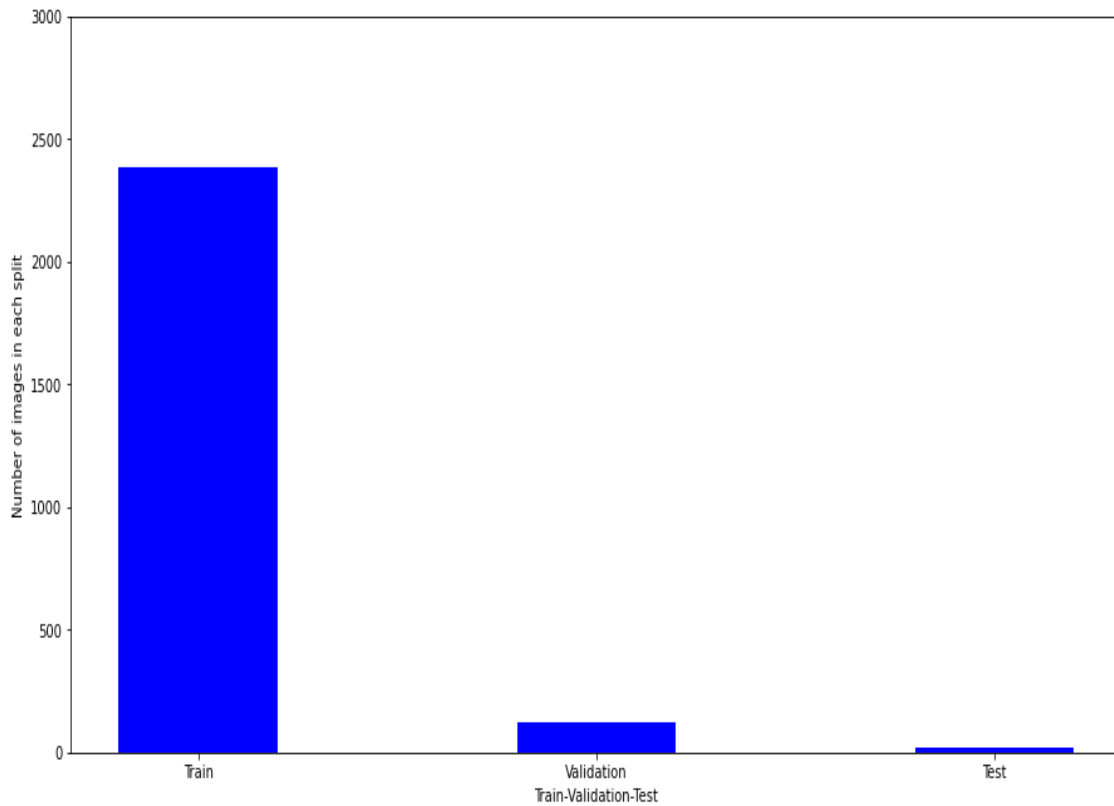


Figure 3.8: Bar chart of distribution of the dataset.

3.4 Proposed Methodology

The proposed methodology of our project is given in the flow diagram in figure 3.9.

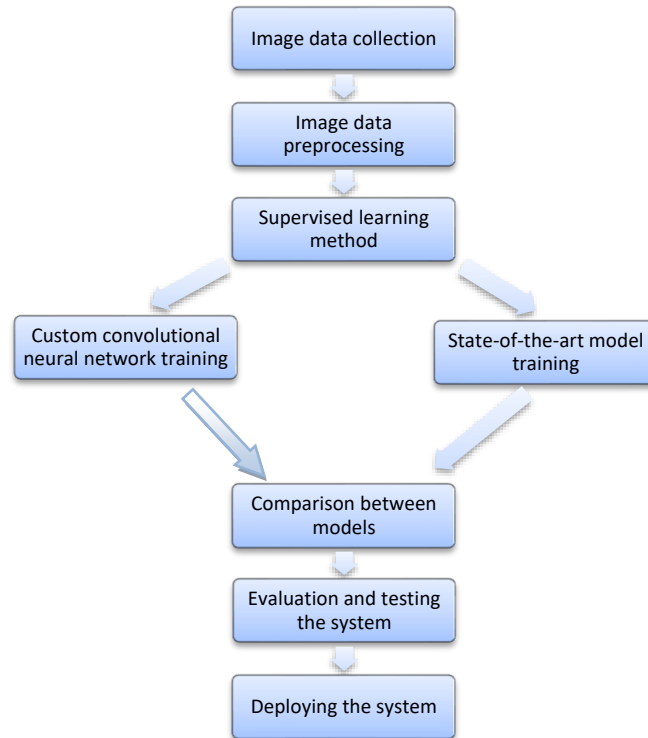


Figure 3.9: Diagram of proposed methodology.

3.5 Implementation Requirements

Coding Environment: Deep Learning task such as image classification requires significant amount of processing power. If the size of dataset is relatively small, then the task can be done by the processing capability of the CPU of the computer alone. But as the dataset gets larger like the pigeon breed dataset of our project, the whole system requires bigger memory and greater processing power. This is why we have chosen ‘Google Colab’ [19] as the coding environment of our project. Colab provides up to 12 GB ram for CPU and up to 16 GB ram for GPU. This setup has been sufficient for the training and testing of our project.

Language: We have chosen ‘Python’ as the programming language for our project. Python is a very modern scripting language that is easy to learn and to use. Python is the main supporting language for many ML and DL frameworks. It also has many libraries for different preprocessing tasks on image, text and other data. A very large and active developer community is behind the development of Python and thus it is a popular choice among DL practitioners.

Libraries:

- ImageDataGenerator: We have used this library to load raw pigeon image data from local directory to variables called as data generators. These variables hold training and validation image data that can be fed into the neural networks. This library has some image preprocessing techniques that have helped us to augment the images.
- Matplotlib: This library is very popular for visualization of data. We have utilized Matplotlib for plotting different kinds of plots and visualize the training metrics.
- TensorBoard: It is mainly a toolkit by TensorFlow for visualization in ML. We have used TensorBoard to visualize different steps of training our model, metrics such as accuracy and loss, distribution of data and many other tasks.

Frameworks: In recent years many frameworks have been developed for DL research purposes. These frameworks provide easy-to-use Application Program Interfaces (APIs) for complex ML and DL algorithms. Complex computational tasks can also be easily done using these frameworks. For the purpose of our project, we have used the following frameworks: -

- TensorFlow: TensorFlow [20] is a ML and DL framework that provides small scale to large scale implementation of sota algorithms in real world applications. It is currently the most used tool in the field of AI. TensorFlow has enabled a whole new era of ML research by its user-friendly interface and

rich collection of resources. We have used TensorFlow to train and test our image classifier models.

- Keras: Keras [21] is an open-source framework that runs on TensorFlow. It is an independent tool that helps to structure ML models and neural networks. We have used Keras to create our neural network model using different layers. Keras provides different layers of CNN such as Convolutional layer, MaxPooling layer, Dropout layer, Dense layer and many others. These layers have been used in our project.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

To implement the training and testing of our project we have used Google Cloud resources. A graphical representation of our experimental setup is given in figure 4.1.

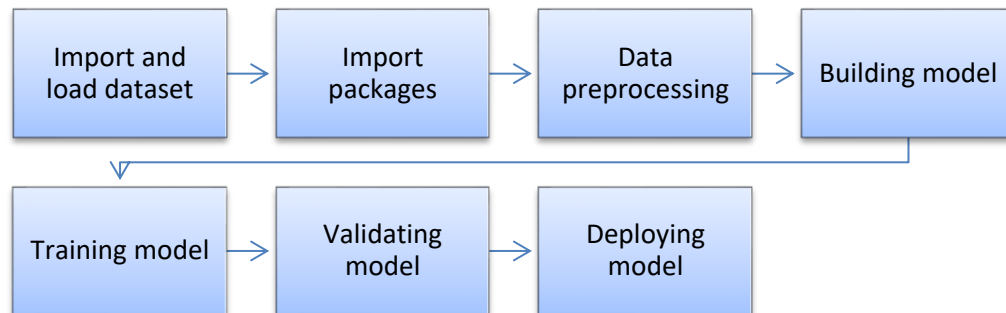


Figure 4.1: Flowchart of experimental setup.

Import and load dataset: The dataset of pigeon breed images has been stored in Google drive by us. We import it by mounting it on Google Colab's disk space and then extract it from compressed format into folders. The hierarchical structure of the dataset is described in figure 4.2.

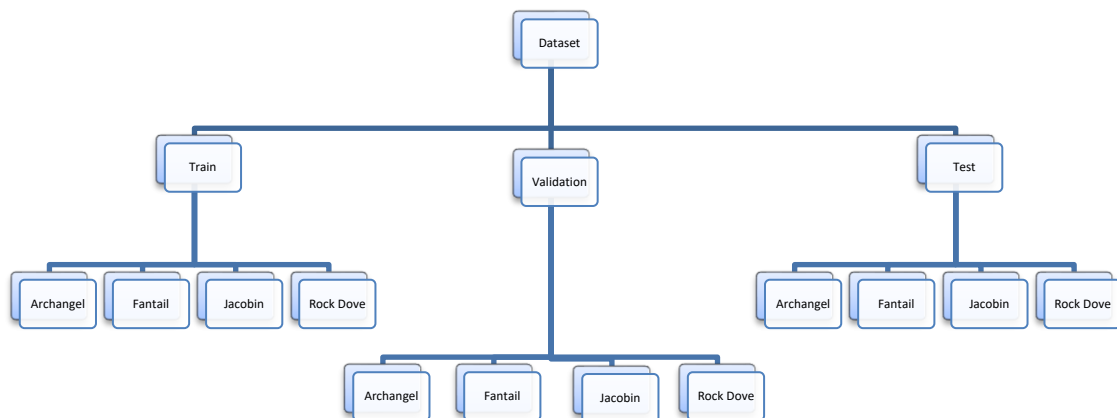


Figure 4.2: Hierarchical structure of distribution in the dataset.

Import packages: We have imported necessary packages from libraries of Python and TensorFlow into the coding environment. These packages are mandatory for specific coding tasks. Table 4.1 below lists these packages and their purpose.

TABLE 4.1: NECESSARY PYTHON AND DEEP LEARNING PACKAGES AND THEIR PURPOSES.

Package Name	Purpose
os	To access and list directories in the dataset
cv2	To visualize images in the dataset
tensorflow	To compile neural network layers
ImageDataGenerator	To load dataset images from directory into variables and to preprocess them
matplotlib	To visualize accuracy and loss metrics of train and validation
datetime	To sync Tensorboard with the local runtime in the coding environment

Data preprocessing: Some preprocessing of image data is needed before feeding into the neural network. We have used the following techniques for this purpose: -

- **Resize:** As the images in the dataset are of different sizes, we resized them to height and width of 150 value each. This is mandatory because the neural network cannot work on images of different sizes.
- **Rescaling:** The images in our dataset are colored which means they consist of RGB co-efficient on a scale of 0 to 255. Each pixel has a value between 0 to 255 depending on the value of RGB. Such values are very complex and time-consuming for neural networks. This is why we rescaled all the pixel values between 0 to 1 by factoring it with 1./255 factor.
- **Augmentation:** Neural networks often get overfitted over the training data if the data is low in quantity. To solve this, we applied some augmentation techniques

or functions before feeding them to the neural network model. Such techniques include rotating images, zooming randomly, horizontal flip etc. These are listed in table 4.2 along with the value we have used.

TABLE 4.2: AUGMENTATION FUNCTIONS AND THEIR CORRESPONDING RANGES.

Function Name	Range/Value
Rotation	40 Degree
Width Shift	20%
Height Shift	20%
Shear	20%
Zoom	20%
Horizontal Flip	True
Fill mode	Nearest

Building model: We have followed three different approaches in building our neural network that would classify pigeon breeds. They are as follows: -

Custom neural network: As an initial baseline method we have built a custom neural network model. This structure consists of four convolutional layers followed by maxpooling layers. It also has two dense layers where the final layer has four neurons to predict the four classes of pigeons. Figure 4.3 shows the overall structure of this neural network.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 64)	1792
max_pooling2d (MaxPooling2D)	(None, 75, 75, 64)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 37, 37, 64)	0
conv2d_2 (Conv2D)	(None, 37, 37, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 18, 18, 128)	0
conv2d_3 (Conv2D)	(None, 18, 18, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 9, 9, 128)	0
flatten (Flatten)	(None, 10368)	0
dropout (Dropout)	(None, 10368)	0
dense (Dense)	(None, 512)	5308928
dense_1 (Dense)	(None, 4)	2052

Total params: 5,571,140
 Trainable params: 5,571,140
 Non-trainable params: 0

Figure 4.3: Custom neural network classifier with four convolutional layers.

Transfer learning: In this approach, we used sota neural networks as base models and put a small classifier on top of them. One of such structures are graphically presented in figure 4.4 where the number of trainable parameters or neurons is very low due to frozen layers.

Model: "functional_3"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 150, 150, 3)]	0
mobilenetv2_1.00_224 (Functional)	(None, 5, 5, 1280)	2257984
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1280)	0
dropout_1 (Dropout)	(None, 1280)	0
dense_1 (Dense)	(None, 4)	5124

Total params: 2,263,108
 Trainable params: 5,124
 Non-trainable params: 2,257,984

The value is very low

Figure 4.4: MobileNet-V2 with frozen convolutional layers and a custom classifier.

Fine-Tuned model: This is similar to transfer learning but there's a difference. In transfer learning, the convolution layers of models are frozen. In fine-tuning, most of the layers are trained alongside the custom classifier. Figure 4.5 shows a clear view of a fine-tuned model where the number of trainable parameters or neurons is much higher than before due to unfrozen layers.

Model: "functional_3"

Layer (type)	Output Shape	Param #
input_4 (InputLayer)	[(None, 150, 150, 3)]	0
mobilenetv2_1.00_224 (Func	(None, 5, 5, 1280)	2257984
global_average_pooling2d_1 (	(None, 1280)	0
dropout_1 (Dropout)	(None, 1280)	0
dense_1 (Dense)	(None, 4)	5124
=====		
Total params: 2,263,108		
Trainable params: 1,867,716		
Non-trainable params: 395,392		

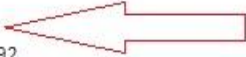
 The value is very high

Figure 4.5: MobileNet-V2 fine-tuned alongside a custom classifier.

Training model: In this step, we have trained all the neural networks on the dataset. A method from Keras library called 'fit_generator' has been used to do the training phase. We have selected different kinds of epochs which are cycles of number of training steps. Thus, different parameters have affected the training phase and produced different results.

Validating model: After training we have completed the validation step. This step has been done using the validation data split from the main dataset. Validation of models makes clear analysis of how the classifier models work on unseen data.

Testing model: This step is the final step of experimental setup. In this step, we test our neural network model using real world pigeon images which have not been seen by the model. Such evaluation is the proof of the capabilities of the model in the task of pigeon breed classification which is the purpose of our project.

4.2 Experimental Results and Analysis

As we have followed three different methods during the training phase of the experimental setup, we show the performance of models of three methods individually. Then we compare the performance on a scale of different metrics and then finally choose the final model which performs best as our pigeon breed classifier.

Baseline method (custom neural network): The custom neural network of four convolutional layers did quite good on the training and validating portion of dataset. Table 4.3 shows the results this model produced at different hyper-parameters.

TABLE 4.3: BASELINE MODEL PERFORMANCE SCORE AND RELATED HYPERPARAMETERS

Training Phase No.	Optimizer Category	Loss Metric	Performance Metric	Number of Epochs	Training Score (in %)		Validation Score (in %)	
					Accuracy	Loss	Accuracy	Loss
1	RMSprop	Categorical Cross Entropy	Accuracy	5	73.24	68.71	65.83	112.59
2	RMSprop	Categorical Cross Entropy	Accuracy	10	89.07	35.26	97.50	39.11
3	Adam	Categorical Cross Entropy	Accuracy	50	99.08	2.3	98.33	22.61

The baseline model performed best up to 50 epochs as we can see the value of accuracy is much high and the loss is quite low. After 50 epochs the result did not change significantly. So, we stopped the training at this step and finalized the model as the baseline. We can observe its performance distribution over the entire period of training and validation in figure 4.6 and figure 4.7.

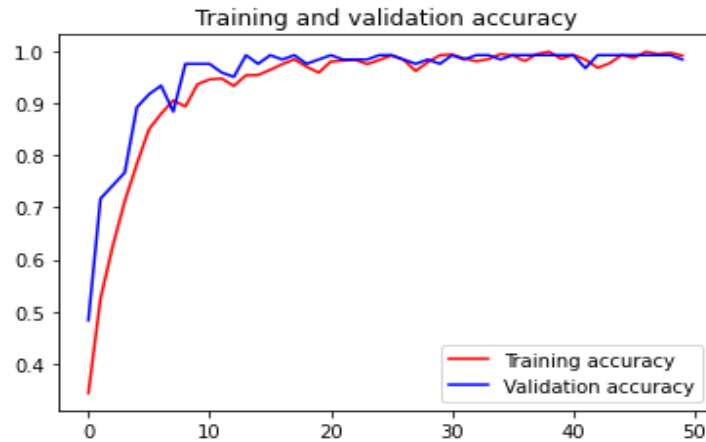


Figure 4.6: Baseline model accuracy metric graph.

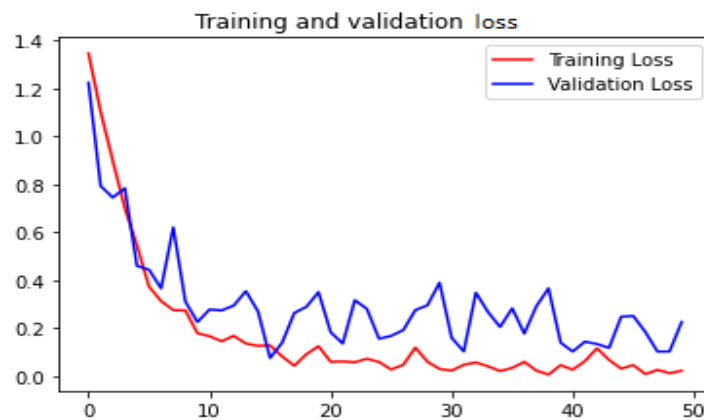


Figure 4.7: Baseline model loss metric graph.

Transfer Learning method: In this approach, we have used different sota models. Mainly, we froze the base of convolutional layers of these models and used them as feature extractors which were intended to find out the significant features in pigeon images. Then we added a small fully connected neural network as the top-level classifier and trained it on the dataset. Table 4.4 shows a comparative analysis of this method.

TABLE 4.4: STATE-OF-THE-ART MODEL PERFORMANCE COMPARISON IN TRANSFER LEARNING.

Model Name	Number of Epochs	Training Score (in %)		Validation Score (in %)	
		Accuracy	Loss	Accuracy	Loss
MobileNet V2 [22]	50	100	0.45	100	0.48
DenseNet-121 [23]	50	99.50	1.51	100	0.25
VGG-16 [11]	50	93.38	31.22	95	29.29
VGG-19 [11]	50	89.03	43.58	95.00	39.56
Inception V3 [24]	50	99.87	0.86	99.17	1.24
NasNet Mobile [25]	50	99.41	3.81	100	1.95
InceptionResNet V2 [26]	50	99.20	2.30	100	0.52
Xception [27]	50	99.83	1.35	100	0.55

Fine-Tuning Method: In this method, we have included the top layers of the previously trained sota models with the custom top-level classifier for training and validating on the dataset. This process is called fine-tuning as the weights of those models are being tuned to learn the features of pigeon images in our dataset. This is a very popular approach in recent research works related to image classification. Fine-tuning allows some layers of very deep NN architectures to be trained. The weights of the deep layers get updated in this case. This helps to produce more efficient models that are better at classification tasks. A comparison between the performance of fine-tuned models are stated in table 4.5.

TABLE 4.5: FINE-TUNED STATE-OF-THE-ART MODEL PERFORMANCE COMPARISON AND ANALYSIS

Model Name	Number of Epochs	Training Score (in %)		Validation Score (in %)	
		Accuracy	Loss	Accuracy	Loss
MobileNet V2	10	100	0	100	0.0038
DenseNet-121	10	100	0	100	0
VGG-16	10	93.17	30.53	95	28.70
VGG-19	10	90.54	42.09	95	38.86
Inception V3	10	100	0	100	0
NasNet Mobile	10	100	0	100	0
InceptionResNet V2	10	100	0	100	0
Xception	10	100	0	100	0

The fine-tuning method has been the most effective in case of training and validating phases. Figure 4.8 shows a clear view of how the accuracy curves converge due to fine-tuning after transfer learning. Here the graph is from the ‘Xception’ model.

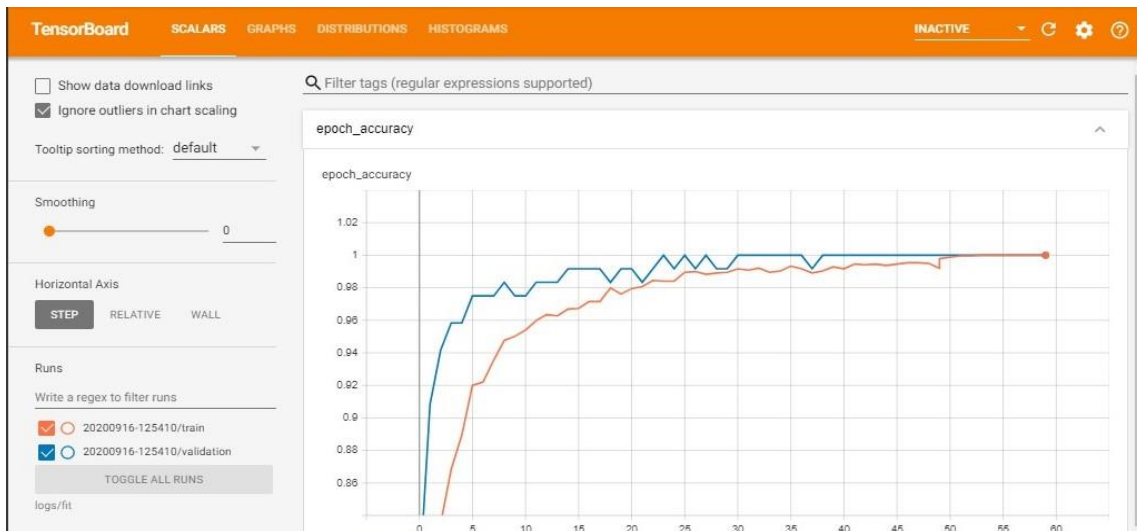


Figure 4.8: Xception model accuracy metric graph.

Moreover, figure 4.9 gives an overview on how the ‘Xception’ model’s loss metric decreases during every epoch due to fine-tuning.

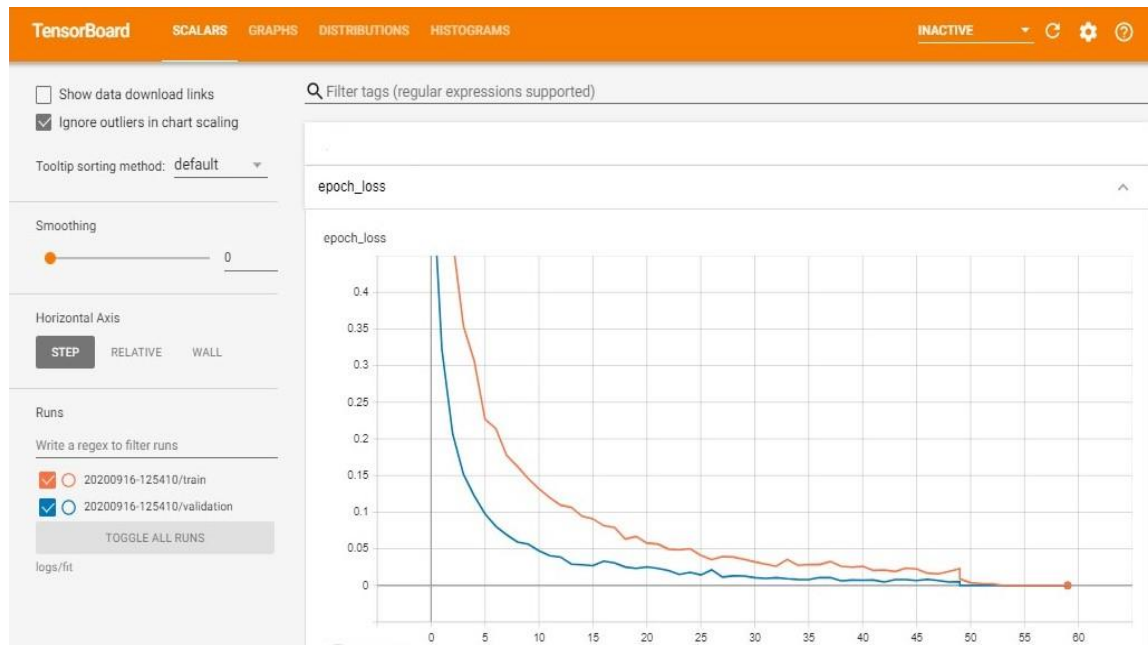


Figure 4.9: Xception model loss metric graph.

4.3 Discussion

The comparative analysis between the baseline model and the fine-tuned models shows a clear view their performance. The baseline model has performed decent despite having only four convolutional layers in its structure. But its loss metric was very high even after 50 epochs. On the other hand, the fine-tuned novel models such as DenseNet-121, Inception V3, NasNet Mobile and InceptionResNet V2 have achieved perfect scores of 100% accuracy and 0% loss. Though these score does not necessarily indicate their performance on real world test data. So we tested the models by deploying them in the browser using TensorFlow.js which is a library for deploying ML models using JavaScript language. We can see the User Interface (UI) of the deployed system which is the web API (Application Program Interface) in figure 4.10.

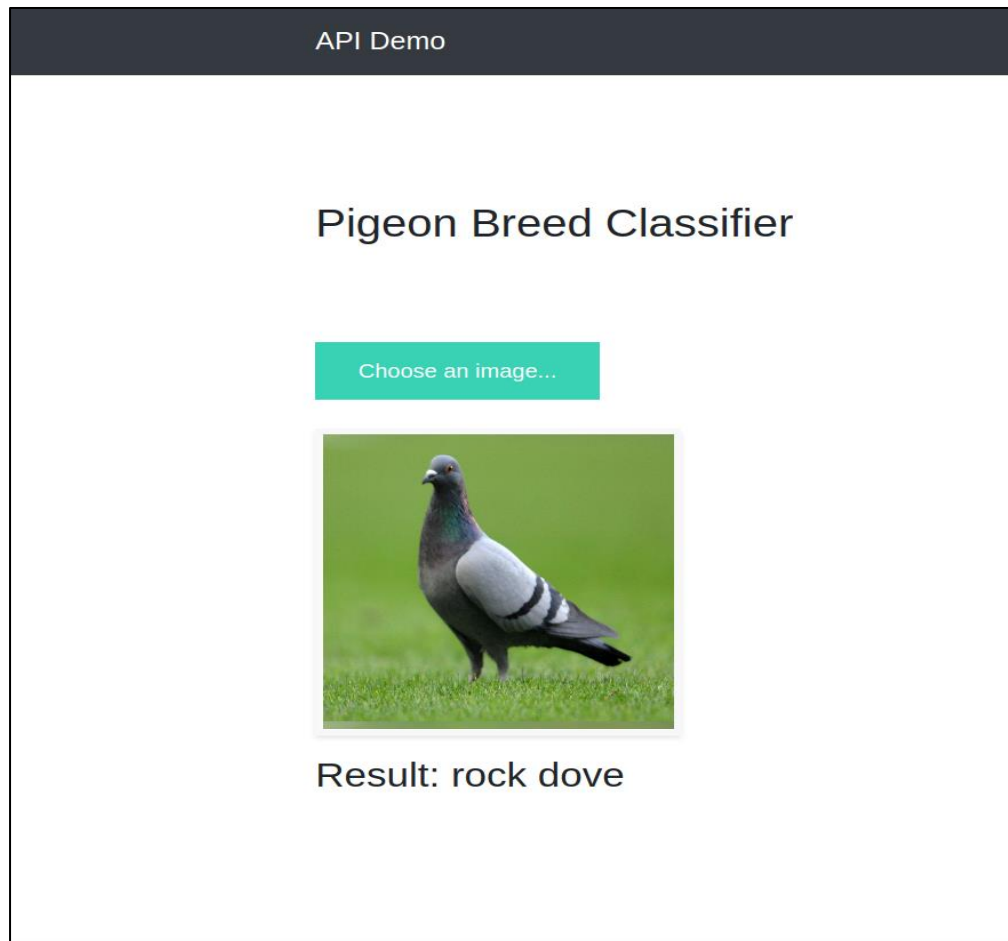


Figure 4.10: Final system testing and user interface.

So, from the UI of the classifier we can observe that the fine-tuned 'Xception' model accurately classifies the uploaded image as 'Rock Dove Pigeon'. The important key point is that this image was unseen to all the models so it represents a real-world test image.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Pigeon is a very common and helpful bird. It is also very healthy. If we can farm it properly it can fill the average protein gap of our daily routine. Also, some of its breed consider as royal bird. People can also make a good business from it. For working with pigeon, you have to know about its breeds and here we can help you. Our model can help you to identify the real breed.

5.2 Impact on Environment

Every creature in our planet has its own role. Everyone is important for the environment but everyone has his own place and own specialty. We can't harvest every fish in pond. Like that we can't use any pigeon breed in anywhere. If we do it then it will not be going to survive and can be harmful for environment. But if we can choose the right breed then it will be a part of environment.

5.3 Ethical Aspects

Our research project provides a standard system that saves the members of our society from being deceived. Moreover, we have considered every point of research ethics in the project. None of the procedures we have followed during the research have violated any moral values of our society. After the deployment of the system, it can used without harming any ethics or morals as it simply solves an economical problem using technology. Thus, it can be stated that our research project is an ethical and feasible system developed with the help of modern technology.

5.4 Sustainability Plan

The pigeon recognition system we developed is moderately sustainable as it is. As its performance depends on the Deep Learning models, it's performance will stay the same in the long run. By upgrading this system to classify more pigeon breeds we can make it more sustainable for future. Moreover, it costs comparatively low resources so it can be expanded into a versatile system in future.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the study

Our project is a research-based project inspired from the application of Deep Learning in image classification problems. At the beginning of our research, we studied the depth of Machine Learning and Deep Learning fields in Computer Science. Then we conducted an in-depth study of novel conference papers and journals on related topics. After gaining sufficient knowledge, we created a unique dataset of pigeon breed images. Then using different sota methods we trained neural networks on the dataset. The best performing architecture was chosen by us as final model and we deployed it. Then we tested this model using real world image data. Thus, we concluded our project.

6.2 Conclusion

To conclude the discussion, the pigeon classification system is the outcome of our project. We have developed this by getting inspired from the wonders of Artificial Intelligence (AI) that is changing our world. There has been some discussion on whether AI will bring disaster to our society or not. But we can state with confident that using AI ethically can help our society progress further. Like our developed system, there are many research works that have been done and are being done in the field of Machine Learning and Deep Learning. These works contribute to the technological advancement of our society by solving different problems. So, we hope and pray that our work will also be a great contribution to the development of our society and our country.

6.3 Implication for further study

The key points that we are keeping in mind for the future improvements of our project are stated below: -

- Expanding the dataset: Our current dataset is small compared to the existing novel datasets. So, we are determined to increase its size by adding more images.
- Increasing pigeon breeds: The dataset has images of only four pigeon breeds. To make it more adaptive to real world we plan to add more different breeds of pigeons to it.
- Improve performance: The model we developed performs well on deployment but it can be improved to be more accurate.
- Scaling to mobile application: Currently our system runs on the browser as a deployed system. So we plan to make a mobile application that would be accessible to everyone.

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APPENDICES

During the period of our undergraduate study we were taught many subjects such as Algorithms, Artificial Intelligence, Robotics etc. We gained fundamental knowledge in these topics under the guidance of our respective teachers. After learning about the capabilities of Artificial Intelligence we became inspired to do something related to it. So we shared the idea of pigeon classification system with our honorable supervisor and he guided us with his valuable advice and scholarly guidance. Thus, after many months of hard work we completed our project with efficiency and perfection.

PIGEON BREED CLASSIFICATION WITH CONVOLUTIONAL NEURAL NETWORK USING SUPERVISED LEARNING METHOD.docx

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