GENDER CLASSIFICATION OF FACIAL IMAGES USING MOBILENET ARCHITECTURE

INTRODUCTION

When a person is uniquely identified then it is because of the face which is the crucial part. With the help of a face, different people are classified and also besides these, a large number of applications can be implemented like for security purposes at banks, various organizations and also in the areas where there is a large public gathering. As the raise in usage of social media and social platforms reached up in the air, gender classification became prominent. In a world increasingly driven by data and automation, gender classification holds the promise of enhancing numerous aspects of our daily lives. From security and marketing to healthcare and entertainment, the ability to automatically discern the gender of individuals from visual data opens doors to tailored experiences, targeted services, and improved decision-making. The core idea behind gender classification is to harness the power of data-driven insights. By training these deep learning models on large and diverse datasets containing images of individuals, the models learn to recognize subtle visual attributes that differentiate between genders. These attributes encompass a wide range of characteristics, including facial features, hairstyle, clothing, and body proportions. A gender categorizing model uses face from a given image to predict the gender (male or female) based on their appearance like baldness, long hair, beard and mustache. By extracting intricate patterns and representations from data, deep learning models can discern and predict gender with remarkable accuracy. In this project, MobileNet architecture has been used to classify the gender using facial images. This model have demonstrated exceptional capabilities in automatically learning relevant features and representations from raw data enabling them to classify the gender with unprecedented accuracy.

METHODOLOGY

The steps involved in this project include data collection, image preprocessing, image augmentation, implementation of architecture and finally the output which is classified as female and male. The flowchart of work is represented in Figure 1.

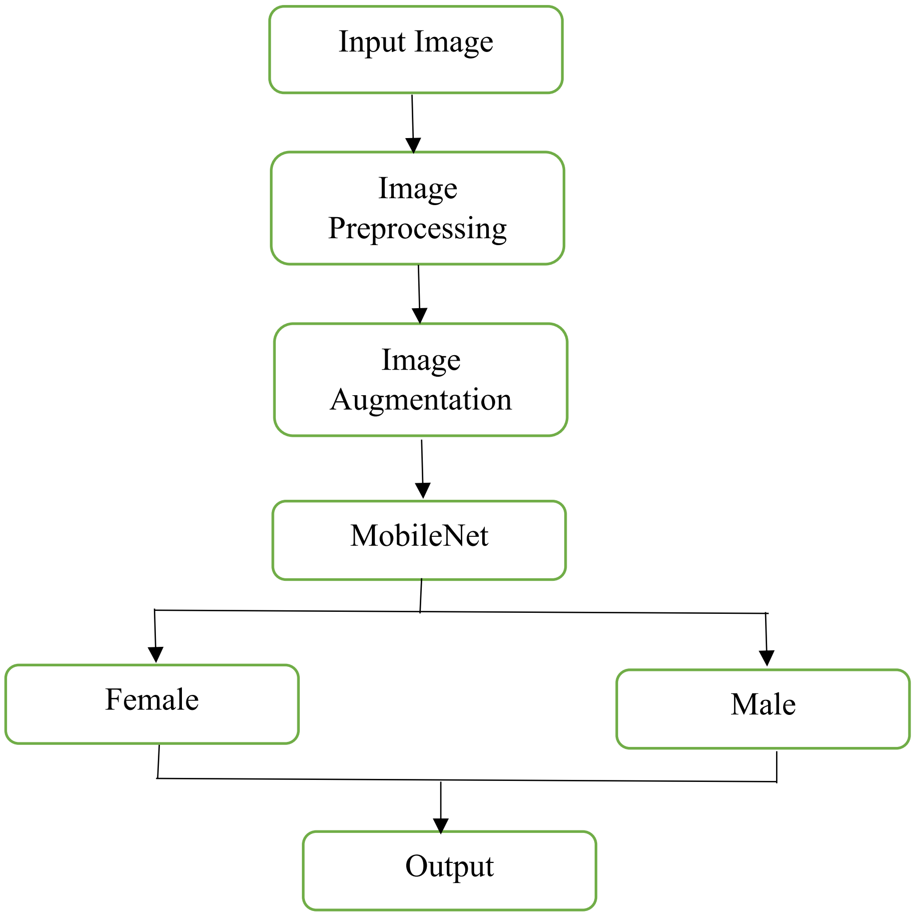

Figure 1 : Flowchart of Gender Classification

IMAGE ACQUISITION :

It is the first and the most important step in the workflow sequence because, without an image, no actual processing is possible by the system. The image that is acquired by the system is usually completely unprocessed. A total of 3686 images were used which are collected from Kaggle dataset. Out of which 2584 images are used for training images and 1102 images are testing images. The female images are labelled as 0 and male images are labelled as 1.

IMAGE PREPROCESSING:

Image preprocessing is the steps taken to format images before model training and inference. Image preprocessing may also decrease model training time and increase model inference speed. In this project Image data generator is used to resize the image to a consistent size of 224×224 pixels.

IMAGE AUGMENTATION:

Image augmentation is a technique of altering the existing data to create some more data for the model training process. In this project, Image Data Generator is used as image augmentation technique. Image Data Generator performs zooming, width shift and height shift and thereby increases the number of datasets.

ARCHITECTURE OF MOBILENET:

The core innovation of MobileNet lies in its use of depth-wise separable convolutions. Traditional convolutions involve applying a single convolutional filter to all input channels, which can be computationally expensive. Depth-wise separable convolutions break down this operation into two separate steps: a depth-wise convolution (applying a single filter to each input channel) followed by a point-wise convolution (1x1 convolution to mix the channels). This reduces both the number of parameters and the computational complexity. MobileNet reduces the number of parameters and computations while maintaining competitive accuracy.

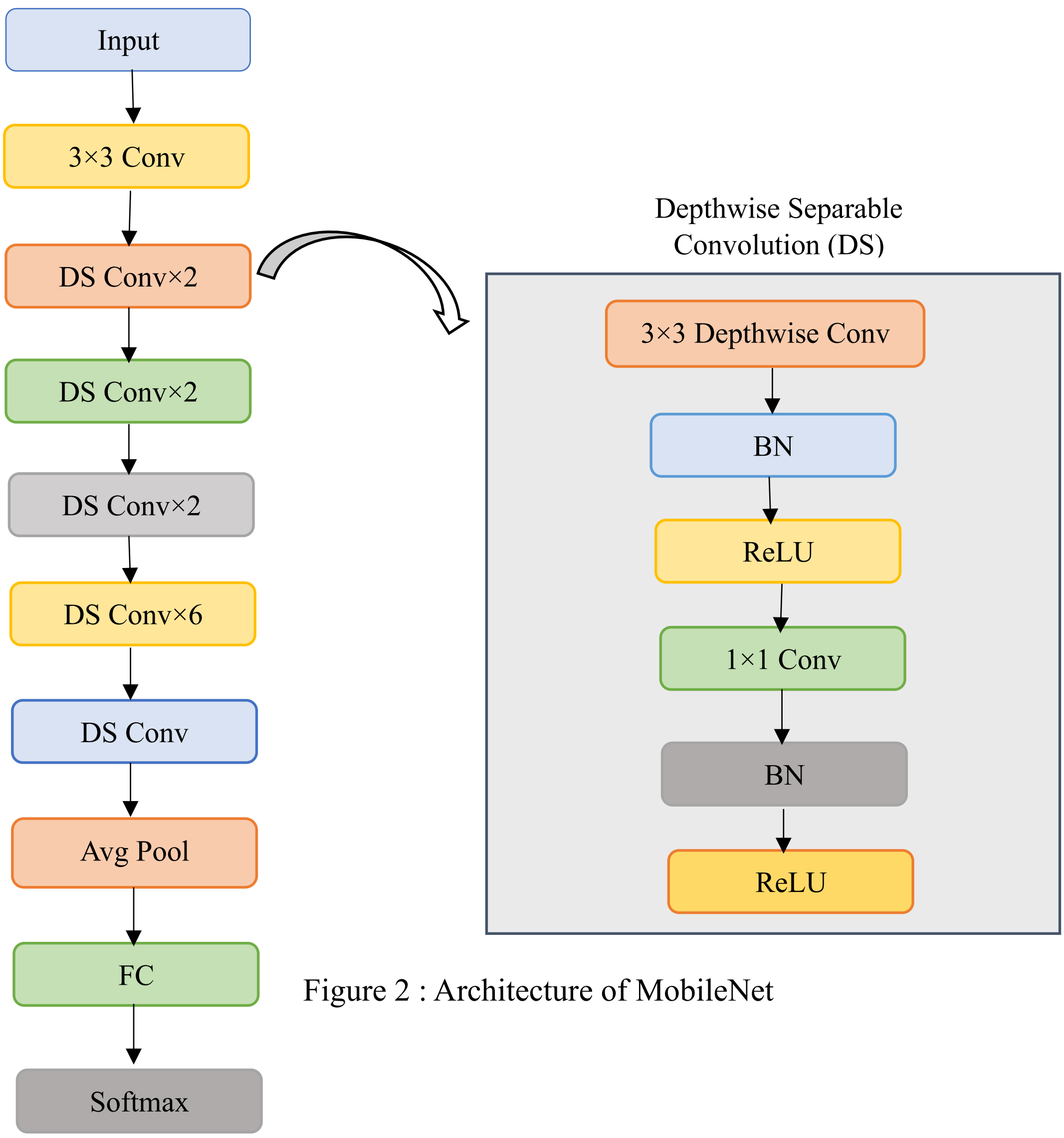

Figure 2 : Architecture of MobileNet

RESULTS AND DISCUSSION

The primary objective of this project is to develop an algorithm to classify the facial images into male and female. A total of 3686 images were used which are collected from Kaggle dataset. Out of which 2584 images are used for training images and 1102 images are testing images. The female images are labelled as 0 and male images are labelled as 1.

Table 1 : Dataset Distribution

Class	Training	Validation
0	1225	348
1	1358	754

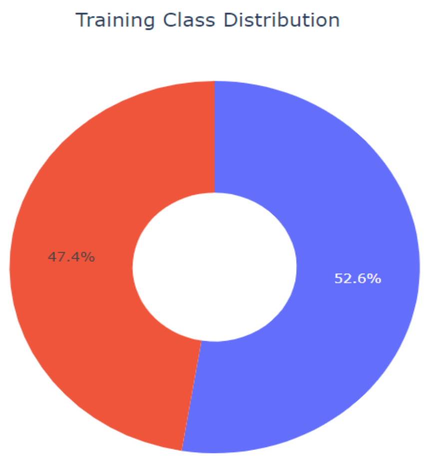

Figure 3 : Training data distribution

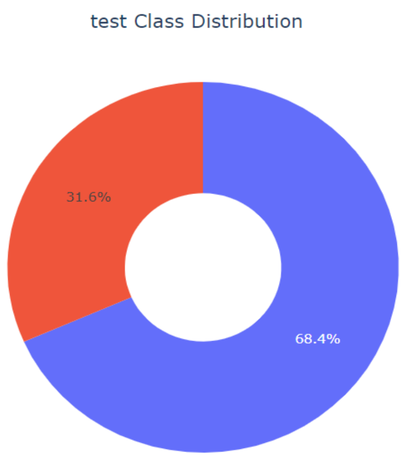

Figure 4 : Testing data distribution

```
Epoch 1/15
81/81 [==============================] - 82s 934ms/step - loss: 0.9667 - accuracy: 0.6047 - val_loss: 1.7514 - val_accuracy: 0.3276
Epoch 2/15
81/81 [==============================] - 48s 591ms/step - loss: 0.6385 - accuracy: 0.7158 - val_loss: 1.4475 - val_accuracy: 0.3947
Epoch 3/15
81/81 [==============================] - 46s 569ms/step - loss: 0.5084 - accuracy: 0.7809 - val_loss: 0.8397 - val_accuracy: 0.6044
Epoch 4/15
81/81 [==============================] - 46s 573ms/step - loss: 0.4685 - accuracy: 0.8022 - val_loss: 0.5192 - val_accuracy: 0.7632
Epoch 5/15
81/81 [==============================] - 44s 545ms/step - loss: 0.3964 - accuracy: 0.8397 - val_loss: 0.3945 - val_accuracy: 0.8267
Epoch 6/15
81/81 [==============================] - 47s 579ms/step - loss: 0.3580 - accuracy: 0.8498 - val_loss: 0.2484 - val_accuracy: 0.9011
Epoch 7/15
81/81 [==============================] - 46s 564ms/step - loss: 0.3315 - accuracy: 0.8602 - val_loss: 0.2189 - val_accuracy: 0.9183
Epoch 8/15
81/81 [==============================] - 45s 556ms/step - loss: 0.3085 - accuracy: 0.8788 - val_loss: 0.2215 - val_accuracy: 0.9174
Epoch 9/15
81/81 [==============================] - 47s 578ms/step - loss: 0.2948 - accuracy: 0.8784 - val_loss: 0.2138 - val_accuracy: 0.9238
Epoch 10/15
81/81 [==============================] - 44s 548ms/step - loss: 0.2603 - accuracy: 0.9032 - val_loss: 0.1910 - val_accuracy: 0.9356
Epoch 11/15
81/81 [==============================] - 45s 554ms/step - loss: 0.2714 - accuracy: 0.8978 - val_loss: 0.1875 - val_accuracy: 0.9383
Epoch 12/15
81/81 [==============================] - 45s 557ms/step - loss: 0.2282 - accuracy: 0.9117 - val_loss: 0.1757 - val_accuracy: 0.9392
Epoch 13/15
81/81 [==============================] - 47s 576ms/step - loss: 0.2135 - accuracy: 0.9152 - val_loss: 0.1638 - val_accuracy: 0.9401
Epoch 14/15
81/81 [==============================] - 44s 545ms/step - loss: 0.2032 - accuracy: 0.9249 - val_loss: 0.1705 - val_accuracy: 0.9428
Epoch 15/15
81/81 [==============================] - 44s 548ms/step - loss: 0.2030 - accuracy: 0.9195 - val_loss: 0.1591 - val_accuracy: 0.9437
```

Figure 5 : Epochs for MobileNet Architecture

The model has achieved an accuracy of 0.94 and loss of 0.15 which is shown in figure 6 and 7.

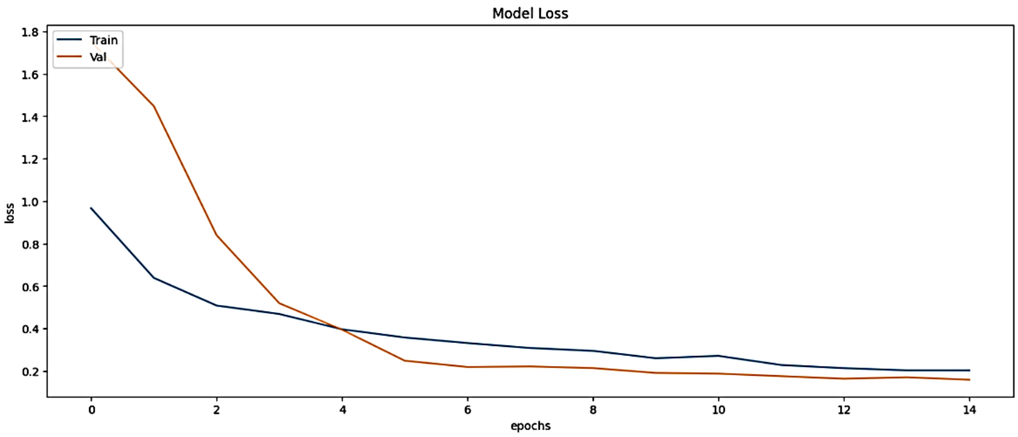

Figure 6 : Model Loss

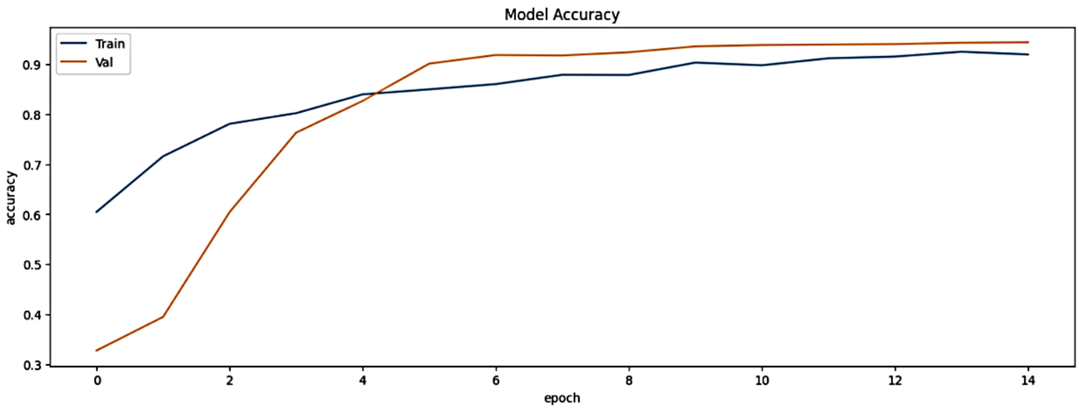

Figure 7 : Model Accuracy

Figure 8 : Prediction of gender

The model's precision, recall and F1-score is mentioned in table 2.

Table 2 : Parameters of MobileNet

Model	Precision	Recall	F1-score
MobileNet	0.96	0.95	0.96

```
y_true = test_generator.classes
y_pred = np.argmax(predictions, axis=1)  # for multi-class

from sklearn.metrics import precision_score, recall_score, f1_score

precision = precision_score(y_true, y_pred)
recall = recall_score(y_true, y_pred)
f1 = f1_score(y_true, y_pred)

print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1 Score: {f1:.2f}")

# or
y_pred = (predictions > 0.5).astype("int32")  # for binary class
```

```
35/35 [==============================] - 3s 80ms/step
Precision: 0.96
Recall: 0.95
F1 Score: 0.96
```

CONCLUSION

In conclusion, the application of deep learning techniques to gender classification has shown remarkable potential in recent years. The ability of deep neural networks to automatically extract intricate patterns from data, such as facial features or voice characteristics, has led to significant advancements in accurately predicting gender based on these features. The proposed model has obtained an accuracy of 0.94 and a loss of 0.15. The utilization of MobileNet architecture has led to impressive advancements in accuracy and robustness.