2022-09

AGE ESTIMATION BY USING TRANSFER LEARNING IN A DEEP NEURAL NETWORK

KIBRET, MOLLA YIGZAW

BAHIR DAR UNIVERSITY

BAHIR DAR INSTITUTE OF TECHNOLOGY

SCHOOL OF GRADUATE STUDIES

FACULTY OF COMPUTING

AGE ESTIMATION BY USING TRANSFER LEARNING IN A DEEP NEURAL NETWORK

MASTER OF SCIENCE IN COMPUTER SCIENCE

BY

KIBRET MOLLA YIGZAW

BAHIR DAR, ETHIOPIA

September, 2022

AGE ESTIMATION BY USING TRANSFER LEARNING IN A DEEP NEURAL NETWORK

BY

KIBRET MOLLA YIGZAW

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Science in the Faculty of Computing.

ADVISOR: ADANE NEGA (Ph.D.)

Bahir Dar, Ethiopia

September, 2022

DECLARATION

I declare that the thesis entitled "Age estimation by using transfer learning in deep learning" is my own It is in compliance with internationally accepted practices and policies. The cited reference materials are taken from the well-known journals and publishers. I have done the thesis with regard to academic honesty and integrity of Bahir Dar University.

Name of the student: Kibret Molla Yigzaw Signature:___________

Date of submission:

Place: Bahir Dar

BAHIR DAR UNIVERSITY
BAHIR DAR INSTITUTE OF TECHNOLOGY
SCHOOL OF GRADUATE STUDIES
FACULTY OF COMPUTING

Approval of thesis for defense result

I hereby confirm that the changes required by the examiners have been carried out and incorporated in the final thesis.

Name of Student___***Kibret Molla yigzaw*** Signature__________Date_9/28/2022 GC

As members of the board of examiners, we examined this thesis entitled "***Estimation of Age by Using Transfer Learning in a Deep Neural Network***" by*Kibret Molla.* We hereby certify that the thesis is accepted forfulfilling the requirements for the award of the degree of Masters of science in ***Computer Science***

Board of Examiners

Name of Advisor	Signature	Date
Adane Nega(PhD)	__________	9/28/2022
Name of External examiner	Signature	Date
Adane Letta (PhD)		9/28/2022
Name of Internal Examiner	Signature	Date
Birhanu Hailu (PhD)	__________	9/28/2022
Name of Chairperson	Signature	Date
Seffi G. (Assis. Prof)	__________	9/28/2022
Name of Chair Holder	Signature	Date
Yirga Yayeh (PhD)	__________	9/30/2022
Name of Faculty Dean	Signature	Date
Bezahegn E.	__________	30/09/2022

Bahir Dar University Bahir Dar Institute of Technology Faculty of Computing

Faculty Stamp

ACKNOWLEDGEMENT

Firstly, I would like to thank my God for helping my success throughout my life. I would like to thank my adviser Adane Nega(PHD) for giving direction and constructive suggestions for the development of this thesis. In addition, this I would like to thanks Bahir Dar University computing faculty Instructors who advice and suggest me to accomplish the thesis.

A special thanks to my wife Meaza Gizachew and my parents in helping for the success of my academic journey and all contributions to my life.

Lastly, I would like to thank you my staff members of ICT directorate of water and Energy who share my work load and suggest me to finalize the thesis.

ABSTRACT

The advancement of machine learning helps for face image processing which is used to recognize the gender, emotion, and age with deep learning. From the studies of image recognition for age estimation there is no data set prepared for this task specially the face image of our society. As we know people intentionally or unintentionally doesn't tell their age. For this reason; this study has been performed by using manually collected data set of our society. For implementing of face image recognition, a large preprocessed data set of face image should have for training the model. In deep learning; the performance of the model depends on the amount of data set used for training the model. With limited data set the model performance becomes degraded. To overcome this problem, we have used pretrained deep learning model of VGG16 by transfer learning and fine tuning the model. We trained the fine-tuned model with manually collected data sets of face images by varying the epoch. The data set has organized in 7 classes grouped in age ranges. In training the VGG16 fine-tuned model with our data set the model gives good result for prediction of age. The model performance depends on the size of data set given to the model for training and the epoch size as observed during training the VGG16 model in this thesis. From this study the performance of the model had evaluated by using RMSE and R^2 and the of VGG16 fine-tuned model results; RMSE= 1.74514 and R^2 score=0. 10599.In addition to this the training loss and validation loss results; loss=3.527 and val_loss=3.3827.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS AND SYMBOLS

AE-Age Estimation

AI-Artificial Intelligence

CNN- Convolutional Neural Network

CS-Cumulative score

DCNN-Deep Convolutional Neural Network

FC- Fully Connected

FG-NET -Face and Gesture Recognition Research Network Aging Database

MAE- Mean absolute error

MORPH -Craniofacial Longitudinal Morphological Face Database

ReLu -Rectified Linear Unit

RMSE- Root Mean Square Error

RESNet-Residual Networks

R^2 - R-squared

VGG-Visual Geometry Group

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

1. INTRODUCTION

1.1. Background

Age is one of the basic futures of a person for classification in any activity for different areas throughout life. Anyone can estimate the specific age or age in the range of someone by simply observing the actual features of a person. From the determinant features of the most highly observable is human face, that changes the appearance of a person with related to age. Based on this, anyone can estimate the age of a person by observing the real features of human face simply without any additional Artificial Intelligence.

With regard to the advancement of technology, artificial intelligence and deep learning, facial recognition technologies have been developed. Deep learning is widely used in image, sound and text analysis. The major research areas in the field are face recognition and detection, age and gender detection (Semiha , Betul , & Galip, 2020). The studies implemented for face analysis includes a variety of specific problems as face detection, person identification, gender and ethnicity recognition. And then it needs the best neural network to estimate the age of persons at any age by using the features of face image processing. Face is a prolific information source; which helps to extract many kinds of useful information from a face image, such as identity, expression, emotion, gender, age (Sudip, Chandrima, & Lovely, 2017).The brain of human being can predict the approximate age of a person to the reverse a computer can't predict the age of a person. Based on this an automation is very interesting to design an expert system which helps for estimating the age of a person automatically by using face image. Age is an essential feature of human beings, which plays a crucial role in many real-world applications (Mengjie & Weiyang, 2021) The model helps to estimate the specific age or the age range of a person according to the visual characteristics of the face image, without any contact person simply by using the face image. The modeling of computing technology helps to solve estimation problem of   the exact age of the face by using the facial features. Aging prediction is by using face image is an application of human-computer interaction. In general deals age estimation by using face image is complicated and it needs an intensive work and it is a hot research area of computer vision, pattern recognition and artificial intelligence.

For modeling of computers to estimate the age of a person by using Convolutional neural network (CNN). Convolutional neural network (CNN), one of the most commonly used deep learning method applied to various computer vision and pattern recognition tasks (Prachi, Rashmi , & Ashwani, 2019).The performance of CNN, gives result of computer vision and pattern recognition with an ability of self-learning and dealing but it needs big data. The frameworks; implementation CNN which helps to learn the mapping from multi-scale image patches to depth on the super-pixel level. It helps for label encoding method to transfer labels to be possibility vectors, which reformulates the regression task to a classification task. The researcher points out that using label encoding method has been used for optimizing the performance of CNN. And again, while the model has been trained with large data set of preprocessed face image data set a Deep Convolutional neural network (DCNN) results better performance of estimating age. Getting large data set of face image is challenging, so that we have used the pretrained model of VGG 16 of convolutional network by using transfer learning and fine-tuned the VGG16 model for classification with the limited data set for of age estimation.

1.2. Statement of the Problem

In Ethiopia, age is one of the main determinant factors of human beings in different areas. Mostly, age will be required in school, in courts, health centers, for athletics, for recruitment, and for immigration. In our country people intentionally or un intentionally does not tell their accurate age. People decrease their age intentionally for the benefit of them, which is the common trend of our society in the areas of athletics and courts, Age is required for diagnosis health but, unintentionally the patient might not know or tell the accurate age. This issue initiates to study the estimation of age by using face image of all age groups and life standards including the face image of our people with the implementation of transfer learning in deep Convolutional neural network (DCNN).

In the areas of age estimation by using our society data set, no study has been performed while browsing the materials. But studies have done with related to age estimation/prediction by using open-source face images in other countries. From those; the study done with a title of "Age Estimation Using Specific Domain transfer Learning" (Arwa & Lamiaa, 2020) applied fine-tuned model of VGG16 by using two approaches. These are; "Fine-tuning the base convolutional layers with including top" and "Fine-tuning the base convolutional layers without including top". The experimental result shows that approach two without including top preforms good result as compared to the first approach. The result of the second approach by open-source data sets of; FG_NET Dataset (MAE= 3.545), UT Face data set (MAE =4.993) and Adience dataset (accuracy= 61.4). The proposed study has been done by frozen the layers and fine-tuned the model and training the model by using manually collected data sets.

The existing data set is not the representative of all races of people in our world. The large amount of preprocessed data set of face image are western people and Asian people. Even though the experiment result of Convolutional neuron network (CNN) gives a better performance, the researches had not still prepared real time face image data set for estimation of age.Thus.it requires an effort of researchers to solve this issue to enhance artificial intelligence of predicting the age of people by considering all races in our world.

As the performance of deep Convolutional neural network depends on the size of data set, we applied the transfer learning model of VGG to evaluate the model with small data set collected manually. Previously trained model for face recognition performs age range classification on the Adience data set (Arafat , Zakariya, & Buket, 2019).This indicates that no data set has been still preprocessed for age estimation. Thus, getting face image data set has been the challenging task for researchers. To overcome this issue the proposed research, applied the transfer learning model of VGG 16. It helps to enhance the performance of estimating age with small data set of manually collected images by retraining the VGG16 fine-tuned model.

1.3. Research Questions

The study attempted to apply face image processing of transfer learning with Deep Learning approaches for estimation of human age by regression. This study undertook to answer the following research questions.

- How to retrain the transfer learning model of deep learning with manually collected data set to predict the age of people?
- What is the impact of the transfer learning in deep learning on the performance of age estimation with small data set?
- How to evaluate the performance of transfer learning model with regard to estimating age?

1.4. Objective of the Study

1.4.1. General Objective

The main objective of the study thus, appalling fine-tuned techniques of pretrained model that helps to predicts the age of people by using manually collected data set of face image processing.

1.4.2. Specific Objectives of The Research

The specific objectives of the research are basically formulated from the general objective and hence helps to achieve the overall objective of the research. For the proposed study the specific objectives are:

- To customize fine-tuned model and retrain the model for prediction of age by using real life data set regardless of race and life standards of all age groups
- Applying transfer learning model by fine-tuning the model and retraining the model with manually collected data set.
- Performing an experiment by using the transfer learning model by using manually collected data set and test the performance of the fine-tuned model in prediction of age.

1.5. Methodology

To achieve the general and specific objectives of the study we have used data collection system design and experimentation.

1.5.1. Data Collection

The face image data set used for this study was collected manually from Bahir Dar and around Bahir Dar by using smart phone from volunteer people. In addition to this; some images of children and elders were taken from social medias for the purpose of increasing data set. The data set has been organized in 7 classes with the age ranges. The classes grouped in age ranges; Class 1(1-10), Class 2(11-20), Class 3(21-30), Class 4(31-40), Class 5(41-50), Class 6(51-60) and Class 7(61+). The Images of children and elders taken from social medias were grouped into the classes of children (in class 1) and elders (in class 7), because it is simple to group it in classes of age. These data are classified into training and testing for the VGG 16 fine-tuned model.

1.5.2. System Design and Experimentation

The model used for study has been transfer learning model of VGG 16 pretrained model. In case of small in size data set so that we applying transfer learning model one alternative. In transfer learning, the previously learned base models modified partially by adding new layers or training on new samples (Issam & Dany, 2020).We have been used fine-tuning of pertained VGG-16 CNN model applied on new samples for the task of age estimation. The top dense layers of fine-tuned model of VGG 16 became prepared for estimation of age by using regression. For experimentation, we used python programming to implement the designed architecture. Python is selected because it has free open-source libraries packages. For evaluation of the model performance, we have used training loss and validation loss graph. To test the model performance, we have used RMSE and R^2-score

1.6. Scope of the Study

The image data has been gathered by taking digital image of face image of the societies of Bahir Dar and around Bahir Dar town starting from infancy up to elders by using smart phone.

1.7. Significance of the Study

The significance or contribution of the proposed study;

- Estimation of age by using the artificial inelegance helps for athletics federation to estimate the age of athletics while they are intentionally decreasing their age for the benefit of participating illegally.
- In courts, when somebody had made crime and to became free from his or her crime cases, he /she might be decreases intentionally. The implementation of age estimation model helps to estimate the age in courts simply.
- For health diagnosis, sometimes the patient might be in emergency case or chronic case and he/she cannot tell his or her age, or sometimes the patient does not now his/her age; during this time the implementation of age estimation model by using face image helps to estimate the age and helps the treatment without any reservation.

1.8. Organization of the study

The study has been organized in the following ways: In Chapter 2; it is about the literature review on Age estimation models and techniques, Chapter 3; mythology and discussed about the proposed model of VGG16 fine-tuned system architecture. The experiment results and discussions are presented in Chapter 4 of the study and finally in Chapter 5 discusses conclusions and recommendations of the study.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Introduction

In this section, we discussed about Computer Vision, Convolutional Neural Network literature review to understand image processing especially about age estimation based on face image processing, the techniques used in age estimation, such as face image preprocessing, feature extraction, and classification techniques.

2.2. Computer Vision

Computer vision in one of an application of AI that trains computers to interpret and understand the visual world (Ishita , Urvi , Sachin , & Vijay , 2019). By using digital images and videos computers can accurately identify and classify objects and then react to what they observed. A typical computer vision system consists on image acquisition module, region of interest recognition or segmentation, image enhancement, feature extraction and analysis and model learning (Raphael, 2017) .Computer Vision helps computers to identify digital images and videos as a human would. Computer Vision follows the steps of acquiring, processing, analyzing, and recognizing digital images to extract high-dimensional data from the real world in order to generate symbolic or numerical information

2.3. Overview Of Deep Learning and Transfer Learning

2.3.1. Deep Learning

Deep learning is the popular area of machine learning which efforts to learn high-level abstractions in data by utilizing hierarchical architectures (Boukaye , Bernard , & Fana , 2018). Hidden layers composed of a set of neurons responsible for training the unique set of features based on the output layer of the previous layer. As the number of hidden layers increases, the complexity and abstraction of data also increase.

As we see from the figure any Deep neural network will consist of three types of layers:

- The Input Layer: it receives all the inputs and the last layer is the output layer which provides the desired output

- The Hidden Layer: all the layers in between these layers are called hidden layers;
- The Output Layer: which gives the result

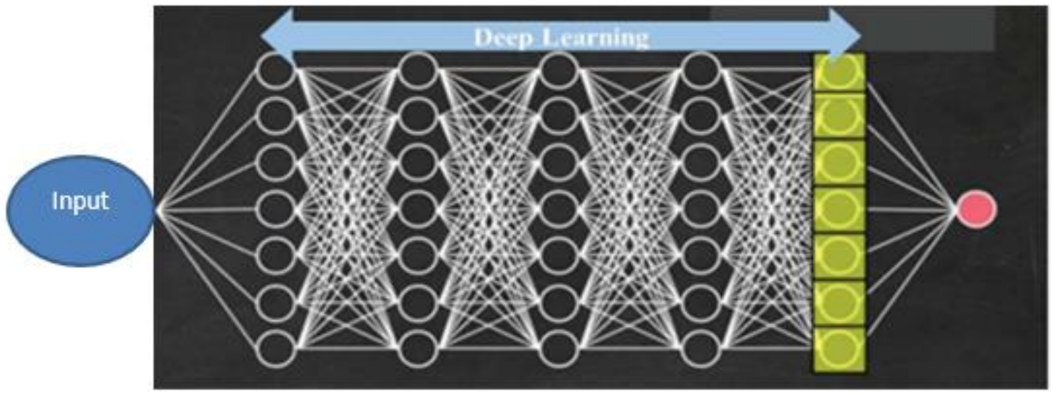


Figure 1:Deep Learning Neural Network *(Boukaye , Bernard , & Fana , 2018)*

A Convolutionary Neural Network (ConvNet / CNN) is a Deep Learning algorithm, which allows an input image to take on different aspects / objects and can be distinguished from one image (learnable weights and biases). The ConvNet architecture is similar to that of neurons in the human brain and was influenced by the Visual Cortex organization.

Machine learned feature extraction methods are based on automatic feature extraction The convolutional neural network (CNN) is the most famous feature extraction technique due to its capability of obtaining generic features. CNN (convolution neural network) is one of the most used techniques for age and gender detection (Avuthu, Sudhakar , Arumugam , Srinivasan , & Kolla , 2020). The CNN was pretrained in an unsupervised way to learn low-level features. A deep Convolutional Neural Network is widely used for the purposes of image recognition and processing (Ishita , Urvi , Sachin , & Vijay , 2019). Convolutional neural network has input and output layers, and hidden layers, many of which are convolutional multilayer perceptron. Convolutional Neural Network (CNN) is one of the most prevalent algorithms that has gained a high reputation feature extraction.

2.3.2. Transfer Learning in Deep Learning

Deep CNNs based on transfer learning (TL) are the key component of age estimation method from human facial images (M. A. H., Md. Ijaj , Shuvendu, & N. , 2020). ImageNet is a research project to develop a large database of images with annotations of images and their labels (Srikanth, 2019). Pretrained models like InceptionV1, Inception V2, VGG-16 and VGG-19 are already trained on ImageNet which comprises of disparate categories of images. In deep learning CNN mostly used in image processing. Transfer learning is mostly applied in deep and machine learning for the implement different strategies. In deep learning, transfer learning technique can be defined as the process of reusing a model that has already been trained for a specific task to perform a similar or related task (Arwa & Lamiaa, 2020).In transfer learning a pre-trained model which is created by someone else to solve a similar problem. VGG is one of the family of CNNs most widely used for face analysis tasks. VGG-16(VGG-Face) is pre-trained for face recognition by using the VGGFace2 dataset (Antonio , Alessia , Mario , & Vincenzo , 2021); which is fine-tuned on specific datasets, achieved state-of-the-art performance in gender, ethnicity and emotion recognition.VGG-16-layer components shown in figure 2.

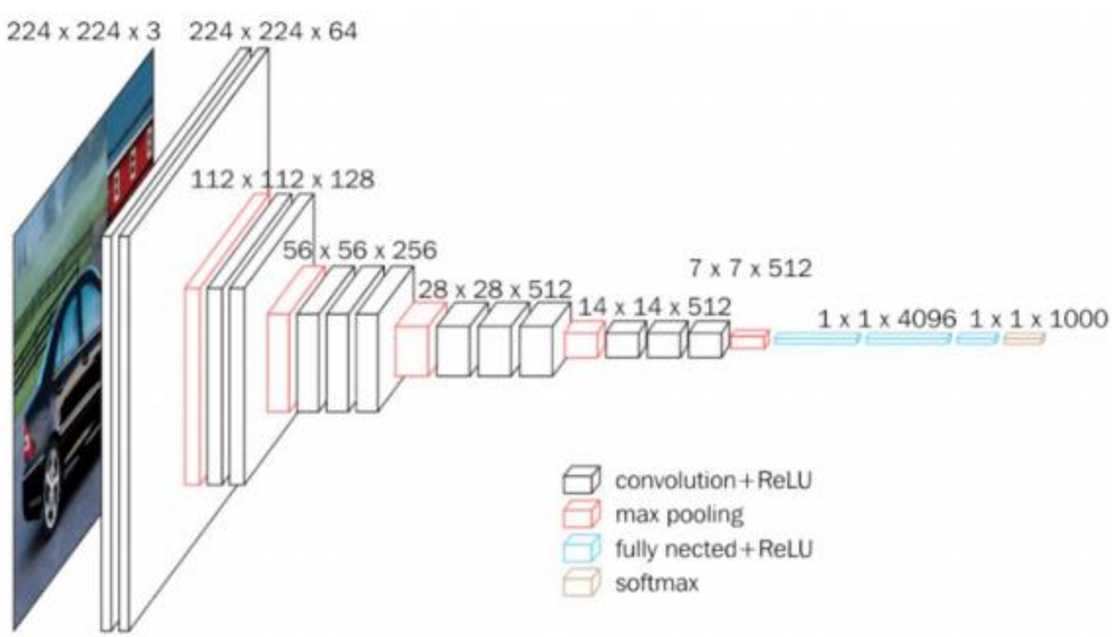


Figure 2:VGG-16 Model structure *(Prachi, Rashmi , & Ashwani, 2019)*

2.3.2.1. When to use transfer learning

Transfer learning of deep neural network mostly used in the case of:

- **Lack of data**: specific target task can be solved using a pre-trained model for a similar source task with limited data set
- **Speed:** decreases training time and allows for building various solutions.

2.3.2.2. Transfer Learning Approaches

Transfer learning approaches applied in deep CNN in the case of limited data set are

2.3.2.2.1. Direct Use of Pre-Trained Models

The simplest strategy is to solve a target task by directly applying a model from a source task. In this case the VGG16 transfer learning model trained for age prediction uses for age estimation in the case of small data set of face images collected manually. The VGG-16 model had trained with the Preprocessed public data set of Adience dataset (Jun, et al., 2016) ,because it is well known public data sets used for face image processing.

2.3.2.2.2. Leveraging Feature Extraction from Pre-Trained Models

In this approach discarding the last fully-connected output layer and then making the pre-trained neural network for feature extractor. In this transfer learning it is used to apply new dataset to solve different problem.

2.3.2.2.3. Fine-Tuning Last Layers of Pre-Trained Models

It is applied by training the output classifier and then fine-tune weights the last block layers of the pre-trained model. The earlier layers of the network (CNN) are made frozen, whereas the last ones are freed up for tuning. This method helps to perform full training on the pretrained model and modify the parameters at last layers. Modification applied at last layers because the earlier layers in a network capture more general features while later ones are very dataset-specific.

2.4. Convolutional Neural Network Model with Fully Connected Layers

Convolutional neural network composed of convolution, pooling, and fully connected layers (Hachim & Harry, 2017).

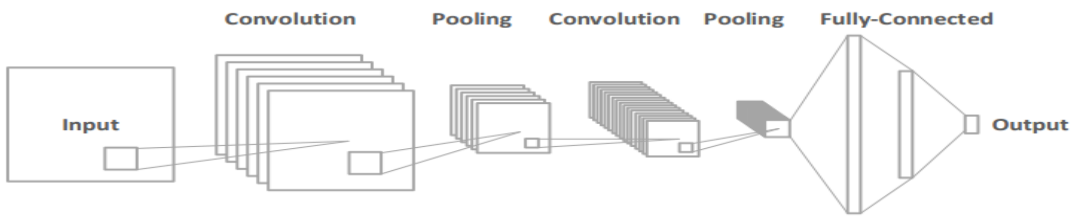


Figure 3:Convolutional neural network composed of convolution, pooling, and fully connected layers *(Hachim & Harry, 2017)*

2.4.1. Automatic Age Estimation (AAE) Model of Convolutional Neural Network

The face is detected and aligned and then resize the image to 224 × 224. Each aligned face is passed through a CNN for features extraction. Finally, a regression output layer estimates the apparent age (Alice , Abdul , Hazem , & Abdenour , 2020).

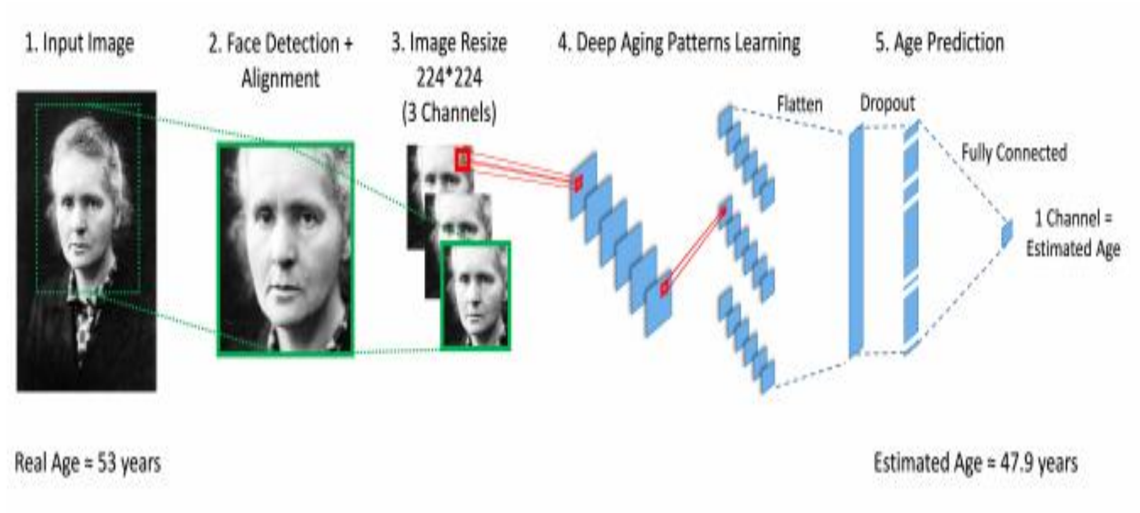


Figure 4:Automatic Age estimation (AAE) model *(Alice , Abdul , Hazem , & Abdenour , 2020)*

2.4.2. CNN Network Architecture for Feature Extraction

The model of CNN has different number of filters to each image in each convolutional layer in the network (Manjaree , Laxmi , Ravipudi Rao, & Jagdish , 2020).

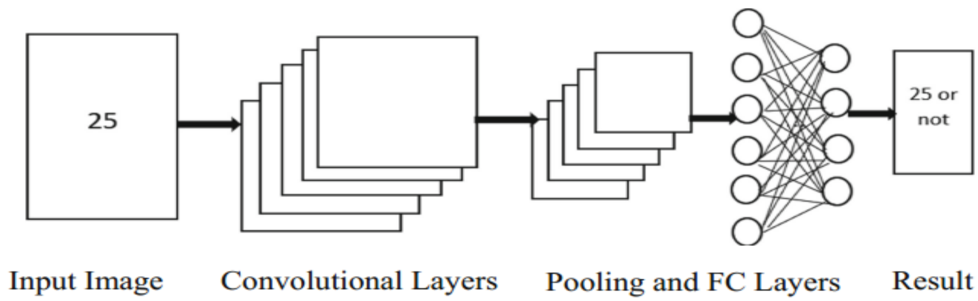


Figure 5:whole process of CNN network Architecture *(Manjaree , Laxmi , Ravipudi Rao, & Jagdish , 2020)*

The filters are responsible for extracting the features of an image. The weights in the layer are trained to recognize the color, edges, shapes, etc. The CNN network has 8 layers in which 5 layers are convolutional layers and the remaining 3 layers are FC layers. The network receives the input of 227 x 227 x 3 of size. The first convolutional layer contains the 96 number of filters with the filter of size 11 x11 using 4 pixels of stride and max pooling. Basically, the output of the first layers goes to the input as a second convolutional layer which contains the 256 number of filters with the filter of size 5 x5. Convolutional layer s third and fourth don' t connects with the pooling and normalization layers. The third convolutional layer contains the 384 of the filters with the size of the filter is 3 x 3. The fourth convolutional layer contains the 384 numbers of the filters with the size of the filter is 3 x 3 and finally last convolutional layer contains the 256 no. of the filter s with the size of the filter is 3 x3. After that perform the max-pooling over the last convolutional layer. At the end of the FC layer s, 4096 neurons have each. All of the layers are followed by ReLu.

2.4.3. Training and Estimation of Age by Using CNN Model with Small Database

The CNN modified architecture helps to study the age range classification. The modification includes the change in the number of convolution layers and their connections. A small deep network is used to overcome overfitting problem.

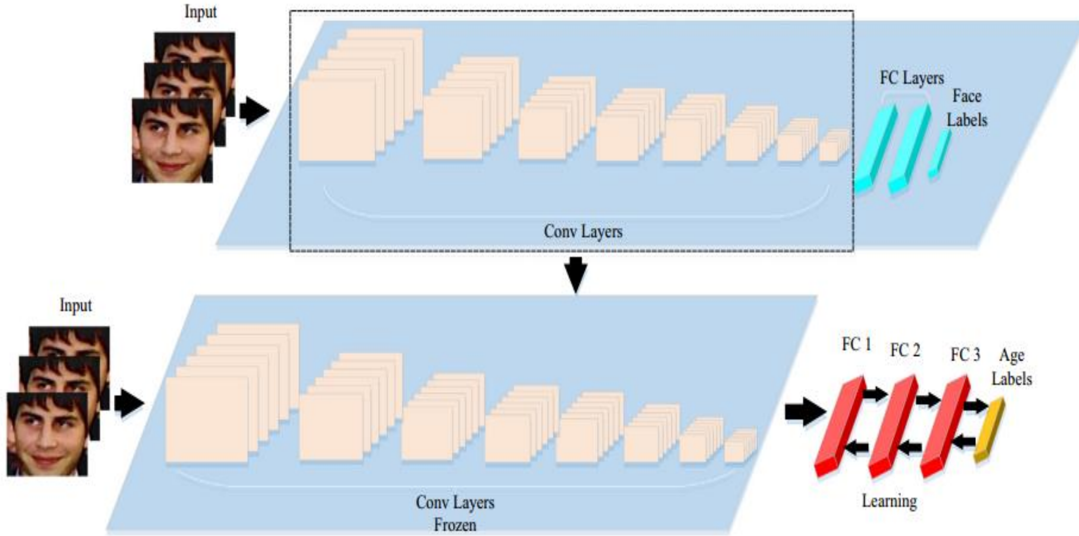


Figure 6:Modified CNN Architecture *(Arafat , Zakariya, & Buket, 2019)*

The architecture includes 8 layers, 5 of which are convolutional layers as filter banks that are used to process the input image. The remainder 3 layers are fully connected layers, where the filters in these layers match the size of the input image. For normalization layers should contain linear manipulator followed by non-linear manipulators as, rectification, drop-out, and pooling. A stride of 4 is used in the first convolutional layer to keep the computation reasonable and the manipulation process fast for training. The first and second convolutional layers are normalized using local response normalization. No pooling or normalization is added to the third and fourth convolutional layers. The first and second fully connected layers contain 4096 neurons; they are regularized with a dropout and normalized with the local response normalization. The last fully connected layer is an N-way classifier with a soft max layer, where N is the number of subjects in the database.

The CNN model trained for face recognition task by using Adience database. Training RGB images are scaled to 256 × 256 pixel. The images were resized to 224 × 224-pixel patches, and then training images becomes subtracted. The goal of the training is to maximize the prediction of the SoftMax layer and to find the optimal network parameters (weights and biases).

In general, three leaning rates are used to train the network. One of the most critical steps in deep networks is the initialization of the network parameters. In this work, biases are initialized to zero and the weights of the filters are initialized by using the random initialization procedure.

The model of CNN which is already trained for face recognition task, it becomes modified for age range classification task. The idea here is to train a deep network to study facial features from image and then retrain and fine-tune this network to estimate the age information. The modification of the CNN is performed by removing the fully connected layers and replacing them with four new fully connected layers of different sizes as shown from figure 5 (Arafat , Zakariya, & Buket, 2019).

2.4.4. CNN Architecture for Age and Gender Estimation

The model consists of eleven layers, including eight convolutional and three fully connected layers. The authors proposed a novel CNN based method, for age group and gender estimation.

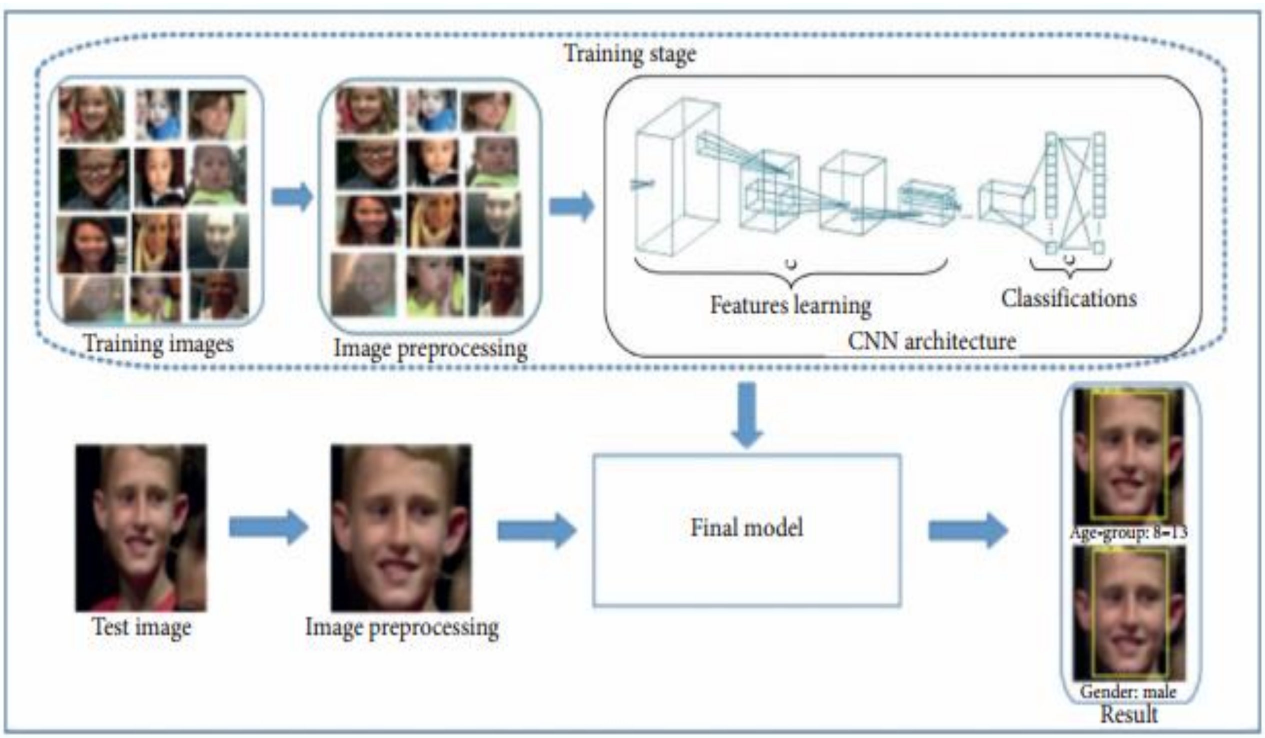


Figure 7:The pipeline frame work of CNN for age group and gender estimation *(Olatunbosun & Serestina , 2020)*

2.5. Overview of Age Estimation Tasks

2.5.1. Hierarchical Age Estimation Using Enhanced Facial Features

2.5.1.1. Face Image Preprocessing

The image is enhanced through preprocessing to make it more suitable for ageing feature extraction (Raphael, 2017). The processes applied for image preprocessing; the image is first converted to single channel gray scale using luminosity method and then smoothened using 2D Gaussian spatial filter defined as:

$$F(a,b) = \frac{1}{2\pi\alpha^2} e \left(-\frac{a^2 + b^2}{2\alpha^2}\right) \qquad (1)$$

where a and b are the displacements from origin in the horizontal and vertical axes respectively and σ is the standard deviation of the Gaussian envelope.

- Given an image I (x, y), an enhanced image IG (x, y) of size m × n is found by performing a convolution of F (a, b) with I (x, y) as

$$I_G(x,y) = \sum_{a=0}^{m-1} \sum_{b=0}^{n-1} F(a,b) I(x-a, y-b) \qquad (2\ )$$

The smoothed image of I(x,y) is I_G(x,y)

Figure 8:Image pre-processing *(Raphael, 2017)*

2.5.1.2. Feature Extraction

The facial features of aging are extracted from the smoothened gray-scale face image and its components are used for age estimation. The authors applied the local binary patterns feature extraction algorithm. The image divided into nine blocks. Histogram of each block is computed and concatenated to make a texture feature vector for age estimation. LBP assigns a code to each pixel in an image by comparing it to neighbors in a particular radius. Local Binary Patterns code is defined as

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{n-1} 2^n \, s(g_n - g_c) \qquad (3)$$

$$\tau(x) = \begin{cases} 1 & if \;\; x \geq 0 \\ 0 & if \;\; x < 0 \end{cases} \qquad (4)$$

where N is number of neighboring pixels, R is distance of neighboring pixel from center pixel, g_c is gray-value of center pixel, g_n for n = 0, 1, 2, … N − 1 correspond the n^{th} to value of neighboring pixel on circular symmetric neighborhood of distance R > 0 and the function τ (x) is a threshold function that generates a binary bit for a particular pixel.

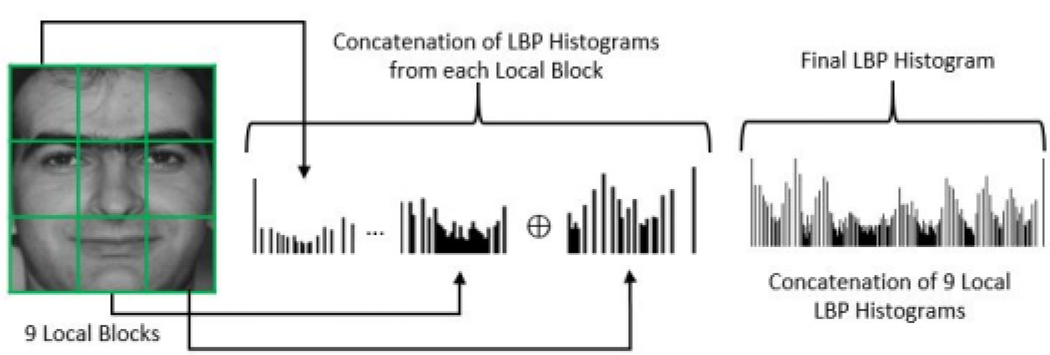


Figure 9:Spatial LBP texture feature extraction *(Raphael, 2017)*

- Shape feature extraction

The 68 landmark points in Face and Gesture Recognition Network (FG-NET) ageing database and ratios of distances between fiducial landmarks to represent global facial shape. These points can be determined by using appropriate 2D landmarking algorithm performed by the author.

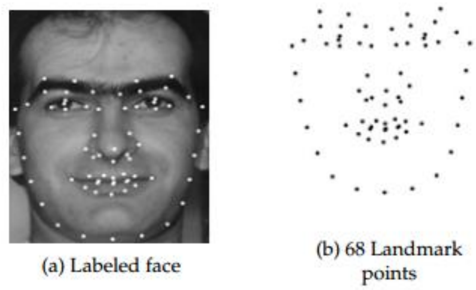


Figure 10:Landmark points used in facial shape *(Raphael, 2017)*

A landmark point p is represented by its x and y coordinates that show its location on the face. For each image, the shape feature vector is created by concatenating each point coordinates to a vector as:

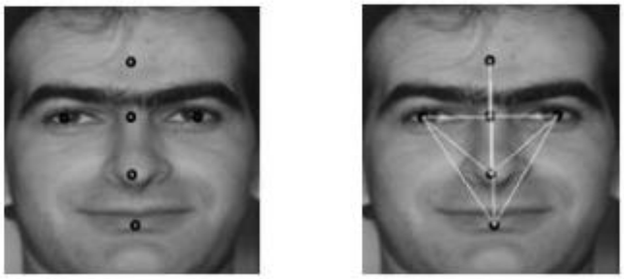
$$\vec{S} \leftarrow [x_1 \oplus y_1 \oplus x_2 \oplus y_2 \ldots \oplus x_n \oplus y_n] \qquad (5)$$

where x_i and y_i are coordinates of point i and $\oplus$ is a concatenation operator

Landmark localization techniques used to locate:

- Left eye (LE),
- Right eye (RE),
- Nose (NO),
- Mouth (MO),
- Nose-bridge (NB) and
- Forehead (FH) fiducial landmarks.

The following figure shows landmark centroids and distances between them.



(a) Centroids (b) Distances

Figure 11:Landmark centroids and distances between them *(Raphael, 2017)*

For each fiducial landmark, a bounding rectangle (circle for NB) is returned. Land mark centroids3 are then determined using spatial and geometric information of the bounding rectangle or circle. For instance, the centroids of the Left-Eye (LE) LEc (x, y) is determined as:

$$LE_c\,(x, y) = \left(LE.TL_x + \frac{W}{2}, LE.TL_y \;+ \frac{H}{2}\right) \qquad (6)$$

where LE. TLx and LE. TLy are coordinates of top-left corner of the LE bounding rectangle, W and H are the width and height of the rectangle respectively.

- Appearance feature extraction

The detected face is resized to 100 × 100 then flattened into a 1 × 10000 row matrix. Linear Discriminant Analysis is used for appearance feature extraction

- Face images are first projected to PCA subspace to reduce the dimensionality of the input image data from 10000 to N − c where N is the number of samples and c is the number of age classes to be estimated.
- Linear Discriminant Analysis on face images projected on PCA space. For each image in all ages, with-class scatter matrix is defined as:

$$S_{w=} \sum_{j=1}^{c} \sum_{i=1}^{N_j} (x_i^j - \mu_j)(x_i^j - \mu_j)^{\tau} \qquad (7)$$

where $x_i^{\,j}$ is the i^{th} image of age j, μ_j is the mean of age j, c is the number of ages to be estimated and N_j is the number of images in age j. Between-class scatter matrix is defined as:

$$S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^{\tau} \qquad (8)$$

where μ is the mean of all ages

- Wrinkle feature extraction

The Wrinkles features are extracted by using Gabor filter. Gabor filters has been extensively used for wrinkle, edge and texture feature extraction due to their capability of determining orientation and magnitude of wrinkles. Wrinkles significantly influence facial appearance and can improve age estimation accuracies.

- A bank of Gabor filters of different scales, frequencies and orientations is used to extract wrinkle features. A 2D spatial domain Gabor is defined as:

$$G(x, y) = exp\left(-\frac{X^2+\gamma^{\,2}Y^2}{2\sigma^{\,2}}\right) xcos\left(\frac{2\pi}{\lambda}X\right) \qquad (9)$$

where X = x cos θ + y sin θ and Y = -x sin θ + y cos θ are angle of rotations of Gabor filters, θ varies from 0 to π, γ and σ are aspect ratio and standard deviation of the Gaussian envelope respectively and λ is the wavelength and determines spatial frequency 1/λ

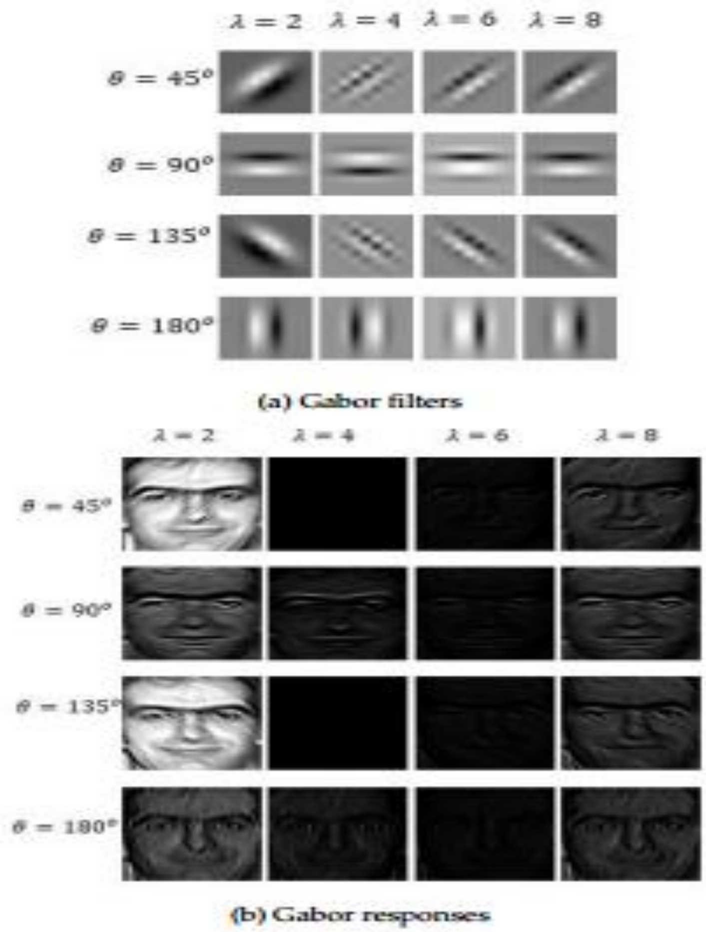


Figure 12:Gabor filters and responses from 4 orientations and 4 frequencies *(Raphael, 2017)*

- The mean is defined as

$$\mu = \frac{1}{N \times M} \sum_{i=1}^{N-1} \sum_{j=0}^{M-1} x(i,j) \qquad (10)$$

- the standard deviation is defined as

$$\mu = \sqrt{\frac{1}{N \times M} \sum_{i=1}^{N-1} \sum_{j-0}^{M-1} \left[\left(x(i,j)\right) - \mu\right]^2} \qquad (11)$$

The mean and standard deviation are concatenated to form a wrinkle feature with 2 ×b dimensionality. This wrinkle feature is used for representing face for age estimation.

2.5.1.3. Age Estimation Approach

Three hierarchical age estimation approaches are:

I. Hierarchical age estimation using a single feature vector for age-group classification followed by within-group age regression

II. Hierarchical age estimation using fused features for age-group classification followed by within-group age regression

III. Hierarchical age estimation using fused features for gender classification, followed by gender-based age-group classification followed by within gender and age-group age regression

- Using MF-BIF for hierarchical age estimation, MF-BIF features are extracted from the face and used for age-group classification with Artificial Neural Network (ANN)Multilayer Perceptron (MLP) followed by age regression with SVR

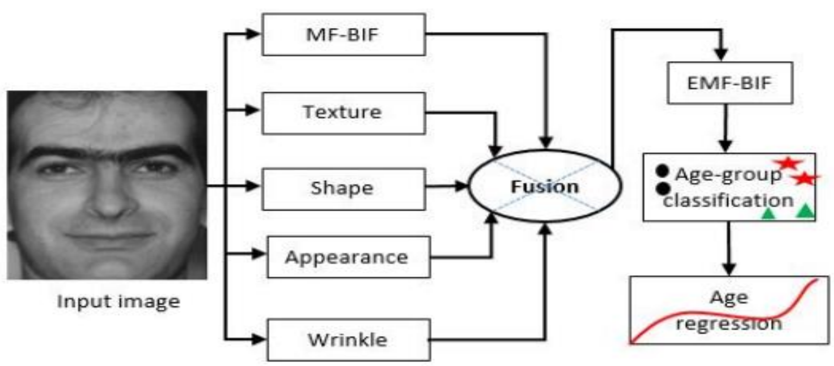


Figure 13:Hierarchical age estimation using EMF-BIF *(Raphael, 2017)*

2.5.2. Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces

The deeply learned classifiers are used for age group and gender classification from unfiltered real-life face images (Olatunbosun & Serestina , 2020). Image preprocessing algorithm follows face detection, landmark detection, and face alignment stages. Which helps the image for preparing the face images before input into the proposed network.

2.5.2.1. Image Preprocessing

- One of the challenges of age and gender classification task is due to unfiltered real images.
- Most unfiltered face images are not aligned and non-frontal and it has different degrees of variations in pose, appearance, lighting, and background conditions

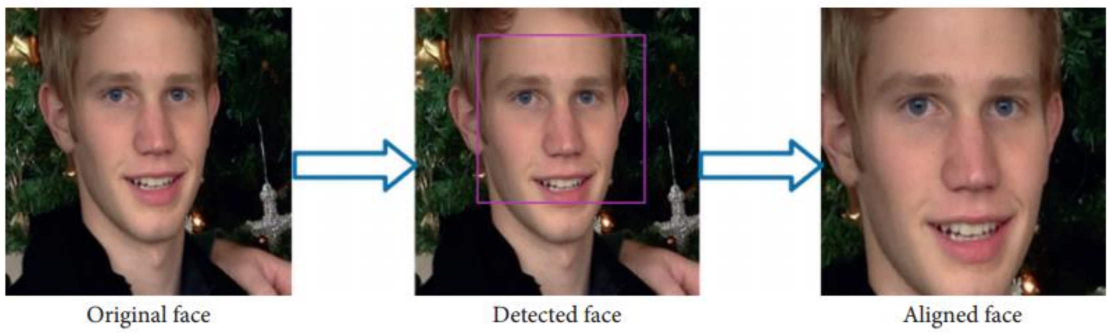


Figure 14:Image preprocessing phase *(Olatunbosun & Serestina , 2020)*

2.5.2.2. Face Detection

- Face detection is the first stage of image preprocessing
- Open-source face detector helps to detect the face
- Images are rotated with the range of −90° to 90° angles
- The face detector results the best output if the input image is detected.
- The original image is resized and face detection algorithm is repeated until a face is detected.

2.5.2.3. Landmark Detection and Face Alignment

The preprocessing algorithm of facial landmark detection uses five landmark detection models; these are

- frontal model,
- two half-profile models
- two full profile models.

The five models are trained to work from one of corresponding facial poses. In side model the affine transformation takes place with the highest confidence score to the predefined optimal settings of landmarks

2.5.2.4. CNN Architecture

The CNN architecture has six-layers of network, which contains four convolutional and two fully connected layers. The model layers are a sequential deep learning architecture, which feature extraction and classification phases. Feature extraction phase has four layers convolutional, and the parameters of number of filters, the kernel size and stride. The convolutional layer, activation layer rectified linear unit (ReLU) batch normalization are the components of the model. Classification layers contains two fully connected layers, which helps to handle the classification phase of the model. Age group and gender classification task in deep classification has its own problem. To overcome the problem, a soft max with cross entropy loss function is adopted to obtain a probability for each age group and gender class. Probabilities for each class label and its function is calculated by the algorithm of soft max function.

Soft max classifier defined as follows:

$$f_j(S) = \frac{e^{s}j}{\sum_k e^{s}k} \qquad (12)$$

where we are using the notation fj to mean the j^{th} element of the vector of class scores f that takes a vector of arbitrary real-valued scores in s.

- A cross entropy loss is used for training the multiclass and binary classifications of age and gender classifiers.
- The cross entropy for binary classification was defined as:

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N}\left[X_i\, log\left(P(\dot{X}_\iota)\right) + (1 - X_i)\, log(1 - P\dot{X}_\iota)\right] \qquad (13)$$

where x is the binary class label, 1 if it is the correct class and 0 otherwise, and p(x) is the predicted probability of the point being green for all N points.

➢ For multiclass, cross entropy is defined as follows:

$$H_{x^i}(X) := -\sum_i X_i^{'} \, log(X_i) \qquad (14)$$

where x^i is the predicted probability value for class i and x'_i is the true probability for that class.

2.5.2.5. Training Details

Using pre-trained weights from a large-scale generic dataset is a common strategy in many applications of deep learning, since it allows to alleviate overfitting and improve convergence (Antonio , Alessia , Mario , & Vincenzo , 2021).The training datasets of the model for classification of age group and gender were IMDb, MORPH-II, and OIU-Adience bench marks. The age group classifier helps for predicting the age groups into eight different classes The gender classifier will classify into two classes for gender.

2.5.2.6. Age Group Classification

The age group CNN model classifier helps to predict face images into age group by passing a series of empirical experiments. The model able to generalize and predict correctly, the researchers applied Adam optimizer to update network weights during training.

➢ Adam optimization algorithm; for each parameter w^j

$$m_t = y_1 * m_{t-1} + (1 - y_1) * g_t \qquad (15)$$

$$v_t = y_2 * v_{t-1} + (1 - y_2) * g_t^2 \qquad (16)$$

$$\Delta w_t = -\eta \, \frac{v_t}{\sqrt{s_t + \varepsilon}} * g_t \qquad (17)$$

$$w_{t+1} = w_t + \triangle \, w_t \qquad (18)$$

where η is the learning rate, g_t is the gradient at time t along w^j, m^t and v^t are the exponential average of squares of gradients along w_j, and c_1 and c_2 are the hyperparameters.

2.5.3. Deep Learning Technique Strengths and Weaknesses

A review of the different deep learning architectural networks used in previous studies revealed several techniques that are frequently used for face age estimation. The main goal of deep learning face age estimation is to find the best method for learning the face aging features from a large sample of data and then use the information to distinguish the different ages of test subjects. Summary of network architectures mostly used by age estimation studies (Hadi , 2021).

Table 1:Summary of Network Architectures Mostly Used by Age Estimation Studies *(Hadi , 2021)*

Architecture	Background	Learning Methodology	Strength	Weakness
LeNet	-Invented in 1998 by Yann Lecun -First popular CNN architecture	Spatial exploitation	- Small and simple design. - A good introduction to neural networks for beginners.	- Problem to detect all aging features. Require extensive training. - Speed and accuracy are outperformed by newer network architecture.
AlexNet	- Introduced in 2012 at the ImageNet Large Scale Visual Recognition Challenge. - Uses ReLu, dropout and overlap pooling. - First major CNN model that used GPUs for training	Spatial exploitation	- Using GPUs for training leads to faster training of models. - ReLu helps lessen the loss of features and improve model training speed.	- Authors require to find design solutions on how to compete with other newer network architectures that are more accurate and faster
VGG-Net	- Visual geometric group (VGG) was introduced in 2014. - It groups multiple convolution layers with smaller kernel sizes	Spatial exploitation	- Homogenous topology. - Smaller kernels. - Good architecture for benchmarking face age estimation - Pre-trained networks for VGG-Net are freely available.	- Computationally expensive as more layer increases. - Face age estimation studies need to consider the vanishing gradient problem to improve the estimation performance

2.5.4. Evaluation of Models

Data collection-processing, feature extraction, and classification technique application are the general steps for designing a machine learning classification model. The performance of the classification model should be evaluated by using the evaluation techniques.

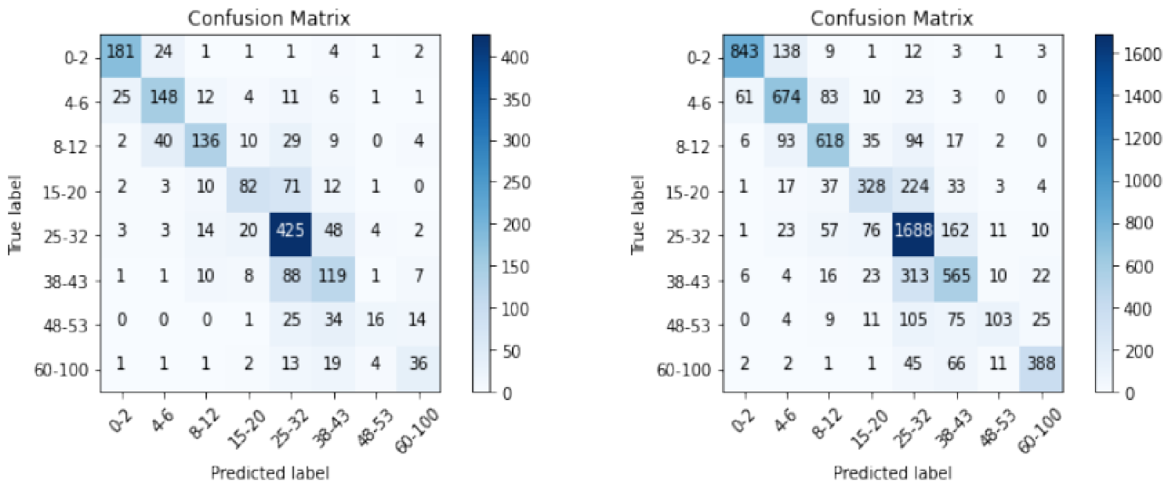
2.5.4.1. Confusion Matrix

The confusion matrix for the multi-class age grouping results as indicated on the table for each group arrangement Adience data set (Anto & R , 2021). The Confusion Matrix, also known as the Error Matrix, is used to evaluate/judge a model's performance on test samples where the actual values are already known.

Table 2:The confusion matrix for the multi-class age grouping *(Anto & R , 2021)*

Age Range in Years	**0-2**	**4-6**	**8-13**	**15-20**	**25-32**	**38-43**	**48-53**	**60-**
0-2	**0.753**	0.147	0.028	0.006	0.005	0.008	0.007	0.009
4-6	0.256	**0.652**	0.166	0.023	0.010	0.011	0.010	0.005
8-13	0.027	0.223	**0.478**	0.150	0.091	0.068	0.055	0.061
15-20	0.003	0.019	0.081	**0.251**	0.106	0.055	0.049	0.028
25-32	0.006	0.029	0.138	0.510	**0.524**	0.461	0.260	0.108
38-43	0.004	0.007	0.023	0.058	0.149	**0.293**	0.339	0.268
48-53	0.002	0.001	0.004	0.007	0.017	0.055	**0.253**	0.165
60-	0.001	0.001	0.008	0.007	0.009	0.050	0.134	**0.456**

Confusion matrices of gender classification models based on pre-augmentation and post-augmentation (Eamon , 2021)



(a) Age classifications pre-augmentation

(b) Age classifications post-augmentation

Figure 15:Confusion matrices of gender classification models *(Eamon , 2021)*

2.5.4.2. Mean Absolute Error (MAE)

For age estimation problem, in order to guarantee the accuracy of the algorithm and provide fair comparison with available state-of-the-art models (Avishek, et al., 2021). MAE (Mean Absolute Error) is taken as the evaluation metric, which minimizes the error between the estimated age and the ground truth label. MAE (J(X) is given:

$$\mathcal{J}(\mathcal{X}) = \frac{1}{M}\sum_{i=1}^{M}\left|\tilde{Y}_i - Y_i\right| \qquad (19)$$

where, $\tilde{Y}_i$ = True Age and Y_i = Predicted Age for i^{th} data point

Table 3:MAEs achieved by the GRA Net model for age classification over five standard benchmark datasets *(Avishek, et al., 2021)*

Dataset	MAE
FG-NET	3.23
AFAD	3.10
Wikipedia Age	5.45
UTKFace	1.07
AdienceDB	10.57

2.5.4.3. Precision

Precision is the measure of all properly identified (actual positive values) among all predicted positive values and calculated as:

$$Precision = \frac{TP}{TP+FP} \qquad (20)$$

2.5.4.4. Recall

Recall is the measure of positive values that are predicted properly among all actual positive values. High Recall Value indicates that the class is known correctly since a number of False Negative is small and it is calculated as:

$$Recall = \frac{TP}{(TP+FP)} \qquad (21)$$

2.5.4.5. F1-score

F1-score: is the weighted average of the precision and recall.which is calculated as:

$$F1\_score = \frac{2*(precision * recall)}{(precision + recall)} \qquad (22)$$

2.6. Related Work

2.6.1. Age-based facial recognition using convoluted neural network deep learning algorithm

The recognition of facial by using image face and age by the application of artificial neural network of CNN. Face recognition uses biometric innovations which can see or validate a person based on the shape of the individuals. (Julius , et al., 2020).The age estimation by using the combination of machine learning and image processing methods on the face image dataset. The methods, data set, strength, limitation and the gap are expressed as follows.

The authors had divided the methods and dataset preparation into three phases. The first Phase; data preparation and preprocessing of the face image data. The BERC database, the PAL database, and FG-Net database are used for the experiment. Face image denoising had done by preprocessing of noise model of Rayleigh noise and Gaussian noise. In the second Phase: preparing the data set for training by segmenting and applying future extraction. At the last phase; it was the training phase by the classical network structure of convolutional neural system. The CCN model contains a few "convolution layers" and "examining layers" to process the information signal which helps for calculating and evaluation of the prediction performance of models. The overall experimental result shows that programmed facial age evaluation strategy dependent on CNN.CNN had been the preferred execution over that of artificial features of SVM. The strength of the study; applying classical structure of CNN model for face image helps for prediction of image. But its limitation was the authors had not compared the results of CNN and SVM models of Artificial features. In addition to this the researchers had not used the data set of face image of persons in different age range. Instead of this they had used the images of Dog, cat, boat and bird. The gap was the authors had used less amount of data set for training the model and the image face data set of persons with all age groups and race was not implemented.so that it is the research gap and inspired to do research with artificial intelligence of of Convolutional neural network (CNN).

2.6.2. Age Invariant Face Recognition Using Convolutional Neural Networks and Set Distances

The authors had interested for addressing the challenge of face recognition subject to aging (Hachim & Harry, 2017). This study had an objective of addressing both identification and verification of face images across time lapse. The methods used, strength, limitation and gap for the researchers are briefly stated below.

The methods used; the data was longitudinal image database for training and testing. By using the data features of the face image are extracted automatically using a deep convolutional neural network. The training data set used; a pre-trained multilayer convolutional neural network (CNN) which helps for automatically extract features from face images. The feature extraction was mor robust to intrapersonal variability. For experimentation the authors used VGG-Face; which composes a sequence of convolutional, rectified linear unit (ReLu), pool, and fully connected (FC) layers. The applied model experimental result shows that it recognizes older subjects rather than younger subjects. The researcher’s strength is they had clearly stated the method and data set. Limitation; the model cannot be fully identified and verify all subjects with equal level of older subjects and young subjects. The gab; all the age levels or groups had not included for identification and verification of age. It had concerned for only young and old ages but infants, children and female and male verification and identification not recognized; which is a researchable area.

2.6.3. Utilizing CNNs And Transfer Learning of Pre-Trained Models for Age Range Classification from Unconstrained Face Images

Due to the advancement of technology human-computer interactions becomes in wellbeing, and then computerized systems can estimate the age from face images (Arafat , Zakariya, & Buket, 2019).The pre-trained CNNs which were trained on large benchmarks for different purposes can be retrained and used for age range classification from unconstrained face images. The previously trained CNNs fits for the age range classification successfully. Because age classification benchmarks are relatively small compared to the benchmarks of face recognition task. One of the most challenging tasks of machine learning is the overfitting problem that occurs when using small benchmarks.to overcome this problem the researchers had used pre -trained CNNs.

The methods and data set used by the authors; to get an efficient classification of age group a pre trained large data base of face recognition model was trained instead of training a new model on a small database. Because a previously trained model for face recognition performs age range classification on the Adience data set. which helps for designing deep neural network (DCNN)with a pre trained large database. As deep network architecture for age range classification or face recognition on small databases it will result poor performance of the model. The author concluded a pretrained model of CNN with large database helps to train CNN age range classification effectively. The strength of the study: the experimental results are clear and understandable. The limitation is the researchers had not tested the model with the real-world face images with regard to different races. Observed gap: all real images were not tested and checked the performance of classification age groups of all societies in gender race and different age groups.

2.6.4. Age Classification Using Convolutional Neural Networks with The Multi-Class Focal Loss

Automatic age classification is a challenging task due to the complexity of facial images (Wei, Lin, & Yajun, 2018). To solve the challenge the authors had proposed model of convolutional neural networks model based on the multi-class focal loss function.

The Methods and data set used; the data set used for the experiment was unconstrained Adience benchmark it helps for age classification. The applied method was a multi-class focal loss, which helps to address the class imbalance for binary classification. For multi-class issue, the Cross Entropy (CE) loss could be calculated. And again, the Adience dataset is split into eight age categories. After the data set had grouped the category, the Network architecture of the model had designed by the authors. That is, age classification was implemented by using CNN with the multi-class focal loss. The CNN network has three convolutional layers and two fully connected layers. The model had achieved a better result as compared to the state-of-the-art models. The Age classification results on the Adience benchmark has been improving the accuracy of aligned faces as well as improving the accuracy of cropped faces. The strength; The authors had presented their experiment with a model and compared its performance with other state of arts with regard to age classification. The limitation is the authors had used the experiment and test its performance of their model with existing data base of Adience only that is not tested with real face images. The gap; the model performance of age classification had not been checked with the real representative face images. It is the research area of classification of age by using real face image from our society.

2.6.5. Image Age Estimation Based on Data Augmentation and Lightweight Convolutional Neural Network.

Age estimation based on face image processing, has been done extensively in order to enhance the performance of model. (Xinhua, Yao, Hailan, & Xiaolin, 2020) the authors had done the study about age estimation by using face image data set. The data sets used; The MORPH (Craniofacial Longitudinal Morphological Face Database). For experiment MORPH2 dataset was used, which is a part of MORPH. And another data set used for experiment was FG-NET (Face and Gesture Recognition Research Network Aging Database) which included the face image of different races and colors of worldwide.

The performance evaluation matrices used by the researcher were mean absolute error (MAE) and cumulative score (CS). These are the objective evaluation index which helps for the researches for estimation of age. The multiple sets of experiments had performed by using the two data sets: The first one is experiment on MORPH2.Here the authors had divided the training data set into MORPH2 and MORPH2_ALIGN for the benefit of face alignment performed or not performed. Classification and the regression layers of the model had organized. At the end of the network, the classification layer and the regression layer are used. The network structure of model was divided into two types of SFV2_l1 and MA_SFV2_l1, for applying mixed attention mechanism: Based on the experimental result, the method had improved the accuracy of age estimation. The second experiment was applied on FG-NET (Face and Gesture Recognition Research Network Aging Database). The deployed network model of FG-NET dataset was MA-SFV2_l1. The researcher divided FG-NET dataset into two sets of comparative experiments, for the use of checking image augmentation operations were performed or not. Its performance of age estimation also resulted better result, even though the data set was not large. At the end, the quantitative comparison experiment had done with other methods. The authors had made comparison by using the data sets of MORPH2 and FG-NET with the mechanism of mixed attention- Mixed Attention-ShuffleNetV2 (MA-SFV2) with other models of previously existing mechanisms. The experimental result shows that IMDB-WIKI pre-training of large face databases was achieved higher age estimation accuracy than the authors model of (MA-SFV2).

The strength, limitation and Gaps of the research. Strength; the authors deeply performed the experimental analysis of the proposed model for comparing their model with the existing model. The limitation of the study; the conclusion part of the researcher did not fully express with regard to the result of the experiment. The gab is the image data set of a person was taken from open sources, so that it cannot represent the real-life standard of all societies and it is not representative.

2.7. Summary of Related Work Papers

Table 4:Summary of related work papers

NO	Literature Review papers	Data set	Used model /method	Result/ Accuracy of the model	Strength, Limitation and Gap
1	Age-based facial recognition using convoluted neural network deep learning algorithm. (Julius , et al., 2020)	BERC database Size=390 Age group=3-81 Private Size and age group not specified FG-Net Size=1002 Age group=0-69	Classical structure of CNN (convolution layers" and "examining layers)	Significant highlights in facial pictures with full frame work of CNN. Mean vector value between 0 and 1	**Target:** to design the classical CNN model for estimating age. **Strength**; Designed classical network structure of CNN to enhance the performance of age estimation. **Gap**: Less amount of data used for training and testing. Also, the data set used was not representative of human face with different age groups and race.
2	Age Invariant Face Recognition Using	FGG-Face (for verification) Size=2.6M	VGG-Face CNN	MIN-D= 0.12 and	**Target**: to find an optimal threshold that minimizes the verification error.

	Convolutional Neural Networks and Set Distances (Hachim & Harry, 2017)	Age group=young/old FG-NET (for identification) Size=1002 Age group=0-69		DM HD=0.12/0.18 UM-HD=0.15 for both training and testing data set The model performers better result for both identification and verification	Threshold for (Verification (EER) (young/old); singleton=2.8 and set means=0.16 **Strength**: the method, data set and experimental result had clearly stated. Gap: the model had not included all age groups and race.
3	Utilizing CNNs And Transfer Learning of Pre-Trained Models for Age Range Classification from	Adience benchmark Size=26 K face images -2284 subjects and 8 age groups (labels of	Model: Transfer learning CNN model by using pretrained face recognize models of (GoogLeNet, ResNet-50, VGG-VD-16, VGG-VD-19, and FNC-8s)	Combined-Models of CNN with dimensionally reduction gives better performance;	**Target**: to employ a previously trained model with large data set for face recognition and performing age range classification on the Adience data set. Strength: the experimental results are clear and understandable Limitation: the model not tested with the real-world face images with regard to different races.

	Unconstrained Face Images (Arafat , Zakariya, & Buket, 2019)	0 –2, 4 –6, 8 – 13, 15 –20 ,25 – 32. 38 –43 ,48 – 53, 60 +)	Algorithm: the stochastic gradient descent, used to train the modified CNN in order to find the optimal parameters.	Accuracy= 62.26% 1-off = 92.63	Gap: the model was not implemented with real world face images to estimate the age of people by considering race and life standards. -Some ages not included in the group of ages like the ages from 33 up to 37; which is excluded the data set age group. So it is the main gap that I have been solve in the proposed study.
4	Age Classification Using Convolutional Neural Networks with the Multi-Class Focal Loss (Wei, Lin, & Yajun, 2018)	unconstrained Adience benchmark of eight age group categories size= 26,000 face images	Method: CNN with the multi-class **focal** loss model.	with aligned faces (Exact = 53.0 ± 6.5%; 1-off = 87.1 ± 2.7%) with cropped faces Exact =54.0 ± 6.4; 1-off =88.2 ± 2.3)	**Target**: to efficiently improve the performance of age classification of CNN model based on the multi-class focal loss function, **Strength**= the authors had presented their experiment with a model and compared its performance with other state of arts with regard to age classification. Limitation: the model not tested with real images Gap: age classification had not been checked with the real representative face images and again its result has not achieved high result with regard to accuracy.

5	Image Age Estimation Based on Data Augmentation and Lightweight Convolutional Neural Network (Xinhua, Yao, Hailan, & Xiaolin, 2020)	MORPH 2(Craniofacial Longitudinal Morphological Face Database) Siz=55,000 -	mixed attention mechanism (MA-SFV2: Mixed Attention-ShuffleNetV2) (MORPH2 and MORPH2_ALIGN	MAE on (MA_SFV2_l1=2.88; ALIGN_MA_SFV2_l1=2.68 MAE on FG-NET (MA-SFV2=3.81, C3AE (IMDB-WIKI) = 2.95	**Target**: to construct a lightweight convolutional neural network for age estimation model based on the mixed attention mechanism. **Strength**: deeply performed the experimental analysis of the proposed model by comparing their model with the existing model. Gap: real face image data not used and the performance of age estimation was under the existing models of IMDB-WIKI.

CHAPTER THREE

3. METHODOLOGY

3.1. Introduction

The methods and materials used for age estimation using face image processing includes: the data set, image processing, the model of deep Convolutional neural network (DCNN) and the classification algorithm of the model.

3.2. Dataset Collection and Preparation

The data set used for this study was collected manually by using smart phone from volunteer people randomly. During data collection we give the written material for them to read it and asking their permission to capture their face. For this study most of collected face image data from Bahir Dar town and around Bahir Dar town by using smart phone by considering all age ranges. In addition to this; some images of children and elders were taken from social medias for the purpose of increasing data set. As the data set has classified in age groups it is simple to group ages of children and elders taken from social medias. The total data set prepared for this study is 1169, The data set has grouped in 7 classes.

- Class 1= ages of children and this class contains 1-10 years old
- Class 2= ages of younger people and this class contains 11-20 years old
- Class 3= ages of youth people and this class contains 21-30 years old
- Class 3= ages of youth people and this class contains 21-30 years old
- Class 4= ages of adult people and this class contains 31-40 years old
- Class 5= ages pre matured people and this class contains 41-50 years old
- Class 6= ages of matured people and this class contains 51-60 years old
- Class 7= ages of old people and this class contains above 61 years old

3.2.1. Dataset Range Classification

The data set classification applied for this study has 7 age range classes. The age classification range and its size in each class is shown in table 6.

Table 5: Age group classification

Class	1	2	3	4	5	6	7
Range	1-10	11-20	21-30	31-40	41-50	51-60	60+
Size of image	200	200	200	200	200	100	69

- For this study the same age range gap used except class 7 for training, testing and validation. The data set divided the images into training, testing and validation with the ratios of 80:10:10 respectively. In addition to this manually collected face images cropped and labeled manually and then prepared for retrain the model of VGG16 transfer learning model. The face images preprocessed by applying a method of face image preprocessing (Leila & Aldjia, 2020);Align all shapes in the same referential, texture representation and then resizing the image and then convert gray scale image to RGB. Finally, the feature extraction of fine-tuning model performed to obtain the feature from preprocessed face image data set to predict age in age range.

The process applied during data collection:

- Ask the voluntariness of a person by telling or giving written document to make brief the objective of getting image.
- Then if someone is agreed with it ask birth of year or age of a person
- Then take photo and label it with the actual age of the person
- Then finally; classify each image into age classes based on the label of actual age.

3.3. System Architecture

The transfer learning of VGG16 system architecture of age estimation which contains; input face image, Image extraction, preprocessing, feature extraction, model building and at the end estimation of age by using transfer learning techniques. The predefined CNN architectures of VGG16/VGG19 and ResNet models mostly used for age estimation and gender recognition from facial images (Gangesh & Nitin N, 2020).For this study the proposed model is VGG16. Even though VGG19 has additional hidden layers and it gives more accurate result than VGG 16; but due to the performance of the machine, this study has been applied by using the transfer learning model of VGG16. As this study has done our people new data set from scratch, ResNet 50 has been used for comparing the performance of the proposed model.

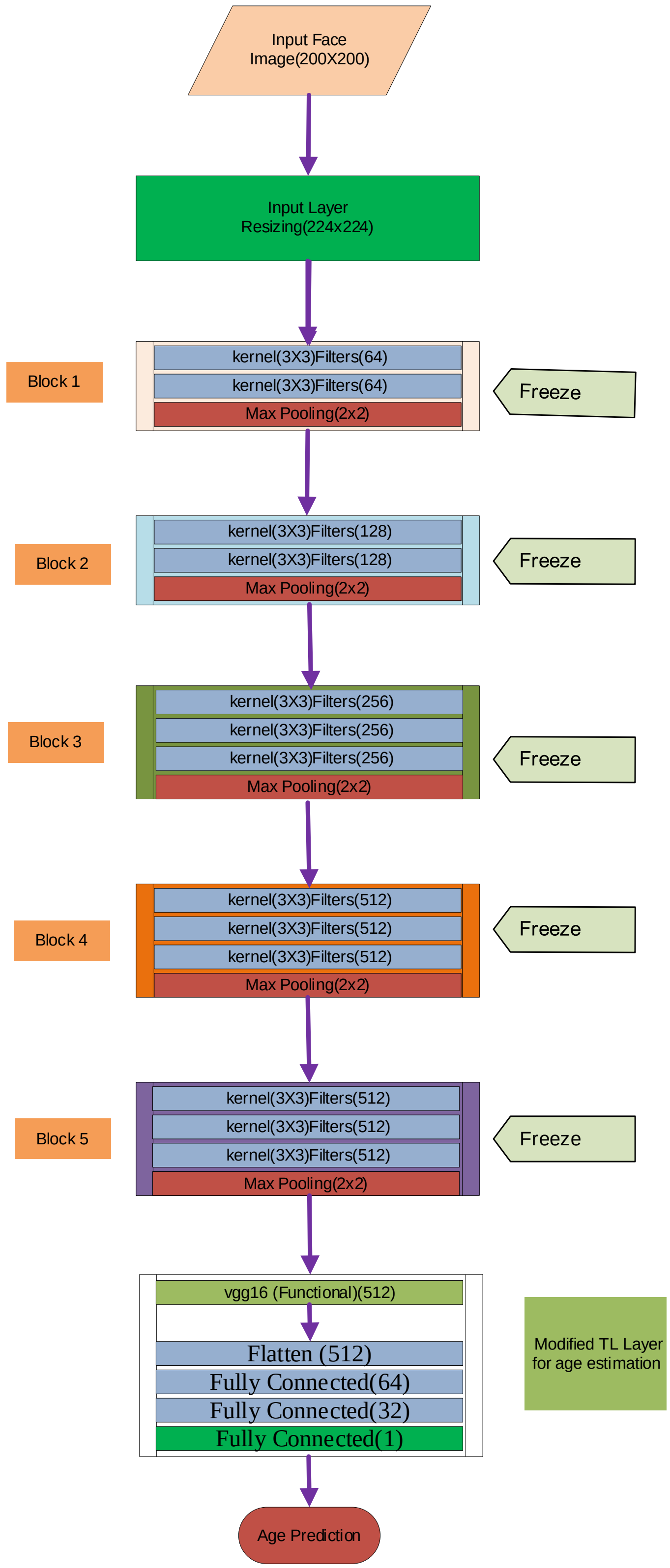


Figure 16:System architecture

3.4. Proposed Model of the Study

3.4.1. VGG 16 Base Model Network Architecture Components

The model applied for this study is VGG 16 transfer learning model with fine tune. (Srikanth, 2019) VGG-16 - Karen Simonyan and Andrew Zisserman introduced VGG-16 architecture in 2014. It is very deep convolutional network for large scale image recognition.

It has been applied by freezing all layers except the top layers of base model of VGG 16. The components of the modified base model of deep convolutional neural network for transfer learning in fine tuning method as shown in table 6.

Table 6:VGG 16 base model network Architecture components

Blocks	**Layer Name**	**Filters**	Feature Map	Stride
	Input Layer		(224, 224, 3)	1
Block 1 (Frozen)	conv1_1	64	(224, 224, 3)	
	conv1_2	64	(224, 224, 3)	
	pool1 (MaxPooling)		(112, 112, 64)	1
Block 2 (Frozen)	Conv2_1	128	(112, 112, 128)	
	Conv2_2	128	(112, 112, 128)	
	Pool2 (MaxPooling)		(56, 56, 128)	1
Block 3 (Frozen)	Conv3_1	256	(56, 56, 256)	
	Conv3_2	256	(56, 56, 256)	
	Conv3_3	256	(56, 56, 256)	
	Pool3 (MaxPooling)		(28, 28, 256)	
Block 4 (Frozen)	Conv4_1	512	(28, 28, 512)	1
	Conv4_2	512	(28, 28, 512)	
	Conv4_3	512	(28, 28, 512)	
	Pool4 (MaxPooling)		(14, 14, 512)	
Block 5 (Frozen)	Conv5_1	512	(14, 14, 512)	1
	Conv5_2	512	(14, 14, 512)	
	Conv5_3	512	(14, 14, 512)	
	Pool5 (MaxPooling)		(7, 7, 512)	
Modified VGG16 Transfer Learning Layer	vgg16 (Functional)	512		
	Flatten layer	512		
	Dense/FC	64		
	Dense/FC	32		
	Dense/FC	1 (Softmax Activation layer removed)		

The top layers of fine-tuned VGG16 model which has taken from the output of the implemented code of python code is as shown in figure 17 ; which is used for estimation of age with regression.

```
In [14]: TL_model_VGG16.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 512)               14714688

 flatten (Flatten)           (None, 512)               0

 dropout (Dropout)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 14,749,633
Trainable params: 34,945
Non-trainable params: 14,714,688
_________________________________________________________________
```

Figure 17:Fine _tuned VGG 16 model for age estimation

Fully Connected Layer in VGG16 model of transfer learning is a top dense or last layer used for prediction task. The output of the last Pooling Layer acts in put to the Fully Connected Layer. (Srikanth, 2019)in fully connected layers each node in the first layer is connected to each node in the second layer.

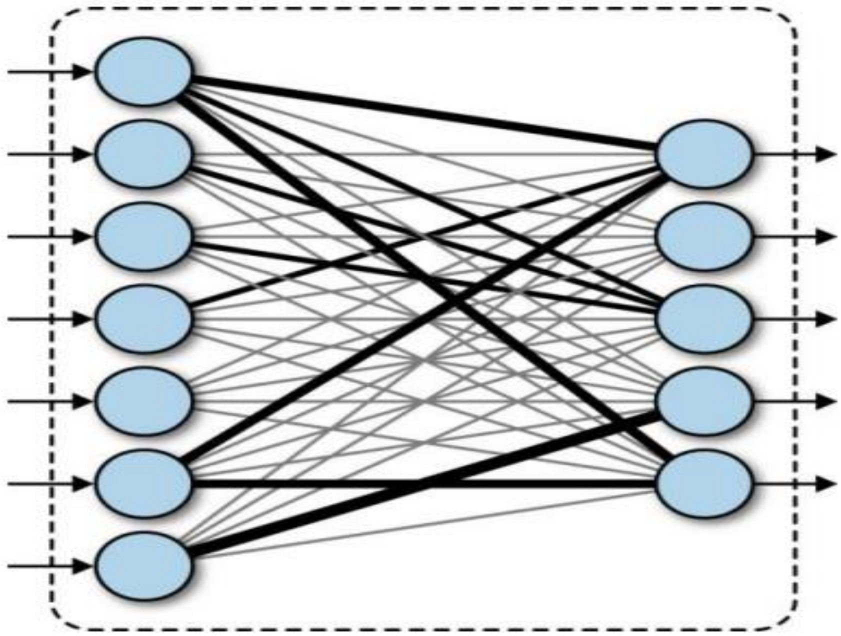


Figure 18:Fully connected layer *(Srikanth, 2019)*

3.4.2. VGG 16 Transfer Learning Model for Age prediction

The model applied for this research for age prediction is VGG16 transfer learning model. Transfer learning provides the ability to re-enhance the existing architectures to be suitable for new tasks instead of building new model from scratch. Our data set is small in size so that we applied transfer learning model of VGG-16. In transfer learning, the previously learned base models modified partially by adding new layers or training on new samples (Issam & Dany, 2020).We used fine-tuning of retrained VGG-16 CNN model applied on new samples for another-related tasks.

The tasks performed in fine tuning model of VGG-16 for our small data set. DCNN helps for face recognition, gender recognition and estimation or prediction of age by using face image (Amit, Ranjit, & Engine, 2018). DCNN helps to extract the feature from an image and gives the output of age range. The model of Deep Convolutional Neural network (DCNN) designed and implemented. The performance of the DCNN checked by training and testing with a preprocessed face image data set by applying transfer learning approach.

3.4.3. Fine Tuned VGG 16 Transfer model

We applied fine tuning model of transfer learning model of VGG16 by modifying the top-class model of the base model of VGG-16. To make the model fine-tuned; the base convolutional layers with the top dense layers fine-tuned by removing the last Softmax activation layer. VGG-16 pretrained model imagenet weights to extract features and feed the output to new layer for the new task. The code to call VGG-16 pretrained model and the main useful syntax to apply transfer learning for VGG 16

In [36]:

```
#VGG 16 Transfer learning Model of fine tuning
feature_extractor_VGG16 = tf.keras.applications.VGG16(
    input_shape=(224,224, 3),
    weights='imagenet',
    include_top=False,
    pooling='max'
)
```

- "weights = 'imagenet' ": helps to fetch VGG-16 model, which is trained on the imagenet dataset.
- "include_top = False": to avoid downloading the fully connected layers of the pretrained model.

➢ The proposed model structure to apply VGG 16 fine-tuned transfer learning model by freezing the rest convolutional layers and then fine-tuned the top layers of the VGG 16. The most top layer which helps for age prediction with regression. The model structure is a shown figure 18.

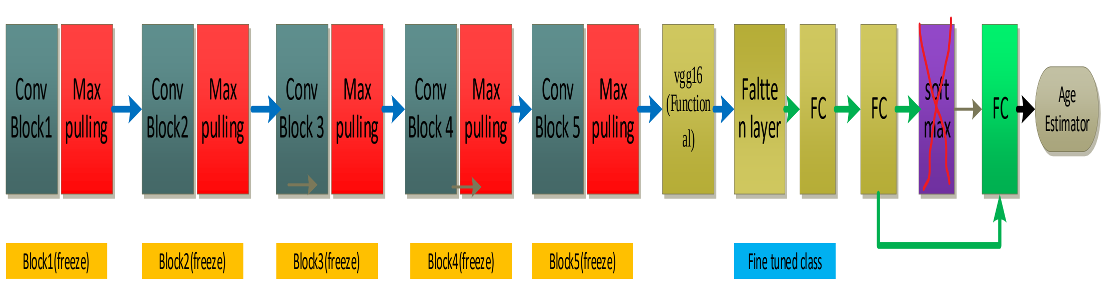


Figure 19:VGG-16 fine-tuned model structure and components

3.5. Algorithm For the Age Estimation

The algorithm applied for estimation of age with VGG 16 fine-tuned CNN model is shown step by step:

1.Initialize pre-trained VGG-16 model with [(weight= imagenet), (include top=False)

2.Define (learning rate, batch size and number of epochs) for training

3. Input crop face image(200x200)
3.Rescale the input image to a fixed size of 224 x 224

4.For each training set{(x1), x2,…x(n)} with corresponding targets y(i) do

5.Add a randomly initialized new head of Transfer learning to the VGG-16

6.Freeze the body of the network of the base model and train the newly added head by using manually collected data set

8.End for

9.. Evaluate the fine-tuned network.

10.Test the accuracy of fine-tuned network with test data set.

The code applied for determining the sample size and for preprocessing the image for enhancing image quality

```
In [6]: image_df = images.sample(1000, random_state=1).reset_index(drop=True)

        train_df, test_df = train_test_split(image_df, train_size=0.8, shuffle=True, random_state=1)

In [7]: train_generator = tf.keras.preprocessing.image.ImageDataGenerator(
            rescale=1./255,
            validation_split=0.1
        )

        test_generator = tf.keras.preprocessing.image.ImageDataGenerator(
            rescale=1./255
        )
```

Figure 20:image preprocessing algorithm based from the given sample size

3.6. Programming Language

The programming language used for this research has been Python, which is an easy to implement and it is a powerful programming language. It has high-level data structures and a simple approach to object-oriented programming. For this study we used the open-source python library; these are: Keras, Tensorflow Numpy, Pandas, Matplotlib, Seaborn. Pathlib, sklearn, matplotlib OpenCV(cv2).

- OpenCV (cv2:is an open-source library for computer vision, machine learning and image processing (Mahija , Dr. Esther , Gadili , Meghana , & Vanarasi , 2021).

3.7. Optimization Algorithm

We have used Adam optimizer for model optimization, because it helps to handle sparse gradients on noisy problems.

3.8. Model Evaluation

The model implementation and its performance for age estimation has been evaluated by applying the regression method. For this research we have used Training and Validation Loss approach. The study has applied the regression models for estimating age of people based on the given age class lables;so that the evaluation methods which has been performed in this study are;

- Root Mean Squared Error (RMSE) and
- R-squared (R^2)
- Training loss
- Validation loss

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Introduction

For this study we have discussed the experimental set up and training result of the VGG16 transfer learning model conducted with manually collected data set. In addition to this we thoroughly discuss the result with regard to training loss and validation loss of the model while trained by varying epochs value for estimating age with in age class label.

4.2. Experimental Setup

The machine used for this study is somehow better for computing but it hasn't high performance when computing very large data set in the learning process. The machine has

- Processor: Intel(R) Core (TM) i7-7500U CPU @ 2.70GHz (4 CPUs)
- 8GB RAM
- Intel(R) HD Graphics 620
- Storge =1TB HDD

4.3. Data Set Organization for Training the Model

We have divided the data set into training and test data set with 7 age class labels. The training data set has 80% the rest are used for validation and testing the model. The data frame of sample images taken 1000 from the total data set. We have used the same image sample size to train and evaluate the model. As the sample size varies the validated training image, validation image and testing image varies in size. Let us see its effect by varying image sample size from the total data set.

The image sample size of 100 from the total data set, the data distribution of validated data prepared for training, validation and testing within each class as shown figure 18.

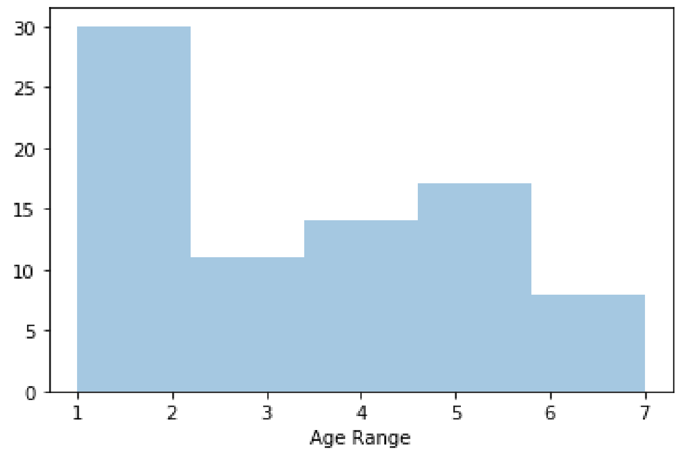


Figure 21:Data set distribution with in each class with sample size becomes 100 from total data set

The image sample size of 500 from the total data set, the data distribution of validated data prepared for training, validation and testing within each class as shown figure 19.

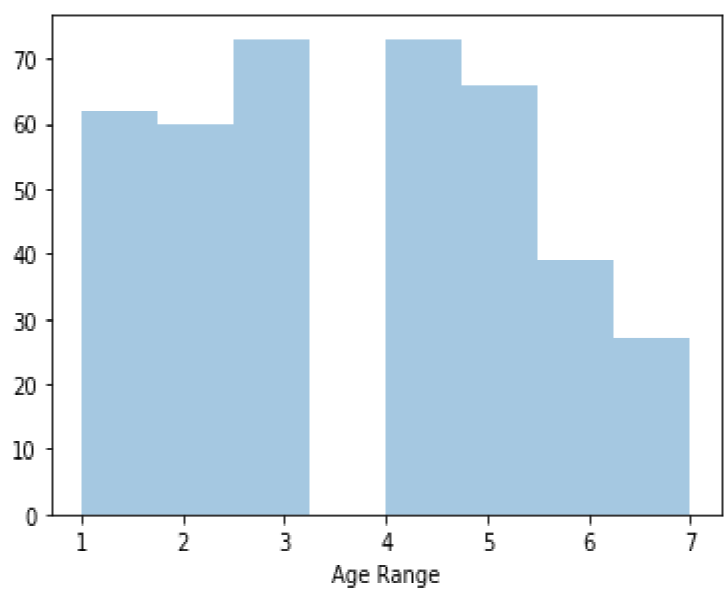


Figure 22:Data set distribution with in each class with sample size becomes 500 from training data set

The image sample size of 1000 from the total data set, the data distribution of validated data prepared for training, validation and testing within each class as shown figure 20

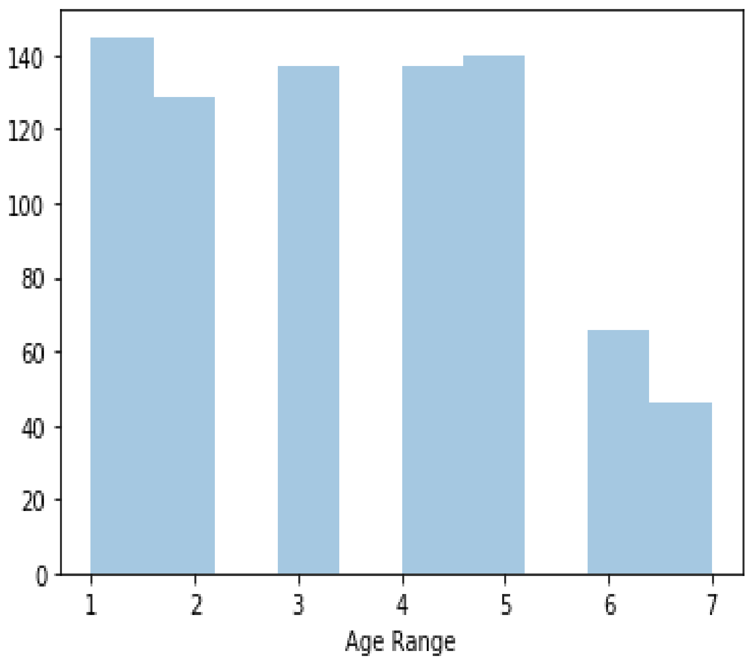


Figure 23:Data set distribution with in each class with sample size becomes 1000 from total data set

As we observed the sample size of the data set affects the performance of the mode. So that the size sample data set should be at least 80% of the total data set.

For our training the data frame generator algorithm results the validated image for training, validation and testing from the given image sample of 1000 from the total data set is;

Total dataset	Image sample	train_images	val_images	test_images
1169	1000	720	80	200

Table 7:validated data for training

Data created with data generator for training and validation images/photos from the total d ata set which has displayed at a time 32 photos; the number of photos displayed depends o n the epoch number. The output of the following image is for epoch size =32

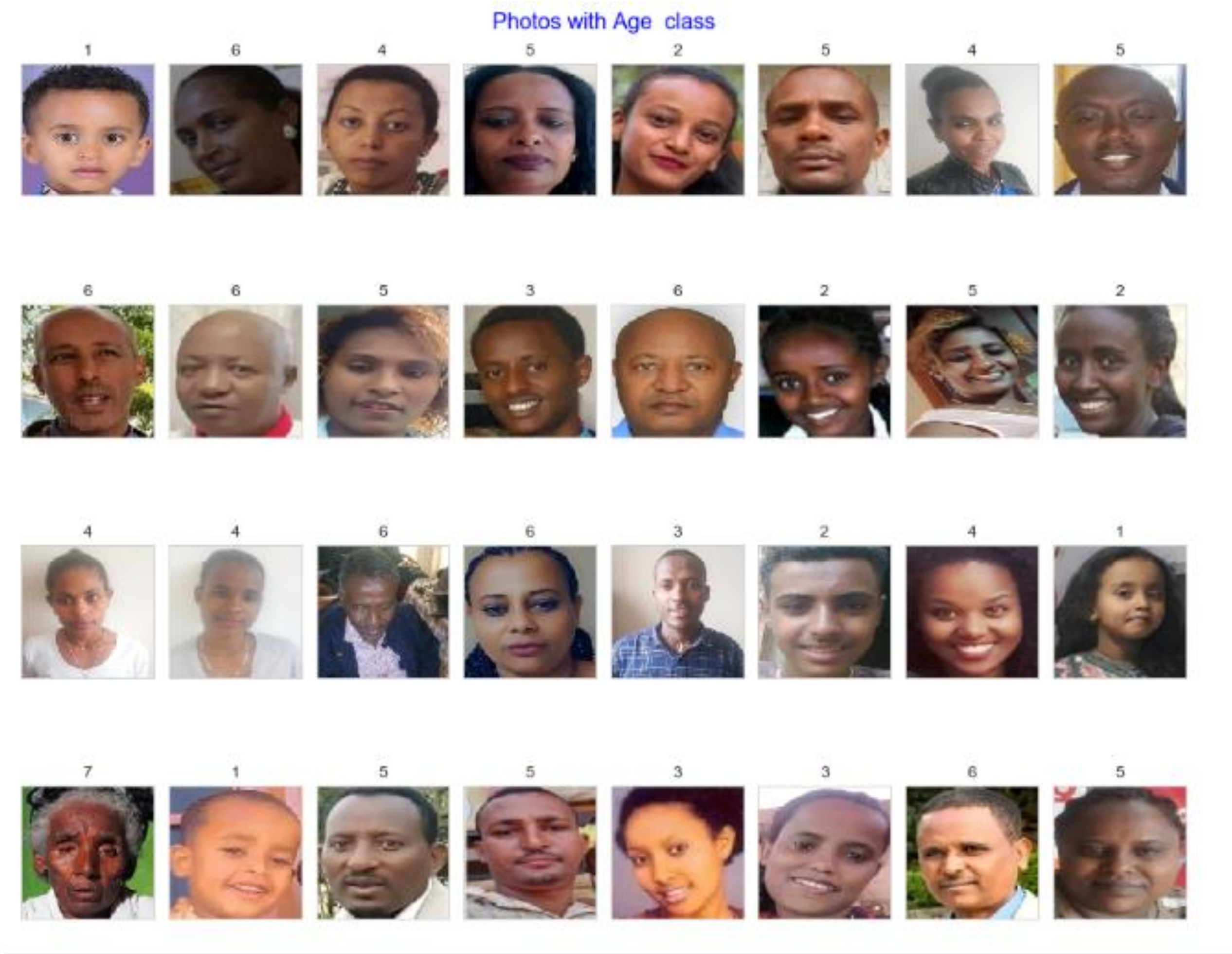


Figure 24:photos resulted from image generator

4.4. Training And Evaluation

The pretrained model of VGG 16 applied for this study has been configured and prepared for age prediction. The model becomes used the most top classification layer by freezing the rest layers and the last soft max layer becomes canceled and connected with other Fully connected layer for prediction of age range. The layers used for the task of age estimation:

- vgg16 (Functional) (512)

- vgg16 (Functional)(512)
- Flatten (512)
- Dense (64)
- Dense (32)
- Dense (1) age estimation head

We have applied fine -tuned model of transfer learning to train models; all the layers were pre-trained with the ImageNet dataset. The total layers of VGG16 have 16 layers but except the top 3 layers the rest became frozen.

4.4.1. Configurations of Training Stages

The training configuration and evaluation parameters for the proposed model of VGG16 and for ResNet50 model. The ResNet model helps for comparing the proposed model of this study.

Table 8:training components

Training stage	Model type	epoch	Batch size	Restore Best weights	Evaluation	
					RMSE	R-squared (R^2)
1	Fine-tuned	5	32	True		
2	Fine-tuned	10	32	True		
3	Fine-tuned	20	32	True		

4.4.2. Training and Validation Result of the Model

Training and validation result of the model expressed with graph. It is the results of 3 stages with epochs 5, 10,20,

- Stage 1 result of epoch=5 and sample size =1000 for both VGG16 Fine-tuned and ResNet50 models

```
Epoch 5/5
23/23 [==============================] - 194s 8s/step - loss: 4.8715 - val_loss: 3.7666
7/7 [==============================] - 50s 7s/step
     Test RMSE: 1.88102
Test R^2 Score: -0.03981
```

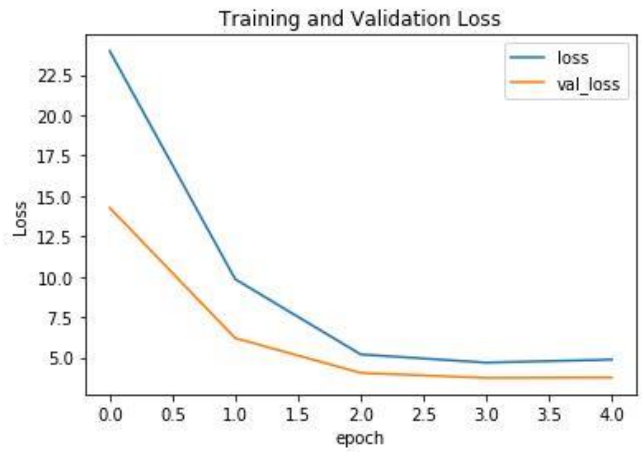


Figure 25: Training result of VGG 16 with epoch 5

```
Epoch 5/5
23/23 [==============================] - 81s 4s/step - loss: 3.7270 - val_loss: 3.8100
7/7 [==============================] - 21s 3s/step
     Test RMSE: 1.86007
Test R^2 Score: -0.01678
```

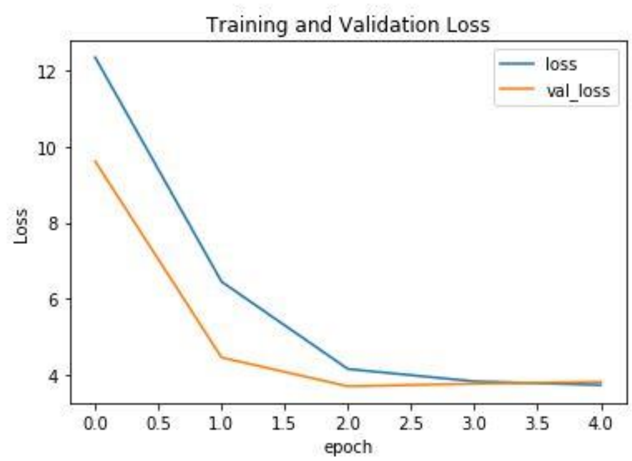


Figure 26:Training result of ResNet50 with epoch 5

- Stage 2 result of epoch=10 and sample size =1000

```
Epoch 10/10
23/23 [==============================] - 198s 9s/step - loss: 3.9886 - val_loss: 4.0501
7/7 [==============================] - 51s 7s/step
     Test RMSE: 1.88985
Test R^2 Score: -0.04959
```

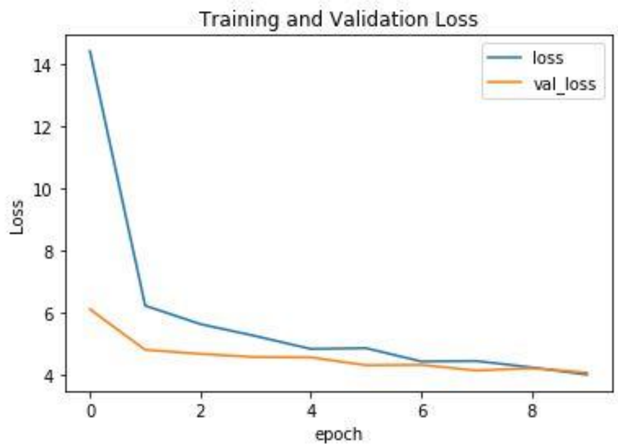


Figure 27: Training result of VGG 16 with epoch 10

```
Epoch 8/10
23/23 [==============================] - 78s 3s/step - loss: 3.5851 - val_loss: 3.5749
7/7 [==============================] - 20s 3s/step
     Test RMSE: 1.86740
Test R^2 Score: -0.02480
```

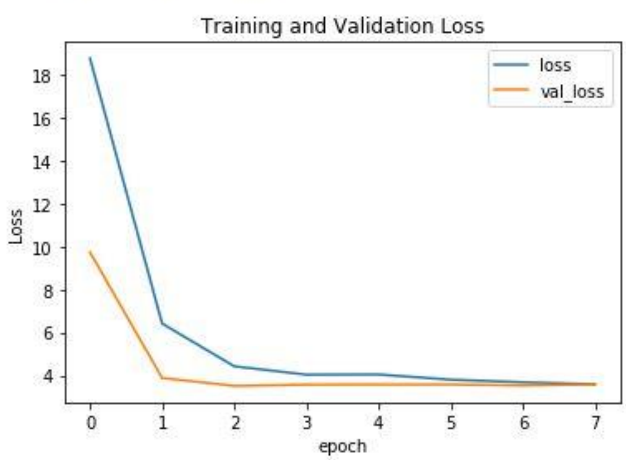


Figure 28:Training result of ResNet50 with epoch 10

- Stage 3 result of epoch=20 and sample size =1000

```
Epoch 20/20
23/23 [==============================] - 189s 8s/step - loss: 3.5273 - val_loss: 3.3827
7/7 [==============================] - 48s 7s/step
     Test RMSE: 1.74514
Test R^2 Score: 0.10499
```

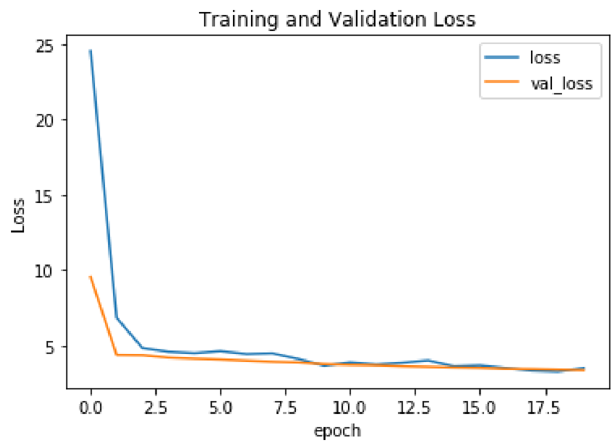


Figure 29: Training result of VGG 16 with epoch 20

```
Epoch 20/20
23/23 [==============================] - 80s 3s/step - loss: 3.6565 - val_loss: 3.5518
7/7 [==============================] - 20s 3s/step
     Test RMSE: 1.80552
Test R^2 Score: 0.04199
```

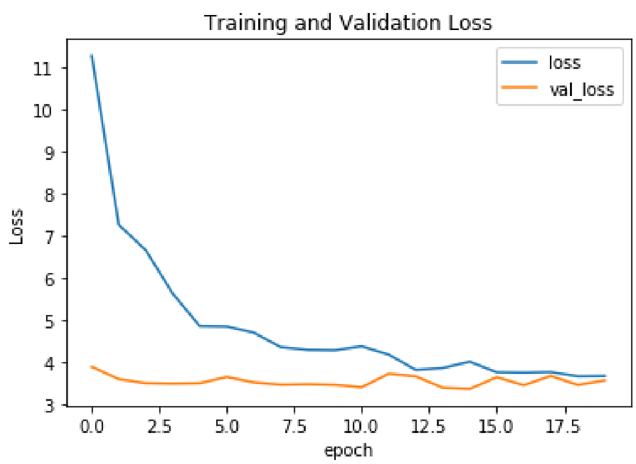


Figure 30:Training result of ResNet 50 with epoch 20

- Training and Validation Result of the Model with table

The training and validation result of the models of VGG16 and ResNet50 has expressed with in graph. To make it clear for discussion the result is shown in table 10.

Table 9:training and validation result comparison

Model	Epoch	Batch size	Restore best weights	Result			
				loss	Val-loss	Test RMSE	Test R^2 score
Proposed model: VGG 16 Fine-Tuned Model	5	32	finished	4.8715	3.7666	1.88102	-0.03981
	10	32	finished	3.9886	4.0501	1.88985	-0.04959
	20	**32**	**finished**	**3.5273**	**3.3827**	**1.74514**	**0.10599**
ResNet50	5	32		3.7270	3.8100	1.86007	-0.01678
	10	32	Yes; restored at epoch 8/10	3.5851	3.5749	1.86740	-0.02480
	20	32	finished	3.6565	3.5518	1.80552	0.04199

4.4.3. Testing the VGG16 Model by Using Test Data Set

The model has been tested by using test images from the test data set after training fine - tuned model of VGG16 and its test result of age prediction is as shown below.

- Test result of stage 1 with epoch 5

(a) (b)

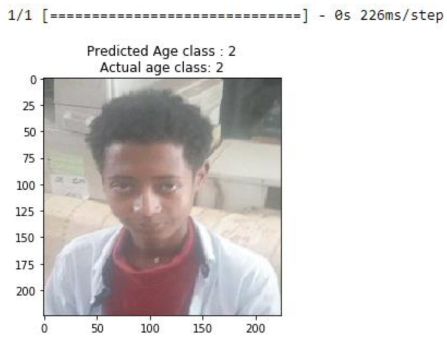
Figure 31:test result with epoch 5

- Test result of stage 2 with epoch 10

(a) (b)

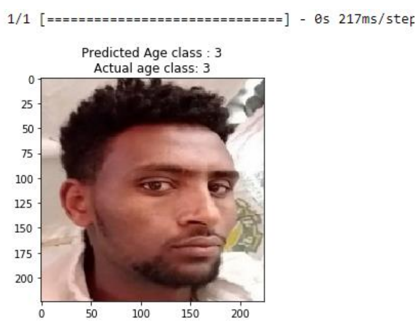
Figure 32:test result with epoch 10

- Test result of stage 3 with epoch 20

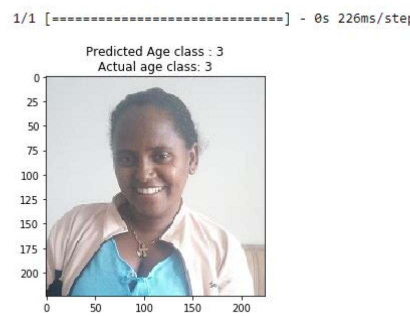


(a)

(b)



(C)



(d)

Figure 33:test result with epoch 20

4.5. Discussion

By using the VGG 16 fine-tuned and ResNet50 models, training has under taken with three stages by increasing the epoch values of 5,10, and 20. As shown the result with training and validation graph and test result of the VGG16 fine-tuned model gives a good result with epoch 20 ;(**RMSE**= **1.74514**) and at epoch 20 (**R^2 score=0.10599**).In addition to this the loss and validation loss in this stage gives good result with epoch 20 as compared epoch 5 and epoch 10;that is for epoch 20(**loss=3.5273)** and (**val_loss=3.3827**) For ResNet50 model it gives a good result with epoch 20 (**RMSE =1.80552**) and (**R^2 score=0.04199**) and again for ResNet50 with epoch10 (**loss=3.5851) and with epoch 20** (**val_loss=3.5518**) as shown in table 9 for comparison. From this result, the fine-tuned VGG16 performs better result as compared to ResNet50 fine-tuned model with regard to estimation of age with regression based on the age classes. This indicates that the VGG16 fine-tuned model performs a good result as compared to ResNet50 while training both models with manually collected data set of our people from scratch.

With regard to testing the performance of the model with test data set of each age classes the test result has shown from figure 31 up to 33. The result indicates that as the model training iteration (epoch value) increases the performance of age prediction also increases in prediction of age class label. From the test result observation at stage 1 and 2(epoch=5 and epoch 10) all models did not give the accurate result; that is the actual age class and the prediction age class had not given the same result. For epoch 20 the VGG16 fine-tuned model gives an accurate result while testing by using test images. But the ResNet50 model had given an accurate result at epoch 20 while testing with test images. The fine-tuned model of VGG16 prediction age in the age class results good performance of age class prediction with training loss, validation loss and again the test result of **RMSE**. And **R^2** score with epoch 20 as compared to ResNet50.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

In the case limited size of face image data for implementation of deep learning results poor performance in prediction of age. To overcome this issue the study has been applied by using pretrained model of VGG16 with transfer learning. The VGG 16 pretrained base model has imported from keras. applications. By using the fine- tuned model and training it with the image sample of 1000, the model performance became enhanced as iteration (epoch size) increases. In this study the performance of the model has been evaluated by using RMSE and R^2. From the result of the VGG16 fine-tuned model (**RMSE= 1.74514**) and (**R^2=0.10599**) with regard to loss and validation loss (**loss=3.5273) (val_loss=3.3827**) which gives good result. So that VGG 16 fine-tuned model performs good result as compared to ResNet50 fine-tuned model in the case of limited data set in prediction of ages in age class by using manually collected data sets of our society.

5.2. Contribution

This study contributes for age prediction task by using manually collected data set collected within unconstraint condition. One of the contributions of the study is preparing a real face image dataset with real condition of all races and life standards of our society, so that it helps as a base for future researchers that are participating in this area or image processing. It is also helpful for researchers in the areas of AI for implementing the model in production areas by adding the data size of locally collected dataset in the real condition.

5.3. Recommendation

The transfer learning model of VGG16 in deep learning model has been used for age prediction by using fine-tuning the model. The proposed model results good performance in prediction of age range in a class. But due to shortage of data set the study has been performed with 7 classes with classification of age range. Even though the proposed model of VGG16 fin-tuned model gives good result, there is large age range gap with in each class. So that it is recommended as a future work for researchers to study by decreasing the age range gap of age classes for performing their study with this area.

REFERENCES

Alice , A. O., Abdul , R. T., Hazem , A., & Abdenour , H. (2020). Age estimation from faces using deep learning: a comparative analysis. Computer Vision and Image Understanding, 22. doi:10.1016/j.cviu.2020.102961

Amit, D., Ranjit, K., & Engine, B. (2018). Gender Recognition Through Face Using Deep Learning. Procedia Computer Scienc. 132, pp. 2-8. Odisha, India: Elsevier Ltd. doi:10.1016/j.procs.2018.05.053

Anto , A. M., & R , S. (2021). Automatic Age and Gender Estimation using Deep Learning and Extreme Learning Machine. Turkish Journal of Computer and Mathematics Education, 12(14), 63-73.

Antonio , G., Alessia , S., Mario , V., & Vincenzo , V. (2021). Effective training of convolutional neural networks for age estimation based on knowledge distillation. Neural Computing and Applications, 16.

Arafat , A. M., Zakariya, Q., & Buket, D. (2019). Utilizing CNNs and transfer learning of pre-trained models for age range classification from unconstrained face images. Image and Vision Computing, 88, 41-51. doi:https://doi.org/10.1016/j.imavis.2019.05.001

AVISHEK , G., BISWARUP, R., PAWAN , K. S., ALI , A., NORAZAK , S., & RAM , S. (2021). GRA_Net: A Deep Learning Model for Classification of Age and Gender From Facial Images. 9, 85672- 85689. doi:10.1109/ACCESS.2021.3085971

Avuthu, S. M., Sudhakar , S., Arumugam , G., Srinivasan , P., & Kolla , B. P. (2020). Age and Gender prediction using Convolution, ResNet50 and Inception ResNetV2. International Journal of Advanced Trends in Computer Science and Engineering, 9, 1328. Retrieved from https://doi.org/10.30534/ijatcse/2020/65922020

Boukaye , B. T., Bernard , K. F., & Fana , T. (2018). Deep convolution neural network for image recognition. HAL, 14. Retrieved from https://doi.org/10.1016/j.ecoinf.2018.10.002

Eamon , K. (2021). Human Age and Gender Classifiation using Convolutional Neural Networks. Technological University Dublin. doi:10.21427/VBE0-WX80

Hachim, E. K., & Harry, W. (2017, July 14). Age Invariant Face Recognition Using Convolutional Neural Networks and Set Distances. Journal of Information Security, 8, 174-185. doi:10.4236/jis.2017.83012

Hadi , A. D. (2021). A Survey on Deep Learning Face Age Estimation Model: Method and Ethnicity. (IJACSA) International Journal of Advanced Computer Science and Applications,, 12(11), 16.

Ishita , V., Urvi , M., Sachin , S., & Vijay , K. (2019). Age Prediction using Image Dataset using Machine Learning. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 8(12S3). doi:10.35940/ijitee.L1020.10812S319

Julius , Y. W., Aslina, B., Shaliza, H. A., Nordin, S., Muhammad, O., & Noorsidi, A. M. (2020). Age-based facial recognition using convoluted neural network deep learning algorithm. International Journal of Artificial Intelligence (IJ-AI), 9(3), 424-428. doi:10.11591/ijai.v9.i3.pp424-428

Jun, C. C., Amit, K., Rajeev, R., Vishal, M., Azadeh, A., & Rama , C. (2016). A cascaded convolutional neural network for age estimation of unconstrained faces. Biometrics Theory, (pp. 1-8). Niagara Falls, NY,USA: IEEE. doi:10.1109/BTAS.2016.7791154

Leila, B., & Aldjia, B. (2020). Deep-learning based descriptors in application to aging problem in face recognition. Journal of King Saud University –Computer and Information Sciences, 1-7. doi:https://doi.org/10.1016/j.jksuci.2020.10.002

Mahija , K., Dr. Esther , S. B., Gadili , M., Meghana , E., & Vanarasi , L. L. (2021). International Journal of Advance Research, Ideas and Innovations in Technology, 7(3), 2268-2273. Retrieved from https://www.ijariit.com

Manjaree , P., Laxmi , S., Ravipudi Rao, V. R., & Jagdish , C. B. (2020). Intelligent Computing Techniques and their Applications (Vol. 13). 6330 Cham, Switzerland, Switzerland: Springer. Retrieved from https://doi.org/10.1007/978-3-030-44758-8

Mengjie, W., & Weiyang, C. (2021). Age prediction based on a small number of facial landmarks and texture features. Technology and Health Care, 497–507. doi:1 0.3233/THC-21 8047

Olatunbosun , A. A., & Serestina , V. (2020). Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces. The Scientific World Journal, 2020, 12. Retrieved from https://doi.org/10.1155/2020/1289408

Prachi, P., Rashmi , G., & Ashwani, K. (2019, September 26). Neural networks for facial age estimation: a survey on recent advances. Artifcial Intelligence Review, 53, 3299–3347. doi:https://doi.org/10.1007/s10462-019-

Raphael, A. (2017). Hierarchical Age Estimation Using Enhanced Facial Features. YAKWAZULU NATALI: ResearchGate. Retrieved from https://www.researchgate.net/publication/324329914

Sai , T. C., Sowjanya , J., Ruchitha , R. R., & Kalathila , U. (2021). Age and Gender Prediction using Face Recognition. International Journal of Engineering and Advanced Technology (IJEAT), 11(2), 4. doi:10.35940/ijeat.B3275.1211221

Semiha , M., Betul , A., & Galip, A. (2020). Average Neural Face Embeddings for Gender Recognition. European Journal of Science and Technology (pp. 522-527). Elazig,Turkey: ARACONF 2020. doi:10.31590/ejosat.araconf67

Sudip, M., Chandrima, D., & Lovely, K. (2017). Automated Age Prediction using Wrinkles Features of Facial Images and Neural Network. International Journal of Emerging Engineering Research and Technology, 5(2), 12-20. doi:DOI: http://dx.doi.org/10.22259/ijeert.0502002

Wei, L., Lin, C., & Yajun, C. (2018). Age Classification Using Convolutional Neural Networks with the Multi-class Focal Loss. IOP Conference Series: Materials

Science and Engineering. 428, pp. 19-22. Chengdu,China: IOP Publishing Ltd. doi:https://doi.org/10.1088/1757-899X/428/1/012043

Xinhua, L., Yao, Z., Hailan, K., & Xiaolin, M. (2020, January 10). Face Image Age Estimation Based on Data Augmentation and Lightweight Convolutional Neural Network. SYmmetry, 12, 1-17. doi:10.3390/sym12010146

APPENDIX A: Permission Requesting from Persons During Data Collection

ቀን ______/______/2014 ዓ/ም

የእርስዎን ትብብር ስለመጠየቅ

የአብክመ ውኃና ኢነርጂ ቢሮ የአይሲቲ ባለሙያ የሆንሁት በሁለትኛ ዲግሪ መርሃ ግብር በባህር ዳር ዩንቨርስቲ የኮምፒውተር ሳይንስ ተማሪ ስሆን በ “AGE ESTIMATION BY USING TRANSFER LEARNING IN A DEEP NEURAL NETWORK” ሪሰርች እየሰራሁ ሲሆን ለዚሁ ስራ በቻ የሚሆን የአገራችንን የፊት ፎቶ በመሰብሰብ ላይ ስለሆንሁ የርስዎን ፎቶ በካሚራ አንስቼ እንድዎስድና የተወለዱበትን ዓ/ም ወይም ትክክለኛውን እድሜ እንዲነግሩኝ የርስዎን መልካም ትብብር እጠይቃለሁ፡፡

ስለትብብርዎ አመሰናለሁ

ክብረት ሞላ