DAYANANDA SAGAR UNIVERSITY

KUDLU GATE, BANGALORE – 560068

Bachelor of Technology
in
COMPUTER SCIENCE AND ENGINEERING

Major Project Report

(REAL TIME AGE AND GENDER CLASSIFIER)

By

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(2021-2022)

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CERTIFICATE

This is to certify that the Major Project work titled **“REAL TIME AGE AND GENDER CLASSIFIER”** is carried out by **SATHWIK J R (ENG18CS0249), SHARAN PATIL (ENG18CS0256), SHRAVANI G R (ENG18CS0266), SPOORTHI V K (ENG18CS0280), VAISHAKH ANIL (ENG18CS0306),** bonafide students of Bachelor of Technology in **Computer Science and Engineering** at the School of Engineering, Dayananda Sagar University, Bangalore in partial fulfillment for the award of degree in Bachelor of Technology in Computer Science and Engineering, during the year **2021-2022**.

Prof. Nazmin Begum	**Dr. Girisha G S**	**Dr. A Srinivas**
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DECLARATION

We, **Sathwik J R (ENG18CS0249), Sharan Patil (ENG18CS0256), Shravani G R (ENG18CS0266), Spoorthi V K (ENG18CS0280), Vaishakh Anil (ENG18CS0306),** are students of the eighth semester B.Tech in **Computer Science and Engineering**, at The School of Engineering, **Dayananda Sagar University**, hereby declare that the major project titled **"Real Time Age and Gender Classifier"** has been carried out by us and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Computer Science and Engineering** during the academic year **2021-2022**.

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ABSTRACT

Gender is a central feature of our personality still. In our social life it is also a significant element. Artificial intelligence age predictions can be used in many fields, such as smart human-machine interface growth, health, cosmetics, electronic commerce etc. The prediction of people's sex and age from their facial images is an ongoing and active problem of research. The researchers suggested a number of methods to resolve this problem, but the criteria and actual performance are still inadequate. A statistical pattern recognition approach for solving this problem is proposed in this project. Convolutionary Neural Network (ConvNet / CNN), a Deep Learning algorithm, is used as an extractor of features in the proposed solution. CNN takes input images and assigns value to different aspects / objects (learnable weights and biases) of the image and can differentiate between them. ConvNet requires much less pre-processing than other classification algorithms. While the filters are hand-made in primitive methods, ConvNets can learn these filters / features with adequate training. In this research, face images of individuals have been trained with convolutionary neural networks, and age and sex with a high rate of success have been predicted. More than 20,000 images are containing age, gender and ethnicity annotations. The images cover a wide range of poses, facial expressions, lighting, occlusion, and resolution.

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Networks
VGG	Visual geometry group
RESNET	Residual Neural Network
ReLU	Rectified linear activation function

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CHAPTER 1
INTRODUCTION

Studies of face recognition have increased due to the large number of application fields, such as user authentication, targeted advertisements, video surveillance and human-robot interaction. As technology increases, the applications that combine the advanced fields of pattern recognition and image processing are used to find age and gender. In today's world, age plays a prominent role, when you appear for an interview, health check-up. The information of age is used in many government, private and advertising sector organizations to find the culprits, employees eligible for the job, and audience to be targeted for their publicity of the product respectively. However, it's not that easy to find the age of a person, and there are constraints that restrict us from seeing the correct age among the set of images. Finding the correct dataset for training the model is a crucial task. Since the real-time data is massive, the computation and the time to prepare the model are high. It's been a tough task after implementing several methods from machine learning, and the accuracy increases drastically. The age estimation plays a prominent role in the applications like biometric evaluation, virtual makeup, and virtual try-on applications for jewelry and eye-ware by mapping the face according to the age found. Lens kart is such an application that gives the try-on option for their customers. Age estimation is a subfield of face recognition and face tracking which in combination can predict the health of the individual. Many health care applications use this mechanism to keep track of health by monitoring their daily activities. China uses this face detection technique in service driver identification and jaywalker identification.

To predict the age and gender, we use a vital range of machine learning algorithms. CNN (convolution neural network) is one of the most used techniques for age and gender identification. In this implementation we will be using OpenCV and CNN to predict the age and gender of any given person.

1.1 Description

To predict the age and gender, we use a vital range of machine learning and deep learning algorithms. CNN (convolution neural network) is one of the most used techniques for age and gender detection. In this implementation, we use Open CV and CNN and other CNN architectures such as Resnet and VGG to predict the age and gender of any given person's image. We'll perform a comparative analysis on all the CNN architectures and do the real time implementation of the best performing model.

1.2 Scope

The recent growth in social media and the social platform has given rise to increasing amountof application. The automatic classification of age and gender has become relevant for an increasing request of applications. The performance which is reports for the related task of face recognition, the performance of current methods on real-world images is lacking considerably.

Age detection plays a key role in many fields like Multimedia Retrieval and Human-Machine Interaction. Vocabulary used to address people changes according to the age groups very often. Gender Identification is one of the major components for developing gender-dependentacoustic modules for speech recognition etc. Salutations and grammar rules of languages varyfrom one gender to the other.

There are different sorts of procedures required for, just as the expulsion of the issue. In a Facial identification strategy: The articulations that the faces contain hold a great deal of data. At whatever point the individual associates with the other individual, there is an association of a ton of ideas. The evolving of ideas helps in figuring certain boundaries. Age assessment is a multi-class issue in which the years; are categorized into classes. Individuals of various ages have variousfacials, so it is hard to assemble the pictures.

To identify the age and gender of several faces' procedures, are followed by several methods. From the neural network, features are taken by the convolution network. In light of the prepared models, the image is processed into one of the age classes. The highlights are handled further and shipped off the preparation frameworks.

CHAPTER 2
PROBLEM DEFINITION

2.1 Problem Statement:

In today's world there is a rise of increased targeted advertising based on a person's characteristics and the age and gender of a person can make a big impact on the advertisements being targeted. The task is to identify the age and gender of a person from his/her image. The project identifies the age and gender from the real time image which is captured using the camera. This project aims to give a comparative analysis between different architectures (RESNET and VGG16) of CNN and sequential CNN.

2.2 Intended Audience:

The age and gender classifier can be employed in certain domains like digital marketing by corporations to run targeted ads to users on social media by classifying their age and gender with help of their profile pictures. This implementation can also be used in security surveillance by surveillance authority for uses such as identity verification and mass surveillance. In OTT platforms to restrict underage persons by verifying their age to allow access to certain shows and entertainment.

2.3 Purpose:

Automatic age and gender classification has become relevant to an increasing number of applications, particularly since the rise of social platforms and social media. Nevertheless, performance of existing methods on real-world images is still significantly lacking, especially when compared to the tremendous leaps in performance recently reported for the related task of face recognition.

CHAPTER 3

LITERATURE REVIEW

In [1], the authors in the paper “Transfer learning with deep CNNs for Gender Recognition and Age Estimation” have showed that good results can be obtained by re-tasking existing convolutional filters towards a new purpose. In this project, competition-winning deep neural networks with pre-trained weights are used for image-based gender recognition and age estimation. A hierarchy of deep CNNs is tested that first classifies subjects by gender, and then uses separate male and female age models to predict age.

The authors of [2] presented a "hybrid Deep Learning CNN-ELM for age and gender classification" in their paper "A hybrid Deep Learning CNN-ELM for age and gender classification." Automatic age and gender classification offers a wide range of applications, especially in human-computer interaction. They created a hybrid structure in this research that combines the synergy of Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) classifiers. Experiments revealed that their hybrid architecture outperforms prior research on the same datasets, demonstrating considerable gains in accuracy and efficiency.

In [3], the authors in the paper “Real-time embedded age and gender classification in unconstrained video” presented a complete framework for video-based age and gender classification that performs accurately on embedded systems in real-time and under unconstrained conditions. They proposed a segmental dimensionality reduction technique using Enhanced Discriminant Analysis (EDA) to reduce the memory requirements up to 99.5%. A non-linear Support Vector Machine (SVM) along with a discriminative demographics classification strategy is exploited to improve both accuracy and performance.

The authors of [4] published a paper titled "Age Prediction Using Image Dataset Using Machine Learning." Because of its rising real-world applications, soft biometrics has become a new topic of interest for researchers. It includes estimating demographic characteristics such as age, gender, scars, and ethnicity. For age estimate using human faces, neural networks currently provide the best classification results. They surveyed and compared all neural network models created and used for facial age assessment from 2010 to 2019 in this research.

In [5], the authors of the paper "Gender Classification and Age Estimation using Neural Networks" Automatic age and gender classification based on unconstrained images has become essential techniques on mobile devices. With limited computing power, how to develop a robust system becomes a challenging task. Lightweight multi-task CNN uses depth wise separable convolution to reduce the model size and save the inference time. On the public challenging Audience dataset, the accuracy of age & gender classification is better than baseline multi-Task CNN methods.

The authors of the study "Age Group Estimation and Gender Recognition Using Face Features" [6] are interested in developing a mechanism for estimating age group and gender using facial features. Pre-processing, Face Normalization, Feature Extraction, and Classification are the four stages of the procedure. The SVM classifier algorithm is used to dynamically classify age ranges based on the number of groups. From facial photos, this research can be used to anticipate future faces, categorize gender, and determine expression.

In [7], the authors of the paper "Age and Gender Classification using Convolutional Neural Networks" Automatic age and gender classification has become relevant to an increasing amount of applications, particularly with the rise of social platforms and social media. However, performance of existing methods on real-world images is still significantly lacking. They showed that by learning representations through the use of deep-convolutional neural networks, a significant increase in performance can be obtained on these tasks.

Researchers have demonstrated increased interest in soft biometrics to cover the communication gaps between humans and machines, according to the authors of the publication "CNN-Based Age Classification through Transfer Learning" [8]. This study discusses soft-biometrics, which include age, gender, ethnicity, height, facial dimensions, and other factors. This paper discusses the researchers' contributions to the fields of gender classification and age estimates using neural networks.

In [9], the authors of the paper “Structured output SVM prediction of apparent age, gender and smile from deep features” They proposed a solution for predicting the apparent age as well as gender and smile from a single face. We use a convolutional neural network with VGG-16 architecture for learning deep features. Gender and smile predictions are treated as binary classification problems. The proposed solution first detects the face in the image and then extracts deep features from around it.

The authors of the study "Age and Gender Using Multiple-Image Features" [10] developed a real-time approach based on multiple frames to estimate age and gender using face images in this paper. The majority of the previously described methods are based on estimating age or gender using a single frame. After that, they used Speeded up Robust Features (SURF) to extract features from the data and used the Support Vector Machine (SVM) to classify it. Both the training and testing data for their trials came from three publicly available sources.

In [11], the authors of the paper “Geological modelling using a recursive convolutional neural networks approach” Resource models are constrained by the extent of geological units that often depend on the lithology, alteration and mineralization. A three-dimensional model must be built from scarce information coming from drill-holes and limited understanding about the geological setting in which the ore deposit is places. They presented a new technique for multiple-point geostatistical simulation based on a recursive convolutional neural network approach (RCNN).

Convolutionary Neural Network (ConvNet / CNN), a Deep Learning method, was offered as an extractor of features in the proposed solution by the authors of the paper "Age Prediction using Image Dataset utilizing Machine Learning" [12]. Other classification techniques require much more preprocessing than ConvNet. More than 20,000 photos have been annotated with age, gender, and ethnicity. Poses, facial expressions, lighting, occlusion, and resolution are all represented in the photos.

In [13], the authors of the paper “Gender Classification and Age Estimation using Neural Networks: A Survey” Researchers have shown more interest in soft biometrics area to fill the commination gaps between humans and machines. Soft-biometric consists of age, gender, ethnicity, height, facial measurements and etc. This paper contains a detail discussion about the Contribution of the researchers in the area of gender classification and age estimation using neural networking. Most of the work is done using Convolutional neural networks and auto encoders.

The authors of the study "Gender classification with support vector machines" [14] discuss their findings. With low-resolution "thumbnails" faces (21-by-12 pixels) processed from 1755 photos from the FERET face database, support vector machines (SVM) are studied for visual gender classification. Traditional pattern classifiers, as well as more contemporary techniques such as radial basis function (RBF) classifiers and large ensemble-RBF networks, perform worse than SVM (3.4 percent error). At the same task, SVM outperformed human test subjects.

In [15], the authors of the paper “ A gender and age estimation system from face images” They developed extraction functions of a face candidate region with color information and parts of its face and combined them with the gender and age estimation algorithm they had already developed so that the algorithm can be applied to real time captured face images. The experimental results have shown hitting ratios of 93.1% and 58.4% for gender and age respectively.

The authors of [16] suggest a customized convolutional neural network for fracture detection in concrete structures in their paper "Performance Evaluation of Deep CNN-Based Crack Detection and Localization Techniques for Concrete Structures." On the basis of training data quantity, data heterogeneity, network complexity, and the number of epochs, the proposed method is compared to four existing deep learning methods. On eight datasets of varying sizes, constructed from two public datasets, the proposed CNN model is tested and compared to pre-trained networks. It demonstrates that on a short quantity of data, the suggested customized CNN and VGG-16 models beat conventional methods in terms of classification, localization, and computing time.

CHAPTER 4

PROJECT DESCRIPTION

The upgrading of image pictures taken from the camera sources and the images caught in everyday lives is called picture processing. Processing of the image based on analysis undergoes many different techniques and calculations. Digital formed pictures need to be carefully imagined and studies.

Image processing has two main steps followed by simple steps. The improvement of an image with the end goal of more good quality pictures; that can be adopted by other programs are called picture upgrades. The other procedure is the most pursued strategy utilized for the extraction of data from a picture. The division of images into certain parts is called segmentation.

The location of the information accessible in the pictures is much-needed information. The information that the image contains is to be changed and adjusted for discovery purposes.

There are different sorts of procedures required for, just as the expulsion of the issue. In a Facial identification strategy: The articulations that the faces contain hold a great deal of data. At whatever point the individual associates with the other individual, there is an association of a ton of ideas.

The evolving of ideas helps in figuring certain boundaries. Age assessment is a multi-classissue in which the years; are categorized into classes. Individuals of various ages have various facials, so it is hard to assemble the pictures.

To identify the age and gender of several faces' procedures, are followed by several methods. From the neural network, features are taken by the convolution network. In light ofthe prepared models, the image is processed into one of the age classes. The highlights are handled further and shipped off the preparation frameworks.

4.1 Proposed Design

We are using Machine Learning algorithms to get more accurate diagnosis to avoid serious consequences. In this project, the approach we used is “Transfer Learning”. Transfer learning has several benefits, but the main advantages are saving training time, better performance of neural networks (in most cases), and not needing a lot of data. Which is why it makes it ideal for this scenario. Our project employs algorithms such as CNN (Convolutional neural network) and other CNN architectures such as Resnet and VGG which both utilize Transfer Learning techniques. Many modules such as Keras, Scikit-image, Scikit-learn for prediction and Matplotlib for visualization of the testing and training data are also used.

The primary construct of this project is to determine the best algorithm that would be suitable for the detection of Age and Gender. Although the first priority would be to evaluate the accurateness and the reliability of the said algorithms. Here the experimental data is being compared and analyzed where the precision of Algorithms are taken into consideration.

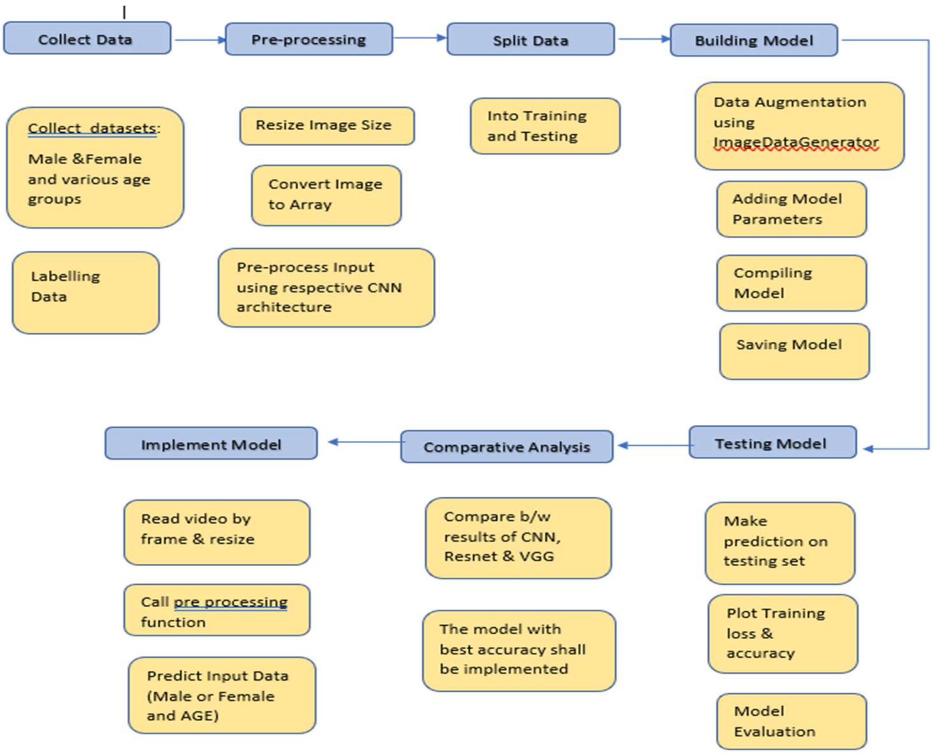

Fig 4.1: Proposed Design

CHAPTER 5
REQUIREMENTS

5.1 Functional Requirements

This implementation should facilitate the users to detect the age and gender of a person as close to the real-life as possible. This implementation should be able to detect the age and gender of the person in less than 5 seconds when used in real-time.

5.2 External Interface Requirements

5.2.1 Hardware Interfaces

- Processor: Intel Core-I5/ Ryzen 5 equivalent andhigher
- Memory: 8 GB of memory
- Hard Disk: 500GB of storage

5.2.2 Software Interfaces

- Operating System: Windows 10 and above
- Domain: Machine Learning
- Programming Language: Python
- Tools: Anaconda Navigator, Google-Colab
- Libraries: NumPy, Pandas, CV2, Matplotlib, SciPy,Sklearn, Keras and TensorFlow

CHAPTER 6
METHODOLOGY

In neural networks, Convolutional neural network (ConvNets or CNNs) is one of the main categories to do images recognition, images classifications. CNN image classifications take an input image, process it and classify it under certain categories. Technically, deep learningCNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernels), Pooling, fully connected layers (FC) and apply Activation function to classify an object.

6.1 Proposed Setup

1) Module 1

In this module, the sequential CNN model, Resnet and VGG are used and the process sets in motion by loading the vital libraries and the images with their respective labels to create a complete dataset. EarlyStopping and ReduceLROnPlateau are the two definitive callbacks used in this process and the model is trained. Data from our source folders are transferred to Keras with the help of a Data Generator. The CNN model is then tested and the results are visualised using a confusion matrix, Precision Recall, and F1-Score. We have varied the dropout rates with the Max pooling layer which helps reduce overfitting. The Relu Activation function is also used.

2) Module 2

In the second module, with the help of the algorithm, this project begins the process by loading the CSV file which is our dataset. Then the column names are assigned which make it easy to examine the data. Then the data is pre-processed to identify missing values and outliers. Then the dataset is split into a training and valuation set in ration of 80:20. The dataset is then fit into the model and the accuracy is examined using the performance metrics and the findings are depicted.

3) Module 3

A comparative analysis is obtained for the contrasting algorithms based on their resulting outcomes and the accuracies are correlated based on the hyper-parameters manipulated in the respective algorithms.

6.2 Algorithms Employed

The content of the project report is primarily divided into four modules which provide pellucidinformation on what takes place in each section of the implementation process.

6.2.1 SEQUENTIAL Model

As the name suggests, here we create our own model layer-by-layer in a step-by-step fashion. The sequential model of CNN which we've implemented has various convolutional layers and pooling layers. The sequential mode is one of the easiest ways to allow developers to create their own convolutional neural networks. This method gives developers the freedom to add any number of convolutional layers, pooling layers and define other model parameters as per the requirements.

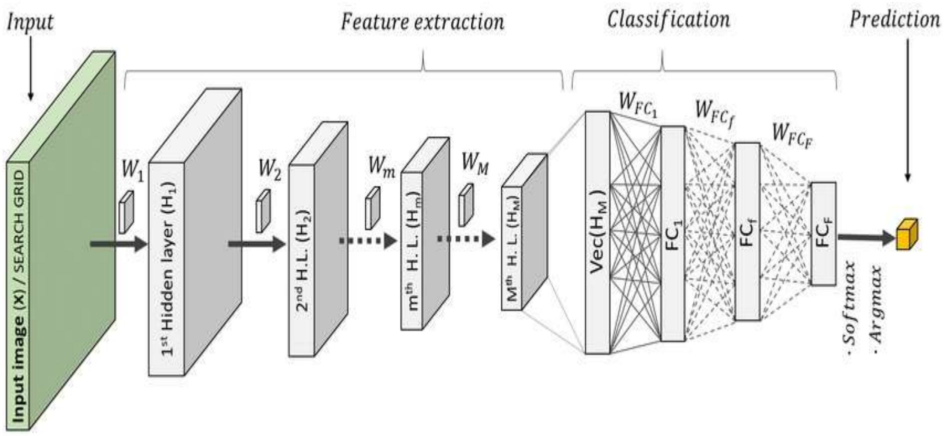

Fig 6.2.1: Sequential CNN Model

6.2.2 RESNET Model

A residual neural network (ResNet) is an artificial neural network (ANN). Residual neural networks utilize skip connections, or shortcuts to jump over some layers. Typical ResNet models are implemented with double- or triple- layer skips that contain nonlinearities (ReLU) and batch normalization in between.

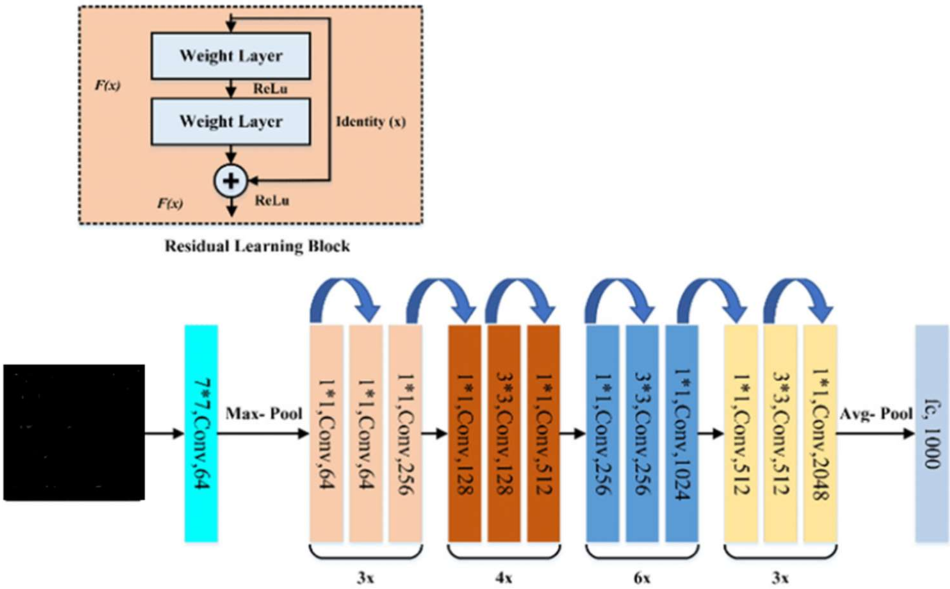

Figure 6.2.2: Resnet Model

6.2.3 VGG Model

VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network(CNN) architecture with multiple layers. The “deep” refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG architecture is the basis of ground-breaking object recognition models. Developed as a deep neural network, the VGGNet also surpasses baselines on many tasks and datasets beyond ImageNet. VGGNets are based on the most essential features of convolutional neural networks (CNN).

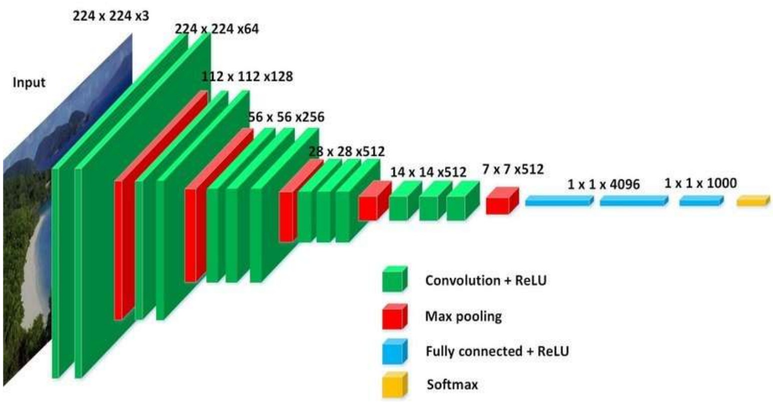

Figure 6.2.3: VGG Model

CHAPTER 7
EXPERIMENTATION

Almost every effort or real-world situation will encounter a challenge or setback. Necessary actions must be done to address these issues and go forward with the search for a solution. We only had a few difficulties throughout our project.

- In our project we are using CNN (Convolutional Neural Network) for classifying age and gender. In the first part of our implementation, we would be creating our own model by using sequential in CNN where we create models' layer-by-layer in a step-by-step fashion. Later, we would be implementing the identifier using VGG Architecture and Resnet Architecture. We also provide a comparative analysis at the end of the project which provides a detailed study and visual representation of the different CNN architectures used in our project.

- After careful consideration, we decided to use Haar Cascades, an object detection algorithm used to identify faces in an image or a real time video. After that it's utilized to detect faces. For each feature extracted, it found the best threshold which will classify the faces to positive faces and negative.
- In this project, we have experimented with tweaking various parameters in the machine learning models to try and increase the models' accuracy.

- We have tweaked parameters like the learning rate, number of epochs we're training the machine learning model for.

- In the machine learning models definitions we have added and removed dense layers, dropout layers.

- For all machine learning models, we have also experimented with various activation functions, optimizers, and the loss functions too.

- We have performed various trial and error methods to arrive at the conclusion for the comparative analysis. The sequential architecture model was able to obtain a slightly higher accuracy compared to other models.

CHAPTER 8
TESTING & RESULTS

The main intent of this project is to find the accuracy of the various models while determining the age and gender of the person. We were able to obtain the real time working model of CNN.

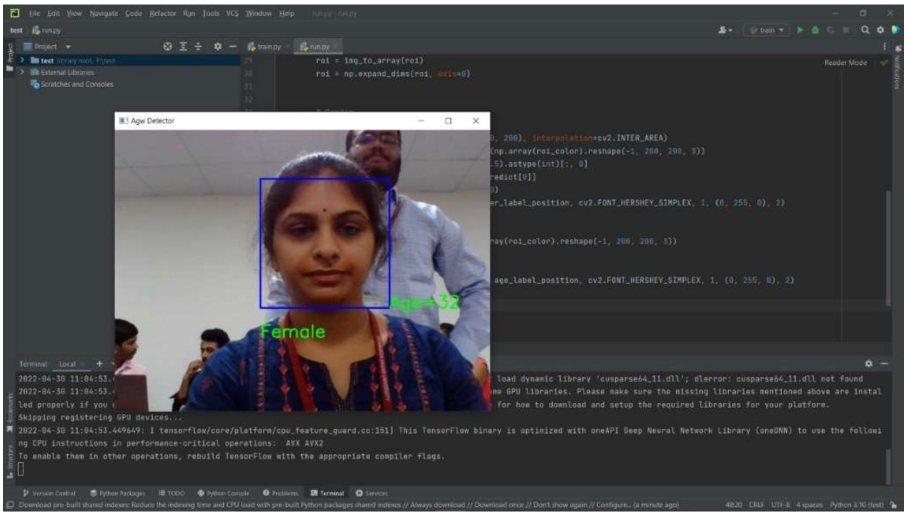

Fig 8.1: CNN model in real time

The performance metrics were used to determine the accuracy and precision of the CNN model.

	precision	recall	f1-score	support
0	0.91	0.91	0.91	2468
1	0.90	0.90	0.90	2273
accuracy			0.90	4741
macro avg	0.90	0.90	0.90	4741
weighted avg	0.90	0.90	0.90	4741

Fig 8.2: Accuracy and Precision of Gender model of CNN

The Confusion matrix as displayed below in Figure 8.11 shows how often the model classified each label correctly and which labels were most often confused for that label

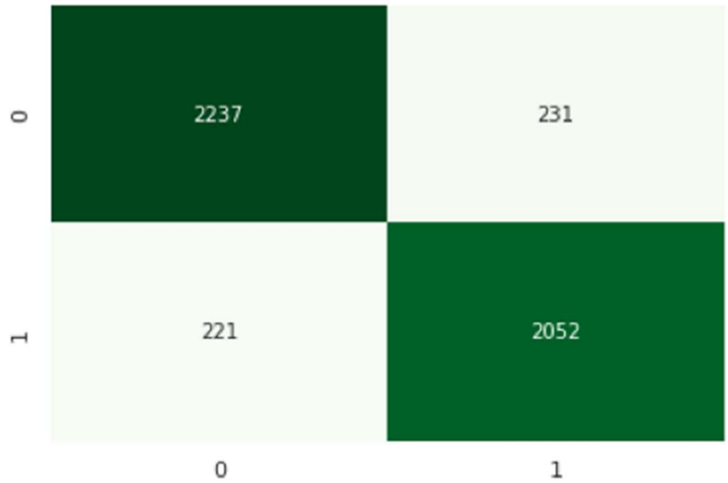

Fig.8.3: Confusion Matrix for Gender model of CNN

We obtained a comparative analysis of all the models to test between the various accuracies.

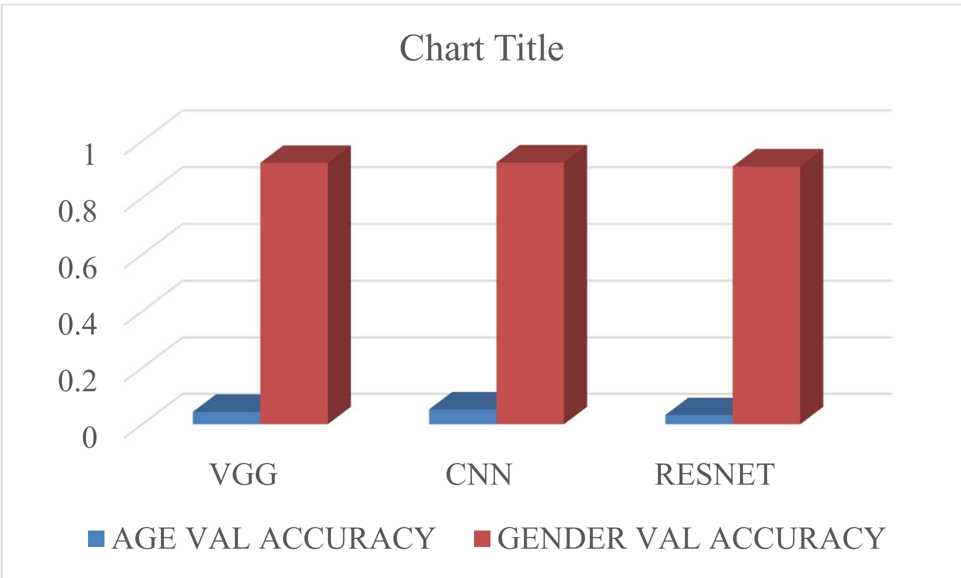

Fig 8.4: Comparison of All Models Accuracies

We have also obtained a table comparing the validation accuracies of the various models used.

	AGE Val Accuracy	**Gender Val Accuracy**
VGG	0.0442	0.9234
CNN	0.0527	0.9248
RESNET	0.0325	0.9107

Table 1. Validation accuracies of models used

As seen in the table above, Sequential CNN obtained the highest Age and Gender Validation accuracies in comparison with other CNN architectures.

CHAPTER 9

CONCLUSION AND FUTURE WORK

In this project, we have proposed a complete framework for real-time and accurate age and gender classification and a detailed comparative analysis between different CNN models. Several improvements were presented for face alignment, illumination normalization, and feature extraction using a multi-resolution binary pattern method. Overall, we propose to createa complete framework for real-time and accurate age and gender classification with the help of machine learning. The Gender model with an accuracy of more than 80% is created and implemented. This project also provides a comparative analysis between different CNN models in a graphical representation which helps in effective analysis. A cost effective, low memory device will result in a viable real time application.

On the future direction, results that are good for gender recognition as well as years opinion can continue to be received utilizing later learning strategies with expansion in reliability. Combos of fusions as well as datasets of attributes might be what is on the horizon for the development of rich learning and from 2D to 3D Facial Data. Moreover, ethnicity estimation, Affective behavior analysis and numerous additional demographic features could be verified for the performance of them by the classifier of Neural Networks.

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APPENDIX

1. **CNNs**: A convolutional neural network (CNN) is a specific type of artificial neural network, a machine learning algorithm for supervised learning, to analyze data. CNNs applied to image processing, natural language processing and other kinds of cognitive tasks. A convolutional neural network is also known as ConvNet.

2. **Resnet:** is an artificial neural network that was introduced in 2015. It is a gateless variant of Highway Net. This network can be used to help ease the trainings of the networks that are substantially deeper than before by eliminating the degradation problem.

3. **VGG:** It stands for Visual geometry group. It is a deep CNN architecture with multiple layers. A VGG network can either have 16 or 19 convolutional layers. VGG is used mostly for object recognition.

PAPER PUBLISHING DETAILS

Paper Title	Real Time Age and Gender Classifier
Journal	International Journal Of Engineering Applied Sciences and Technology (IJEAST)
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Abstract	Gender is still a prominent element of our personalities. It also plays an important role in our social lives. Artificial intelligence age forecasts have applications in a variety of disciplines, including smart human-machine interface development, health, cosmetics, and electronic commerce, among others. The ability to estimate people's sex and age from their face photographs is a current and active research topic. The researchers proposed a number of solutions to the problem, but the criteria and actual results are still insufficient. This paper proposes a statistical pattern recognition strategy to solve this challenge. In the proposed method, a Deep Learning technique called Convolutional Neural Network (ConvNet / CNN) is employed to extract features. CNN takes input images and assigns a value to distinct characteristics / elements of the image (learnable weights and biases) and can distinguish between them. Other classification techniques require far more pre-processing than ConvNet.
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GitHub Link: https://github.com/Sharanpatil2000/Age-and-Gender-Classifier