KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

COLLEGE OF SCIENCE

FACULTY OF PHYSICAL AND COMPUTATIONAL SCIENCES

DEPARTMENT OF COMPUTER SCIENCE

TOPIC:

AGE ESTIMATION FROM FACIAL IMAGES USING TRANSFER LEARNING

BY

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A PROJECT WORK SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF BACHELOR OF SCIENCE (BSc.) DEGREE IN COMPUTER SCIENCE

SEPTEMBER, 2022

DECLARATION

We declare, without any reservation, that we personally undertook the study herein submitted under supervision.

EMMANUEL AWUAH	………………………	………………………
STUDENT	**SIGNATURE**	**DATE**
ISSAKA RAFAT HAMMED	………………………	………………………
STUDENT	**SIGNATURE**	**DATE**

I declare that I have supervised the student in undertaking the study submitted herein and confirm that the student has my permission to present it for assessment.

DR. KWABENA OWUSU-AGYEMANG	…………………….	……………………….
SUPERVISOR	**SIGNATURE**	**DATE**

DEDICATION

This project work is dedicated to our parents who have supported us in diverse ways in helping us to achieve this fantastic journey. Also, We dedicate it to all the lectures in the computer science department that impacted our knowledge and helped us in all diverse to reach this far.

ACKNOWLEDGEMENT

Our profound gratitude goes to the Almighty God who has been faithful to me during the course of this project work. Without his protection and strength, this work would not have been possible. Again, We would like to thank our parents for believing in us and supporting us during our studies.

Our uttermost gratitude goes to our supervisor, Dr. Kwame Owusu-Agyemang whose guidance and supervision made this work successful.

ABSTRACT

In our societies, age has been an important attribute or factor that determines how people approach and interact with you, and how you are even spoken to, making age an essential factor that contributes to social interaction. Humans over time have intrinsically been able to guess people's age, this is due to certain factors we look at that contribute to adding knowledge to the person doing the prediction. These elements can include wrinkles on the face and intonation are some of the factors that contribute to the prediction of the person's age. In many works, knowing an individual's age is essential for things like security, medicine, and transport.

Age estimation based on the human face remains a significant problem in computer vision. In order to accurately estimate age from a facial image, most of the existing algorithms require huge amounts of face data while training models from scratch. In our project, we develop an age estimation model using transfer learning. A technique used by employing a pre-trained machine or deep learning model The ResNext101 model, an extension of Resnet that allows extremely deep neural network training of 150+ layers compared to other models like VGG16, was the model used in the project.

The aim is to build a model capable of identifying faces and accurately estimating the age of individuals using photos or live video from a webcam feed.

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CHAPTER ONE
INTRODUCTION

1.0 Background of Study

In many countries, proof of being under or over the legally defined age limits is required for legal decisions about procedural privileges or social benefits, for example, the right to shelter and services of the child care facilities by youth welfare offices after taking in unaccompanied refugee minors. The relevant age limits in a country like Germany for various legal issues range between 14 and 21 years of age. Increasing cross-border migration has resulted in more people in Germany who can not prove their chronological age with valid identification documents. If doubts about the given age of an individual cannot be otherwise eliminated, authorities and courts can request a medical age assessment issued by an expert. In general, every physician who has the necessary expertise can be called a medical expert. In our estimation, age assessments are prepared mainly by forensic physicians, radiologists, dentists, primary care physicians, and pediatricians. It should be noted that a medical expert is not bound under the care principle of the physician-patient relationship but is rather obliged to maintain strict neutrality.[1]

Age is the interval of time between the day, month, and year of birth and the day and year of occurrence of the event expressed in the largest completed unit of solar time, such as years for adults and children and months, weeks, days, hours, or minutes of life, as appropriate, for infants under one year of age.[2]

Age estimation is the determination of a person's age based on biometric features. Although age estimation can be accomplished using different biometric traits, this project is focused on facial age estimation that relies on biometric features extracted from a person's face from a given picture or photo or from a live video feed from a web camera. The appearance of a human face is considerably altered by aging. The aging effect is attributed to facial bone movement, growth, and skin deformations associated with wrinkles and a reduction in the strength of facial muscles. Humans have been able to predict the ages of individuals in most cases, but research shows that humans are not as accurate in age estimation. In automated facial estimation, algorithms are used to estimate the age of individuals based on facial features derived from their faces.

1.2 Aim of Project

The project is aimed at developing a state-of-the-art machine learning model using transfer learning techniques by utilizing pre-existing image recognition models. The goal is to build a neural network capable of identifying and accurately estimating the age of individuals from still images or live video from a webcam feed, making use of pre-trained models on large datasets built for use in computer vision and machine learning, to help personnel that requires age identification such as forensics experts, border patrol personnel, or security personnel who need to estimate the age of individuals during the course of their work activities.

1.3 Specific Objectives

The objectives of this project are to;

- Estimating the age of an individual using a live video feed from a web camera.
- Estimating the age of an individual using a photo.
- Classify the age of faces detected in the photo or video feed.

1.4 Project Scope

The project shall involve the implementation and development of a machine learning model leveraging computer vision techniques in facial recognition and classification and utilizing pre-trained models for image classification for the identification and estimation of ages.

1.5 Project Justification

Age estimation of the living can be required in cases involving individuals who deliberately falsify their birth year to increase or lower their age too, for example, legally marry, achieve the required age threshold for employment in a particular industry, or enlist in a military program. Age estimation also in forensic science helps in identifying and also knowing the setting of a crime investigation or a mass disaster. A recent inquiry by the Australian Human Rights Commission into suspected people smugglers claiming to be children highlighted the growing need for a more informed understanding of age estimation assessments performed on living individuals. [3]

1.6 Project Motivation

The motivation for doing this project was primarily an interest in undertaking a challenging project in an interesting area of research. It has given us the opportunity to learn about a new area of computer science not covered in lectures, which is appealing. We have learned how to use machine learning frameworks such as PyTorch, which is used in computer vision and natural language processing applications, to name a few.

1.7 Project Beneficiaries

The importance of age estimation is manifold, and there are lots of beneficiaries, not limited to;

- For the purpose of identifying a victim's mutilated body (in forensic identifications),
- Knowledge of age will aid in the evaluation of age group distribution and provide a picture of life in a specific era or area in anthropological studies research.
- Treatment planning for various abnormalities.
- Civil issues such as a marriage contract or for insurance.

CHAPTER TWO
REVIEW OF RELATED WORKS

2.0 Review of Related Works

This chapter presents some different age estimation models we found to be developed.

2.1 OVERVIEW OF SYSTEM 1

Methods of Skeletal Age Estimation

Reconstruction of the biological profile of unknown individuals would be incomplete without age determination. Forensic anthropologists use skeletal indicators involved in processes of bone resorption, deposition, and remodeling which are time-related to estimate the age of the individual. Estimating age in adults remains a challenging task for forensic anthropologists because of the complexity and individual variations seen in the aging process and the gamut of environmental factors influencing the same. Age provided by anthropologists is determined as an age range rather than a specific age. It has been noticed that the age range determined for younger individuals is narrower than for older individuals[4].

2.1.1 GOOD FEATURES

- Quick execution and is Used by more than 76%of pediatricians
- Accuracy and precision
- Standardized evaluation of errors which is very useful for forensic uses
- Accessibility
- Quick scan
- Low cost
- Multiplanar capacity
- Comparison with contralateral

2.1.2 BAD FEATURES

- Operator-dependent
- Difficulty of standardization
- Needs further improvements
- Automated evaluation, but not totally eliminated radiologist and pediatrician evaluation

2.2 OVERVIEW OF SYSTEM 2

Dental Age Estimation

Age is one of the essential factors in establishing the identity of the person. It plays an important role in forensic medicine, clinical dentistry, and archaeology. Age estimation is crucial in medico-legal cases and important in forensic medicine, not only for identifying deceased victims but also in connection with crimes and accidents. Age estimation of unknown human bodies is very important in the setting of a crime investigation as well as mass disaster. The age of the individual can be assessed as skeletal, morphological, secondary sex character, and dental age. This paper reviews various dental age estimation methods that have been used by the scientist in order to help the identification of remains[5]

2.2.1 GOOD FEATURES

- Demirjian and Goldstein's method is simple, as it is an orthopantomogram-based method and it enables a more reliable standardization and has good reproducibility and intra-examiner/inter-examiner reliability.
- One of the reasons for the widespread acceptance of this method is that the maturity scoring system that it creates is universal in application, although the conversion to dental age depends on the population being considered.
- Furthermore, this conversion can be made with the use of relatively small local samples and can reach an equivalent dental age by comparison for different populations.

2.2.2 BAD FEATURES

- The Demirjian method uses orthopantomogram which are difficult to obtain in young children, due to both technical reasons, as well as legal and ethical considerations.
- Since the simultaneous evaluation of seven left mandibular teeth are required, it cannot apply in children with lacking teeth inborn or acquired.
- This method may not express agenesis of teeth, distinctive retardation of dental development (excluding third molars), and systemic diseases and various developmental stages of the tooth.
- The appreciation of the developmental stage may become difficult as the choice of the tooth developmental stage is quite subjective.

2.3 OVERVIEW OF SYSTEM 3

Ranking Model for Facial Age Estimation

Feature design and feature selection are two key problems in facial image-based age perception. In this paper, we proposed using a ranking model to do feature selection on the haar-like features. In order to build the pairwise samples for the ranking model, age sequences are organized by personal aging patterns within each subject. The pairwise samples are extracted from the sequence of each subject. Therefore, the order information is intuitively contained in the pairwise data. The ranking model is used to select the discriminative features based on the pairwise data. The combination of the ranking model and personal aging pattern is powerful to select the discriminative features for age estimation. Based on the selected features, different kinds of regression models are used to build prediction models. The experiment results show the performance of our method is comparable to the state-of-art works. [6]

2.3.1 GOOD FEATURES

- The fully connected layers in the binary CNN first flatten the features obtained in the previous layers and then relate them to a binary prediction.

2.3.2 BAD FEATURES

- Difficulties when binary outputs are aggregated to make the final age prediction.

2.4 OVERVIEW OF SYSTEM 4

Preliminary Abstraction Model

In the first stage, we use the CNN network to extract features to mimic the initial visual abstraction of images of humans. Specifically, this module has two main challenges as follows:

1. extracting specific visual features from face images, which could lead to a higher estimation accuracy
2. Compressing the image size without loss of important information.

To address these two problems, we use a face recognition model, sphere-net to carry out the initial visual feature extraction task due to the two following metrics:

1. it is obvious that the features extracted from the face recognition model can better express the original face images.
2. Features extracted by the face recognition model contain rich information about both identity and age.

On the basis of these two reasons, we believe that it is reasonable to utilize the face recognition model as the basic feature extraction procedure.[7]

2.4.1 GOOD FEATURES

- Following origin model settings, feature maps are scared from to in B3. To save more detailed information, the stride of the first convolution layer in B3 was changed to 1; the feature map size is still without decrease. For the same reason, B4 in the original model is removed either.

2.4.2 BAD FEATURES

- Loss of spatial information caused by the stretching of two-dimensional features into a vector.

CHAPTER THREE
METHODOLOGY

3.0 Overview of the Proposed System

The currently proposed system is going to be a CLI-based program where users will enter a command from their terminal by passing in the image data source and other configuration options like if the image should be margined. These configurations will be needed by the machine learning model to run analysis on the image data. with our focus on developing a state-of-the-art machine learning model for age estimation using transfer learning. Our primary goal was to build a good enough model for estimating the age of input images fed into the model.

3.1 Project Method Adopted and Justification

In order to quickly reiterate and adjust to shifting requirements at the initial stages of the development of the machine learning model, the Rapid Application Development (RAD) methodology was chosen for developing the model. Even though RAD was chosen as the model for this proposed project, the development leaped between using the Waterfall methodology and RAD due to the model's linear timeline and fixed phases, which were needed to follow a strict deadline needed for the project. Some reasons for adopting these models:

- Lots of prototyping was done to get the requirements clear.
- A linear approach helped outline the various phases of what needed to be done.
- Re-use of code components to accelerate the development timeline

3.2 Requirement Specification

Requirement specification helps identify key areas of the system that we wish to tackle or solve. It is also a document or set of documentation that describes the features and behavior of a system or software application

3.2.1 Functional Requirements of the System

- The system shall estimate the age of an individual from a photo
- The system shall estimate the age of an individual from a webcam video feed

3.2.2 Non-functional Requirements of the System

3.2.3 UML Models

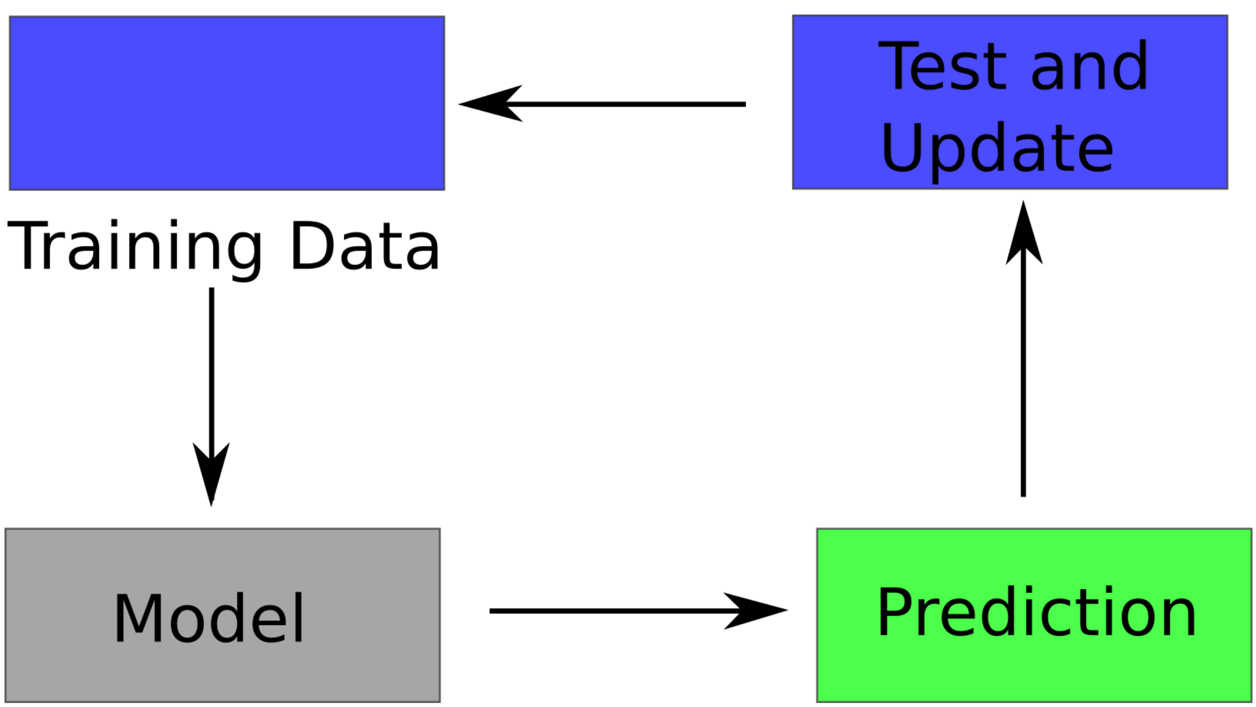


Figure 1. Our training UML Pipeline - Generalized

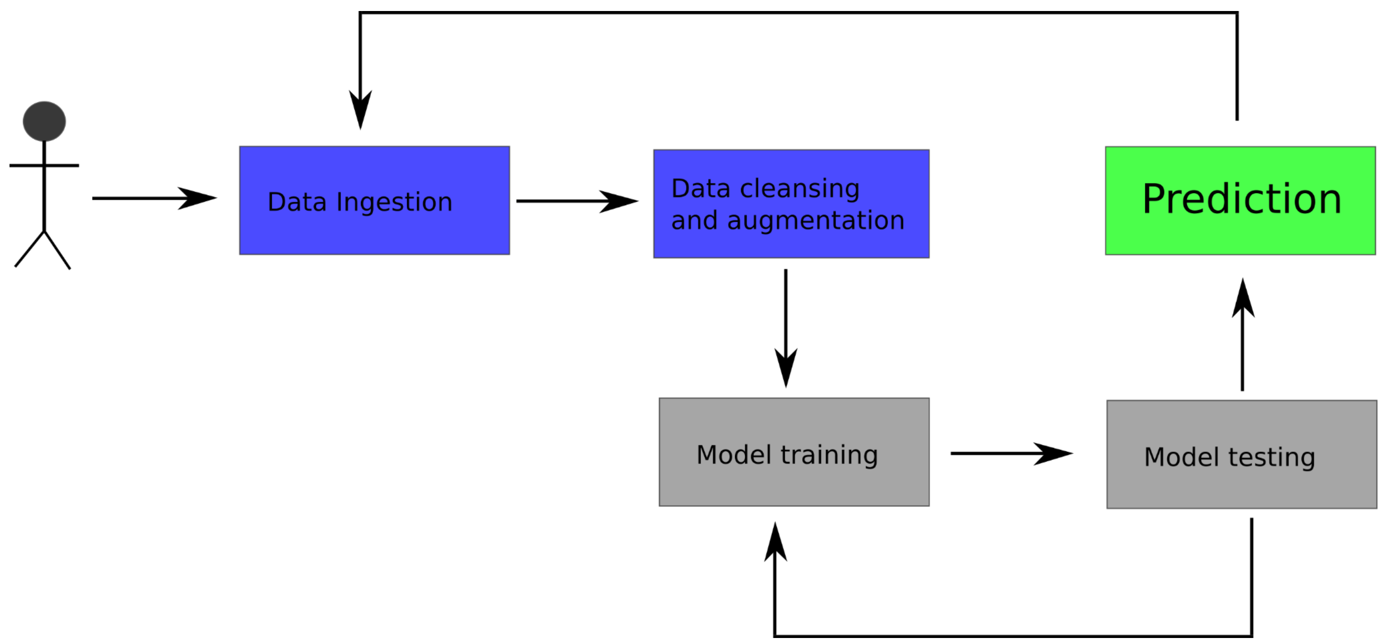


Figure 2. Our training UML Pipeline - Detailed

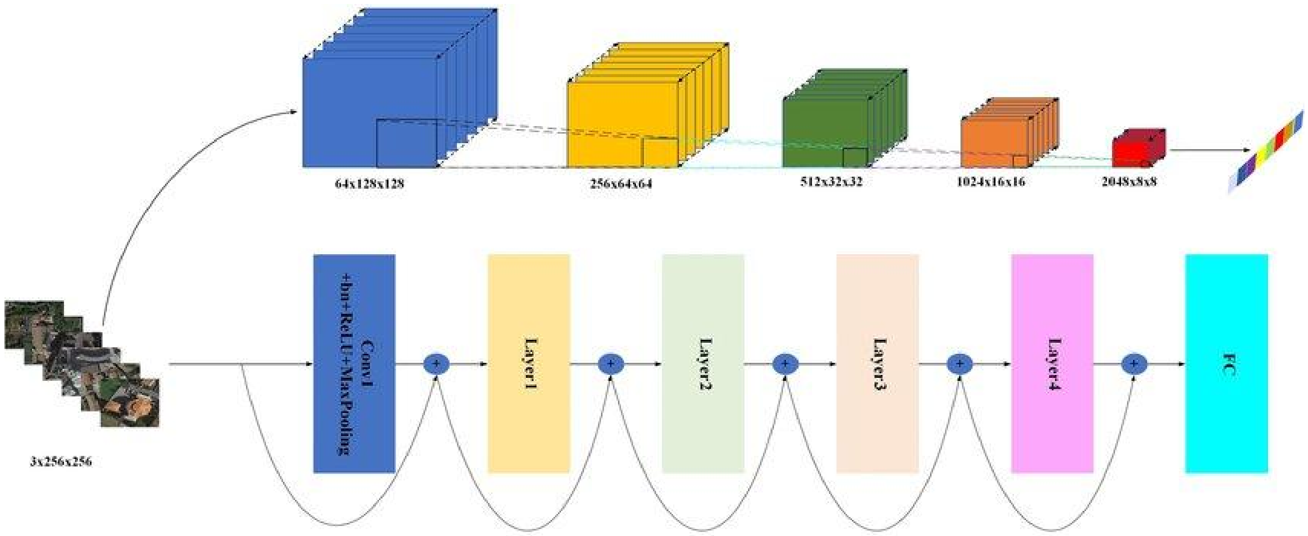


Figure 3. Architecture of Resnext101 for Reference [5]

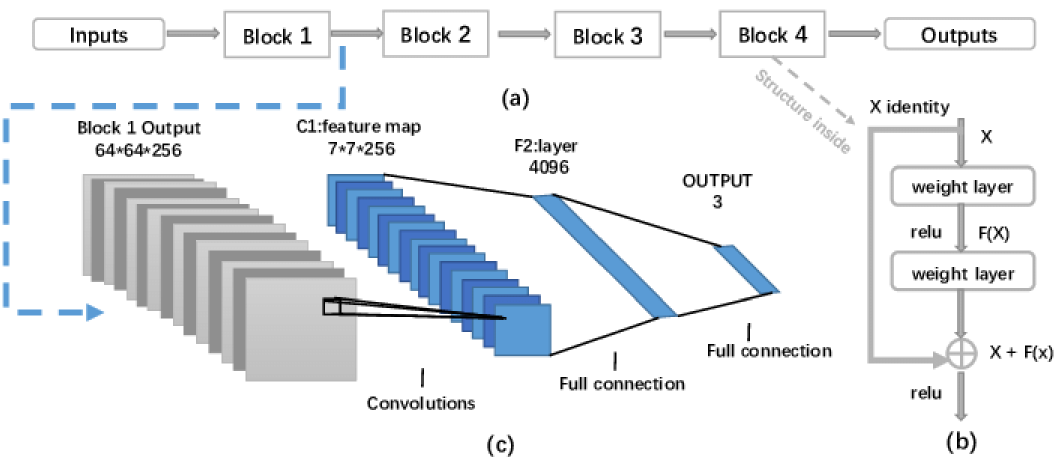


Figure 4. Architecture of Resnext101 for Reference [6]

Figure 5. Resnext101 Model Architecture before transfer learning

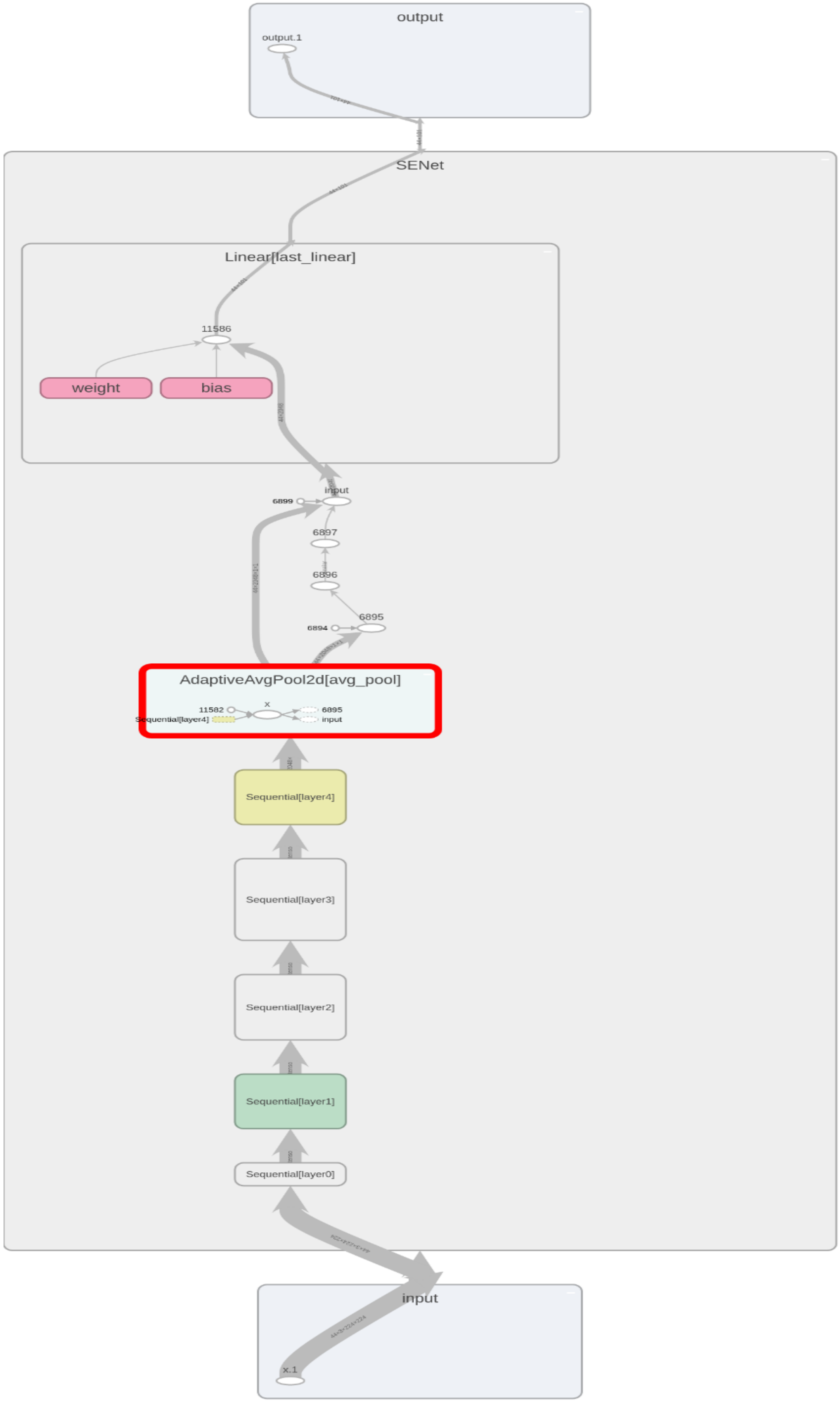

output
output.1
SENet
Linear[last_linear]
11586
weight
bias
input
6899
6897
6896
6895
6894
AdaptiveAvgPool2d[avg_pool]
11582
x
Sequential[layer4]
6895
input
Sequential[layer4]
Sequential[layer3]
Sequential[layer2]
Sequential[layer1]
Sequential[layer0]
input
x.1

Figure 6. Resnext Model Architecture after transfer learning

3.3 Architectural Design of the Proposed System

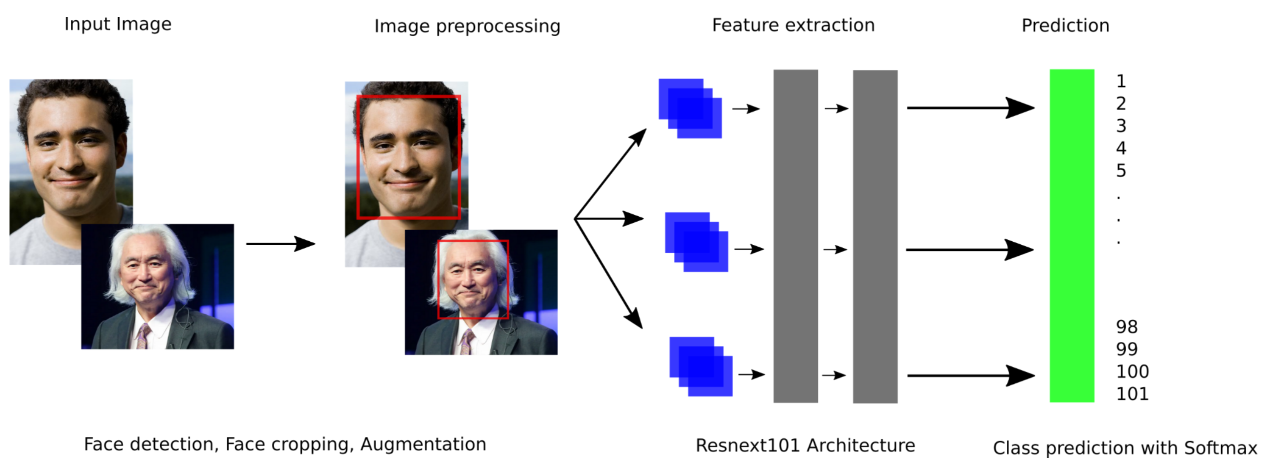


Figure 7. Over of architecture for age estimation

3.3.1 Components Design

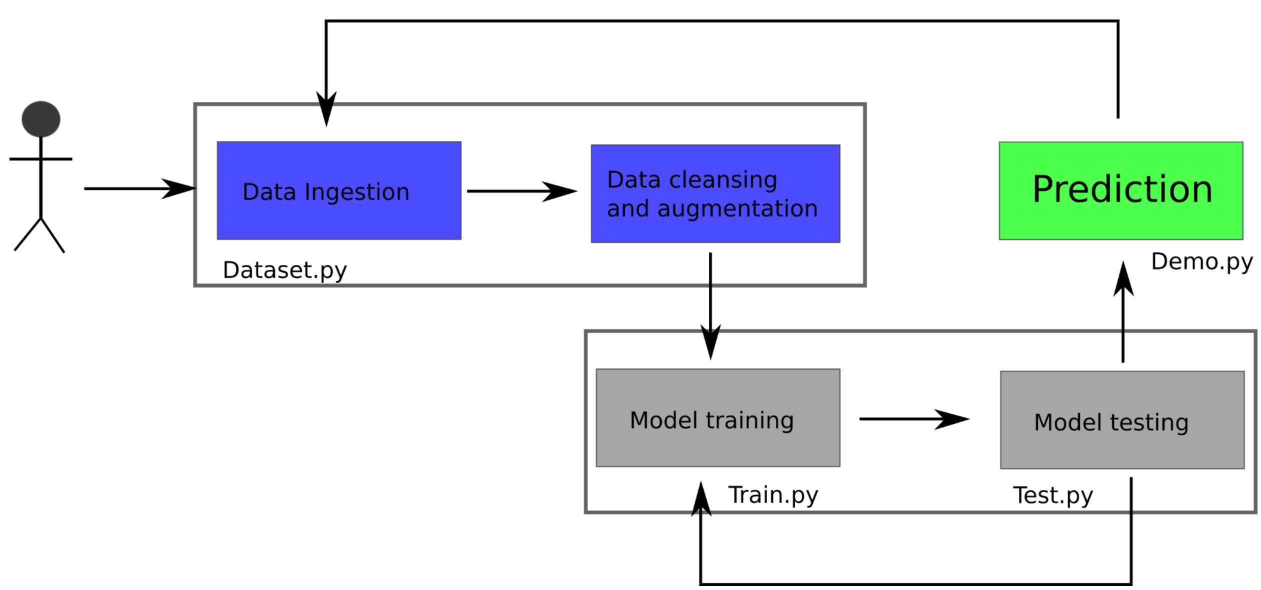


Figure 8. Components Design

CHAPTER FOUR
IMPLEMENTATION AND TESTING

4.0 Development Tools and Platforms Consideration

Using a framework to speed up development and avoid having to build our model and training from scratch was necessary during the project development of our machine learning model. We had to choose a framework and a language that is easy to use and friendly for small projects. Tensorflow and PyTorch are the go-to options for machine learning and deep learning projects; PyTorch's particular strength is in rapid prototyping and smaller projects. Its ease of use and flexibility also makes it a favorite for academic and research communities.

The machine learning and deep learning framework we chose is PyTorch. PyTorch is especially popular with Python developers because it's written in Python and uses that language's imperative, define-by-run eager execution mode in which operations are executed as they are called from Python.

IntelliJ PyCharm IDE was the IDE we decided to use next for project coding and development. For code assistance, PyCharm provides smart code completion, code inspections, on-the-fly error highlighting, and quick fixes, along with automated code refactorings and rich navigation capabilities. [9] For web development frameworks, PyCharm offers great framework-specific support for modern web development frameworks such as Django, Flask, Google App Engine, Pyramid, and Web2Py. [10] For scientific tooling, PyCharm integrates with IPython Notebook, has an interactive Python console, and supports Anaconda as well as multiple scientific packages including Matplotlib and NumPy. [11]

Training of the model and testing was done on the cloud using Google Colab, Colab provided us with free GPUs for training our machine learning model on the cloud. Collaboratory, or “Colab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser and is especially well suited to machine learning, data analysis, and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing access free of charge to computing resources including GPUs. [12]

4.1 Dataset

In this project, we use one dataset for model training, since we utilize transfer learning, the pre-trained model does not require that we train it from scratch all over, relearning model weights. In the preprocessing of a dataset, we first resize images to 224 x 224 and transform the image by using a series of augmentation techniques. An Image augmentation class written to transform the data first applies additive gaussian noise and gaussian blur to the image batch, Moving forward in the pipeline, A series of transformations are applied, rotation, scaling, translation, hue saturation, gamma contrast, and flipping is applied to images. Since the model requires images to be tensors, the images are converted into tensor arrays and fed into the model for training.

The APPA-REAL database contains 7,591 images with associated real and apparent age labels. The images are split into 4113 train, 1500 valid, and 1978 test images, provided in the folders train/, valid/, and test/. For each image X.jpg, we also provide a corresponding X.jpg_face.jpg which contains the cropped and rotated face with a 40% margin obtained from the Mathias et. al. face detector at multiple rotations. (http://markusmathias.bitbucket.org/2014_eccv_face_detection/) Furthermore, an X.jpg.mat file is provided with meta-information about the detected face. [7]

The real age and apparent age ratings are provided in the files gt_train.csv, gt_test.csv, and gt_valid.csv, with a separate row for each rating. The table below shows per-image summaries in gt_avg_train.csv, gt_avg_valid.csv, and gt_avg_test.csv, showing the number of ratings, average apparent age, standard deviation of apparent age, and the real age for each image.

TABLE I

AGE-BASED DATABASES AND THEIR CHARACTERISTICS.

Database	#Faces	#Subj.	Range	Age type	Controlled Environment
FG-NET [20], [19]	1,002	82	0 - 69	Real Age	No
GROUPS [12]	28,231	28,231	0 - 66+	Age group	No
PAL [26]	580	580	19 - 93	Age group	No
FRGC [30]	44,278	568	18 - 70	Real Age	Partially
MORPH2 [32]	55,134	13,618	16 - 77	Real Age	Yes
YGA [11]	8,000	1,600	0 - 93	Real Age	No
FERET[29]	14,126	1,199	-	Real Age	Partially
Iranian face [3]	3,600	616	2 - 85	Real Age	No
PIE [35]	41,638	68	-	Real Age	Yes
WIT-BD [39]	26,222	5,500	3 - 85	Age group	No
Caucasian Face Database [4]	147	-	20 - 62	Real Age	Yes
LHI [1]	8,000	8,000	9 - 89	Real Age	Yes
HOIP [37]	306,600	300	15 - 64	Age Group	Yes
Ni's Web-Collected Database [27]	219,892	-	1 - 80	Real Age	No
OUI-Adience [7]	26,580	2,284	0 - 60+	Age Group	No
IMDBWIKI [34]	523,051	20,284+	0 - 100	Real Age	No
APPA-REAL (ours)	**7,591**	**7,000+**	**0 - 95**	**Real and Apparent Age**	**No**

Figure 9. A comparison of Age datasets characteristics. [7]

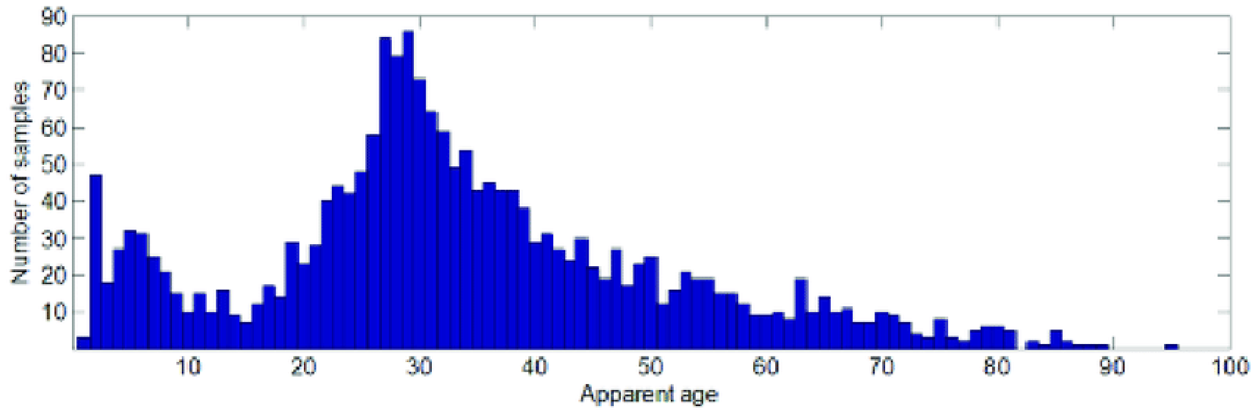


Figure 10. Graph of Images to Ages[8]

4.2 Model

In building our transfer learning model, we used a Python library called pretrainedmodels that contains pre-trained models, of which we chose se_resnext101_32x4d. Se_resnext101_32x4d is based on a regular ResNet model, substituting 3x3 convolutions inside the bottleneck block for 3x3 grouped convolutions. ResNet, short for Residual Networks, is a classic neural network used as a backbone for many computer vision tasks. This model was the winner of the ImageNet Challenge in 2015. The fundamental breakthrough with ResNet was that it allowed us to train extremely deep neural networks with 150+ layers successfully. Prior to ResNet, training very deep neural networks was difficult due to the problem of vanishing gradients.[14]

The ResNext architecture is an extension of the deep residual network which replaces the standard residual block with one that leverages a "split-transform-merge" strategy (ie. branched paths within a cell) used in the Inception models. Simply, rather than performing convolutions over the full input feature map, the block's input is projected into a series of lower (channel) dimensional representations to which we separately apply a few convolutional filters before merging the results.[13]

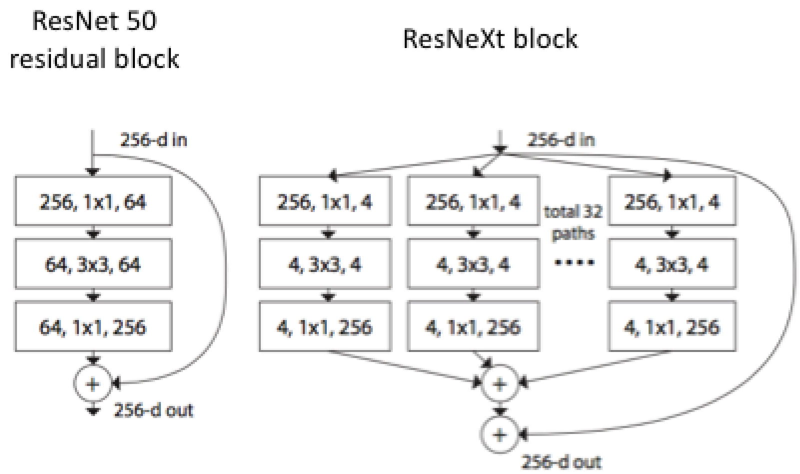


Figure 11. Model Architecture

4.2.1 Transfer Learning

Building the model from scratch would take time and involve using resources that may be inaccessible to us. So we chose to build our model using transfer learning. The main benefits of transfer learning include savings in resources and improved efficiency when training new models. It can also help with training models when only unlabeled datasets are available, as the bulk of the training of the model will be pre-trained.

A model developed for a task is reused as the starting point for a model on a second task. In our case, we use the se_resnext101 model which is developed for image classification. Image classification is a process of categorizing images into classes that are most relevant to the image provided. The ResNext paper refers to the number of branches or groups as the cardinality of the ResNeXt cell and performs a series of experiments to understand relative performance gains between increasing the cardinality, depth, and width of the network. The experiments show that increasing cardinality is more effective at benefiting model performance than increasing the width or depth of the network. The experiments also suggest that "residual connections are helpful for optimization, whereas aggregated transformations are (helpful for) stronger representations." [15]

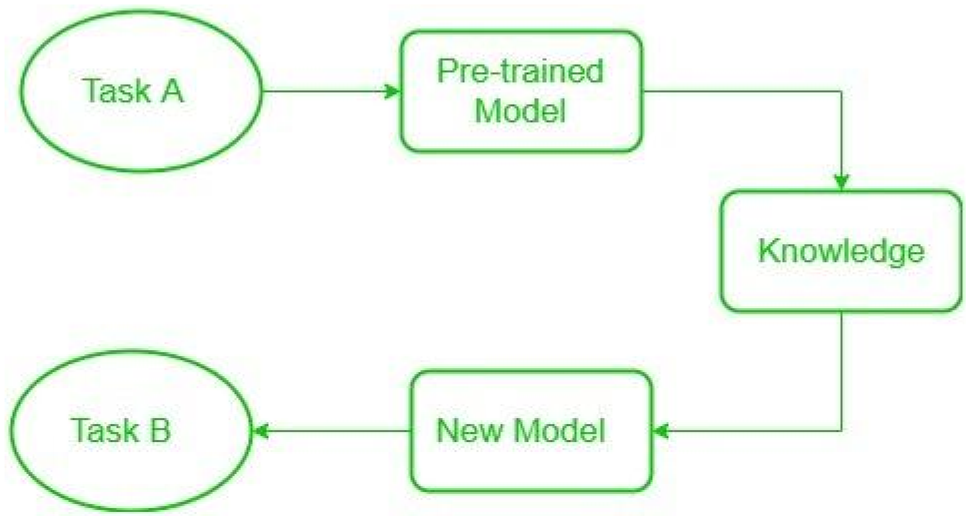


Figure 12. Transfer learning illustration. [16]

Our transfer learning with a pre-trained model development approach:

- Select source model: A pre-trained source model is chosen from available models. Many research institutions release models on large and challenging datasets that may be included in the pool of candidate models from which to choose.

- Reuse model: The model pre-trained model can then be used as the starting point for a model on the second task of interest. This may involve using all or parts of the model

- Tune model: the model may need to be adapted or refined on the input-output pair data available for the task of interest.

4.2.2 Pre-trained Model Development

In our technique, we modified the last layer of the se_resnext101 to have a fully connected layer of 101 outputs, to match the output of the last bottleneck block of 2048 as output. The input layer of our fully connected layer takes 2048 into its input channel. This is due to the fact that we have 101 classes for our classification. The original model is modified by replacing the last layer by using the last_linear variable from the pre-trained model's library. The library makes it convenient to go into the models and easily access different blocks or layers just by referencing the name of the layer or block. You can then replace the stored layer or block with a custom block or layer that you have created.

Model tuning, also called hyperparameter optimization, is later done during the training of the model to improve the model's accuracy and generate acceptable outcomes.

4.3 Model Training

The training pipeline begins after the images are fed out of the dataset ingestion and augmentation phase. During training, the images are fed in batches to the model. Our model configuration for training uses the Adam optimizer with a learning rate of 0.001. The images are fed into the model using a batch size of 42 images. and a training epoch of 80 rounds. The se_resnext101 model's first convolution layer takes an input image size of 224 x 224. The images are resized during the ingestion and augmentation pipeline of development.

An AdaptiveAvgPool2d layer is introduced with an input size of 1 to apply a 2D adaptive average pooling over an input signal composed of several input planes. To reduce the dimension of the feature map, thus reducing the number of parameters to learn and the amount of computation performed in the network. It is a downsampling operation.

To also ensure the model training time is reduced. The blocks of the model are frozen to prevent relearning of model weights.

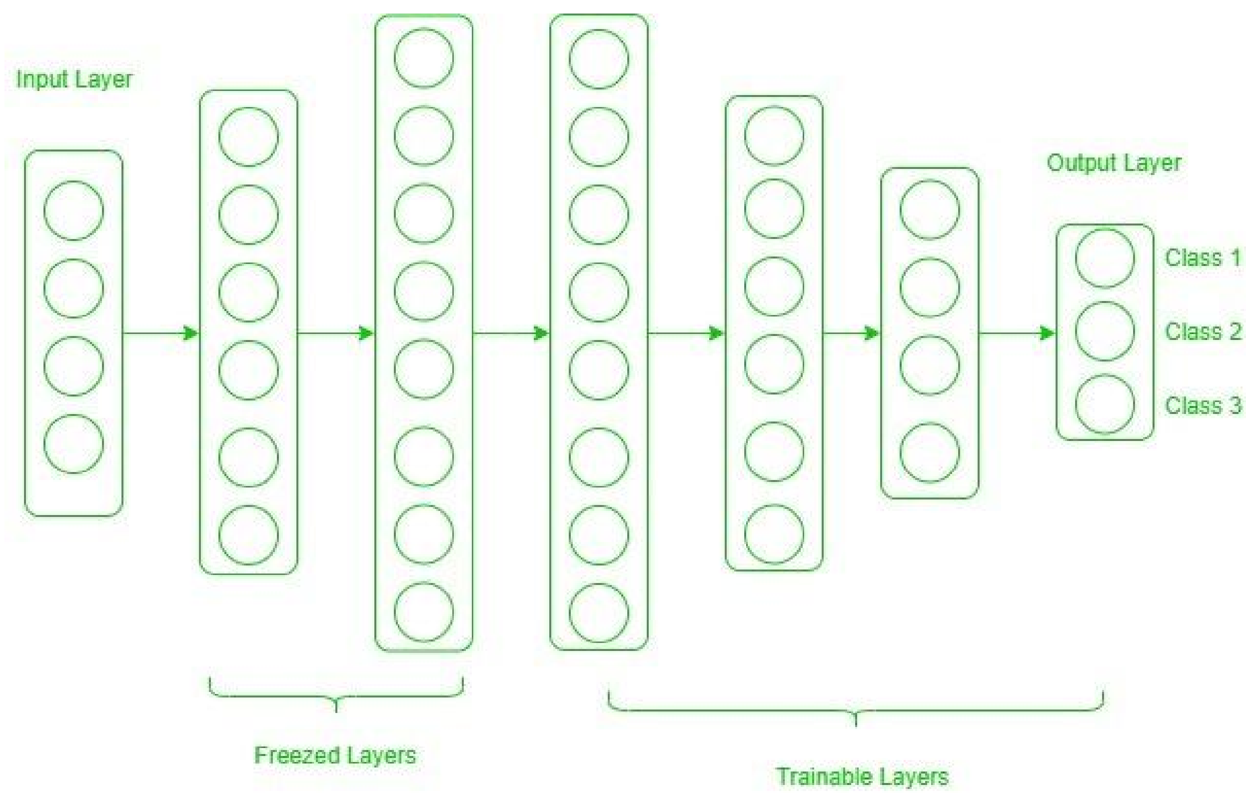


Figure 13. Transfer learning illustration with frozen and trainable layers[17]

4.4 Model Testing

The model dataset is split into training, validation, and testing datasets. During training, the model is evaluated against the validation dataset and the training dataset. After each epoch, the model is run against a method for calculating the accuracy, after which the model is saved after the current training epoch if the accuracy is better than the previous. This is called saving the checkpoint of the model. Doing this ensured that, when we run out of computing time using the free Google Colab session, we can continue the training of the model. Also, by saving a checkpoint of the model after each epoch, we can quit and continue training the model whenever it's appropriate.

For testing our model, we use the MAE method for quantifying the magnitude of errors of the model. MAE is short for Mean Absolute Error and refers to the magnitude of difference between the prediction of observation and the true value of that observation. MAE can be referred to as L1 loss function. We choose to use MAE because it also serves as an easy-to-understand measurement of errors for regression problems. In our tests, we obtained an MAE of 7.579 on the validation dataset and 8.914 on the test dataset.

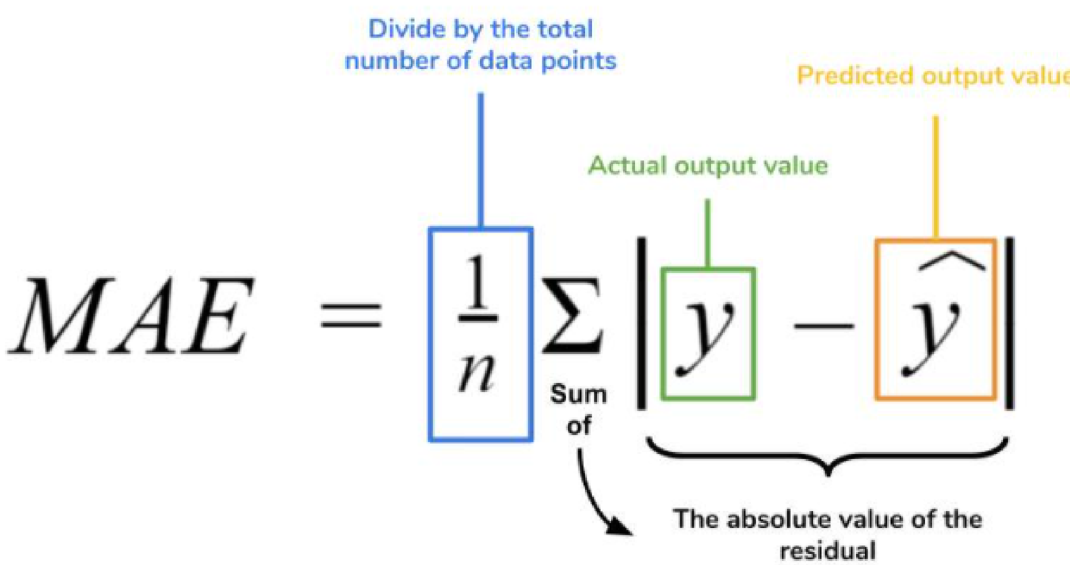
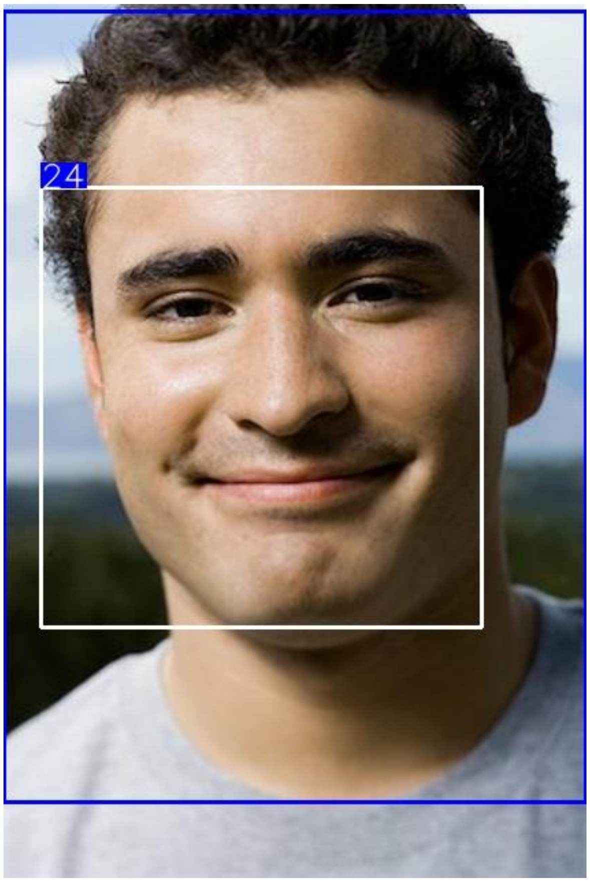
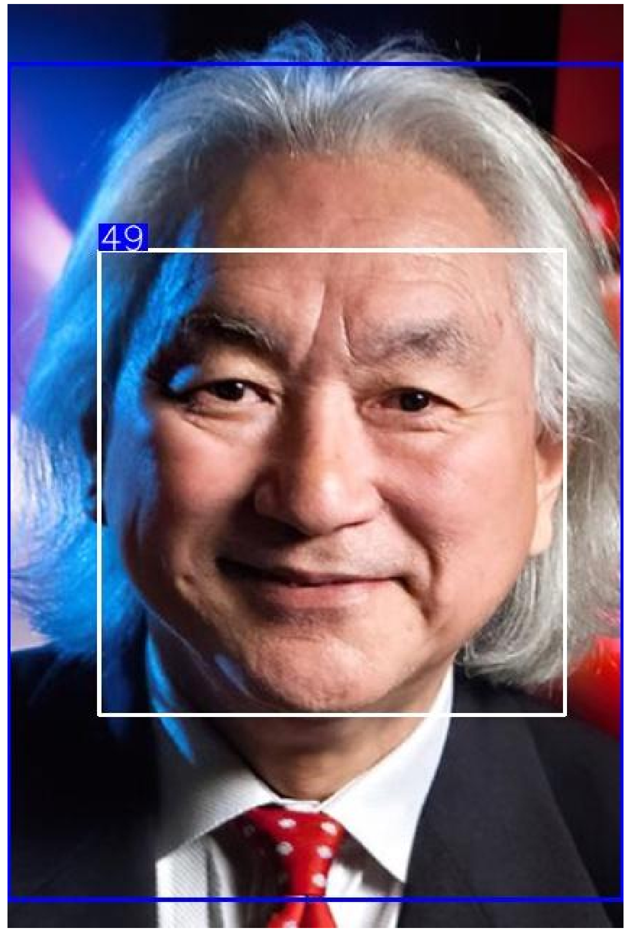


Figure 14. MAE Formula[17]





4.5 Model Performance

During training and testing, an performance assessment test is conducted using Tensorflow’s Tensorboard. Tensorboard helps provides visualization and tooling needed for machine learning experimentation. It helps track and visualize metrics such as loss and accuracy, visualize the model graph, and view histograms of weight, biases, or other tensors as they change over time.

The below images show our model’s performance and MAE results after training and testing.

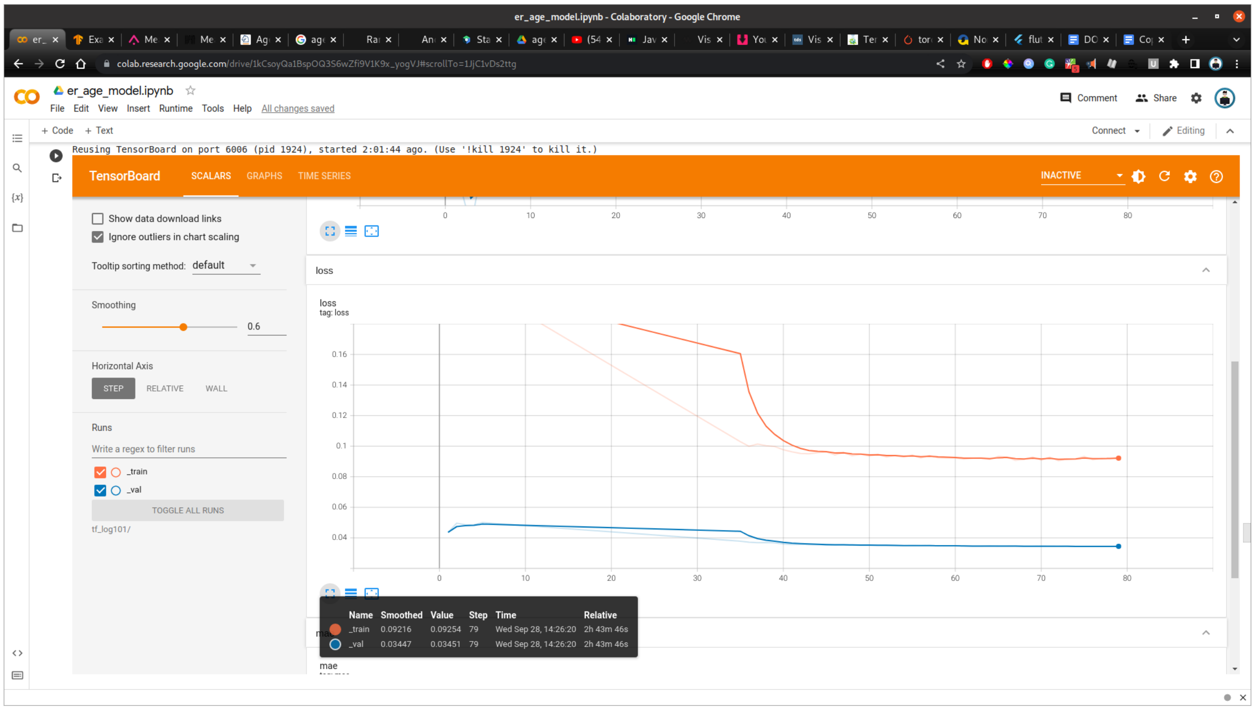


Figure 15. Loss Graph

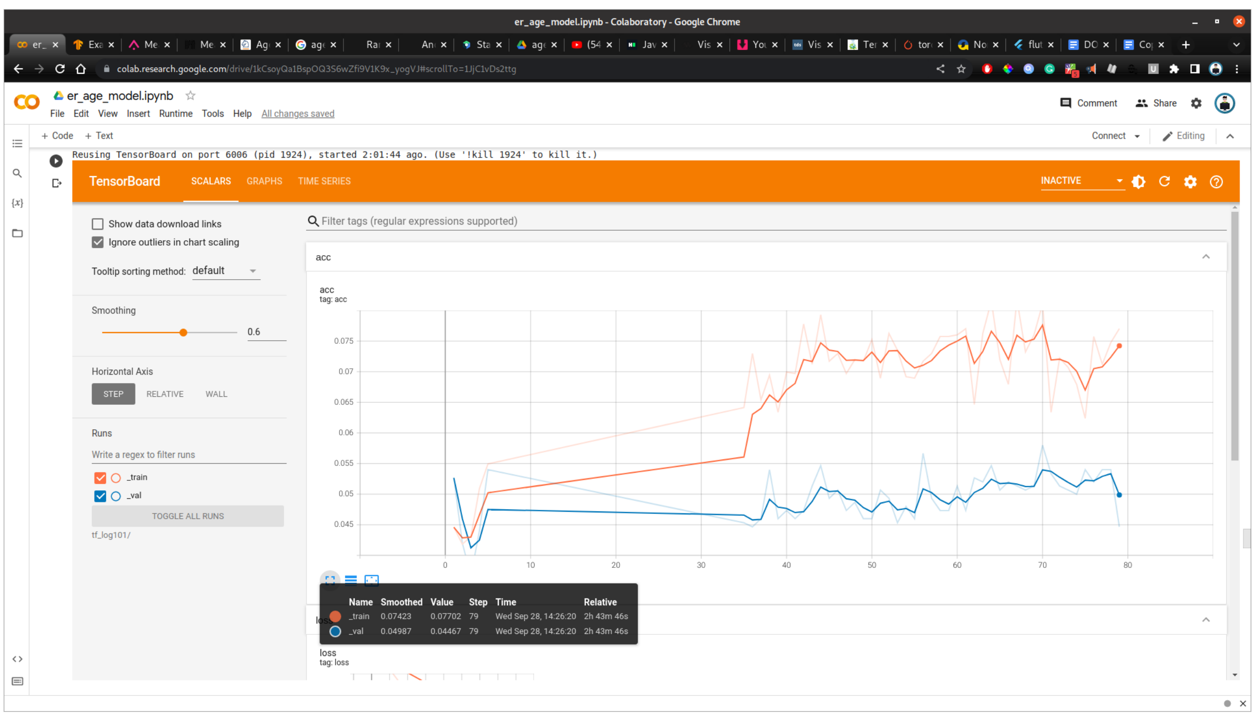


Figure 16: Accuracy Graph

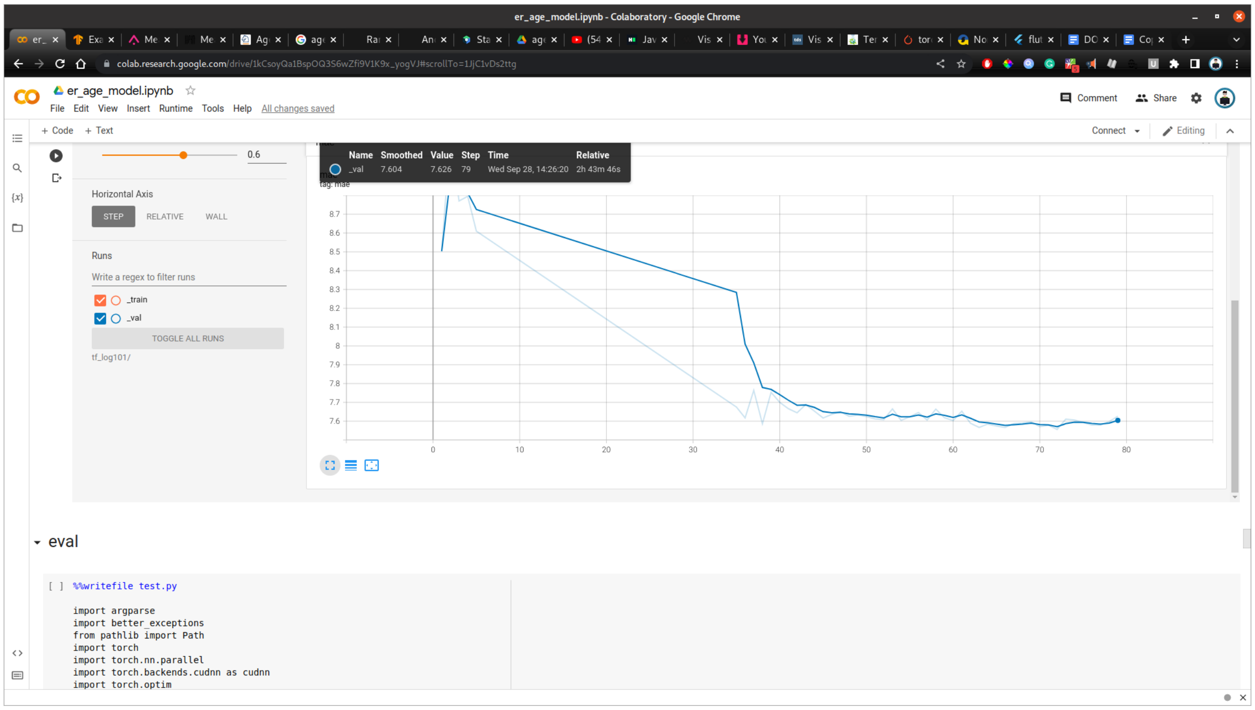


Figure 17: MAE Graph

Results on validation and test dataset

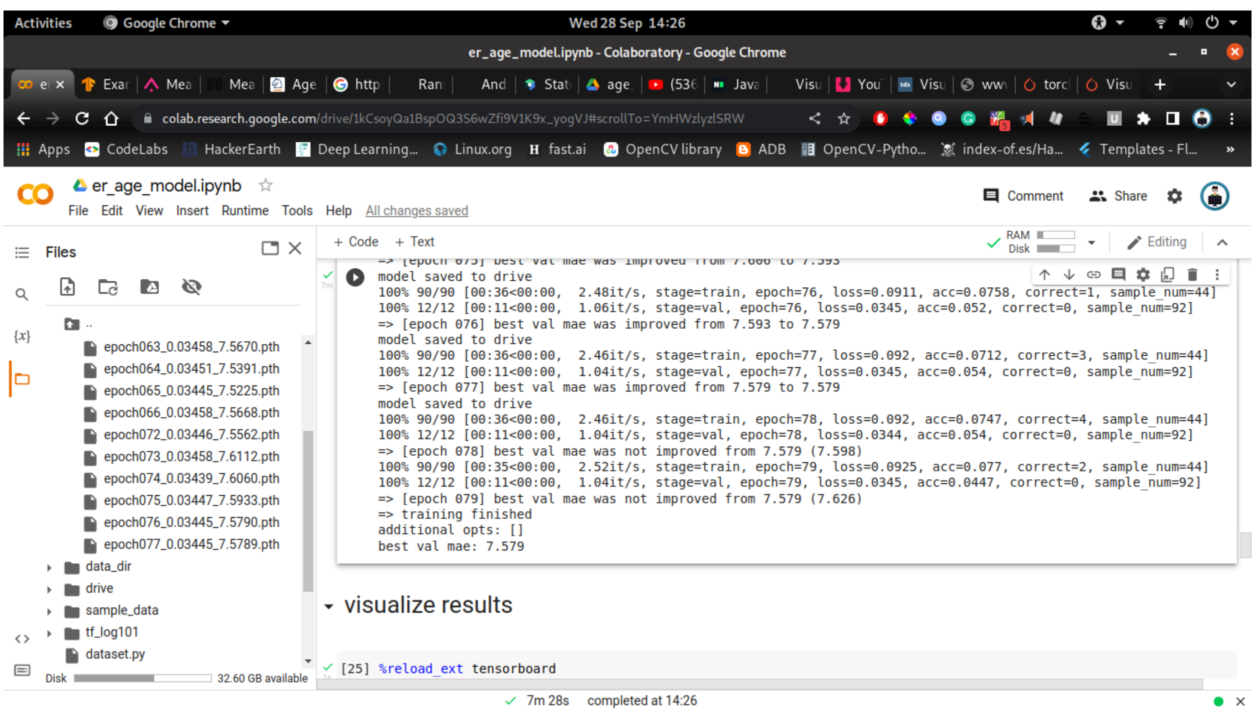


Figure 18: MAE on validation dataset:

Results: 7.579

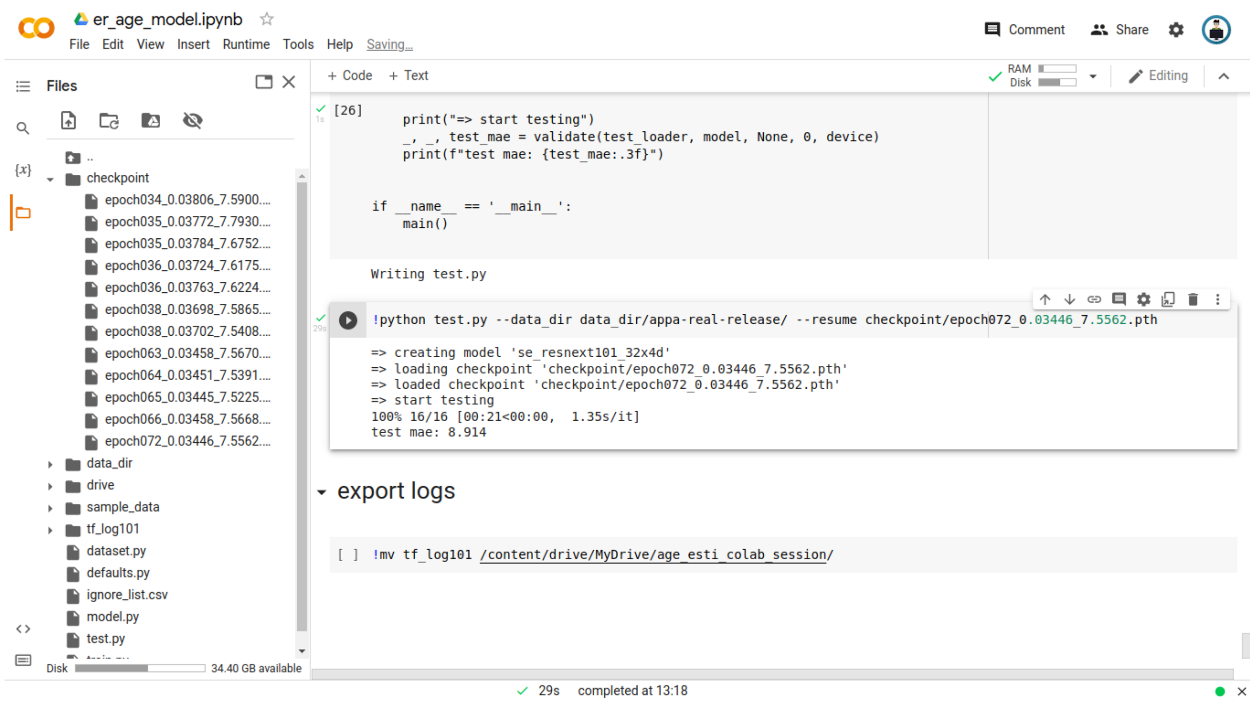


Figure 19: MAE on testing dataset

Results: 8.914

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

5.0 Discussions

Age estimation is essential when you can not prove the chronological age with valid identification documents. Suppose doubts about the given age of an individual cannot be otherwise eliminated. In that case, authorities and courts can request a medical age assessment issued by an expert, with the growing rise of computerized systems. Need for an automated age estimation model devoid of bias or human intervention is necessary. The purpose of age assessment is to provide the most likely age of an individual and report it to the authority that requested it.

With the focus on different age estimation techniques, we have explored during our project development different age estimation techniques. An example of such a technique is using the skeletons which are good examples of age markers for age estimation because teeth and bones mature at fairly a predictable rate. Lab reports required for this method of age estimation can take weeks to months hence, during the development of our project we explored several methods and settled for a more automated system or way to quickly predict or estimate the age of individuals.

5.1 Achievements

The goal of the system was to develop a machine learning model to help estimate the age of individuals. This was achieved through dedication and support from our supervisor, friends, and people around the world from the internet. Also, a great deal of knowledge learned from class activities was successfully applied in the development of the system.

5.2 Recommendations

There is more room for improvement in the accuracy and prediction of our model as the development of machine learning models can be improved with much more refined data and computer power. With most machine learning algorithms associated with the “black box” effect, this often does not allow us to completely understand the relationships among features and labels and how they are estimated. We recommend different datasets should be used in the training of the model, fine-tuning the model during training, and using the ensemble method where we chained different models to improve the accuracy of the model.

5.3 Conclusions

In developing a machine learning model to estimate the age of individuals from an image or using a live camera feed. We decided to cut down the training time and to have a model with a good performance by repurposing a pre-trained classification model using transfer learning. We developed our model using the se_resnext101 model as the base of our model and achieved better performance which would have taken more computation power and data to achieve without transfer learning.

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