Bias Assessment and Explainable(XAI) Driven Region-Based Prediction of Human Age and Gender Using Facial Images.

MD.RUFSAN JANI SHANTO

Bachelor of Science

DAFFODIL INTERNATIONAL UNIVERSITY

DAFFODIL INTERNATIONAL UNIVERSITY

DECLARATION OF THESIS AND COPYRIGHT

Author’s Full Name	:	MD.RUFSAN JANI SHANTO
Date of Birth	:	20 March 2002
Title	:	Bias Assessment and Explainable(XAI) Driven Region-Based Prediction of Human Age and Gender Using Facial Images.
Academic Session	:	2022-2026

I declare that this thesis is classified as:

☐	CONFIDENTIAL	(Contains confidential information under the Official Secret Act 1997)*
☐	RESTRICTED	(Contains restricted information as specified by the organization where research was done)*
☐	OPEN ACCESS	I agree that my thesis to be published as an online open-access (Full Text)

I acknowledge that Daffodil International University reserves the following rights:

1. The Thesis is the Property of Daffodil International University.
2. The Library of Daffodil International University has the right to make copies of the thesis for the purpose of research only.
3. The Library of Daffodil International University has the right to make copies of the thesis for academic exchange.

Certified by:

(Student’s Signature)	(Supervisor’s Signature)
221-35-1064	Ms. Ishrat Sultana
Student ID	Name of Supervisor
Date:25/12/2025	Date:25/12/2025

NOTE : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach a thesis declaration letter.

THESIS DECLARATION LETTER (OPTIONAL)

Librarian,
Daffodil International University,
Daffodil Smart City,
Ashulia.Dhaka,Bangladesh

Dear Sir,

CLASSIFICATION OF THESIS AS RESTRICTED

Please be informed that the following thesis is classified as RESTRICTED for a period of three (3) years from the date of this letter. The reasons for this classification are as listed below.

Author's Name

Thesis Title

Reasons (i)

(ii)

(iii)

Thank you.

Yours faithfully,

____
(Supervisor's Signature)

Date:25/12/2025

Stamp:

Note: This letter should be written by the supervisor and addressed to the Librarian, *Daffodil International University* with its copy attached to the thesis.

Department of Software Engineering

Faculty of Science and Information Technology

Supervisor Approval Form

Fall 2025	B.Sc. In SWE	Campus: DSC

Student Name	Student ID
MD.Rufsan Jani Shanto	221-35-1064

Project/Thesis Information	
Project/Thesis Title	Bias Assessment and Explainable(XAI) Driven Region-Based Prediction of Human Age and Gender Using Facial Images.
Type of work	Thesis

Supervisor information	
Supervisor Name	Ms. Ishrat Sultana
Supervisor Initial	IS
Completed Credit till now	135
How many credits in this semester	06
Supervisor Consent	☑ Yes ☐ No

Sultana 26.11.25

Supervisor Signature

APPROVAL

This thesis titled on "**Bias Assessment and Explainable(XAI) Driven Region-Based Prediction of Human Age and Gender Using Facial Images**", submitted by **MD Rufsan Jani Shanto (ID: 221-35-1064)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

BOARD OF EXAMINERS

-- **Chairman**

Dr. Imran Mahmud
Professor & Head
Department of Software Engineering
Faculty of Science and Information Technology Daffodil International University

-- **Internal Examiner 1**

Afsana Begum
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

-- **Internal Examiner 2**

Md. Shohel Arman
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

-- **Internal Examiner 3**

Nadira Islam
Assistant Professor
Department of Software Engineering
Faculty of Science and Information Technology
Daffodil International University

-- **External Examiner**

Md Manowarul Islam
Professor
Department of Computer Science and Engineering
Jagannath University, Bangladesh

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Bachelor of Science.

(Supervisor's Signature)

Full Name : Ms. Ishrat Sultana

Position : Lecturer

Date:25/12/2025

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Daffodil International University or any other institution.

(Student's Signature)

Full Name : MD. Rufsan Jani Shanto

ID Number : 221-35-1064

Date :

Bias Assessment and Explainable(XAI) Driven Region-Based Prediction of Human Age and Gender Using Facial Images.

MD.Rufsan Jani Shanto

Thesis submitted in fulfillment of the requirements
for the award of the degree of
Bachelor of Science

Department of Software Engineering (Major in Data Science)

DAFFODIL INTERNATIONAL UNIVERSITY

DECEMBER 2025

ACKNOWLEDGEMENTS

All the praises and thanks be to Allah (SWT), who is the Most Gracious, the Most Merciful. It is by His infinite grace, strength, and guidance that this journey was made possible, and by His divine will that this work has been realized.

I would like to show my utmost gratitude to my supervisor, Lecturer Ms. Ishrat Sultana. You have been an invaluable support, an excellent counsellor, and a great treasure trove of wisdom in finishing this thesis. Not only have your instructions influenced the research, but they have both inspired me in the process, and I am grateful to have that.

I also owe huge gratitude to my family, whose unconditional love, patience, and support have always been my driving force. I also like my friends, who provided me with cooperation and support, which drove this work.

DEDICATION

To all individuals striving for fairness, transparency, and inclusivity in technology, and to those whose identities and stories remind us that ethics and empathy must always guide innovation.

ABSTRACT

With the advancement of Artificial Intelligence (AI) connected real-world, the accurate prediction of age and gender has become a concerning issue nowadays. In order to perform an independent analysis of bias in the UTKFace dataset, metadata of 23,645 pictures was obtained with the help of custom Python scripts and tabulated in Excel to be reviewed in detail. Analysis has revealed that where the number of male and female samples was almost equal, statistically significant, age difference between the groups of half a decade existed. The imbalance was also validated by a randomly chosen sample of 7,000 images, as the sample has some age-related bias that can be measured. EfficientNetB0, MobileNetV2, ShuffleNetV2, and the custom CNN are four deep-learning models that were trained to make sure there was a fair comparison. EfficientNetB0 gave the best results with over 90 percent accuracy in gender classification and credible age estimation. Further testing with confusion matrices, TPR comparisons and classification reports served to test potential bias in the algorithm. TPR difference between males and females was not large (0.90 and 0.91 respectively) which indicated that the general model structure and analysis adequately minimized the performance differences. Grad-CAM was used to deal with model interpretability, highlighting the most influential and important regions of the face in prediction. The significance of the method is that focusing with the forehead and mid-face region as per the human visual intuition which facilitated openness of judgment. Each stage of the working process was biased to check, statistically verified and interpretable.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

d	Depth (Number of Layers)
w	Width (Number of Channels)
r	Resolution (Input Image Size)
ϕ	Compound scaling factor
α	Scaling constants for depth
β	Scaling constants for width
γ	Scaling constants for resolution
S(i, j)	Value at (i, j) in output feature map after convolution
I	Input image or feature map
K	Kernel (convolution filter)
N	Number of samples
y_i	True value (target/label) for ith sample
ẏ	Predicted value for ith sample

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
XAI	Explainable Artificial Intelligence
MAE	Mean Absolute Error
CCE	Categorical Cross Entropy
TPR	True Positive Rate
TNR	True Negative Rate
FPR	False Positive Rate
FNR	False Negative Rate
FP	False Positive
TN	True Negative
TP	True Positive
FN	False Negative
ROC	Receiver Operating Characteristic
PR	Precision-Recall
UTKFace	University of Tennessee, Knoxville Face Dataset
FRE-2013	Facial Expression Recognition 2013 Dataset
SVM	Support Vector Machine
FC	Fully Connected (layer)
molU	mean Intersection over Union
FPS	Frames per Second
SHAP	Shapley Additive exPlanations
LIME	Local Interpretable Model-agnostic Explanations
CLAHE	Contrast Limited Adaptive Histogram Equalization
F1	Harmonic mean of Precision and Recall
LBP	Local Binary Patterns

PCA	Principal Component Analysis
et al.	And others
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
Grad-CAM	Gradient-weighted Class Activation Mapping
FLOPs	Floating-point math operation
NaN	Not a Number

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

Facial image automatic age and gender prediction (especially when using deep learning) is an important thing in computer vision, particularly when it comes to human-computer interaction, biometrics, security, and social media (Dey et al., 2024). Conventional approaches that relied on hand-crafted characteristics, such as LBP, PCA, and SVM, were fairly effective on clean and controlled images but collapsed once applied to real-life images (Kumar et al., 2024). Along with the advent of deep learning, and more specifically, convolutional neural networks (CNNs), there has been an immense increase in accuracy of age and gender classification (Hamza et al., 2025). The hierarchical and robust features learned by modern CNNs are directly learned out of pictures, and models such as EfficientNet and VGG literally crush it on such datasets as UTKFace (Kumar et al., 2024). Even a basic CNN can provide the state-of-the-art estimates of age and gender, in cases when it is found that the faces are not perfectly aligned, or the lighting is poor (Levi et al., 2015). However, you also require good preprocessing face recognition, face alignment, and face normalization to cope with occurrences of pose, illumination, and occlusions (Dey et al., 2024). The tricks of choice are transfer learning on large-scale datasets such as ImageNet, as well as robust data augmentation in order to prevent overfitting and correct small sample bias (Kumar et al., 2024). Although on gender and pretty decent age we can reach 95-98 percent accuracy, at the same time, models are not yet ready to resolve demographic diversity, occlusion, and data imbalance issues in real-world deployments (Levi et al., 2015). Scholars are now seeking increased scores as well as justice, reduction of bias, and interpretability in order to make the technology feel reliable and transparent, particularly in sensitive aspects (Rasheed et al., 2022).

It is easier to understand that AI systems such as Grad-CAM or Saliency Maps allow us to understand what areas of a face are influencing the predictions and where the biases or errors may be (Dwivedi et al., 2023) Ensemble XAI is auditing age and gender tasks. Those tasks are also additional explainability checks to build morphed-face-detection models are both age- or gender-fair and more likely to perform in the real world (Dwivedi et al., 2023) Itis one of the important tasks in a wide range of applications, such as social science researches, public security field, personal service customizations and so forth. Many organizations are unable to afford experts with experience in facial analysis and may not be able to make timely or accurate decisions regarding system design. Human annotators get tired over the day when they have to work for many faces. In such a condition, they could miss some details or make mistakes, especially if the images are diverse in age and background. Not only is this process time-consuming, it is even subjective since different people could tag the same image with different labels. In order to be able of exploiting technology in these objective, it is necessary to develop systems for an accurate estimation of human age and gender (on the basis of not only facial) even under large-scale alternation on facial attributes, illumination setting, and image prerequisites. False age or gender predictions, and systems is that are biased towards certain classes can cause serious problems in data interpretation and real-world applications.

1.2 Problem Statement

There are serious problems with automatic prediction of age and gender based on facial images as it depends on changes in the facial structure, pose, light, ethnicity, image resolution, and occlusions. Large-scale face datasets are both labor intensive and prone to human bias since annotation and demographic analysis is done manually as real-world data is very unconstrained. Most of the systems implemented in practice are not transparent and users and stakeholders can hardly rely on model decisions and interpret them in sensitive areas, such as identity verification, surveillance, and healthcare. Moreover, bias and the absence of fairness in machine learning models might lead to wrongful or unjust predictions of underrepresented group demographics, helping to enforce social inequality and reduce the system credibility.

The technical challenge of deep neural networks is gathering interpretations, especially of complex models like EfficientNetB0. In the case of unspecified AI mechanisms, it is almost impossible to check if models pay attention to meaningful facial areas or simply encode gender, age, or racial bias. With AI penetrating the realm of everyday use, it is essential to make sure that automated age and gender recognition is fair, transparent, and interpretable in order to introduce responsible and ethical use.

Real-time, precise, and equitable demographic forecasting is invaluable to individualized technology, security and interactivity, though it must be verifiable that models are prejudice-free, rely on soundness, and be comprehensible to laymen. Such challenges should be tackled using better approaches, visualization that can be explained, and bias assessment to transform the field and make up on the promise of fair AI systems.

1.3 Motivation

The development of deep-learning has benefited well the field of facial image analysis and recognition in recent years. The high accuracy of models predicting the age and gender of individuals based on face photographs is supported by large datasets such as UTKFace, which are fast and provide high-performance. Nonetheless, the issue of fairness in all ages, genders and backgrounds remains a matter with several of these models. It is becoming clearer that it is useful to know what actually the model is doing, which face areas it is basing itself on, and whether it has some sort of bias. Tools exist that offer region-based explainability and bias analysis, allowing researchers to evaluate the predictions made by algorithms and fairness. This paper examines the extent of fairness and transparency of different deep learning models with respect to predicting age and gender. The comparison of model structures and their results on the UTKFace dataset must also illustrate future research opportunities in the field of age and gender prediction, which will not only help scientists in the AI community but also increase confidence in face analytics.

1.4 Significance of the Study

We discuss in the present work some of the significant issues in the automatic estimation of the age and gender of people via their facial images, considering the aspects of fairness and explainability as the two areas of research that are not well investigated. Judging a number of deep-learning models and considering the impacts of biases and respective parts of the face on predictions, this study can be used to point out practical and scientific conclusions.

Main implications include:

- **To AI/Computer vision researchers:** The article represents a credible substantiated foundation of deep-learning architectures using UTKFace dataset, with advantages and disadvantages. It also provides limited experimental evidence of explainability tools on regions and bias analysis on face attributes detection systems.
- **To real-life examples:** More accurate and interpretable age and gender recognition can minimize the mislabeling and error in decision-making, which benefits the community, social studies, and individualization systems.
- **To have reasonable and reliable technology:** This piece provides a guideline towards the creation of more reliable and fairer face analytics among developers, and provides a guideline to keep the ethical implications well observed by revealing the biases in demographic and model development.

All these findings can be applied in future to inform the future development of fair, explicable and practical face analysis models in both research and practice.

1.5 Research Questions

This study want to answer the question:

- What types of deep learning models (EfficientNetB0, MobileNetV2, ShuffleNetV2, custom CNN) are more effective in using the UTKFace dataset to predict age and gender based on the dataset?
- Are there any strong bias or differences in performance for age and gender on the models?

- How do region-based explanation tools (such as Grad-CAM), contribute to our interpretation and trust on prediction of those models?
- Can fairness analysis and interpretability techniques help us build fair? And interpretable age and gender prediction systems that can be really used in practice?

1.6 Research Objective

The aims of this study were as follows:

- We will implement and train several deep learning models (EfficientNetB0, MobileNetV2, ShuffleNetV2 and a custom CNN) for age and gender prediction extracting from the UTKFace dataset while strictly pre-processing to keep up with data quality.
- To evaluate and compare the accuracy, absolute error, and group-wise performance of these models in various age groups as well as gender using standard evaluation metrics.
- Bias in model predictions and demographic fairness was examined based on statistical tests and visualization methods.
- Through this approach, we can also utilize region-based explainability techniques (e.g., Grad-CAM) and study facial regions (Zone: Forehead, Midface, Jaw) that impact model predictions and make model outputs more interpretable

1.7 Research Scope and Limitations

This section highlights the limitations of the study and the limitations arising from the dataset, chosen techniques, and evaluation process.

1.7.1 Scope

- The studies in this group are on automatic gender and age estimation using the UTKFace dataset.
- The major models evaluated are EfficientNetB0, MobileNetV2, ShuffleNetV2 and plain CNN.
- Here, consider not only accuracy metrics (e.g., classification rate, mean absolute error), but also fairness/interpretablity metrics (region-based explanation, bias analysis).
- All experiments are conducted on publicly accessible datasets of faces which can readily be applied to by others for result reproducibility.

1.7.2 Limitations

- Model selection: We compared only four deep learning models in this study. Performance could be different between other architectures.
- Dataset coverage: The conclusions are based on the only UTKFace dataset. For the reason, it might limit the generalization to other facial datasets or tasks.
- Hardware: Experiments were performed on some hardware, results (runtime, speed) may vary on different environments.
- Testing in real-life examples: This work does not contain direct spread, while model and bias analysis was fulfill .

1.8 Thesis Organization

This article covers five chapters:

Chapter 1 discusses the background, research problems, motivation, significance, questions, objectives, scope and constraints.

In Chapter 2, we look at the literature on age and gender detection, bias issues in facial analytics, deep learning techniques for facial analysis.

Chapter 3 shows in detail the research methodology: UTKFace data set, data preprocessing, model architectures, training, metrics for evaluation and techniques to mitigate bias.

Chapter 4 presents the experimental results, compares model performance, explains in-depth analysis of bias, and interpreting model prediction explanations.

Chapter 5 is ending it with a summary of findings, contributions made or implied from these results and suggestions for future work are needed.

CHAPTER 2

LITERATURE REVIEW

2.1 Related Works

Age and gender prediction from face images has become an important problem in computer vision because of its use in security, marketing, health, and many other fields. The development of machine learning (ML) and deep learning (DL) has transformed the way of prediction. That holding the promise for efficient and effective outcomes. In this chapter, some methodologies varying from traditional machine learning techniques, convolutional neural networks (CNNs), to transfer learning approaches, and their strengths and limitations in age, gender prediction, bias analysis and XAI are explored.

Facial image based age and gender prediction Automatic age and gender prediction was first proposed by using hand-crafted features and traditional classifiers. Initial studies have been based on the descriptors such as Local Binary Patterns (LBP), Principal Component Analysis (PCA), and Support Vector Machines (SVM) to encode facial representations, which performed well in the confined environment but had shown weaknesses in diverse real-life conditions (Dey et al.,2024). Additionally, these traditional methods frequently involved heavy manual work in terms of extracting feature and were challenged by their inability to be resistant to pose, illumination, occlusion, and demographic variations (Rajiv Kumar et al., 2024).

The emergence of deep learning and, in particular, Convolutional Neural Networks

(CNNs) meant that it was now possible to extract these features automatically, and models learned hierarchical representations of faces directly based on image data (Hamza et al., 2025). By demonstrating that even a basic CNN can be more effective than previous age and gender estimation algorithms in unconstrained conditions,(Levi et al., 2015) revealed the power of data-driven learning (Levi et al., 2015).

The newest research compared VGG16, ResNet50, and EfficientNetB0 architectures and concluded that deeper and transfer-learned models yield even better prediction reliability, especially with the involvement of data augmentation and normalization techniques (Kumar et al., 2024). The lightweight models (MobileNetV2) can also be deployed in real-time at a low cost of computation (Hamza et al., 2025).

The dataset and preprocessing trend contains data about Cocaine and Alcohol Abuse Statistics in the United States in 2007-2016.

Research papers always underline the significance of thorough preprocessing a face detection, face alignment, normalization, and Augmentation to be robust in response to image quality, pose, and lighting variations (Dey et al., 2024). Such common datasets as UTKFace are commonly utilized to train and evaluate the approaches in various demographic and lighting situations (Kumar et al., 2024).

Although the gender accuracy was high, as well as the competitive age classification are high, researchers have reported some outstanding issues associated with the demographic bias, occlusion (e.g., veiled/masked faces), and generalization to uncontrolled in-the-wild image (Levi et al., 2015; Jawad Rasheed et al., 2022). (Rasheed et al. 2022) emphasized the necessity of subgroup-specific assessment and architecture that is aware of fairness due to the effects of race, gender, and age group diversity on predictive.

The use of explainable artificial intelligence (XAI), including Grad-CAM and saliency mapping, is becoming a common practice in age and gender models studies. They can be used to visualize salient body parts of the face affecting the model choices, which is essential in the model auditing and detecting bias (Dwivedi et al., 2023). It has been proposed that Ensemble XAI methods, which are a combination of several explainability tools, will offer more stable and trustworthy diagnostics (Dwivedi et al., 2023).

2.2 Research Gap

Most research till now on age and gender prediction from facial images uses common deep learning models. They focusing on simple accuracy and error rates. And this method still has many unresolved problems. In particular, very few studies have addressed the fairness or bias of these models through different genders, age groups, or races, let alone done so in line with the UTKFace database. In addition, much of the research so far has not really looked at why certain demographically-bound groups might be excluded from models for no reason at all. Some researchers have begun to use explainable AI methods, but they only present a small number heat maps typically. They haven't yet analyzed which specific facial features are important for the models at all when it comes to predicting age groups and genders. There are very few studies that connect feature importance with bias. All of the previous works draw on the complete UTKFace data set. But none make any effort to think through the implications of using a balanced, a smaller sample. How data balance might affect bias and model fairness that still now needs investigating. The lack of literature includes not only that there has been no comparison of several lightweight models—EfficientNetB0, MobileNetV2 and ShuffleNetV2—together in one framework, where traditional metrics are integrated with bias analysis. In general the results marks accuracy rather than bias or explain ability. Finally, there simply isn't enough research that brings all of these factors together. Where a model is superior and more appropriate than another in practice becomes much harder to tell. Model performance, spread bias analysis and explanations that region-based importance are all necessary for age and gender prediction. Evidence from datasets which are both large and sampled should be provided to support these three aspects.

CHAPTER 3

METHODOLOGY

Age/gender prediction is needed as fast and precisely as possible by many applications, like security, user profiling, and demographic analysis. Deep learning models have been capable of analyzing facial images promptly, accurately, and automatically in the past few years. This paper will particularly target two uses of EfficientNet-B0, namely, age and gender prediction. It uses UTKFace data of subjects as well as additional tests in bias and explainable artificial intelligence results.

The model suggested has a set practice, step by step:

Step 1: Prepare the Dataset

Any images are scrutinized, filtered, and passed through a scrutiny with Excel and Python scripts. In fairness analysis, a random balanced sample of 7,000 pictures is developed. The next step is that each image is downsized to 128x128 pixels and finally normalized to serve as input into the model.

Step 2: Skills in Data Splitting and Augmentation.

The full set with all the data and the random sample of 7,000 images are separated into training and testing sets (80/20). The augmentation techniques, which include rotating, flipping, and changing of brightness, are also used in order to enhance the strength of the model.

Step 3: Model building and training:

EfficientNet-B0 is taken as the main backbone. This architecture has two branch. One of them is age regression: to predict age.
The other is gender detection: predicting whether one is male or female.

The model used in the case of derivative learning uses age prediction loss (mean absolute error, MAE), a loss used in gender classification (binary cross-entropy), and early stopping and dropout as means to avoid overfitting.
Depending on the size and complexity of the dataset, the model is trained in 50-200 epochs. The model is checked in terms of precision, recall, and F1 score at the end of every epoch.

Step 4: Inspection & Bias Analysis.

At the end of the training, the model is evaluated in terms of its possible bias: age (MAE) and gender (accuracy, F1 score, true positive rate). With massive and balanced samples, the bias analysis checks the fairness by comparing the findings of various age groups and genders.

Step 5: Visualization XAI:

GradCAM is used in testing samples to visualize the parts of the face on which the model depends for age and gender prediction. The critical areas are considered and compared to the outcomes of bias analysis.

Step 6: Result and Conclusion Reporting.

All findings are summarized in diagrams and tables—that is, accuracy, MAE, bias analysis, and XAI regional interpretations. This information is applied to highlight what succeeded in addition to the limitations of the existing model.

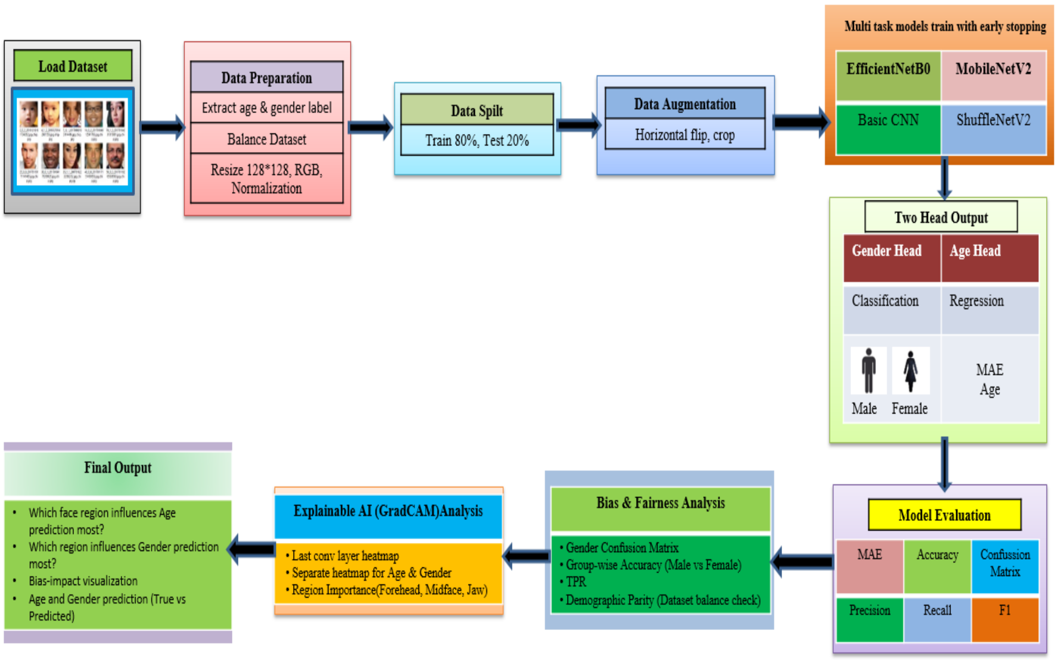


Figure 2.2.1 Workflow Diagram

3.1 Data Collection

The dataset is collected from Kaggle. It was created by Zhifei Zhang, Yang Song and Hairong Qi - a large dataset built for helping ML and DL researchers to build and evaluate models for age, gender and race detection and classification. It was created By using advanced computer vision, deep learning and automatic face detection techniques from worldwide. It contains over 23000 face images. Each image is labeled with person's real age, gender and race for example: 25_0_2_201701161745.jpg where, [age] _ [gender] _ [race] _ timestamp[] .jpg. It contains -

Gender groups : Male, Female.

Table 6.1 Gender groups:

Label	Gender
0	Male
1	Female

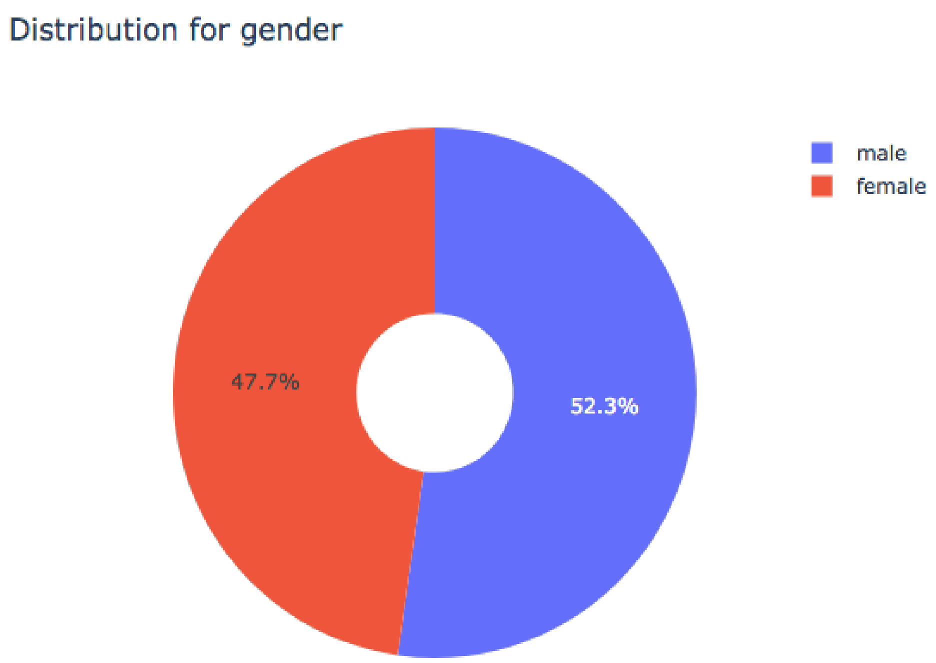


Figure 3.1.1 Class Distribution

Age range : 0-116 years.

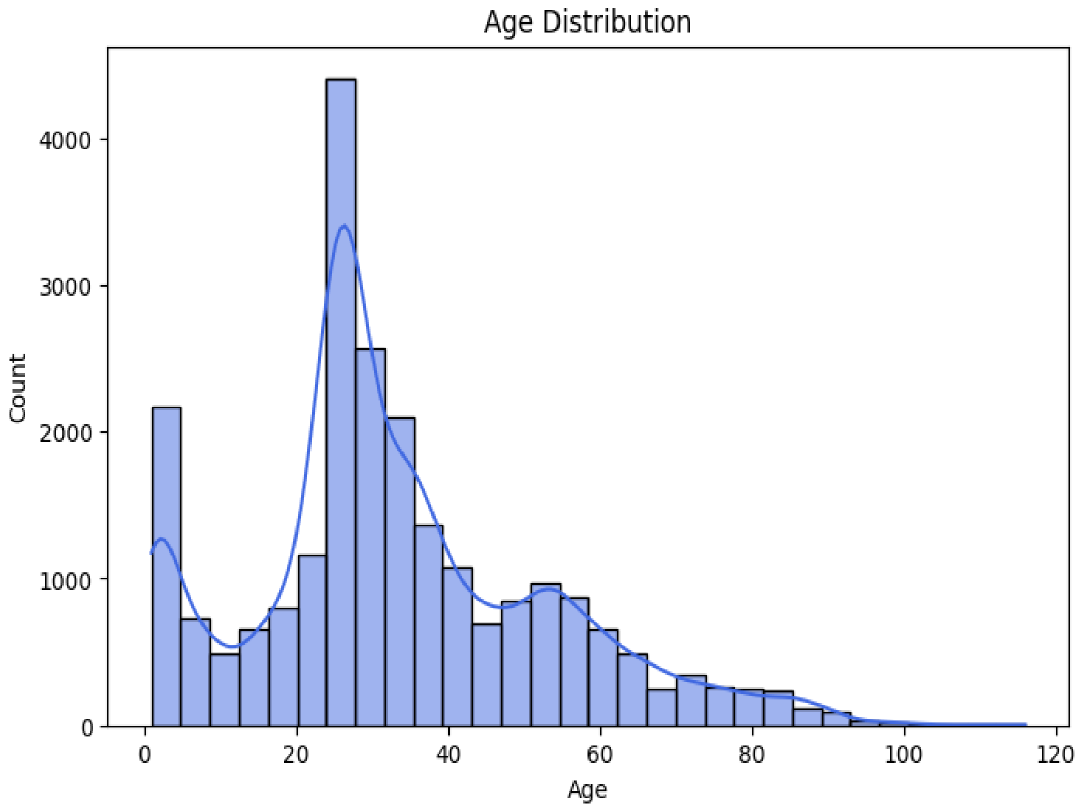


Figure 3.1.2 Age Distribution

Races: 5 races- white, black, Asian, Indian, others(mixed).

Table 6.2 Race Label:

Label	Race
0	white
1	black
2	Asian
3	Indian,
4	others(mixed).

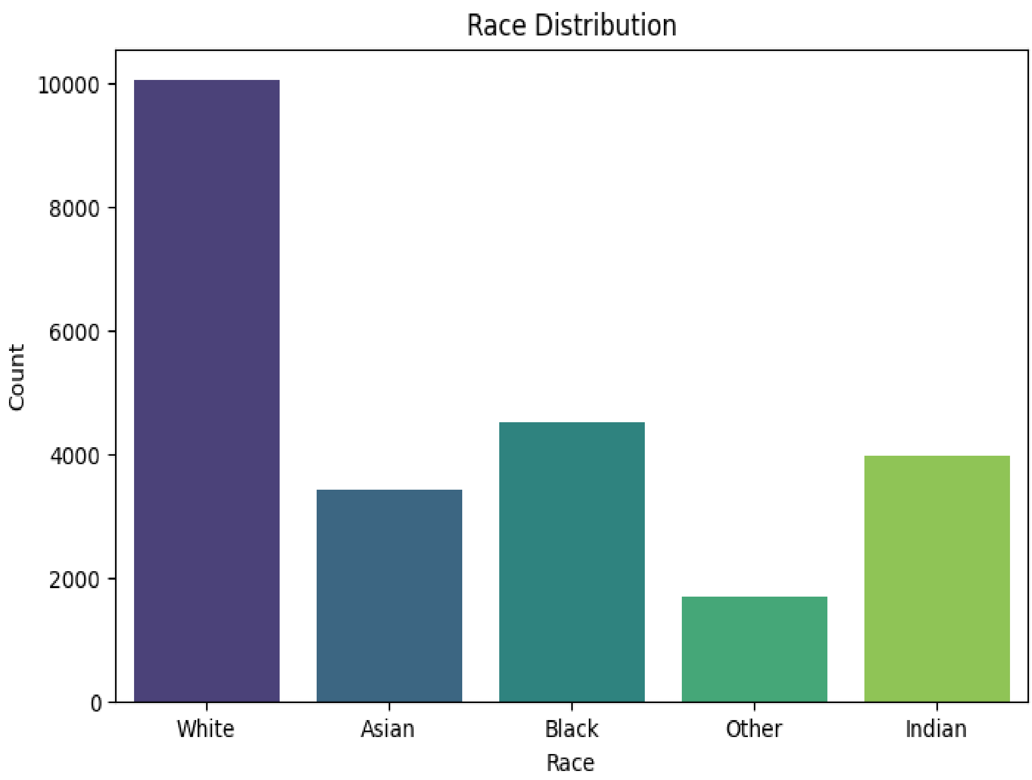


Figure 3.1.3 Race Distribution.

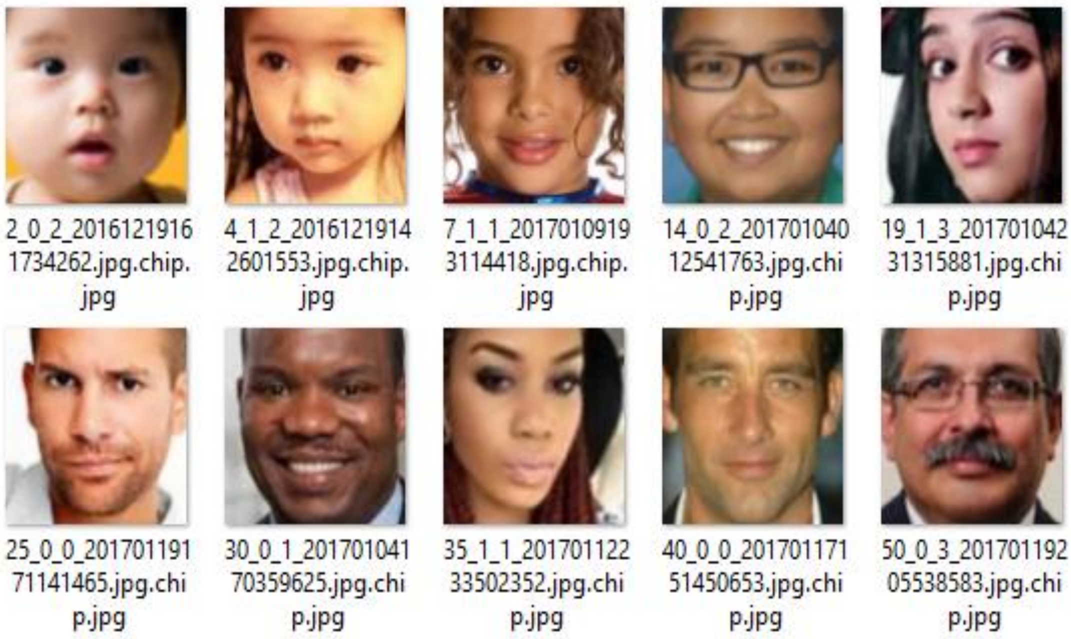


Figure 3.1.4 Sample of dataset

3.2 Data Preprocessing

3.2.1 Data Cleaning and study

Remove duplicate, corrupted or unlabeled image file using Excel and Python to ensure good quality input file. For fairness take 7000 images that was leveled.

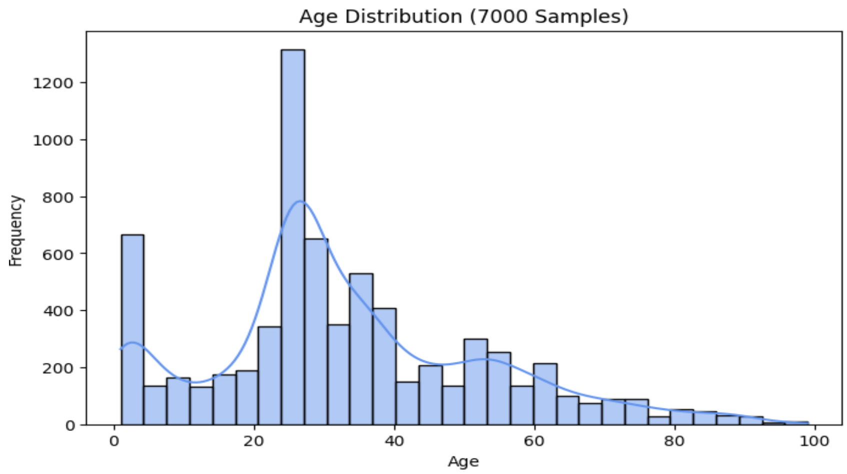


Figure 3.2.1.1 Age Distribution in 7000 samples

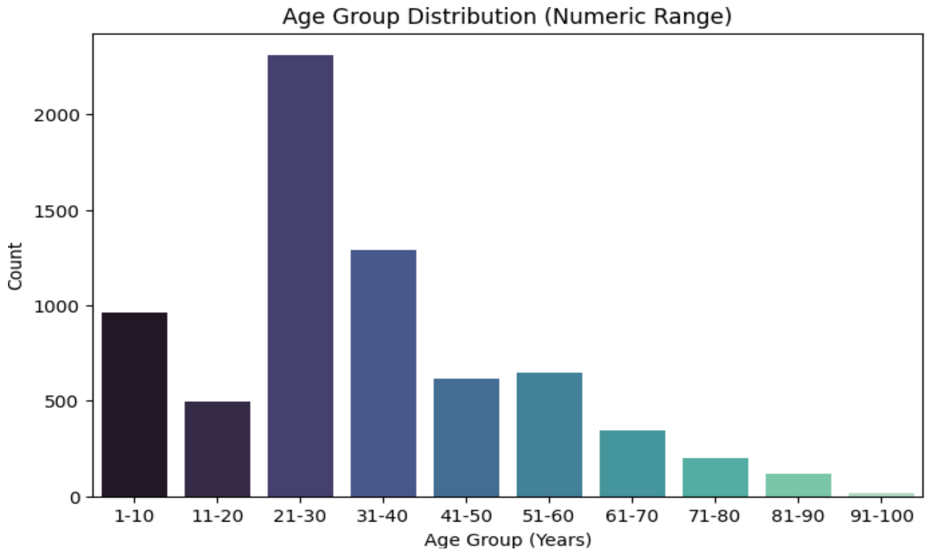


Figure 3.2.1.2 Age Distribution in 7000 samples

3.2.2 Data Splitting

We split the dataset in a ratio of 80:20. This is a common machine learning practice, where the dataset is divided into two subsets: training set (80%) used to train the model and prevent overfitting is used to fine-tune; testing set (20%) used to perform a final and unbiased evaluation of the model, to see how well the model performs on new data.

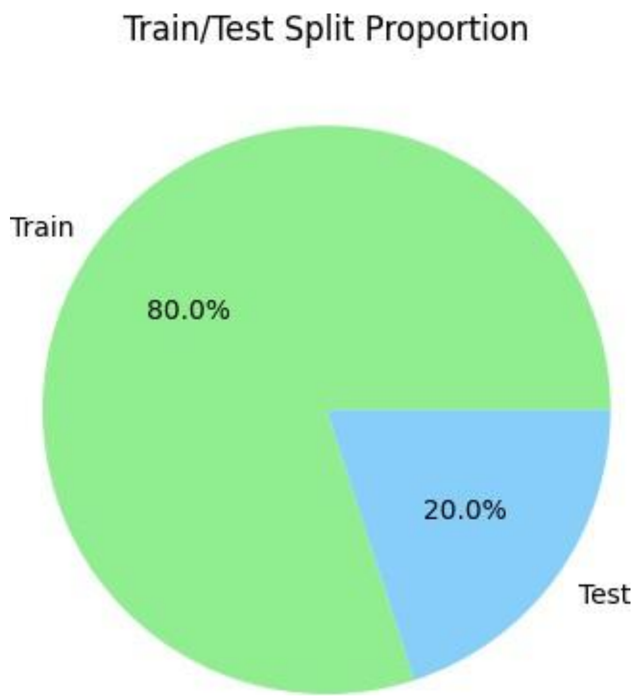


Figure 3.2.2 Train-Test Split pie-chart

3.2.3 Resizing:

Each image has been cropped to a square shape, preserving important areas. Each image has been resized to 128 X 128 pixels for all model's expected input size.

3.2.4 Normalization:

Image pixel values scaled to the range, dividing by 255. That helps the model to effective learn.

3.2.5 Data Augmentation:

Applied some techniques like horizontal flip rotation and adjust brightness during training to reduce overfitting and increase data diversity.

3.2.6 Label Encoding:

Kept age labels are in continuous values for regression On the other hand, for classification, gender labels are as like as binary values (0 for female and 1 for male).

3.2.7 Parameters and Hyperparameters:

During our works we use same parameters and hyperparameters (some different) both my proposed dual mode/hybrid model (**EfficientNetB0)** and compared models (MobileNetV2**,** ShuffleNetV2 ,Custom CNN) that are given the table.

Table 6.3 Parameters and Hyperparameters:

	EfficientNetB0 (proposed)	**MobileNetV2**	**ShuffleNetV2**	**Custom CNN**
Backbone	EfficientNetB0	MobileNetV2	ShuffleNetV2	Custom CNN
Input Size	128×128×3	128×128×3	128×128×3	128×128×3
Batch Size	64	64	64	64
Learning Rate	0.0002	0.0002	0.0002	0.0002
Optimizer	Adam	Adam	Adam	Adam
Epochs (Early Stopping)	50-200(patience 16)	50 - 200(patience 12)	50 - 200(patience 12)	50 - 200(patience 12)
Loss Functions / Weights	MAE (age,3.2) CCE(gender,1)	MAE (age,3.2) CCE(gender,1)	MAE (age,3.2) CCE(gender,1)	MAE (age,3.2) CCE(gender,1)
Dropout	0.5	0.5	0.5	0.5
L2 Regularization	0.01	0.01	0.01	0.01
Augmentation	Random Horizontal flipping	Random Horizontal flipping	Random Horizontal flipping	Random Horizontal flipping
Train/Test Split	80/20	80/20	80/20	80/20

3.3 Models

3.3.1 EfficientNetB0

EfficientNetB0 is a high-performing convolutional neural network (CNN) and is entirely about picture recognition. It was designed a balance system and it was both more accurate with less parameters and less processing power. EfficientNetB0 does not merely make any one of these (depth, width or resolution) bigger, but scales all three simultaneously with one scaling rule in a clean and well-organized manner. This is why it is efficient and performs well with devices of low computing power.

EfficientNetB0 belongs to CNN family which is based on the regular convolution layer, depthwise separable convolution layer and squeeze-and-excitation block. It constructs feature maps progressively and employs a channel-attention mechanism in order to emphasize most important information within each channel.

The major concept of EfficientNetB0 is the compound scaling strategy. Instead of merely sneaking the model size up on the model, this algorithm follows a set formula and scales depth (layers of the model), width (number of channels), and input size (size of an image) simultaneously. In this manner network would learn valuable features more efficiently without losing computations. EfficientNetB0 is mostly applied to image classification, face recognition, age regression, and other image projects that require a small yet powerful model.

Formula and Equations:

The original EfficientNetV2 compound scaling method is the basic concept, and it scales the network depth, width, and resolution together with a compound coefficient ϕ.

Depth (Number of Layers):

$$d = \alpha^{\phi} \tag{1}$$

Width (Number of Channels):

$$w = \beta^{\phi} \tag{2}$$

Resolution (Image Size):

$$r = \gamma^{\phi} \tag{3}$$

Where:

- Φ is a **global scaling factor** (user-defined).

- α, β, γ are **constants** determined by a small grid search on the baseline model, subject to the constraint: $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$ .This constraint ensures that for a larger ϕ the total FLOPS (computational cost) increases by roughly 2^6.

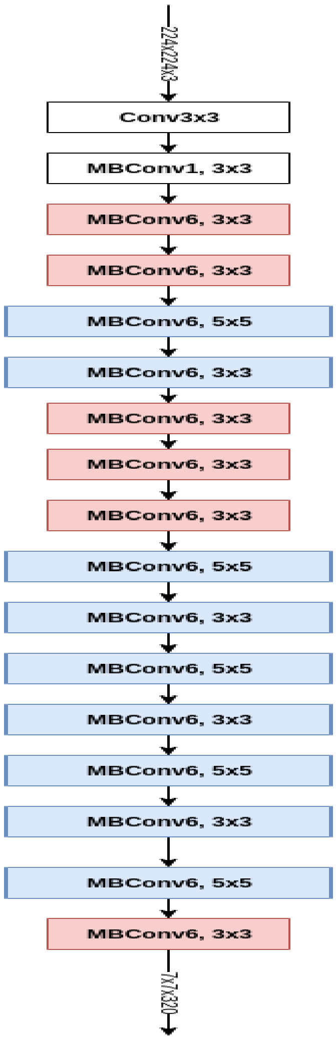


Figure 3.3.1 The architecture of EffecientNetV2 Model
(Taken from Amin et al., 2022)

3.3.2 MobileNetV2

MobileNetV2 is a small CNN model. This model is generally used in mobile and low-power devices. It is also portable. It seeks to minimize calculations and, as much as possible, maintain the accuracy. The model brings about two significant concepts, such as inverted residual blocks and linear bottlenecks. These minimize wasteful operations and assist the network in operating at a high speed without losing information. MobileNetV2 is a member of the CNNs that employ the depth wise separable convolution. Convolution is divided into two easy operations in this operation depth wise convolution and pointwise convolution. This design enables the model to be efficient and can operate on low-power hardware. The main concept of MobileNetV2 is to do the processing on features in a small bottleneck space and then expand the features to a larger dimension, apply depth wise convolution, and contract them to a smaller size once more. The process assists the model to learn improved patterns of features at a low cost of computation. MobileNetV2 is usually utilized in mobile applications such as face recognition, gender classification, age classification, object classification, and real-time image recognization. MobileNetV2 is usually utilized in mobile applications such as face recognition, gender classification, age classification, object classification, and real-time image recognition.

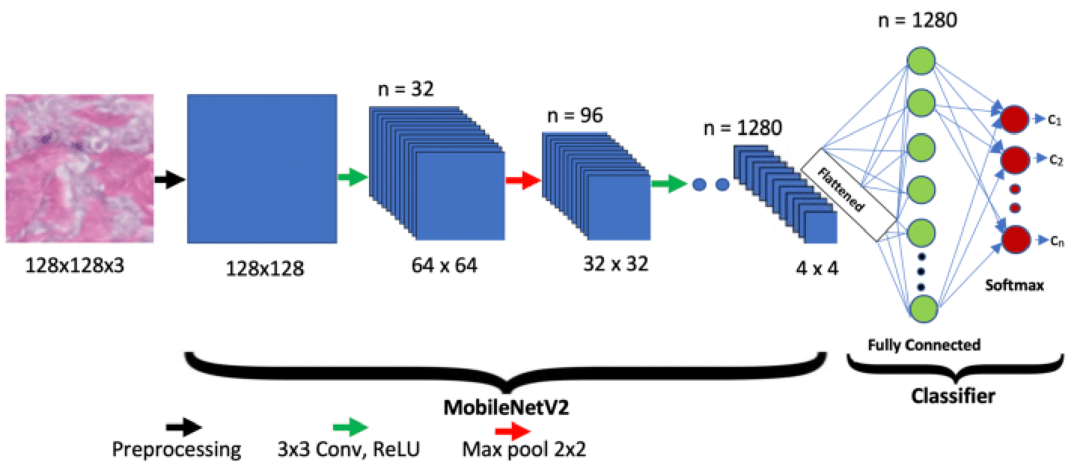


Figure 3.3.2 Diagram of MobileNetV2 Architecture.
(Taken from Akay et al., 2021)

3.3.3 ShuffleNetV2

This small convolutional neural network is called ShuffleNetV2, and it was designed to work extremely fast on mobile devices and other low-power devices. It is all about reducing the memory consumption and in fact accelerating the real world things as opposed to boasting about reduced FLOPs on paper. Its design is very simple and its operations are very well working on actual hardware.

It belongs to that category of CNNs channel split, channel shuffle and depth wise separable convolutions in order to reduce the work load. It is essentially cutting the channels in half, half of one of those through the channels in easy mode, then mixing and matching them to allow stuff to mix harmoniously. And then it evades the heavy stuff and keeps it exceptionally fast.

Individuals find themselves utilizing ShuffleNetV2 to identify faces, detect objects, and mobile vision app, as well as other real-time classification problems in which you require speed rather than accuracy. However, SSD has difficulty detecting small objects, especially in low-resolution feature maps. Its fixed box size and aspect ratio do not fit all objects well, which can reduce the accuracy of predictions.

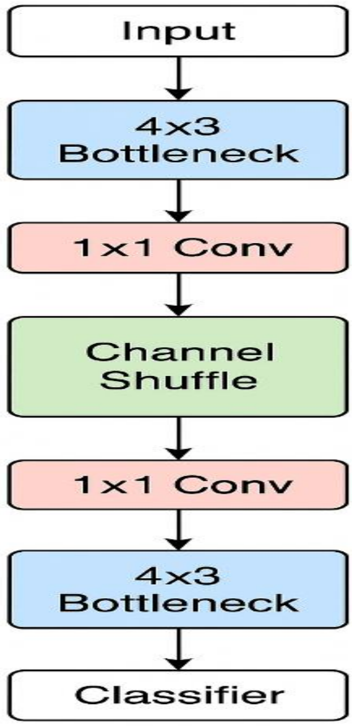


Figure 3.3.3 ShuffleNetV2 Model Architecture.

3.3.4 Custom CNN

One of such deep learning tools is the convolutional neural network, or CNN, which does a lot with images, such as classifying them, finding objects, and even identifying faces. They work out peaky information such as edges, colors, textures, and shapes themselves, and therefore, you do not need to pick features by hand. The CNN basically includes convolution layers to scan the image and extract more complex objects bit by bit.

CNNs belong to the entire neural network team and incorporate the convolution operations, pooling layers, activation functions, and fully connected layers. They do not scan the whole image at the same time but concentrate on small areas and draw feature maps with one layer at a time. The more abstract and more extravagant the patterns, the deeper you are.

CNNs are used in many more amazing things people do, such as medical scans, security cameras, robots, self-driving vehicles, and even facial recognition, such as gender or age.

Formula and Equations:

Convolution operation is a mathematical process that computes the dot product between a small learnable matrix that is known as the Kernel (or Filter) and a patch of the input image or feature map. The output feature map S at position (i, j) is calculated by:

$$S(i,j) = \sum_{m} (I * K)(i,j) \sum_{n} I(i-m, j-n)K(m,n) \quad (4)$$

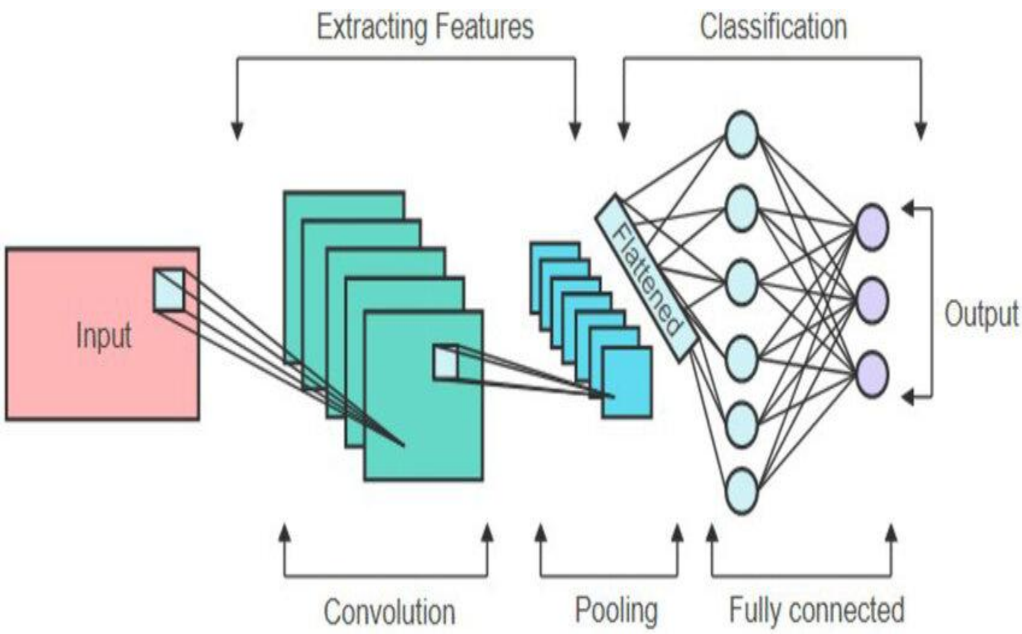


Figure 3.3.4 CNN model Architecture. (Taken from Ismail et al., 2023)

3.4 Model Evaluation Matrix

The metrics used for:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP+FN} \quad (6)$$

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{TN+FP} \quad (7)$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{FP+TN} \quad (8)$$

$$False\ Negative\ Rate\ (FNR) = \frac{FN}{FN+TP} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$F1 - Score = 2\times \frac{Precision\times Recall}{Precision+Recall} \quad (11)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y\, i - \hat{y}| \quad (12)$$

The percentage of Face images that are correctly classified among all evaluated images is called accuracy.

Precision measures the proportion of gender cases that are correctly predicted.

Recall refers to the model's ability to detect all true gender cases.

The F1-score is a balanced metric, calculated as the harmonic mean of precision and recall.

MAE measures the average magnitude of errors in a set of predictions, without considering their direction.

CHAPTER 4

RESULTS

4.1 Result Analysis

This chapter presents experimental results obtained by implementing various deep learning models for XAI based predicting age, gender and bias analysis. To ensure a comprehensive evaluation, four widely used object detection frameworks: EfficientNetB0, MobileNetV2, SuffelNetV2, and normal CNN are applied to the collected dataset. The performance of these models is systematically evaluated using standard evaluation metrics such as accuracy, precision, recall, and F1-score also determined the region importance (Zone: Forehead, Mid face, Jaw) and bias analysis. A comparative analysis is conducted to determine the relative strengths and weaknesses of each model to identify the most effective method for reliable for XAI-based predicting age, gender, bias analysis.

4.1.1 Proposed Model (EfficientNetB0)

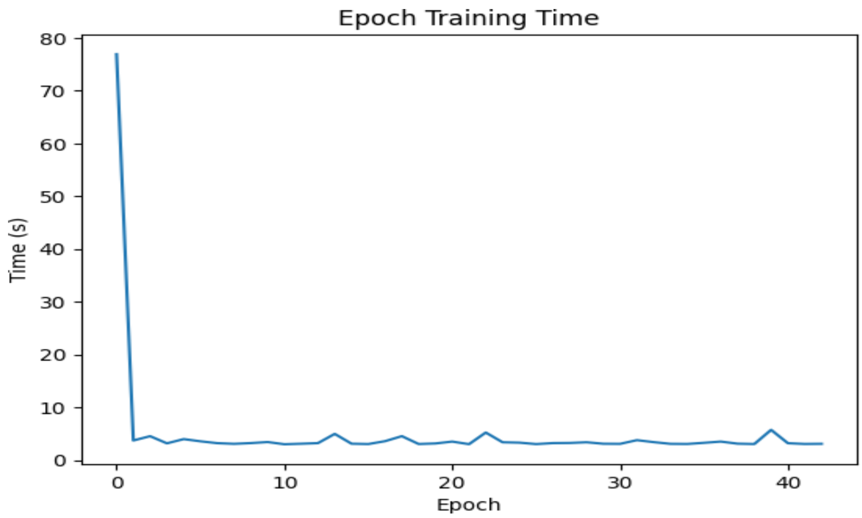


Figure 4.1.1 EfficentNetB0 Epoch Training Time Graph

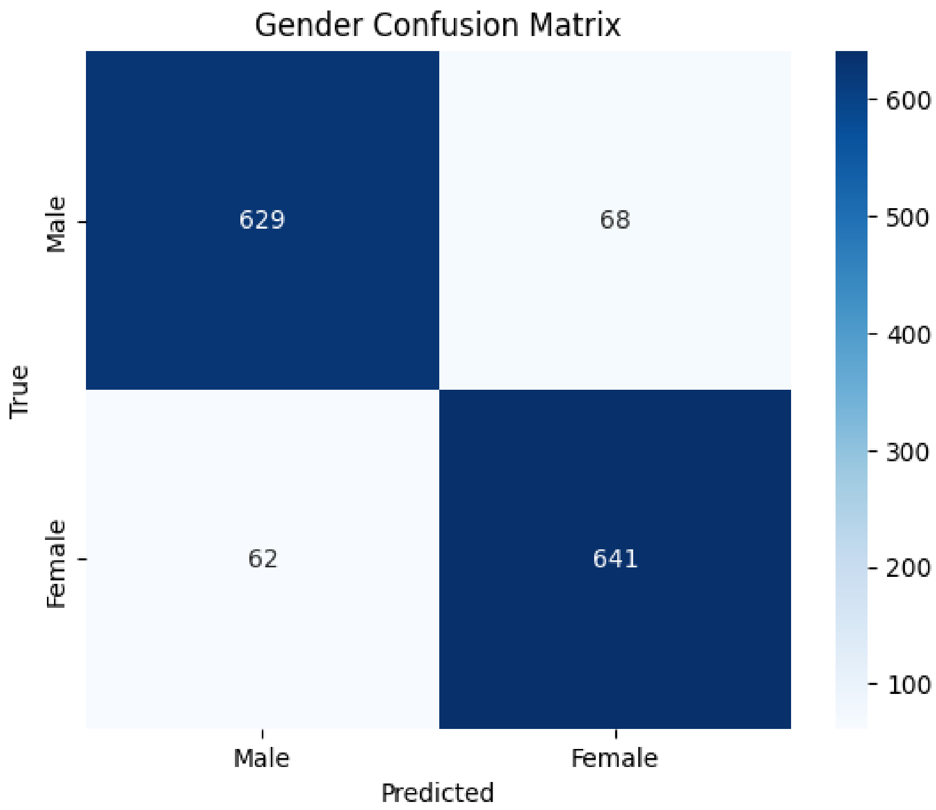


Figure 4.1.2 EfficentNetB0 Classification (for gender) Confusion Matrix

Table 6.4 EfficentNetB0 Model Gender Classification Report

Class	**TP**	**TN**	**FP**	**FN**	**TPR/ Recall**	**FPR**	**TNR Specificity**	**FNR**	**Accuracy**	**F1-Scotr**	**Precision**
Male	629	641	62	68	0.902	0.088	0.912	0.098	0.907	0.906	0.910
Female	641	629	68	62	0.912	0.098	0.902	0.088	0.907	0.908	0.904
Overall	641	629	68	62	0.912	0.098	0.902	0.088	0.907	0.908	0.904

Male MAE: 7.07
Female MAE: 8.37

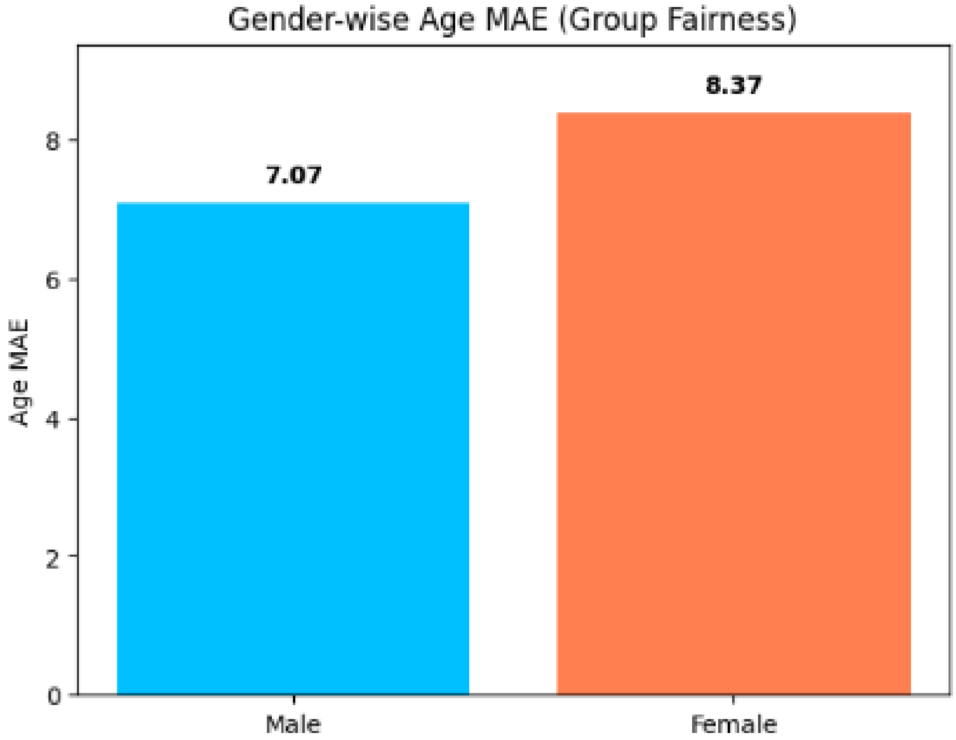


Figure 4.1.3 EfficentNetB0 Regression (MAE for age) chart

Table 6.5 EfficentNetB0 Model Age Regression Report:

Class	MAE
Male	7.07
Female	8.37
Overall	7.07

Table 6.6 EfficentNetB0 Model Gender Classification Demographic Parity Report:

Class	Parity
Male	49.8%
Female	50.2%

Table 6.7 EfficentNetB0 Model Zone Importance Report:

Important Zone	Gender Prediction(in avg)	Age Prediction(in avg)
Forehead	High (around 60%)	High (around 50%)
Midface	nan	nan
Jaw	nan	nan

The EfficientNetB0 model that I proposed has high overall classification accuracy of 90.7%, but with closer analysis of errors distribution. We can find that there are slight difference between False Negative Rate and False Positive Rate: FNR for female class is slightly less than FNR for male class (0.088 vs. 0.098), which means that there is a little bias in the model's ability to identify true female samples, while FPR is slightly less than that for male class (0.088 vs. 0.098).It meaning that there are fewer false positive .Critically, the age regression task reveals an extreme predictive bias and absence of Group Fairness in that the Mean Absolute Error (MAE) for females (8.37) is significantly higher - by 1.30 years - than the MAE for males (7.07). Furthermore, explainable AI (XAI) analysis shows a serious weakness. The model's decision-making relies too much on the forehead region (60% in gender, 50% in age prediction) and no weight is evident in the midface and jaw region. This hyper-localized focus makes the model more brittle and implies that the successful performance is precariously dependent on features that are extracted from one narrow zone of a facial region. For this model, may be needed more training data or improved feature learning.

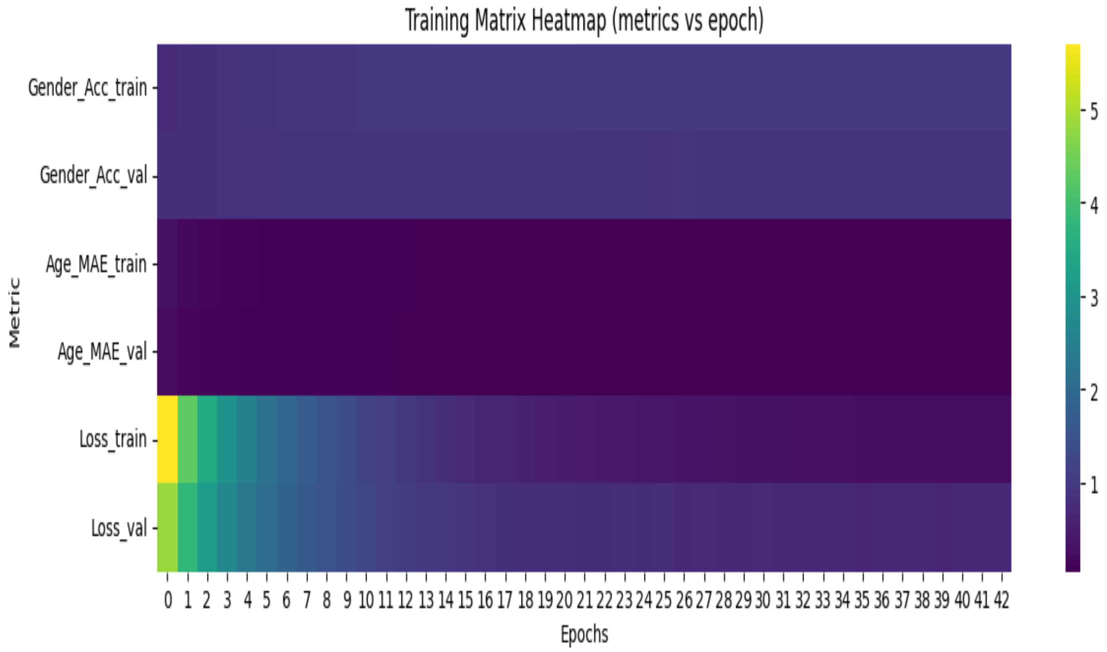


Figure 4.1.4 Training metrics heat map visualization of the EfficientNetB0 model

Epoch	Gender_Acc_train	Gender_Acc_val	Age_MAE_train	Age_MAE_val \
1	0.715893	0.792143	0.308910	0.221926
2	0.803214	0.821429	0.175680	0.129210
3	0.827321	0.839286	0.131462	0.112935
4	0.857321	0.850000	0.109691	0.096904
5	0.873214	0.862143	0.103042	0.087106

Figure 4.1.5 Training metrics (First few rows) of the EfficientNetB0 model

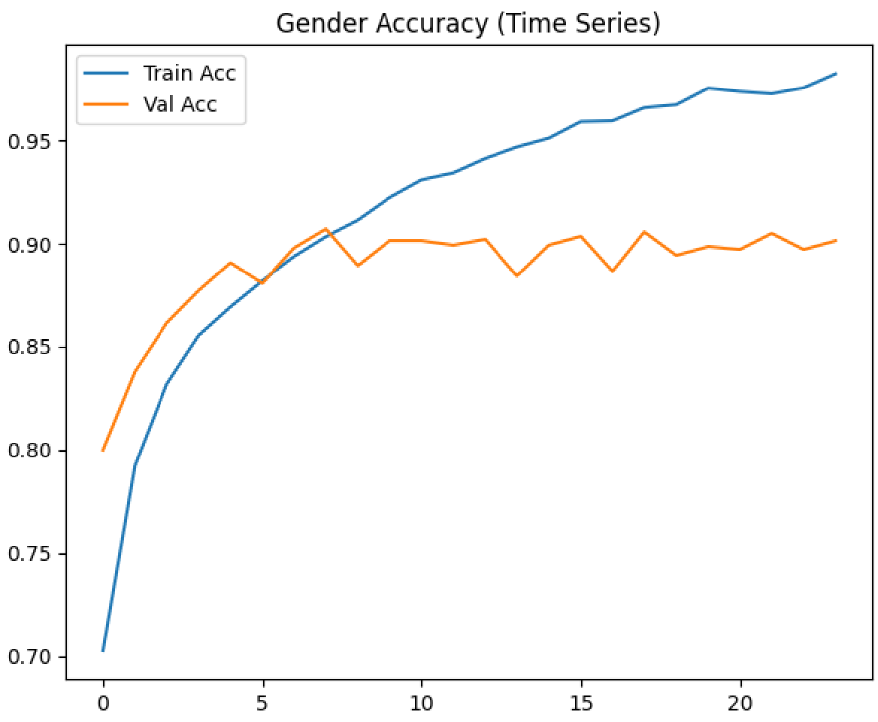


Figure 4.1.6 Gender Accuracy Time Series of the EfficientNetB0 model

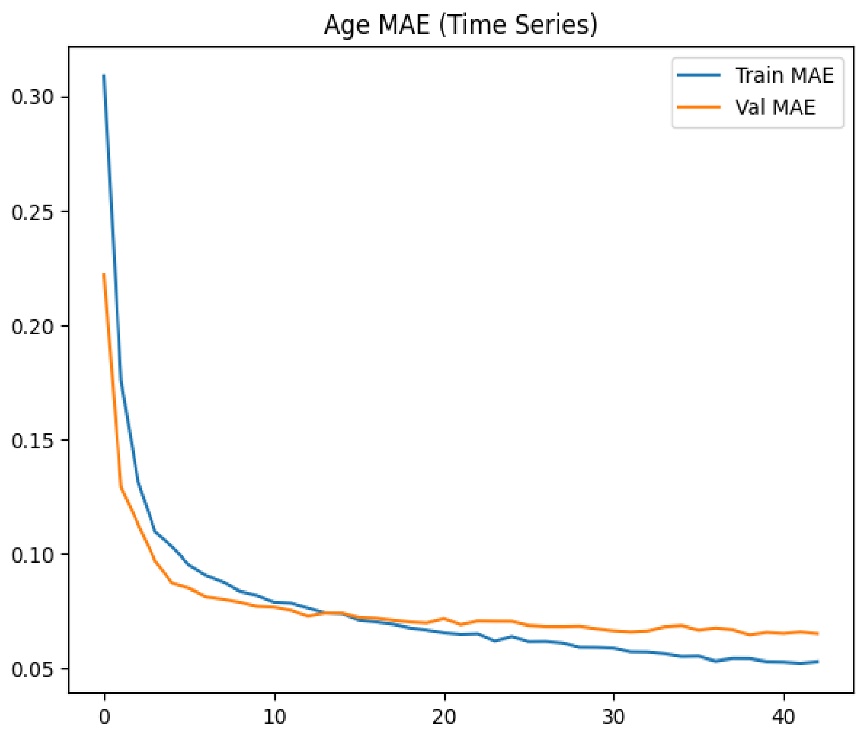


Figure 4.1.7 Age MAE Time Series of the EfficientNetB0 model

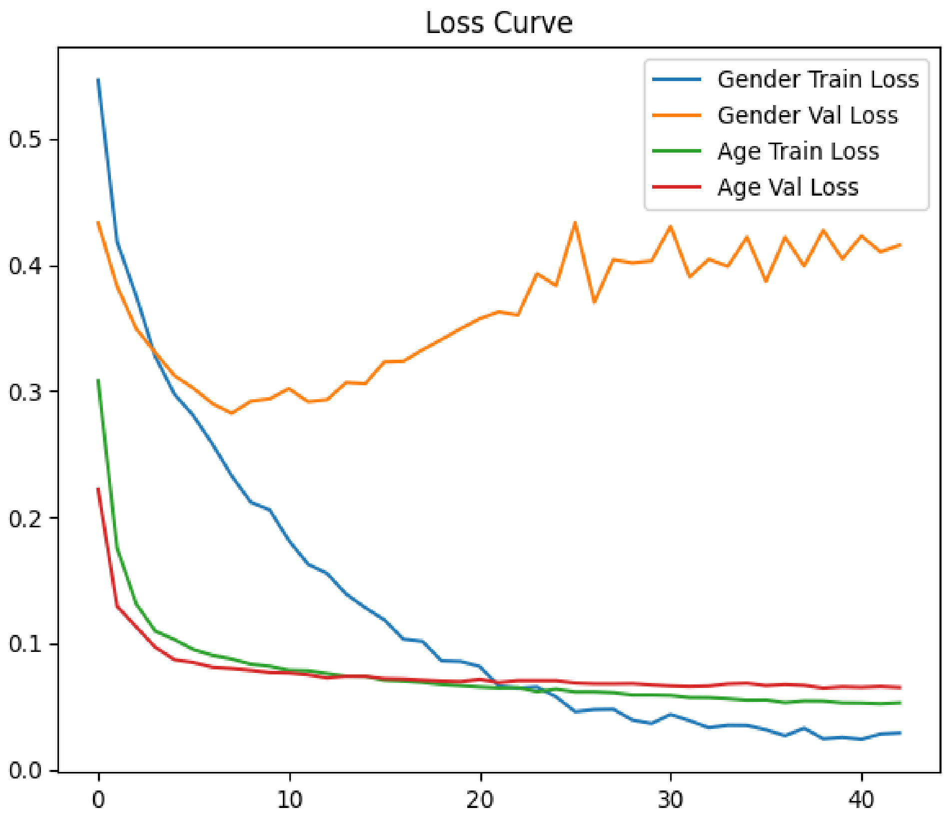


Figure 4.1.8 Loss Curve of the EfficientNetB0 model

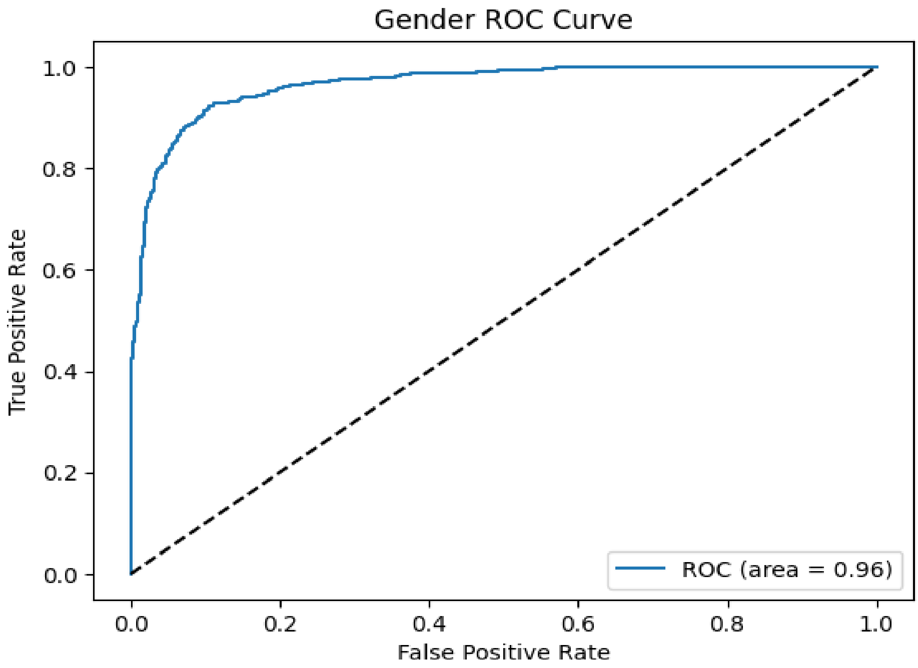


Figure 4.1.9 Gender ROC Curve of the EfficientNetB0 model

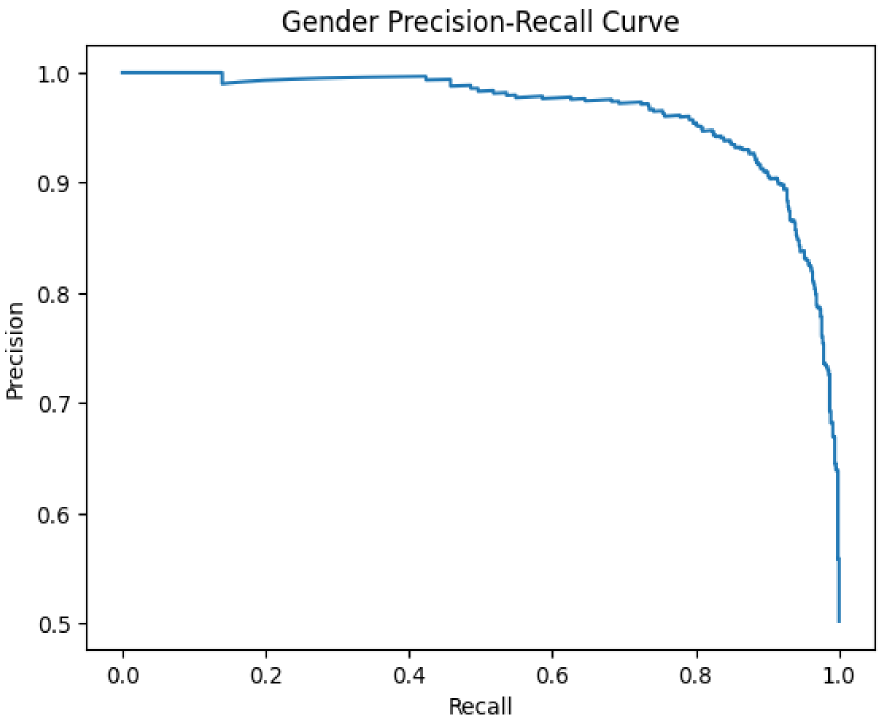


Figure 4.1.10 Gender PR Curve of the EfficientNetB0 model

4.1.2 MobileNetV2

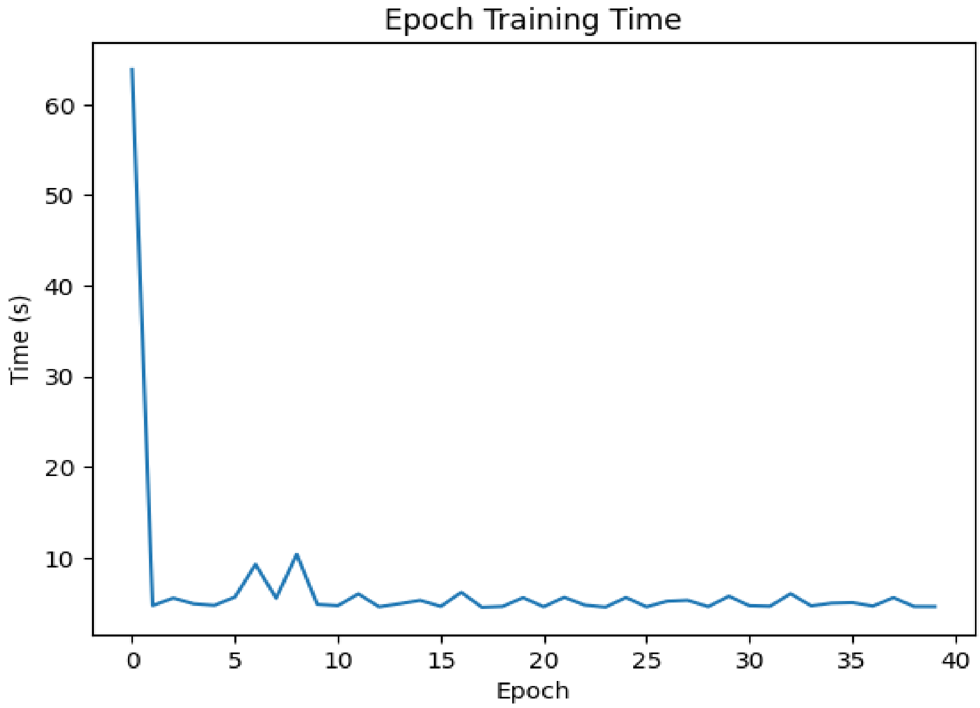


Figure 4.1.11 MobileNetV2 Epoch Training Time Graph

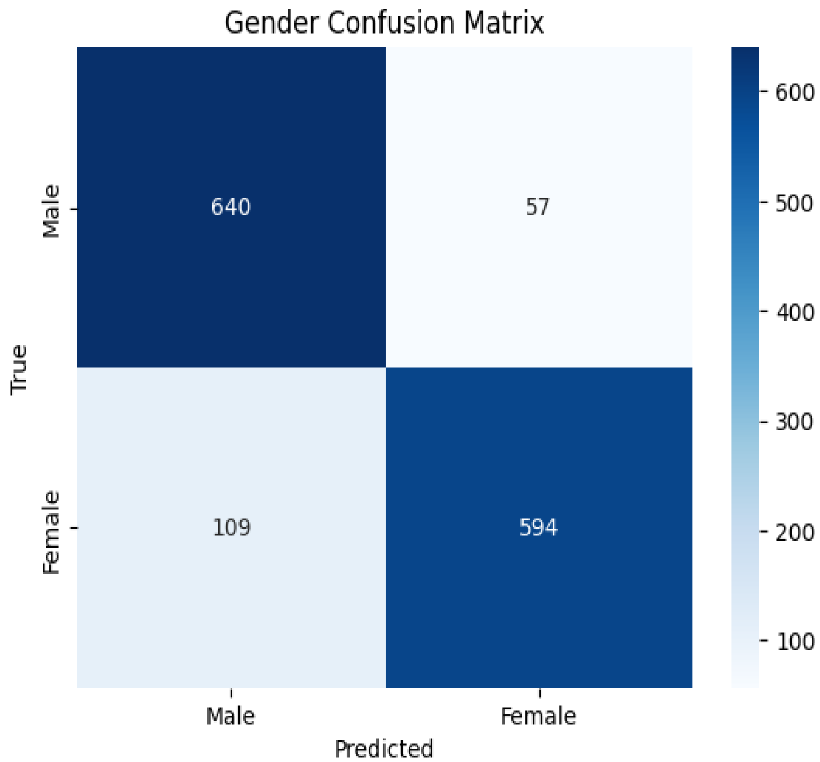


Figure 4.1.12 MobileNetV2 Classification (for gender) Confusion Matrix

Table 6.8 MobileNetV2 Model Gender Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy	F1-Score	Precision
Male	640	594	109	57	0.918	0.155	0.845	0.082	0.887	0.900	0.856
Female	594	640	57	109	0.845	0.082	0.918	0.155	0.887	0.880	0.912
Overall	640	594	57	109	0.882	0.118	0.882	0.118	0.887	0.890	0.918

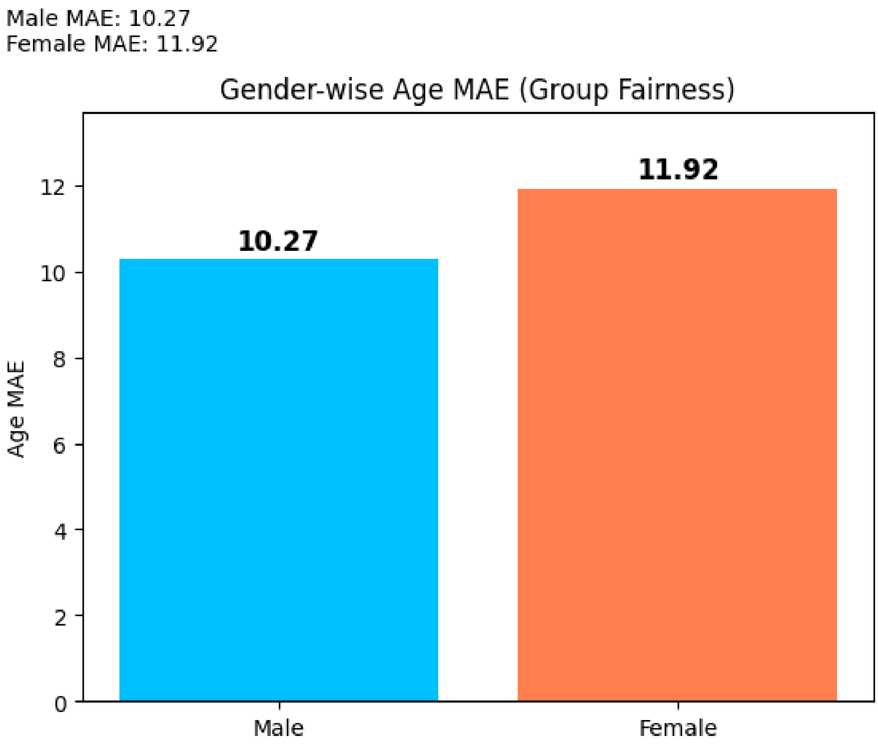


Figure 4.1.13 MobileNetV2 Regression (MAE for age) chart

Table 6.9 MobileNetV2 Model Age Regression Report:

Class	**MAE**
Male	10.27
Female	11.92
Overall	10.27

Table 6.10 MobileNetV2 Model Gender Classification Demographic Parity Report:

Class	**Parity**
Male	49.8%
Female	50.2%

Table 6.11 MobileNetV2 Model Zone Importance Report:

Important Zone	**Gender Prediction(in avg)**	**Age Prediction(in avg)**
Forehead	Very Low (around 3%)	Very Low (around 3%)
Midface	Low (around 13%)	Very Low (around 1.1%)
Jaw	nan	nan

Thus, I was examining the MobileNetV2 outputs and, frankly speaking, it is not as successful as the predecessor in general classification. It is in fact higher in Accuracy (0.887) and bigger in class imbalance, but that is because its F1-Score (0.900) and Recall (0.918) score higher in male class. The fact that makes me really annoyed is that it has better False Positive Rate (FPR) in the female class (0.098 vs. 0.155). And the age regression is really poor, it is highly biased with mean absolute error (MAE) of 11.92 in females and 10.27 in males a difference of 1.65 years, and worse in Group Fairness than EfficientNetB0. On the same way this model gives more parity in female classification (49.8%) than male classification (50.2%). On one hand, the report of XAI in MobileNetV2 reveals that it does not have one weakness. The importance of features is decentralized (only 3 percent is to the forehead and 13 percent to the midface) and thus there is no single bad spot, but rather the inner processes are less understandable. All in all the performance degrades of both regression and classification accuracy.

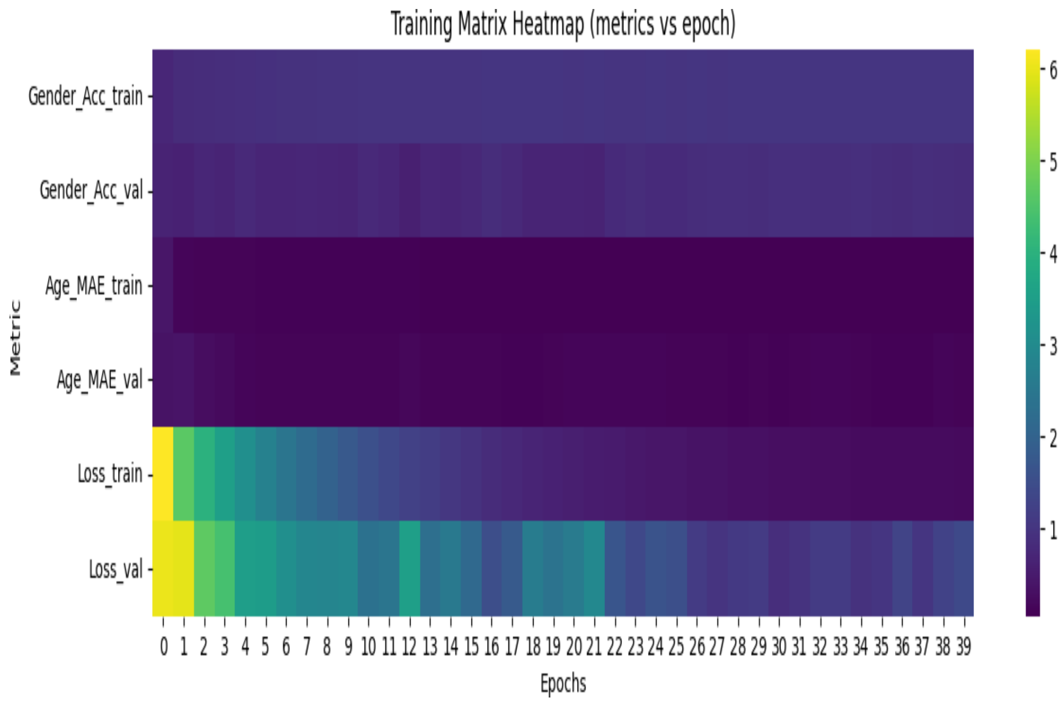


Figure 4.1.14 Training metrics heat map visualization of the MobileNetV2 model

	Epoch	Gender_Acc_train	Gender_Acc_val	Age_MAE_train	Age_MAE_val \
0	1	0.705893	0.637143	0.401422	0.354848
1	2	0.805000	0.611429	0.147224	0.380686
2	3	0.835714	0.720714	0.122075	0.264122
3	4	0.865536	0.673571	0.109467	0.207520
4	5	0.890000	0.754286	0.103420	0.127763

Figure 4.1.15 Training metrics (First few rows) of the MobileNetV2 model

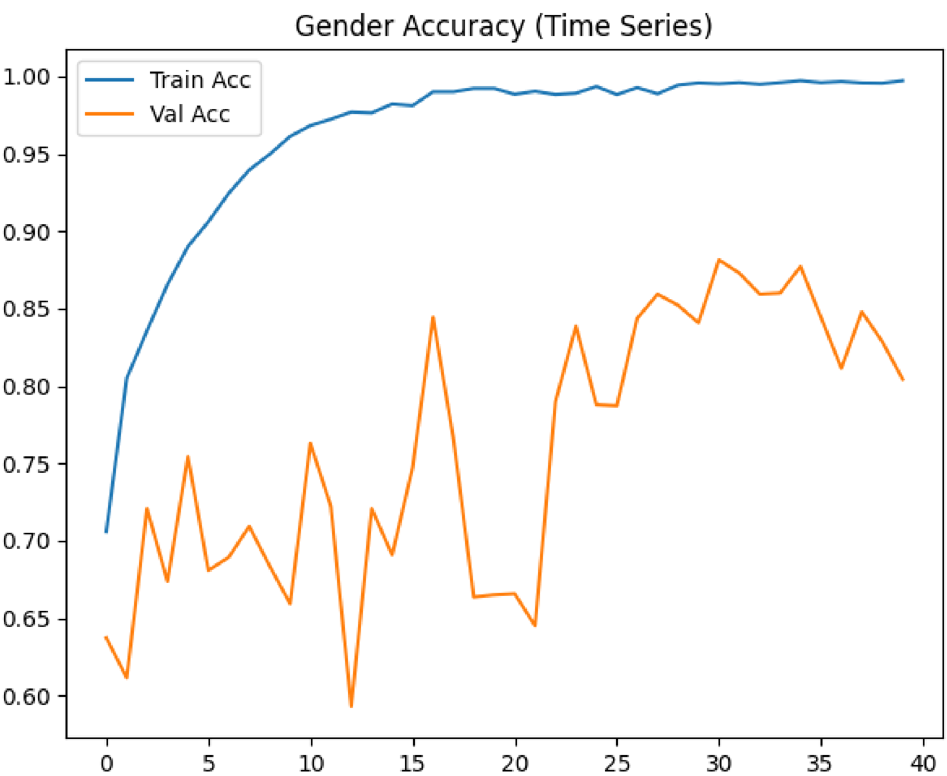


Figure 4.1.16 Gender Accuracy Time Series of the MobileNetV2 model

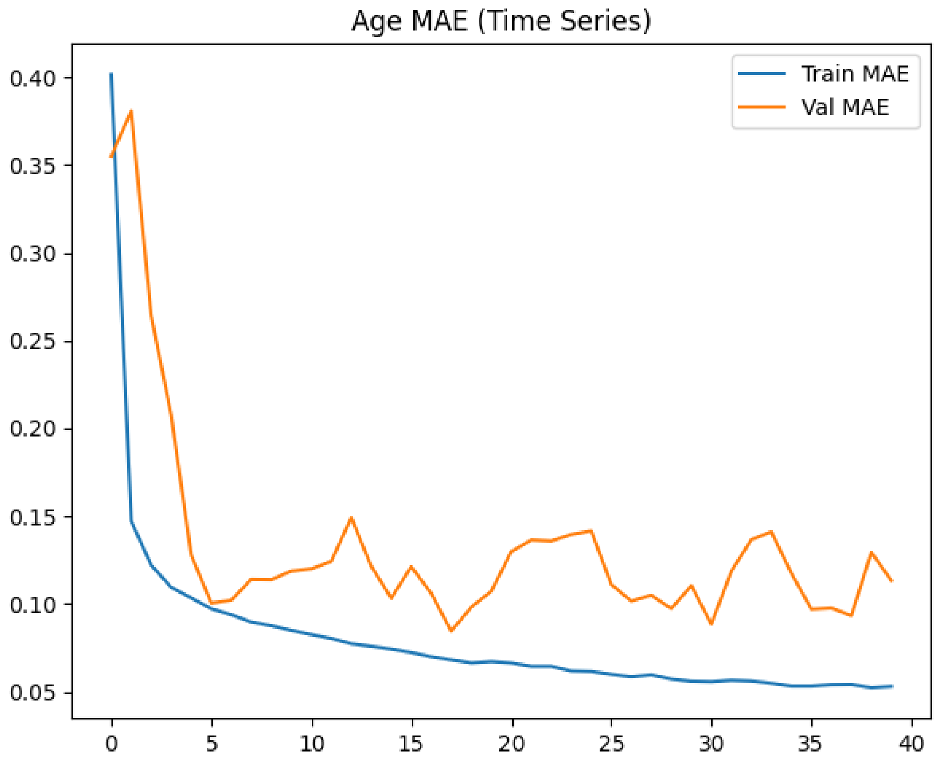


Figure 4.1.17 Age MAE Time Series of the MobileNetV2 model

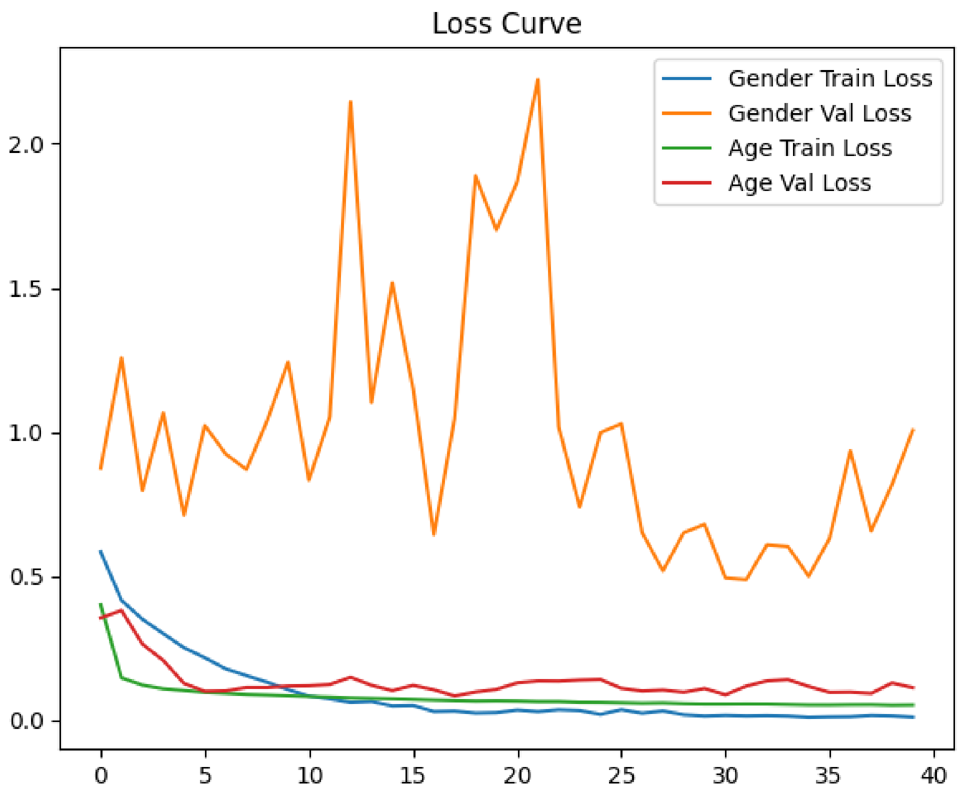


Figure 4.1.18 Loss Curve of the MobileNetV2 model

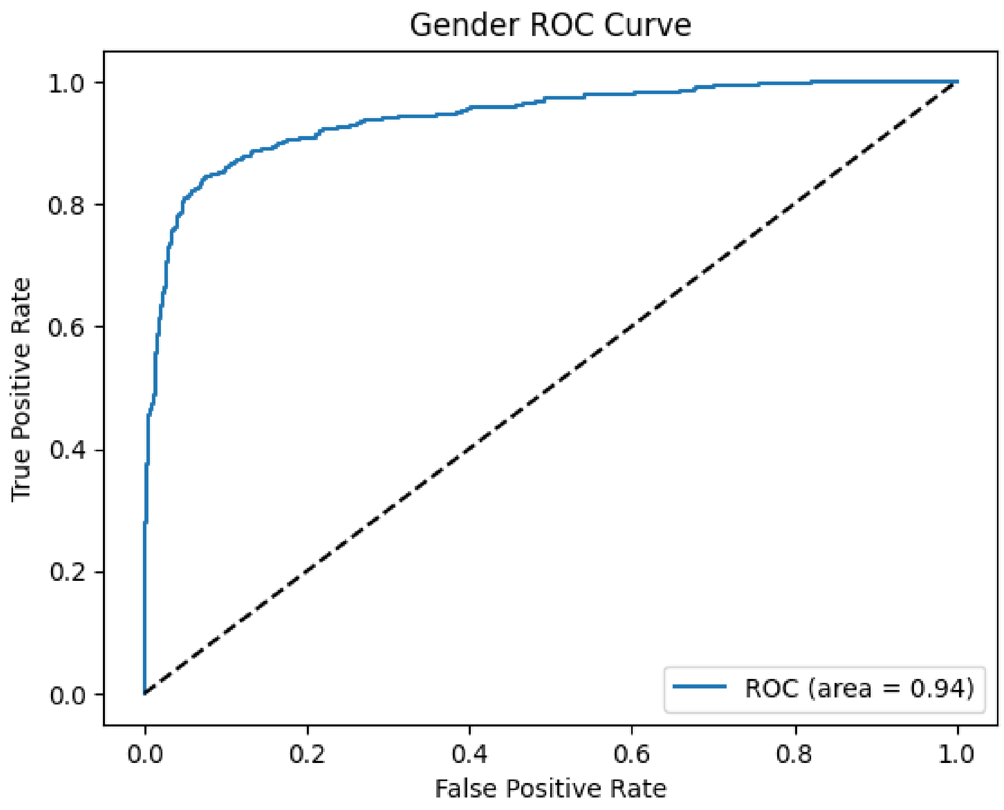


Figure 4.1.19 Gender ROC Curve of the MobileNetV2 model

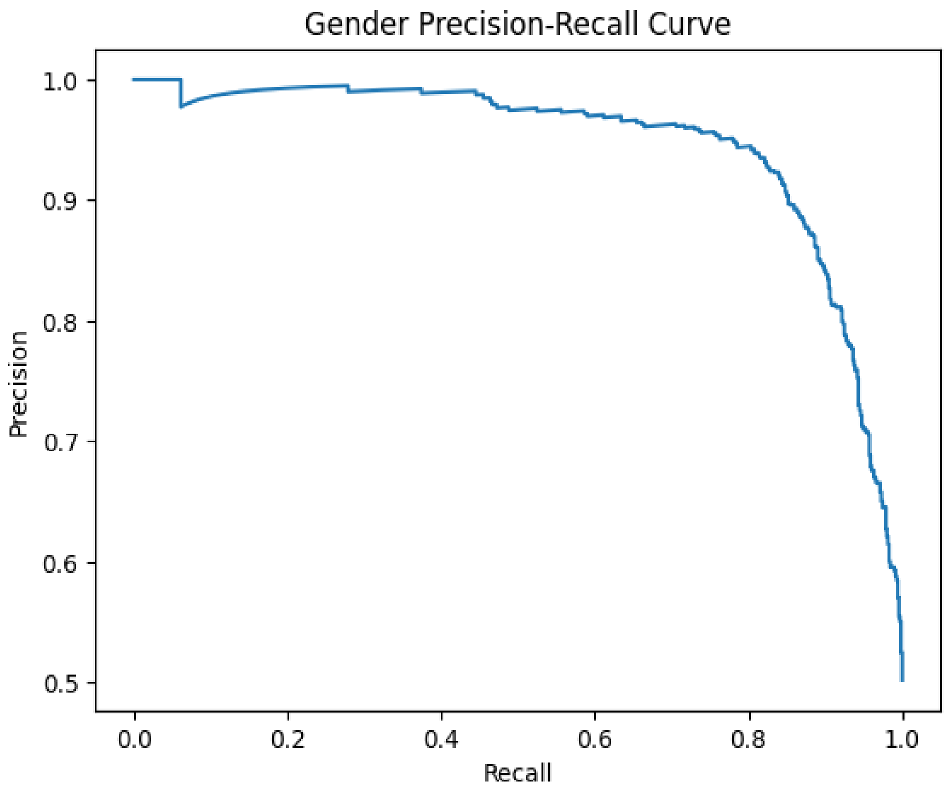


Figure 4.1.20 Gender PR Curve of the MobileNetV2 model

4.1.3 ShuffleNet V2

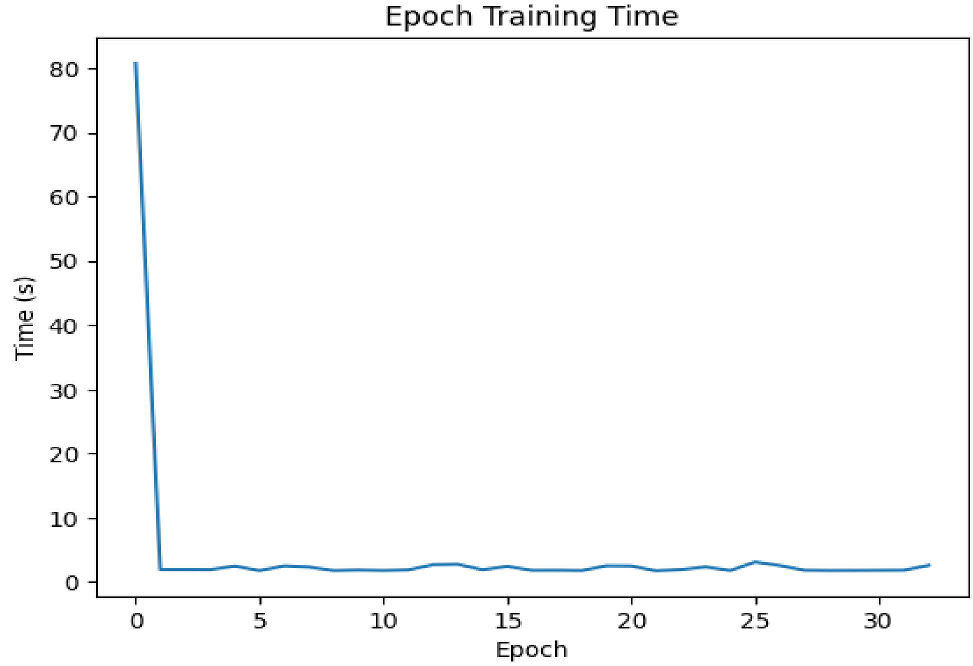


Figure 4.1.21 ShuffleNet V2 Epoch Training Time Graph

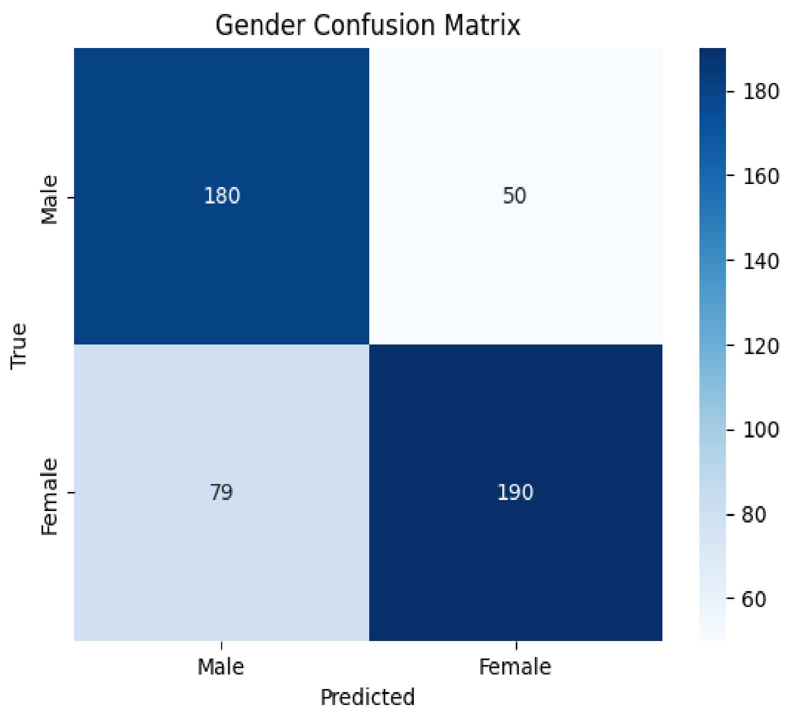


Figure 4.1.22 ShuffelNetV2 Classification (for gender) Confusion Matrix

Table 6.12 ShuffelNetV2 Model Gender Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specif icity	FNR	Accuracy	F1-Score	Precision
Male	180	190	79	50	0.783	0.293	0.707	0.217	0.741	0.749	0.695
Female	190	180	50	79	0.707	0.217	0.783	0.293	0.741	0.743	0.790
Overall	190	180	50	79	0.745	0.255	0.745	0.255	0.741	0.746	0.790

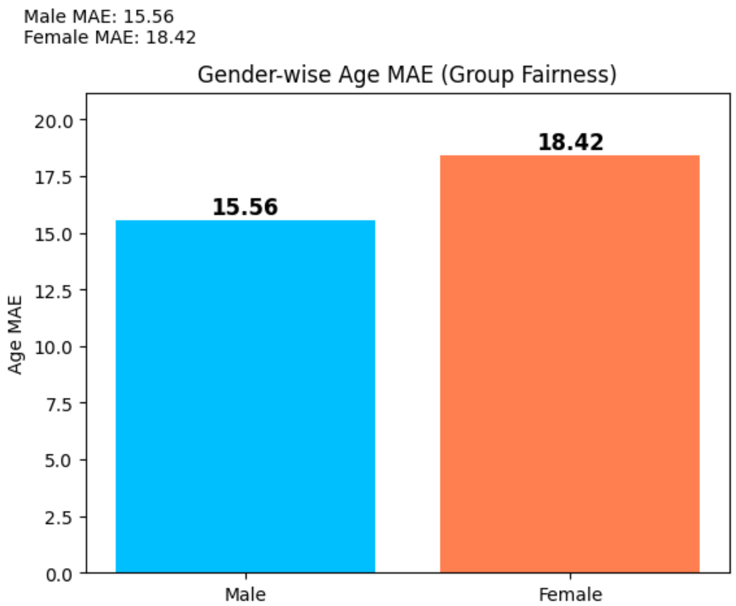


Figure 4.1.23 ShuffleNet V2 Regression (MAE for age) chart

Table 6.13 ShuffelNetV2 Model Age Regression Report:

Class	MAE
Male	15.56
Female	18.42
Overall	15.56

Table 6.14 ShuffleNet V2 Model Gender Classification Demographic Parity Report:

Class	Parity
Male	46.1%
Female	53.9%

Table 6.15 ShuffleNet V2 Model Zone Importance Report:

Important Zone	Gender Prediction(in avg 3)	Age Prediction(in avg 3)
Forehead	Mid (around 27%)	Very Low (around 8%)
Midface	nan	nan
Jaw	nan	nan

ShuffleNet V2 is much worse than EfficientNetB0, with only 0.741 accuracy. It appears to have problems, especially with the gender classification aspect, where it exhibits a strange trend of misconduct. Although it is accurate in the number of real males identified (recall of 0.783), it continues to produce a colossal number of male false positives (0.293 versus 0.217 of the female class). This, in practice, misclassifies many of the real females as male. As far as age prediction is concerned, the model is off by a good margin for both sexes. Both error rates are high; however, the female MAE is 18.42, and this is 2.86 years lower than the 15.56 MAE of males—the largest difference between all the models that we applied. So on top of mere accuracy, it is most unjust, particularly to women. In the same way, this model gives more parity in female classification (53.9%) than male classification (46.1%). The ShuffleNetV2 is in the middle of the bell curve with XAI. It primarily focuses on the forehead (60% gender importance), just as EfficientNetB0 does; however, it gives a medium gender importance to the forehead (27%) and very minor importance to age (only 8%). It simply disregards the midface and the jaw depicted by the NaN values. Consequently, the model does not actually perform well or make sense; it is more or less like an average, risk-based model in comparison to the much more precise single-zone-dependent EfficientNetB0.

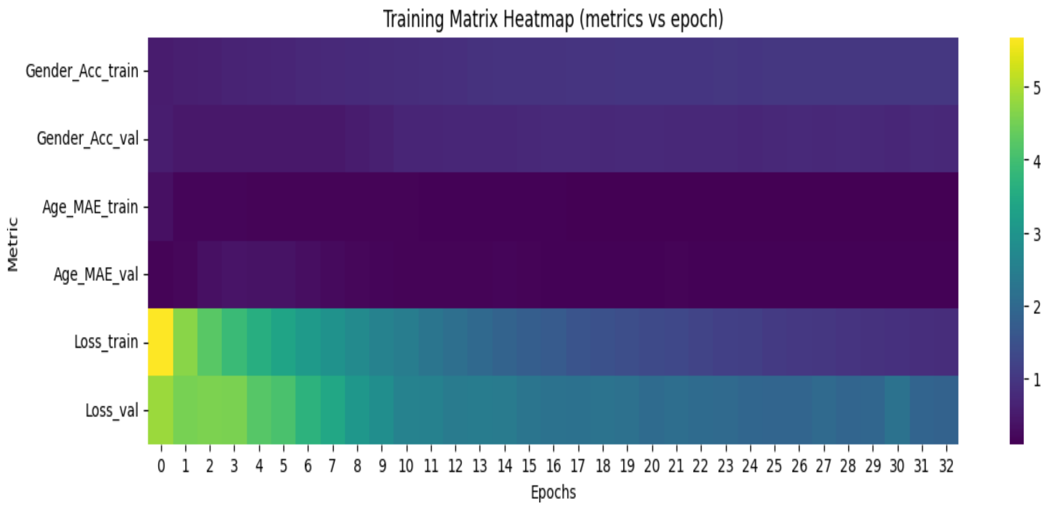


Figure 4.1.24 Training metrics heat map visualization of the ShuffleNetV2 model

	Epoch	Gender_Acc_train	Gender_Acc_val	Age_MAE_train	Age_MAE_val \
0	1	0.511791	0.539078	0.327343	0.157450
1	2	0.556949	0.460922	0.180007	0.194135
2	3	0.584546	0.460922	0.165505	0.311874
3	4	0.625690	0.460922	0.159247	0.390515
4	5	0.652283	0.460922	0.155626	0.359434

Figure 4.1.25 Training metrics (First few rows) of the ShuffleNet V2 model

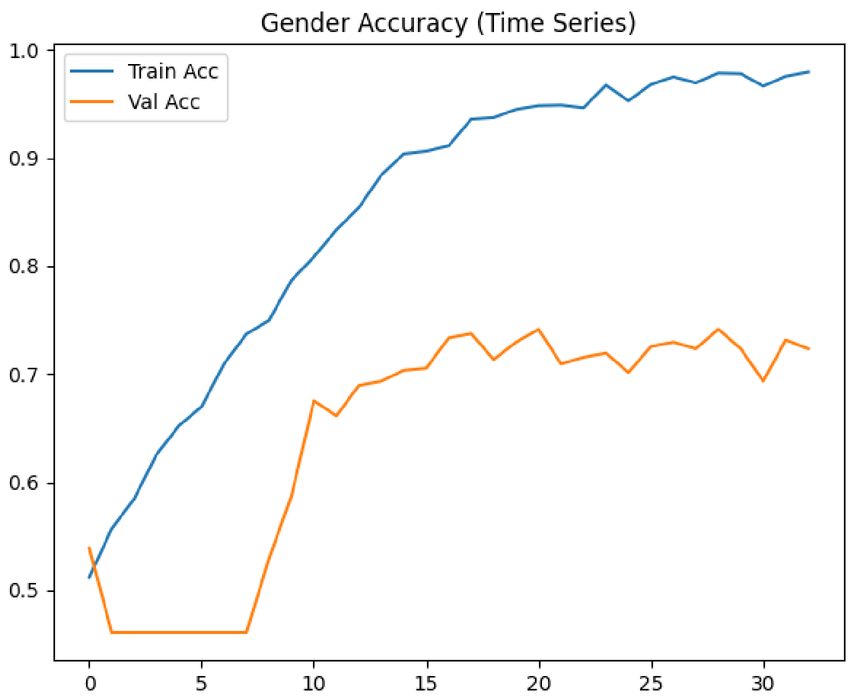


Figure 4.1.26 Gender Accuracy Time Series of the ShuffleNet V2 model

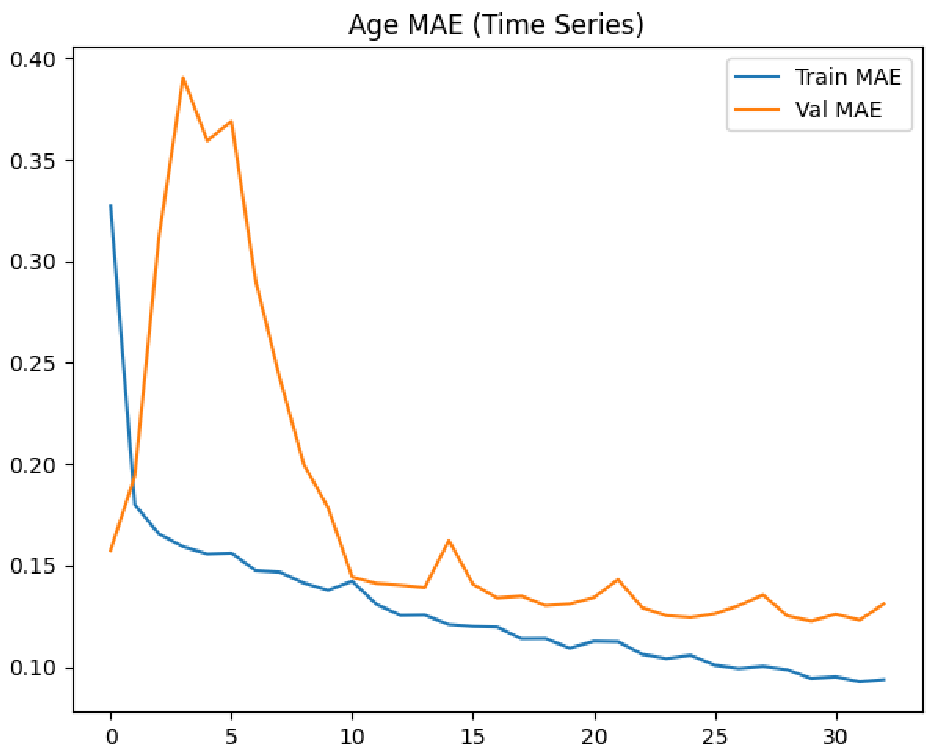


Figure 4.1.27 Age MAE Time Series of the ShuffleNet V2 model

Figure 4.1.28 Loss Curve of the ShuffleNet V2 model

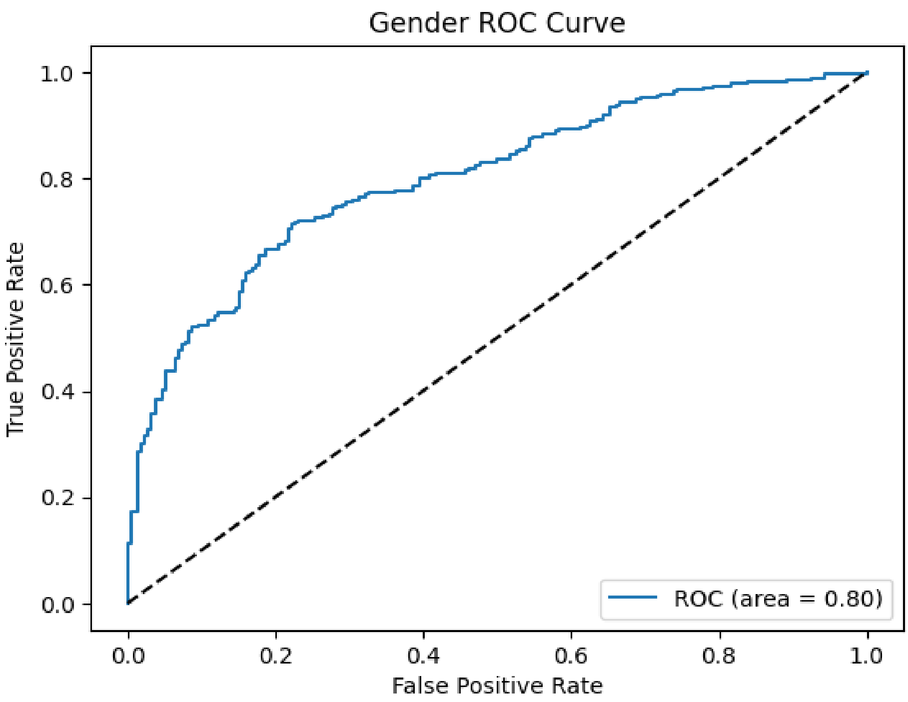


Figure 4.1.2 9 Gender ROC Curve of the ShuffleNet V2 model

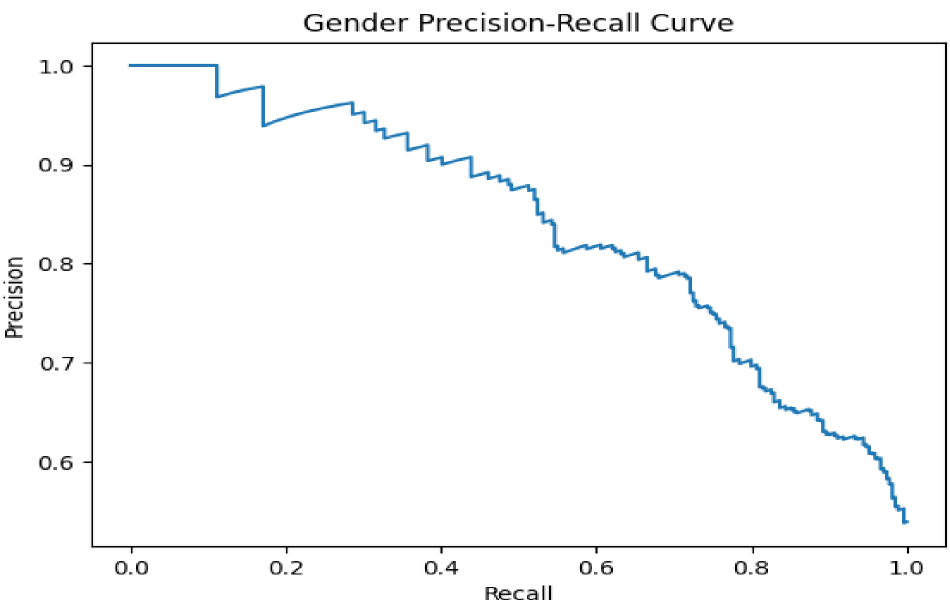


Figure 4.1.30 Gender PR Curve of the ShuffleNet V2 model

4.1.4 Custom CNN

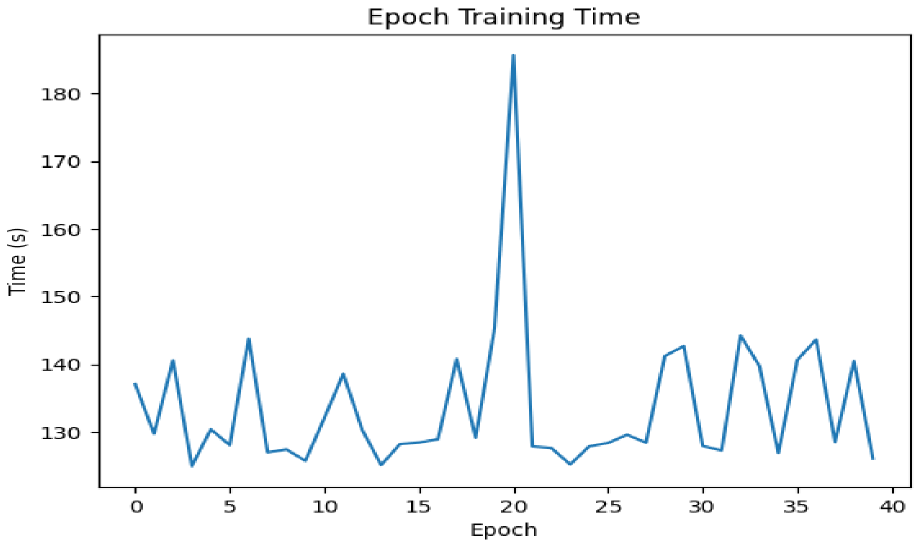


Figure 4.1.31 Custom CNN Epoch Training Time Graph

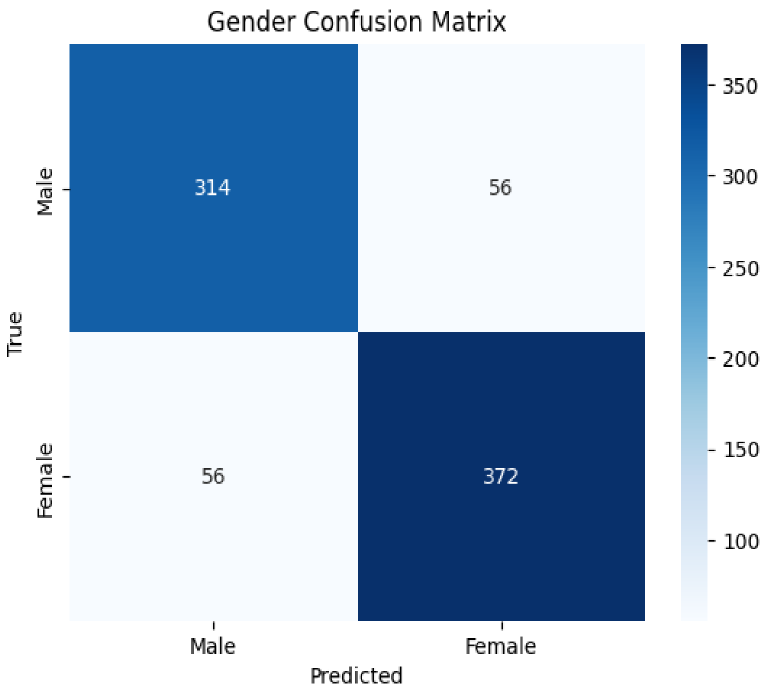


Figure 4.1.32 Custom CNN Classification (for gender) Confusion Matrix

Table 6.16 Custom CNN Model Gender Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy	F1-Score	Precision
Male	314	372	56	56	0.849	0.131	0.869	0.151	0.859	0.865	0.849
Female	372	314	56	56	0.869	0.151	0.849	0.131	0.859	0.868	0.869
Overall	372	314	56	56	0.859	0.141	0.859	0.141	0.859	0.867	0.869

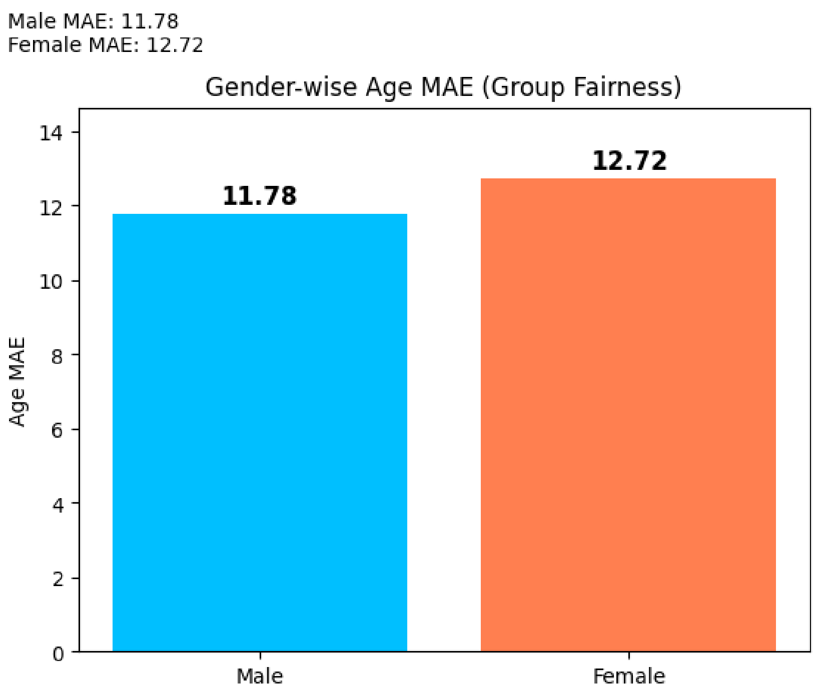


Figure 4.1.33 Custom CNN Regression (MAE for age) chart

Table 6.17 Custom CNN Model Age Regression Report:

Class	MAE
Male	12.72
Female	11.78
Overall	11.78

Table 6.18 Custom CNN Model and Gender Classification Demographic Parity Report:

Class	Parity
Male	46.4%
Female	53.6%

Table 6.19 Custom CNN Model Zone Importance Report:

Important Zone	Gender Prediction(in avg 3)	Age Prediction(in avg 3)
Forehead	High(around 49%)	Mid(around 40%)
Midface	nan	nan
Jaw	nan	nan

The Custom CNN Model possesses significantly lower classification accuracy in comparison with EfficientNetB0 with 0.859 and 0.907 respectively. Nonetheless, it has a rather balanced distribution of F1-score (0.865 and 0.868, respectively). Conversely, the error profile is slightly more one-sided: the rate of false-positives in the female class is larger (0.151) than the male one (0.131). Interestingly, in the case of age regression, there is a group-fairness problem: MAE of males (12.72) is 0.94 years greater than that of females (11.78) and this indicates that the Custom CNN is more effective at presuming the age of a female. However, on the whole, both male and female MAEs remain very poorer than that of EfficientNetB0 (7.07 and 8.37). On the same way this model gives more parity in female classification (53.6%) than male classification (46.4%). In the case of explainable AI, Custom CNN also acts like EfficientNetB0, where much feature weight is placed on the forehead (49) -gender, 40) age). Nevertheless, this emphasis is not as excessive as the 60 proportion gender significance in EfficientNetB0. Bottom line: the Custom CNN has a little more balanced classification statistics and a slightly weaker XAI fragility, but is otherwise less accurate and has more regression errors that is why it is worse in comparison to the best-performing EfficientNetB0.

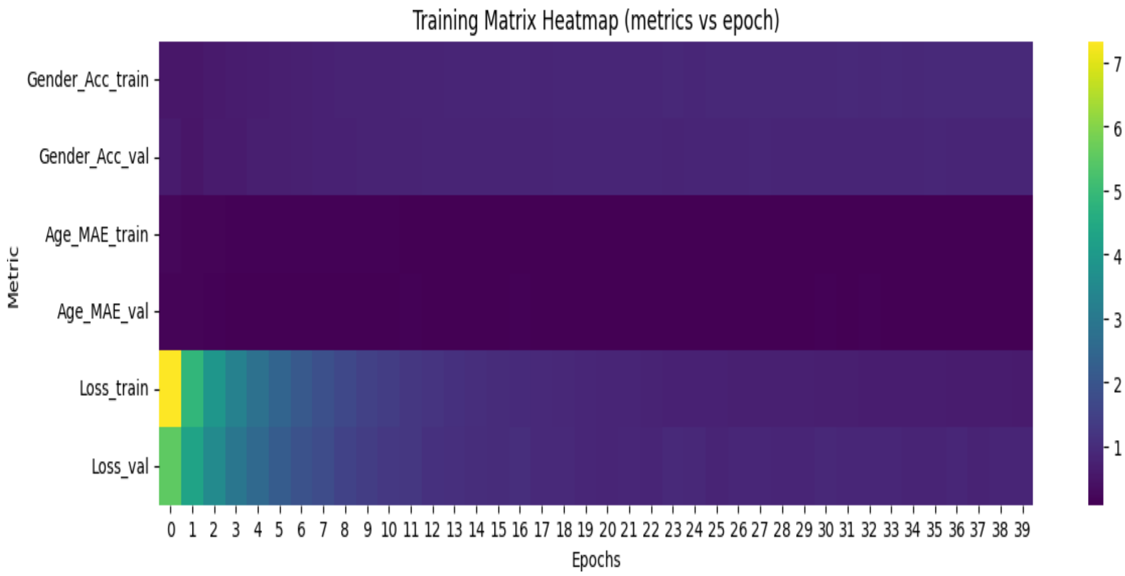


Figure 4.1.34 Training metrics heat map visualization of the Custom CNN model

	Epoch	Gender_Acc_train	Gender_Acc_val	Age_MAE_train	Age_MAE_val	\
0	1	0.521930	0.600251	0.202228	0.166682	
1	2	0.532581	0.494987	0.166596	0.149712	
2	3	0.583020	0.610276	0.144834	0.132662	
3	4	0.631579	0.619048	0.136558	0.116066	
4	5	0.671992	0.684211	0.129138	0.116424	

Figure 4.1.35 Training metrics (First few rows) of the Custom CNN model

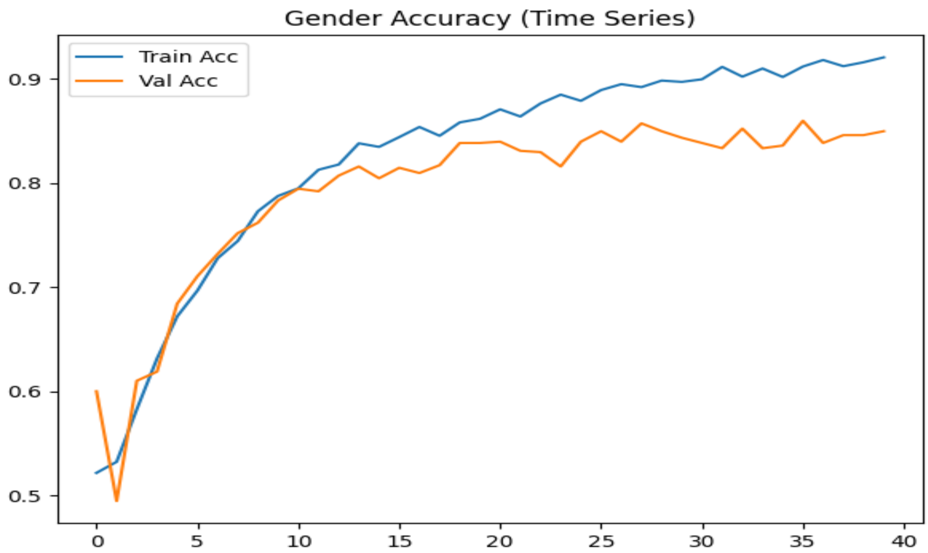


Figure 4.1.36 Gender Accuracy Time Series of the Custom CNN model

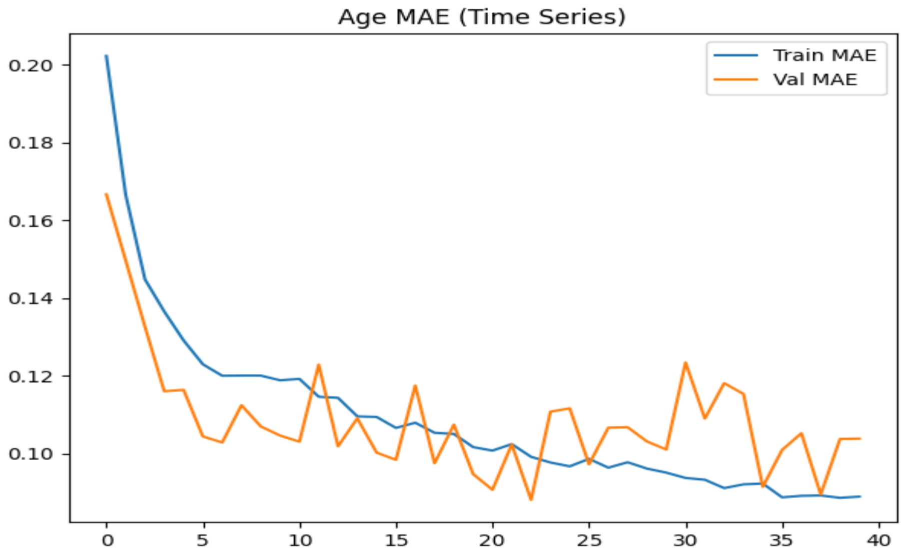


Figure 4.1.37 Age MAE Time Series of the Custom CNN model

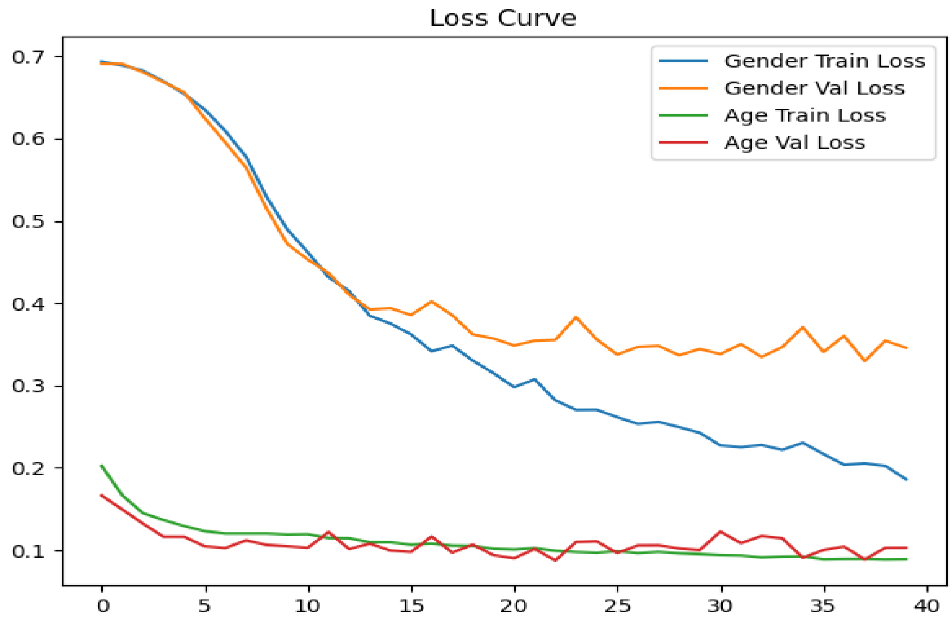


Figure 4.1.38 Loss Curve of the Custom CNN model

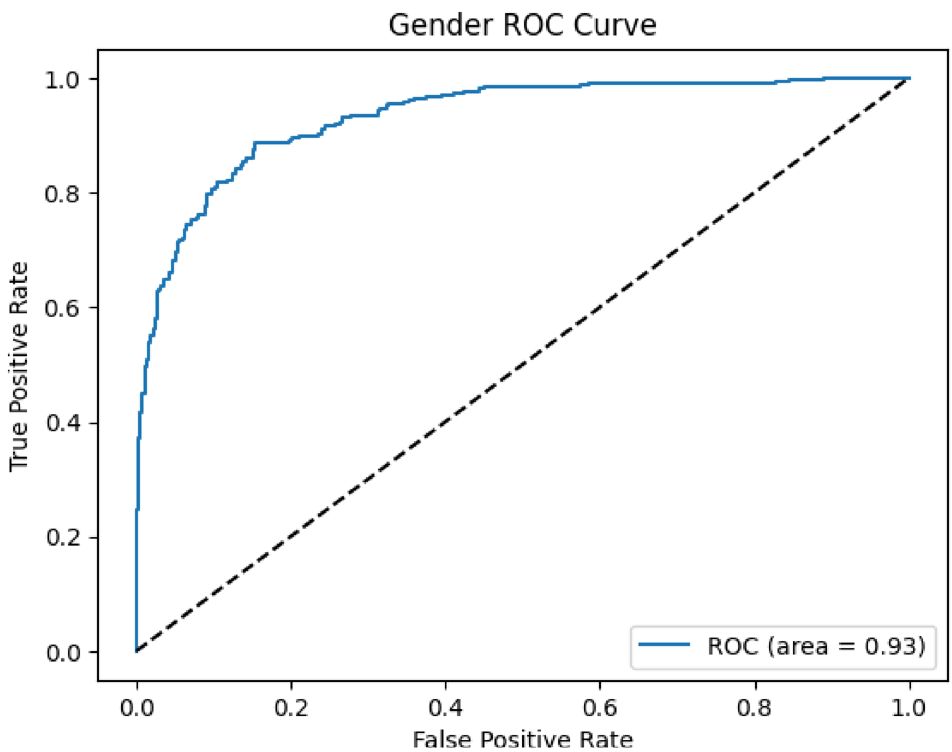


Figure 4.1.39 Gender ROC Curve of the Custom CNN model

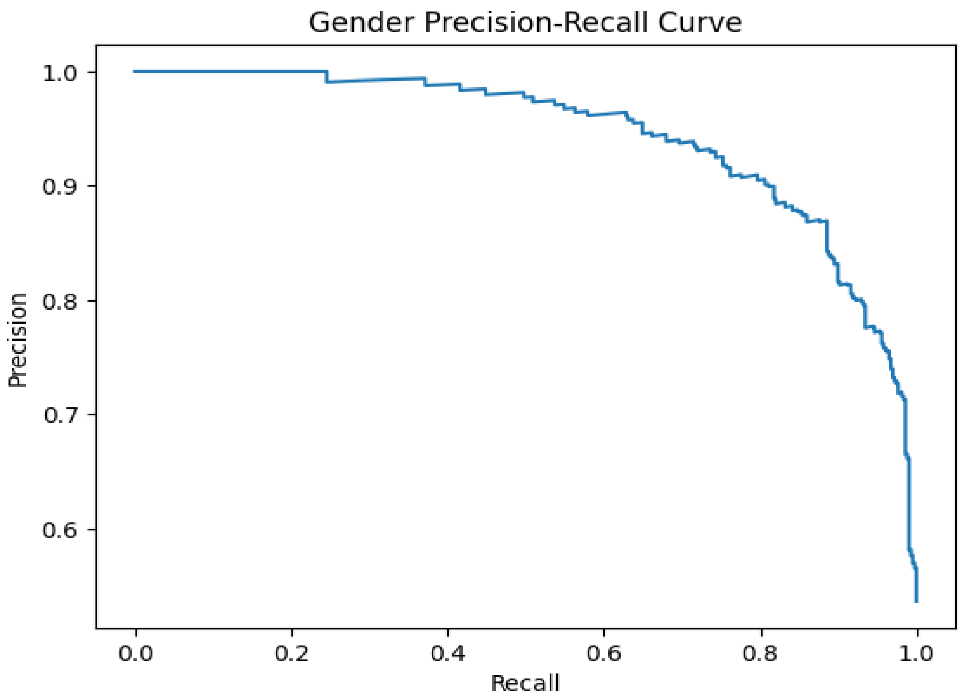


Figure 4.1.40 Gender PR Curve of the Custom CNN model

4.2 Visualization

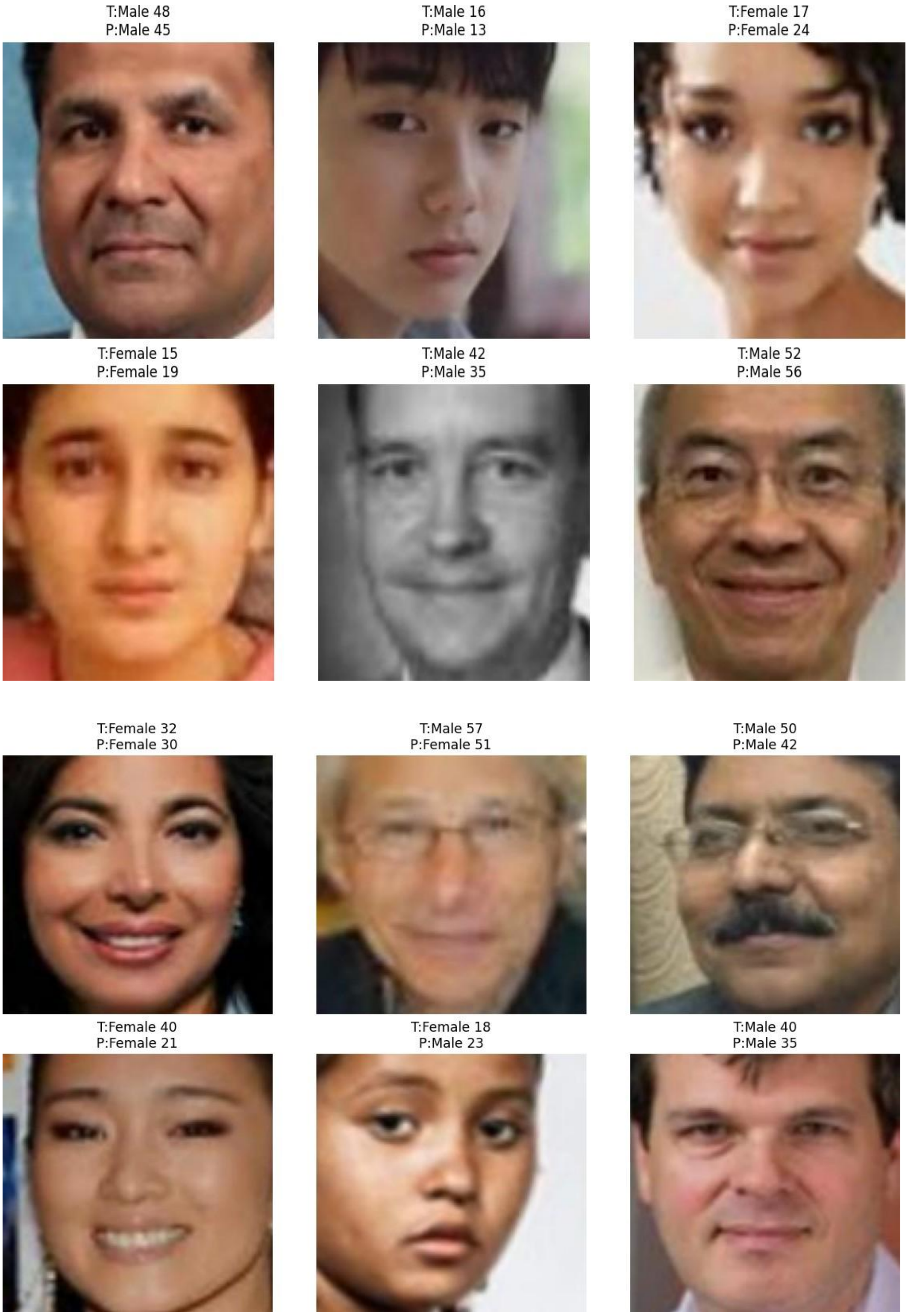
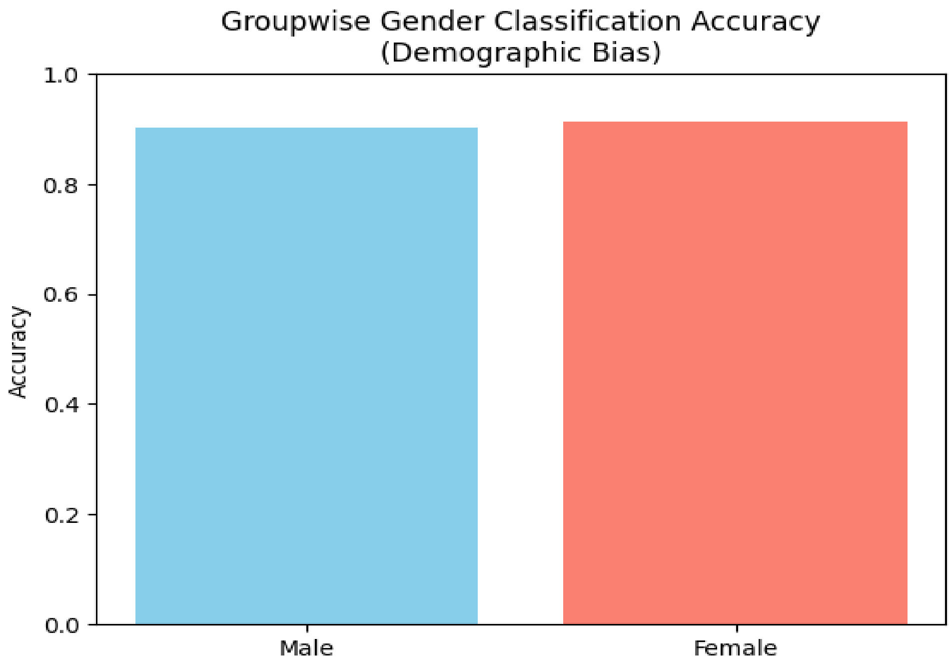


Figure 4.2.1 Examples of output of EfficientNetV2 Model Gender and Age Prediction.



TPR_ Male = 0.90, TPR_ Female = 0.91,

Figure 4.2.2 Output of EfficientNetB0 Model Demographic Bias

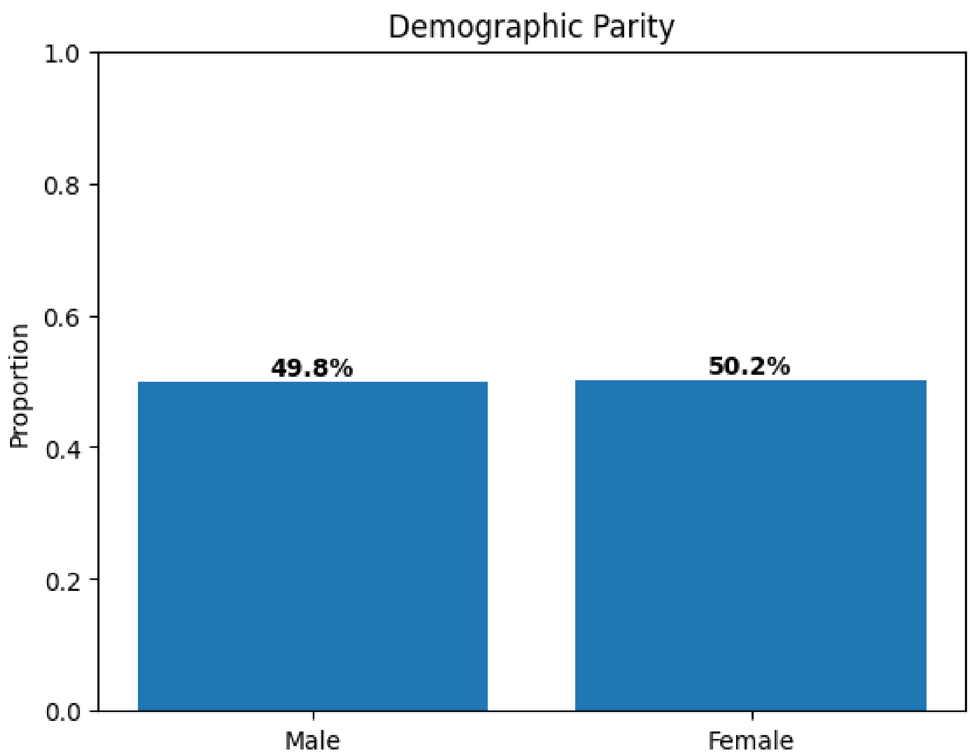


Figure 4.2.3 Output of EfficientNetB0 Model Demographic Parity

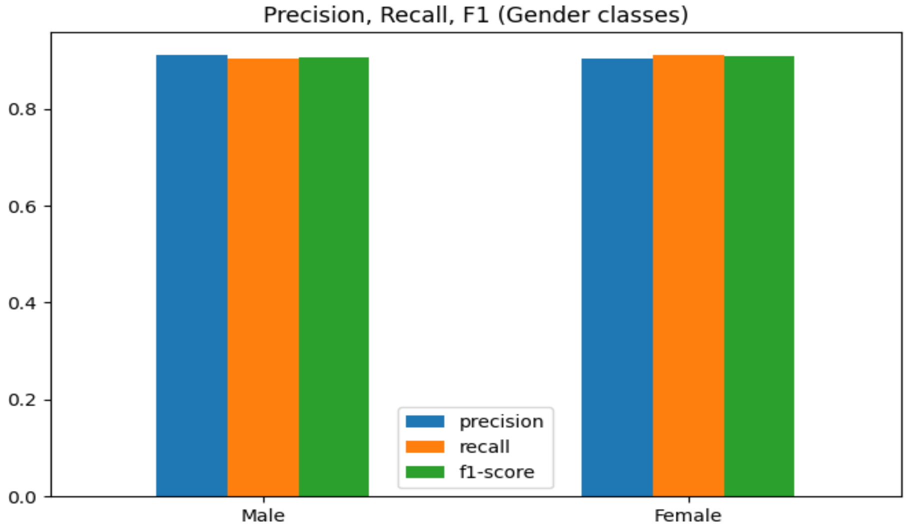


Figure 4.2.4 Output of EfficientNetB0 Model Gender Bias Analysis Graph.

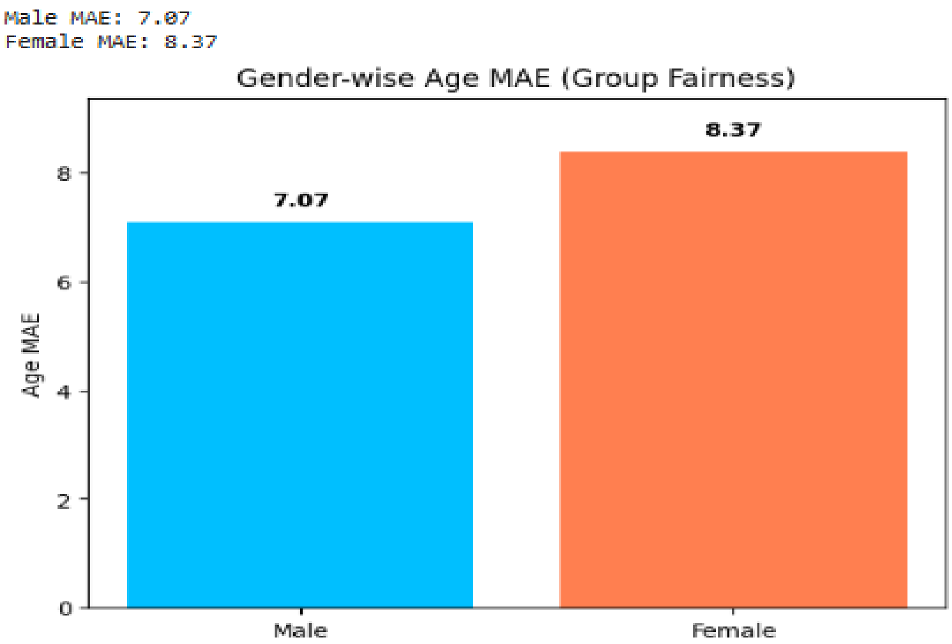


Figure 4.2.5 Output of EfficientNetB0 Model MAE Fairness


```
Zone importances: {'Forehead': np.float32(0.60815), 'Midface':
np.float32(nan), 'Jaw': np.float32(nan)}
```


```
Zone importances: {'Forehead': np.float32(0.43339884),
'Midface': np.float32(nan), 'Jaw': np.float32(nan)}
```

Figure 4.2.6 Output of EfficientNetB0 Model Gradcam/XAI optimized zones (for Gender and Age prediction)

4.3 Discussion

Table 6.20 All models comparison summary

Model	Age MAE	Gender Acc.	Precision	Recall	F1	XAI Optimization
EfficientNetB0	**7.07**	**90.71**	**90.40**	**91.20**	**90.80**	**high**
MobileNetV2	10.27	88.70	91.80	88.20	89.00	moderate
ShuffleNetV2	15.56	74.10	79.00	74.65	74.60	low
Custom CNN	11.78	85.90	86.90	85.90	14.1	mid

When we consider all the four models simultaneously, it is obvious to observe the difference in performance and also the ease with which they can be interpreted. EfficientNetB0 is practical the best, and has the lowest age MAE and the greatest gender accuracy, precision, recall, F1 score, and XAI score. The feature-importance map of it is particularly good on the forehead and this makes it feel reliable and transparent. In addition, it reduces both bias in age estimation and gender misclassification more than the other one, thus its forecasts are more reasonable between various groups.

MobileNetV2 isn't far behind. It has good performance in the majority of measures and its XAI score indicates that it is somewhat interpretable. However, its age MAE is a little higher implying that it is less predictive at age than EfficientNetB0. Still fair on average but MobileNetV2 is more likely to be fooled into making more substantial errors in odd cases.

ShuffleNetV2 is not so good. It is aged and its MAE is highest and the gender accuracy is lowest and its precision and recall are also low. The low XAI score indicates that it is a poor self-explaining variable and might be discriminatory towards some groups. That is why ShuffleNetV2 is not an appropriate option when it is important to have accuracy and fairness.

Custom CNN is a decent job. It has a higher age MAE and a higher gender accuracy as compared to ShuffleNetV2, but not as the first two. It is average to interpret and its equity is also reasonable, though not great in any of the aspects. It may be a sensible point of reference however it does not have a defined strength.

Simply put, EfficientNetB0 is ranked first followed by MobileNetV2 and Custom CNN and finally ShuffleNetV2. Not only is EfficientNetB0 the most predictive but it is also more explainable and less predictive bias, which is why it is the most reliable and just in this comparison.

Here,

EfficientNetB0 > MobileNetV2 > Custom CNN > ShuffleNetV2

Table 6.21 All models comparison summary (Bias and Fairness)

Model	Demographic Parity (Dataset balance Checks)		Demographic Bias In Classification - TPR		Group Fairness (Age MAE)	
	Male	Female	Male	Female	Male	Female
EfficientNetB0(main)	49.80%	52.2%	90.20%	91.20%	7.07	8.37
MobileNetV2	49.80%	50.2%	91.80%	84.50%	10.27	11.92
Custom CNN	46.40%	53.6%	84.90%	86.9%	11.78	12.72
ShuffleNetV2	41.10%	53.90%	78.30%	70.50%	15.56	18.42

The table discusses four models based on the dataset balance, the gender classification true positive rate (TPR), and the error of age estimation (MAE) of male and female groups. EfficientNetB0 demonstrates almost balanced sex ratios of males and females in the data set and near equal TPRs of both sexes, as well as the lowest age MAE values of both sexes, indicating high levels of group fairness in age prediction. The balance and close TPR of MobileNetV2 are similar, with slightly higher MAE scores indicating marginally lower age fairness but reasonably constant with genders as well.

There is a higher imbalance in demographic parity that is found in the Custom CNN, and the TPR between males and females is larger with significantly higher values of MAE, which presupposes a greater prejudice and low reliability of the age estimation of both groups. ShuffleNetV2 is the worst on average: it has the most uneven demographic parity (with an underrepresentation of males in particular), the lowest TPRs, and significantly higher age MAE of both gender, indicating an indication of significant fairness concerns as well as inadequate predictive accuracy. To recap it all, using parity, TPR, and age MAE as the three fairness measures, the EfficientNetB0 (best), MobileNetV2, Custom CNN, and ShuffleNetV2 were ranked as the most fair and accurate, respectively

CHAPTER 5 CONCLUSION

5.1 Findings & Contributions

The study will entail a rather straightforward comparison of four deep-learning models, namely, EfficientNetB0, MobileNetV2, ShuffleNetV2, and a Custom CNN, to infer age and gender on the basis of faces. It is a cool thing that EfficientNetB0 is winning the entire contest: it has the minimum age error (MAE) and the overall highest gender accuracy. It is also higher in the precision, recall and F1 scores as compared to others, hence it appears strong in the face analysis in real world. Moreover, its XAI tweaks continue to point to the most important spots of the face such as the forehead, which does aid in understanding why it is making such guesses.

The second competitor is MobileNetV2; it has good accuracy but the age estimates are a little bit inaccurate. ShuffleNetV2 is the least good one, it does not have high accuracy and has high age error, thus cannot be used seriously. The Custom CNN performs fairly well on most measures and can be used as a reference, but it can hardly compete with the more sophisticated ones.

We were keen on prejudice and justice towards all the models. EfficientNetB0 is less biased in age and gender prediction across groups and ShuffleNetV2 is characterized by a prominent lack of symmetry. And with XAI, more explainable models are also less biased.

The lesson learned here is that EfficientNetB0 can provide accurate, strong, and fair face analysis. It is very accurate and explainable thus a good go-to tool in both school assignments and professional tasks that require recognition of facial features. The paper also indicates the significance of XAI in maintaining transparency of features and reducing bias.

Lastly, this evidence discusses the influence of a model in fairness. The findings can assist the researchers and the classmates, who desire less partisan and more articulate models, in having more reliable and equilibrium-oriented results in carrying out sensitive work.

5.2 Recommendations for Future Works

A larger dataset and demographic diversity (balance of age and gender) should be used in future studies to enhance the robustness of the model, as well as minimize bias even more.

The EfficientNetB0 model had a high gender classification score (90.71) and a moderate age estimation score (MAE 7.9). Running the model on more in-the-wild images and different ethnic/demographic groups will assist in proving the generalizability.

Bias analysis of group wises revealed that the TPR of male = 0.90 and female = 0.912. Further research and practice towards more sophisticated approaches to fairness training and the measurement of subgroup fairness should be welcomed in the future in order to have fair performances.

The results of GradCAM showed that, the model primarily targets the forehead area when estimating age and gender. To enhance interpreting the model decisions and exposing possible biases in facial attribution, the development of region-based or multi-modal XAI procedures may be beneficial.

Though EfficientNetB0 is already quite lightweight, it will be easy to consider even smaller or more mobile-friendly variants of the model when it will be deployed on a limited-resources device.

Further improvements in the age and gender prediction using EfficientNetB0 should be compared with transformer-based models or multi-task architecture in future research.

In order to gain more credibility and practical significance, it is suggested that cooperation with the social scientists should be considered in order to test the model fairness and interpretability in the real-life context.

It is possible to use synthetically generated faces, to use advanced augmentation, as well as adversarially robust training to achieve better resilience to a wide range of situations.

CHAPTER 6

References:

Akay, M., Du, Y., Sershen, C. L., Wu, M., Chen, T. Y., Assassi, S., Mohan, C., & Akay, Y. M. (2021). Deep learning classification of systemic sclerosis skin using the MobileNetV2 model. *IEEE Open Journal of Engineering in Medicine and Biology*, *2*, 104–110. https://doi.org/10.1109/ojemb.2021.3066097

Amin, H., Darwish, A., Hassanien, A. E., & Soliman, M. (2022). End-to-End Deep learning model for corn leaf disease classification. *IEEE Access*, *10*, 31103–31115. https://doi.org/10.1109/access.2022.3159678

Devi, V. S., Ramisetty, U., Ramisetty, K., & Thimmareddy, A. (2025). Real-Time age, gender and emotion detection using YOLOv8. *ITM Web of Conferences, 74*, 01015. https://doi.org/10.1051/itmconf/20257401015

Dey, P., Mahmud, T., Chowdhury, M. S., Hossain, M. S., & Andersson, K. (2024). Human Age and Gender Prediction from Facial Images Using Deep Learning Methods. *Procedia Computer Science, 238,* 314–321. https://doi.org/10.1016/j.procs.2024.06.030

DSpace. (n.d.). https://hdl.handle.net/10057/27838

Dwivedi, R., Kumar, R., Chopra, D., Kothari, P., & Singh, M. (2023). An Efficient Ensemble Explainable AI (XAI) Approach for Morphed Face Detection. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2304.14509

Gaya-Morey, F. X., Sanchez-Perez, J., Manresa-Yee, C., & Buades-Rubio, J. M. (2025). Bridging the gap in FER: addressing age bias in deep learning. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2507.07638

Hamza, N. R. (2025). Gender Classification from Human Face Images Using Deep Learning Based on MobileNetV2 Architecture. *Journal of Al-Qadisiyah for Computer Science and Mathematics*, *17*(1), 145–156. https://doi.org/10.29304/jqcsm.2025.17.11970

Hassan, B. a. R., & Dawood, F. a. A. (2024). Face-based gender classification using deep learning model. *Journal of Engineering*, *30*(01), 106–123. https://doi.org/10.31026/j.eng.2024.01.07

Ismail, W. N., Alsalamah, H. A., Hassan, M. M., & Mohamed, E. (2023). AUTO-HAR: An adaptive human activity recognition framework using an automated CNN architecture design. *Heliyon*, *9*(2), e13636. https://doi.org/10.1016/j.heliyon.2023.e13636

Kumar, R., Singh, K., Mahato, D. P., & Gupta, U. (2024). Face-based age and gender classification using deep learning model. *Procedia Computer Science, 235,* 2985–2995. https://doi.org/10.1016/j.procs.2024.04.282

Levi, G., & Hassncer, T. (2015). Age and gender classification using convolutional neural networks. *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW),* 34–42. https://doi.org/10.1109/cvprw.2015.7301352

Liu, J., Li, J., & Huang, G. (2025a). Research on deep learning-based image processing and classification techniques for complex networks. *Applied Mathematics and Nonlinear Sciences*, *10*(1). https://doi.org/10.2478/amns-2025-0351

Manresa-Yee, C., Ramis, S., & Buades, J. M. (2023). Analysis of gender differences in facial expression recognition based on deep learning using explainable artificial intelligence. *International Journal of Interactive Multimedia and Artificial Intelligence*, *9*(1), 18–27. https://doi.org/10.9781/ijimai.2023.04.003

Mohamed, E., Ashraf, A., Tarek, M., & Matar, W. (2025). Age and Gender Detection using Facial Images. *International Integrated Intelligent Systems*, *2*(1), 0. https://doi.org/10.21608/iiis.2025.292070.1003

Rasheed, J., Waziry, S., Alsubai, S., & Abu-Mahfouz, A. M. (2022). An Intelligent Gender Classification System in the Era of Pandemic Chaos with Veiled Faces. *Processes*, *10*(7), 1427. https://doi.org/10.3390/pr10071427

Sheoran, V., Joshi, S., & Bhayani, T. R. (2021). Age and Gender Prediction using Deep CNNs and Transfer Learning. *arXiv (Cornell University).* https://doi.org/10.48550/arxiv.2110.12633

Singhal, A., Agrawal, K. K., Quezada, A., Aguiñaga, A. R., Jiménez, S., & Yadav, S. P. (2024a). Explainable Artificial Intelligence (XAI) model for cancer image classification. *Computer Modeling in Engineering & Sciences*, *141*(1), 401–441. https://doi.org/10.32604/cmes.2024.051363

Uddin, S. S., Morshed, M. S., Prottoy, M. I., & Rahman, A. A. (2021). Age Estimation from Facial Images using Transfer Learning and K-fold Cross-Validation. *Proceedings of the 2021 International Conference on Pattern Recognition and Intelligent Systems*, 33–36. https://doi.org/10.1145/3480651.3480659

Zhang, B., Xu, L., Liu, K., Yang, R., Li, M., & Guo, X. (2024). Piecewise convolutional neural network relation extraction with self-attention mechanism. *Pattern Recognition*, *159*, 111083. https://doi.org/10.1016/j.patcog.2024.111083

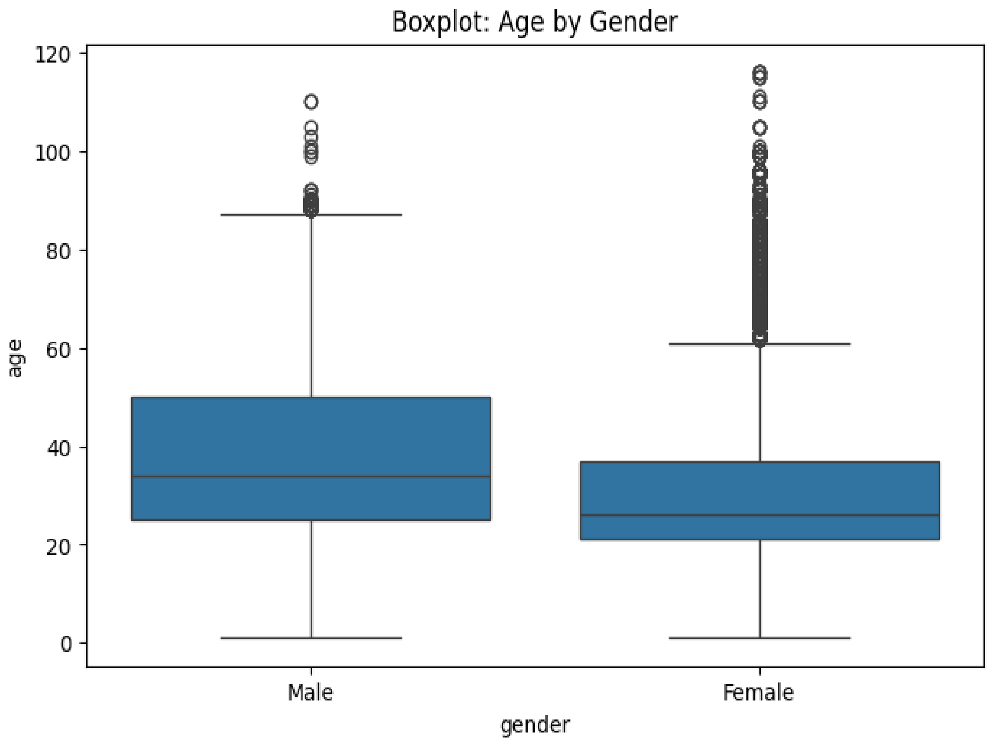
Zhang, Z., Song, Y., & Qi, H. (2017). *Age Progression/Regression by Conditional Adversarial Autoencoder*. https://openaccess.thecvf.com/content_cvpr_2017/html/Zhang_Age_ProgressionRegression_by_CVPR_2017_paper.html

APPENDICES

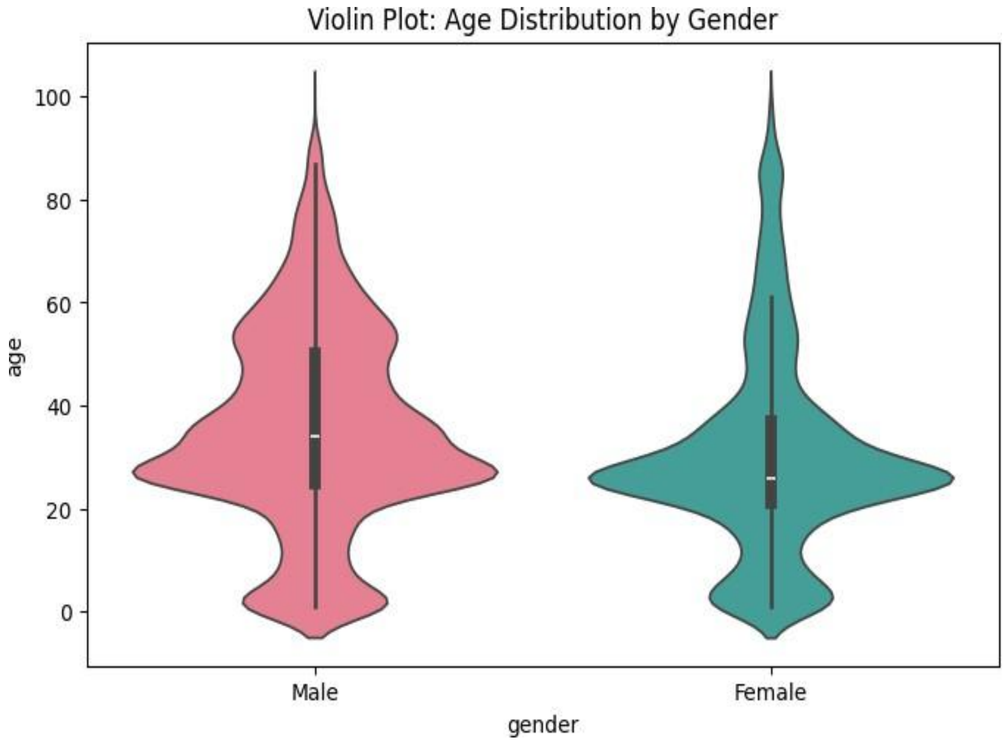
Appendix A: Dataset Availability

Dataset Link: https://www.kaggle.com/datasets/jangedoo/utkface-new

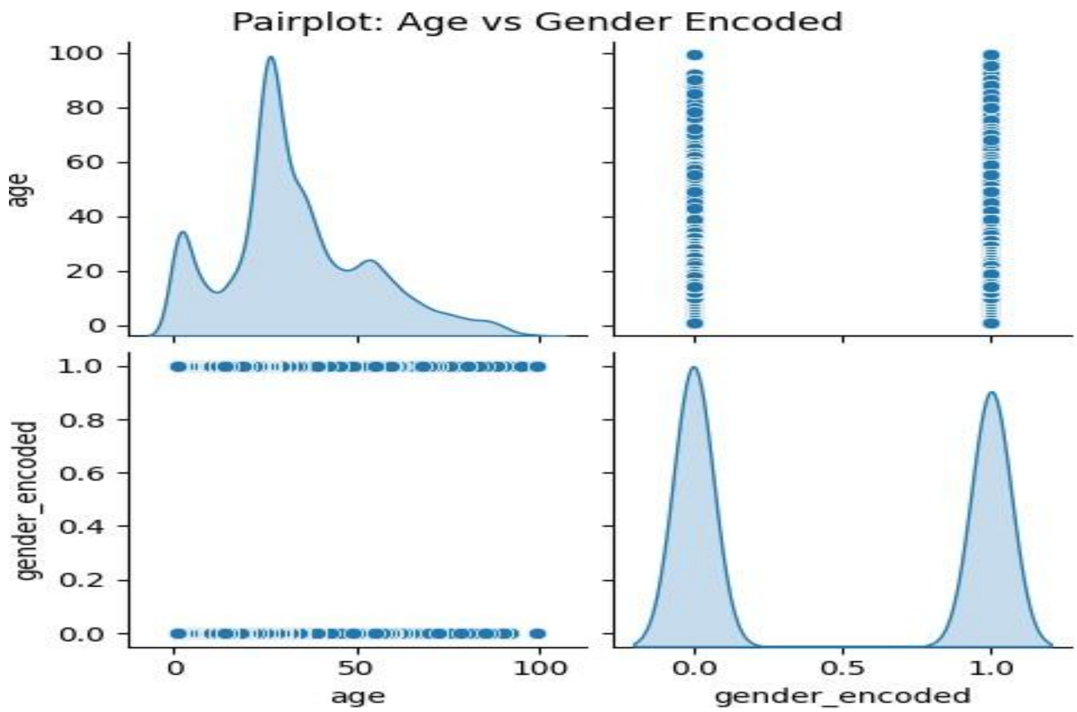
Appendix B : Age VS Gender Boxplot



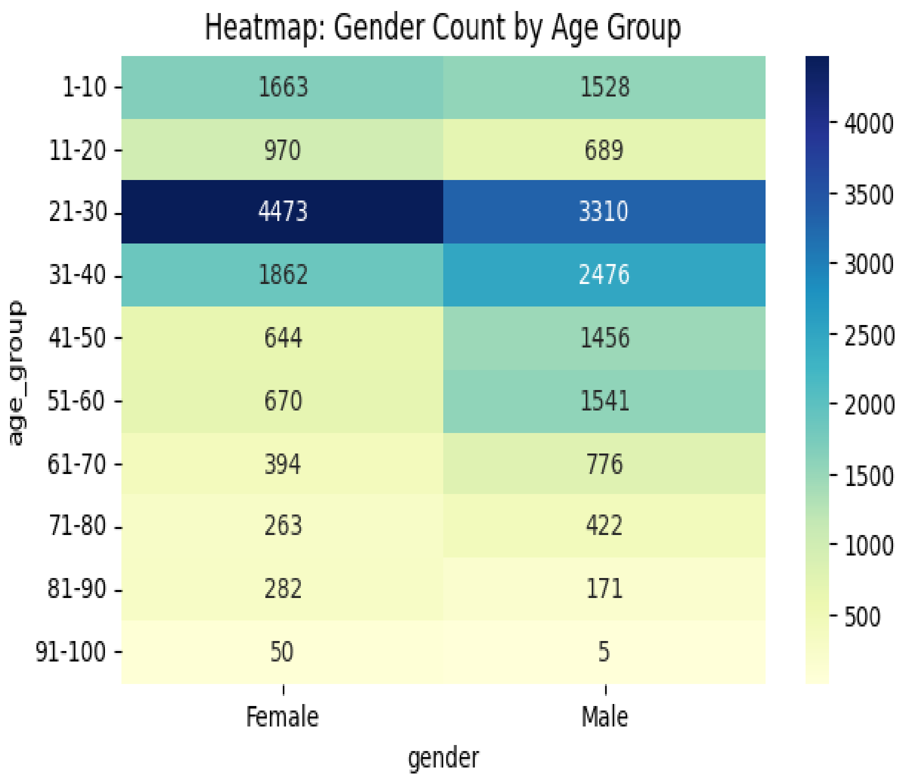
Appendix C: Age Distribution by Gender



Appendix D: Age and Gender Encoded



Appendix E: Gender Count by Age group



LIBRARY CLEARANCE

PLAGIARISM REPORT

221-35-1064

ORIGINALITY REPORT

23%	15%	13%	14%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	4%
2	Submitted to Midlands State University Student Paper	2%
3	Submitted to Coventry University Student Paper	1%
4	eprints.utar.edu.my Internet Source	1%
5	He, Zhiwen. "Performance Evaluation of Deep Learning Architectures for Facial Attribute Recognition: A Multi-Model, Cross-Dataset Analysis", North Carolina Agricultural and Technical State University, 2024 Publication	1%
6	idr.niser.ac.in:8080 Internet Source	1%
7	www.coursehero.com Internet Source	1%
8	arxiv.org Internet Source	1%

9	Submitted to University of Technology, Sydney Student Paper	<1%
10	Submitted to Manchester Metropolitan University Student Paper	<1%
11	Submitted to University of Maryland, Global Campus Student Paper	<1%
12	Arwa Albelaihi, Dina M. Ibrahim. "DeepDiabetic: An Identification System of Diabetic Eye Diseases Using Deep Neural Networks", IEEE Access, 2024 Publication	<1%
13	Submitted to Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) Student Paper	<1%
14	Alessandro Benito Putra Bayu Wedha, Ben Rahman, Djarot Hindarto, Bayu Yasa Wedha. "Drowsy Detection in the Eye Area using the Convolutional Neural Network", SinkrOn, 2023 Publication	<1%
15	Roman BUCHUK, Pavlo FEDORKA, Mykhailo KLYMENKO, Andrii PETRUSHYN, Fedir SAIBERT. "The Use of Adaptive Artificial Intelligence (AI) Learning Models in Decision	<1%

Support Systems for Smart Regions", Journal of Research, Innovation and Technologies (JoRIT), 2025
Publication

16	Puja Dey, Tanjim Mahmud, Mohammad Sanaullah Chowdhury, Mohammad Shahadat Hossain, Karl Andersson. "Human Age and Gender Prediction from Facial Images Using Deep Learning Methods", Procedia Computer Science, 2024 Publication	<1%
17	joe.uobaghdad.edu.iq Internet Source	<1%
18	www.irjet.net Internet Source	<1%
19	Submitted to unistgallen-plagiat Student Paper	<1%
20	Submitted to Khulna University of Engineering & Technology Student Paper	<1%
21	Rajesh Kannan Megalingam, Sakthiprasad Kuttankulangara Manoharan, Dasari Hema Teja Anirudh Babu, Ghali Sriram et al. "Coconut trees classification based on height, inclination, and orientation using MIN-SVM algorithm", Neural Computing and Applications, 2023 Publication	<1%

22	"Intelligent Systems and Applications", Springer Science and Business Media LLC, 2025 Publication	<1%
23	Wade Downton, Hima Vadapalli. "Age and Gender Estimation using Optimised Deep Networks", Proceedings of the South African Institute of Computer Scientists and Information Technologists 2019, 2019 Publication	<1%
24	bura.brunel.ac.uk Internet Source	<1%
25	Submitted to Aalto Yliopisto Student Paper	<1%
26	Submitted to LTI 202223 Student Paper	<1%
27	Submitted to Birla Institute of Technology Student Paper	<1%
28	indah.ump.edu.my Internet Source	<1%
29	www.mdpi.com Internet Source	<1%
30	Aafke Schipper. "Ecosystem services across Europe. D4.2 Current and future natural capital and ecosystem services", Pensoft Publishers, 2025	<1%

Publication

31	stannescet.ac.in Internet Source	<1%
32	Surya Krishnamurthy, Kathiravan Srinivasan, Saeed Mian Qaisar, P. M. Durai Raj Vincent, Chuan-Yu Chang. "Evaluating Deep Neural Network Architectures with Transfer Learning for Pneumonitis Diagnosis", Computational and Mathematical Methods in Medicine, 2021 Publication	<1%
33	Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical and Computer Technologies", CRC Press, 2025 Publication	<1%
34	Submitted to University of East London Student Paper	<1%
35	essay.utwente.nl Internet Source	<1%
36	Shankar Babu, Mahesh Babu Kota. "Synergies in Smart and Virtual Systems using computational intelligence", CRC Press, 2025 Publication	<1%
37	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1%

38	umpir.ump.edu.my Internet Source	<1%
39	"Forthcoming Networks and Sustainability in the AIoT Era", Springer Science and Business Media LLC, 2024 Publication	<1%
40	Amoakoh Gyasi-Agyei. "Detection of explosives in dustbins using deep transfer learning based multiclass classifiers", Applied Intelligence, 2024 Publication	<1%
41	Erdal Güngör, Husam Vehbi, Mehmet Batu Ertan, Ahmetcan Cansın. "Automated detection and segmentation of chondromalacia patella on axial knee MRI using YOLOv11 and a custom CNN: a deep learning-based diagnostic model", BMC Musculoskeletal Disorders, 2025 Publication	<1%
42	Sujata Dash, Subhendu Kumar Pani, Joel J. P. C. Rodrigues, Babita Majhi. "Deep Learning, Machine Learning and IoT in Biomedical and Health Informatics - Techniques and Applications", CRC Press, 2022 Publication	<1%
43	iiis.journals.ekb.eg Internet Source	<1%

44	Dinesh Goyal, Payal Bansal, Ritam Dutta, Madhav Sharma. "Intelligent Systems Using Semiconductors for Robotics and IoT - First International Conference, ICISRI-2024, Jaipur, India, November 29-30, 2024 Proceedings", CRC Press, 2025 Publication	<1%
45	"Proceedings of 5th International Conference on Artificial Intelligence and Smart Energy", Springer Science and Business Media LLC, 2025 Publication	<1%
46	"Proceedings of World Conference on Artificial Intelligence: Advances and Applications", Springer Science and Business Media LLC, 2023 Publication	<1%
47	neptjournal.com Internet Source	<1%
48	Kader Khan, Md. Rahat. "An Advanced Machine Learning Framework and Multi-Label Heart Disease Classification With UNet-Based Nucleus Segmentation", The University of Mississippi Publication	<1%
49	S.P. Jani, M. Adam Khan. "Applications of AI in Smart Technologies and Manufacturing", CRC	<1%

Press, 2025
Publication

50	Submitted to Hofstra University Student Paper	<1 %
51	amns.sciendo.com Internet Source	<1 %
52	www.ijfmr.com Internet Source	<1 %
53	Submitted to Jordan University of Science & Technology Student Paper	<1 %
54	Submitted to University of Hull Student Paper	<1 %
55	dspace.daffodilvarsity.edu.bd:8080 Internet Source	<1 %
56	wolbrom.pl Internet Source	<1 %
57	Submitted to University of Leicester Student Paper	<1 %
58	Submitted to Université Internationale de Rabat Student Paper	<1 %
59	oulurepo.oulu.fi Internet Source	<1 %
60	repository.charlotte.edu Internet Source	

<1%

61	www.scitepress.org Internet Source	<1%
62	Jasem Almotiri. "Dynamic Spatial Focus in Alzheimer's Disease Diagnosis via Multiple CNN Architectures and Dynamic GradNet", Computers, Materials & Continua, 2025 Publication	<1%
63	www.arxiv-vanity.com Internet Source	<1%
64	www.ijsr.net Internet Source	<1%
65	Matthias Omotayo Oladele, Temitope Adeyemo, Temilola Morufat Adepoju, Oluwafemi Olayanju Awodoye et al. "Chapter 17 A Hybrid Differential Evolution and Reinforcement Learning Approach for Optimizing Convolutional Neural Networks in Facial Age Group Classification", Springer Science and Business Media LLC, 2025 Publication	<1%
66	P Vinayagam, V Nithesh Kumar, G Bhuvan. "Experimental Evaluation of IoT based Human Gender Classification and Record Management using Intelligent Hybrid Learning Principles", 2023 Second	<1%

International Conference on Advances in Computational Intelligence and Communication (ICACIC), 2023
Publication

67	Submitted to Universiti Sultan Zainal Abidin Student Paper	<1%
68	ijsrst.com Internet Source	<1%
69	kobra.uni-kassel.de Internet Source	<1%
70	"Green Artificial Intelligence and Industrial Applications (G-AIIA)", Springer Science and Business Media LLC, 2026 Publication	<1%
71	"The International Conference on Image, Vision and Intelligent Systems (ICIVIS 2021)", Springer Science and Business Media LLC, 2022 Publication	<1%
72	Sangyoon Yun, Sungkook Hong, Sungjoo Hwang, Dongmin Lee, Hyunsoo Kim. "Analysis of masonry work activity recognition accuracy using a spatiotemporal graph convolutional network across different camera angles", Automation in Construction, 2025 Publication	<1%

73	Shen Pan, Gidon Shavit, Marta Penas-Centeno, Dong-Hui Xu, Linda Shapiro, Richard Ladner, Eve Riskin, Wim Hol, Deirdre Meldrum. "Automated classification of protein crystallization images using support vector machines with scale-invariant texture and Gabor features", Acta Crystallographica Section D Biological Crystallography, 2006 Publication	<1%
74	easyprojectmaterials.com Internet Source	<1%
75	feb.unair.ac.id Internet Source	<1%
76	norma.ncirl.ie Internet Source	<1%
77	ojs.aaai.org Internet Source	<1%
78	vdoc.pub Internet Source	<1%
79	www.bpasjournals.com Internet Source	<1%
80	www.diplomarbeiten24.de Internet Source	<1%
81	"Computer Vision and Image Processing", Springer Science and Business Media LLC, 2021	<1%

Publication

82	"Proceedings of International Conference on AI Systems and Sustainable Technologies", Springer Science and Business Media LLC, 2026 Publication	<1 %
83	Jiquan Li, Zhiquan Liu, Wang Zhou, Amin Ul Haq, Abdus Saboor. "FERmc: Facial expression recognition framework based on multi-branch fusion and depthwise separable convolution", Information Fusion, 2025 Publication	<1 %
84	Amit Kumar Singh, Stefano Berretti, Ashima Anand, Amrit Kumar Agrawal. "Digital Image Security - Techniques and Applications", CRC Press, 2024 Publication	<1 %
85	K. Srinivasan, Jude Hemanth, V. Rukkumani. "Transforming Healthcare - Artificial Intelligence, Machine Learning, and 5G Innovations for Enhanced Patient Care", CRC Press, 2025 Publication	<1 %
86	Qianlong Wang, Yongjie Liu, Jingwen Liu, Yanlei Gu, Shunsuke Kamijo. "Critical areas detection and vehicle speed estimation system towards intersection-related driving behavior analysis", 2018 IEEE International Conference on Consumer Electronics (ICCE), 2018 Publication	<1 %

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		

221-35-1064

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

PAGE 18

PAGE 19

PAGE 20

PAGE 21

PAGE 22

PAGE 23

PAGE 24

PAGE 25

PAGE 26

PAGE 27

PAGE 28

PAGE 29

PAGE 30

PAGE 31

PAGE 32

PAGE 33

PAGE 34

PAGE 35

PAGE 36

PAGE 37

PAGE 38

PAGE 39

PAGE 40

PAGE 41

PAGE 42

PAGE 43

PAGE 44

PAGE 45

PAGE 46

PAGE 47

PAGE 48

PAGE 49

PAGE 50

PAGE 51

PAGE 52

PAGE 53

PAGE 54

PAGE 55

PAGE 56

PAGE 57

PAGE 58

PAGE 59

PAGE 60

PAGE 61

PAGE 62

PAGE 63

PAGE 64

PAGE 65

PAGE 66

PAGE 67

PAGE 68

PAGE 69

PAGE 70

PAGE 71

PAGE 72

PAGE 73

PAGE 74

PAGE 75

PAGE 76

PAGE 77

PAGE 78

PAGE 79

PAGE 80

PAGE 81

PAGE 82

PAGE 83

PAGE 84

PAGE 85

PAGE 86

PAGE 87

PAGE 88

PAGE 89

PAGE 90

PAGE 91

PAGE 92

PAGE 93

PAGE 94

ACCOUNT CLEARANCE