Product Recommendation System
(Targeted Recommendation using Deep Learning in Computer Vision)

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Bachelor of Computer Science
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ABSTRAK

Paparan produk tradisional di pusat membeli-belah sering gagal untuk melibatkan pelanggan dengan berkesan disebabkan sifatnya yang umum. Laporan ini menyajikan satu projek untuk membangunkan sistem cadangan produk yang menggunakan teknologi pengenalan wajah untuk meramal umur dan jantina pengguna. Sistem ini memanfaatkan algoritma Multi-task Cascaded Convolutional Networks (MTCNN), bersama-sama dengan pengelas dan perpustakaan OpenCV, untuk mengenal pasti wajah dengan tepat dan mengekstrak maklumat umur dan jantina.

Objektif utama projek ini adalah untuk mencipta satu sistem cadangan yang peribadi yang mengesyorkan produk yang disesuaikan dengan kumpulan umur dan jantina individu. Dengan menggunakan teknik pengenalan wajah, sistem ini mampu mengenal pasti wajah pengguna secara masa nyata dan membuat ramalan mengenai umur dan jantina mereka. Aliran kerja projek melibatkan beberapa langkah utama. Pertama, algoritma MTCNN digunakan untuk mengesan dan mengekstrak ciri-ciri wajah daripada imej atau aliran video. Setelah wajah berjaya dikenal pasti, model pengelas digunakan untuk meramalkan umur dan jantina pengguna berdasarkan ciri-ciri yang diekstrak. Perpustakaan OpenCV menyediakan alat yang diperlukan untuk melaksanakan fungsi-fungsi ini. Cadangan kemudian dihasilkan dengan memetakan umur dan jantina yang diramalkan kepada kumpulan umur dan kategori jantina yang khusus. Setiap kumpulan umur dan kategori jantina dikaitkan dengan satu set produk yang sesuai untuk demografi yang berkaitan. Untuk menilai keberkesanan sistem, ujian dan pengesahan yang meluas dijalankan dengan menggunakan pelbagai set data. Metrik prestasi yang dipertimbangkan termasuk ketepatan, kejituan, dan Ralat Mutlak Min (MAE).

Keputusan projek ini menunjukkan potensi penggunaan teknologi pengenalan wajah untuk membangunkan sistem cadangan produk yang tepat dan cekap. Keupayaan sistem untuk meramalkan dengan tepat umur dan jantina pengguna menyumbang kepada pengalaman pengguna yang lebih peribadi dan disesuaikan. Penemuan projek ini membuka kemungkinan untuk penyelidikan dan pembangunan lanjutan dalam bidang sistem cadangan, membuka jalan untuk meningkatkan penglibatan pengguna dan kepuasan pelanggan dalam pelbagai industri.

ABSTRACT

Traditional product displays in shopping malls often fail to effectively engage customers due to their generic nature. This report presents a project on developing a product recommendation system that utilizes facial recognition technology to predict a user's age and gender. The system leverages the Multi-task Cascaded Convolutional Networks (MTCNN) algorithm, along with a classifier and the OpenCV library, to accurately recognize faces and extract age and gender information.

The primary objective of this project is to create a personalized recommendation system that suggests products tailored to an individual's age group and gender. By employing facial recognition techniques, the system is capable of identifying a user's face in real-time and making predictions regarding their age and gender. The project workflow involves several key steps. First, the MTCNN algorithm is utilized to detect and extract facial features from images or video streams. Once the face is successfully recognized, a classifier model is employed to predict the user's age and gender based on the extracted features. The OpenCV library provides the necessary tools for implementing these functionalities. The recommendations are then generated by mapping the predicted age and gender to specific age groups and gender categories. Each age group and gender category are associated with a set of products suitable for the corresponding demographic. These recommendations aim to enhance the user experience by providing relevant and personalized suggestions that align with their specific needs and preferences. To evaluate the effectiveness of the system, extensive testing and validation are conducted using various datasets. The performance metrics considered include accuracy, precision and Mean Absolute Error (MAE).

The results of the project demonstrate the potential of utilizing facial recognition technology to develop accurate and efficient product recommendation systems. The system's ability to accurately predict a user's age and gender contributes to a more personalized and tailored user experience. The project's findings open up possibilities for further research and development in the field of recommendation systems, paving the way for improved user engagement and customer satisfaction in various industries.

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CHAPTER 1

1.1 Introduction

Advertisement or product recommendation is one of the major and important marketing strategies that is used to introduce or promote events, products, and brands to the people. The advertisements that are commonly used by shopping stores are usually static posters or digital displays that are general for all, and it is not for targeted customers. A digital advertisement screen in a mall runs on a slideshow mode, where all products and brands that are advertised runs in a loop of timer where if a 10-year-old kid approaches the screen it could display anything that is not in favor of that child, for example by displaying a make-up product advertisement. Thus, nothing is gained from the advertisement there unless people tend to wait for the slideshow to display items that they want to see which is very inefficient. The advertisements should be displayed according to the person that is viewing it and display the products in favor of that person, considering their age and gender in order to catch the attention of customer to a targeted products or brands or events.

Besides, advertisements cost a large amount of money for both small and large businesses. Based on the Gartner 2022 CMO Spend and Strategy Survey, across almost all industries, the average marketing spend has risen from 6.4% to 9.5% of company revenue where a net balance of 14.1% of companies increased their marketing budgets in the first quarter of 2022 (Turner, 2022). The total investment in advertising expenditure in Malaysia has inclined to about 4.36 billion Malaysian ringgit in 2021 and 4.78 billion Malaysian ringgit in 2022 (Baron, 2022). Furthermore, advertisement such as static posters, or electronic posters or billboards in Malaysia cost around hundreds to thousands of ringgits per day. Digital billboards cost a minimum of RM 1,800 per day. Thus, small companies cannot afford to lose their money on marketing and advertisement plans that do not benefit their companies (303Events, 2022).

As such, the project proposed is to develop a targeted product recommendation system using deep learning in computer vision to overcome the highlighted problems. The system will be a smart recommendation bot to recognize the person’s age and gender who approaches it and automatically prompt products that are related to that specific age and gender group. The proposed project is expected to be beneficial for shop owners and shoppers where the smart recommendation bot will bring targeted customers or shoppers according to the advertisement that are displayed.

1.2 Problem Statement

The current product recommendation system lacks targeted advertisements for each user, leading to random and non-personalized recommendations. This limitation hinders the system's ability to deliver tailored and relevant advertisements to individual users, resulting in decreased user engagement and potentially lower conversion rates. Moreover, without targeted advertisements, the system fails to leverage valuable user data and preferences, missing opportunities to enhance user satisfaction and maximize advertising effectiveness.

Additionally, the absence of personalized advertisements may lead to user dissatisfaction, as users may receive recommendations that are irrelevant or not aligned with their interests and needs. Furthermore, the random nature of the recommendations may also result in missed opportunities for advertisers to effectively reach their target audience and promote their products or services. To address these challenges, it is crucial to develop an enhanced product recommendation system that incorporates targeted advertisements based on user preferences, demographic data, and browsing behavior, ensuring personalized and engaging recommendations for each user. By tailoring the advertisements to individual users, the system can foster user engagement, increase the likelihood of conversions, and optimize the advertising experience for both users and advertisers.

1.3 Objective

The objectives of this project are:

i. To study the existing computer vision technology on digital advertisement.
ii. To design and develop a product recommendation system using deep learning in computer vision.
iii. To evaluate the functionality of computer vision on the developed smart targeted product recommendation system.

1.4 Scope

User:

i. Residents in Kuantan.
ii. Shoppers from the age of 15 - 60.

System Scope:

i. Covered certain products and materials in Mr. DIY such as Hardware, Household, Electrical, Car Accessories, Toys and Computer & Mobile Accessories.
ii. Customer’s face will be the input for the product recommendation and the output will be products from Mr. DIY shop and others.

Development Scope:

i. Develop using deep learning and computer vision.
ii. Uses webcam to capture human face image.
iii. The system only captures one user at a time.

1.5 Significance of the project

The development of the product recommendation system is very crucial as it is the preparation for future. The system helps people to get suggestions to buy items that they might need, or they want once they walk into a mall or shop lots. It also helps to bring targeted customers to each specific product. Shops can avoid investing in advertisement that may or may not bring customers as this system will provide statistics on head count on product views as people approach and view each product that are advertised. Guiding customer to their intended or wish list products will be big game changer in product recommendation.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There are many advertisings and product recommendation mediums that uses Artificial Intelligence (AI) and machine learning to promote products/items which are available in online platforms. While surfing the internet, users are served with online advertisements that are related and based on the user’s previous search history. These types of targeted product recommendation are done to global products where users get recommendation of products from all around the world. In order to produce precise predictions or recommendations, recommender systems use machine learning (ML) techniques to analyse user data, including browsing history, purchasing behaviours, and demographic data. Facial recognition algorithms can be used to determine users' age and gender, which is an essential component of personalisation. This data can be used to identify trends and patterns that can be used to target ads more effectively. There are a few machine learning algorithms that are used on product recommendations which will be further discussed below.

2.2 Existing System

2.2.1 Collaborative Filtering

A popular machine learning approach called collaborative filtering drives recommendation systems across numerous industries. Its main goal is to offer tailored recommendations by assessing user preferences and behaviour. Despite not directly using age and gender data, collaborative filtering can nevertheless make useful product recommendations based on previous user interactions as in Figure 2.1.

The gathering of user information, such as browsing history, purchasing trends, and ratings, is the first step in the collaborative filtering process. For instance, well-known streaming provider Netflix compiles data on users' viewing patterns and their evaluations of films and television episodes. The system then determines user similarity scores based on the gathered data. (Kumar, 2020). Their previous interactions and preferences are compared using measures like cosine similarity or Pearson correlation as in Figure 2.2.

Collaborative filtering creates a neighbourhood of people that have similar preferences and behaviours based on the similarity scores that are computed. Users in this area are thought to be the most comparable to the target user. The system then creates suggestions by finding goods or things that local people have liked or favoured. These suggested things are ranked according to how relevant or likely to appeal to the target user they are. (Ajitsaria, 2022).

While collaborative filtering is effective at providing personalized recommendations, it's important to note that age and gender information is not explicitly incorporated in this algorithm. To introduce age and gender factors into the recommendation process, additional techniques like demographic-based filtering can be employed. By combining multiple algorithms, recommendation systems can enhance the accuracy and personalization of their suggestions, catering to the specific needs of users based on age, gender, and other relevant factors.

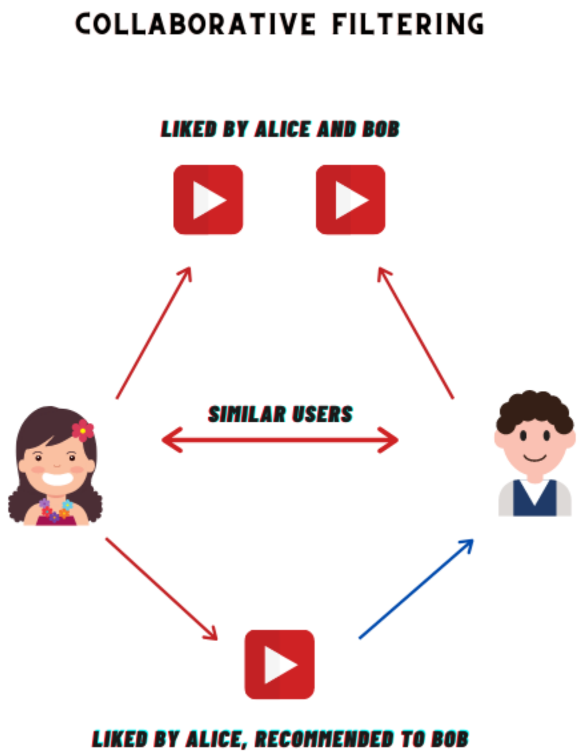


Figure 2.1 Collaborative Filtering Model

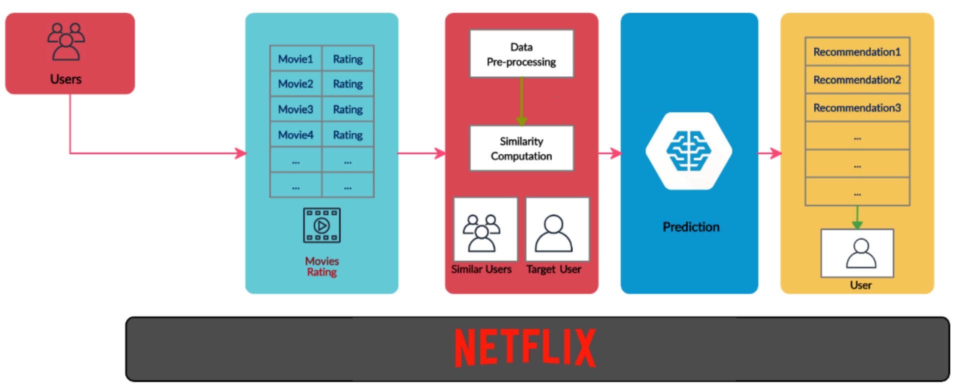


Figure 2.2 Netflix Collaborative Filtering Model

2.2.2 Content-Based Filtering

An ML algorithm known as content-based filtering bases its suggestions on the idea of comprehending the characteristics and qualities of products. It involves a number of procedures to produce tailored recommendations depending on the user's preferences and the features of the product.

Prior to starting the content-based filtering algorithm, data about the products are gathered and examined. This entails retrieving pertinent metadata, including aspects deemed crucial for recommendation purposes, such as gender-specific features, age suitability, and other characteristics. Age suitability, for instance, can relate to the range of ages that a given toy or article of clothing is suitable for, whereas gender-specific qualities might be characteristics like colour or design.

The algorithm then focuses on comprehending the user's preferences after identifying the product qualities. This can be done by looking into the user's previous interactions, including past purchases, browsing patterns, or ratings. The algorithm learns about the user's tastes and preferences through analysis of these interactions, which is essential for producing precise recommendations. (Roy, 2020).

Spotify is a music streaming service that uses content-based filtering as an example of a system. Based on its users' listening history and musical interests, Spotify uses content-based filtering to suggest songs and playlists to them. The lyrical themes, tempo, instrumentation, and other characteristics of songs are examined by Spotify's content-based filtering algorithm. It creates a profile for each user based on their listening habits, chosen artists, and favourite genres. The algorithm determines songs and playlists that fit the user's musical preferences based on this profile.

In conclusion, content-based filtering is an ML algorithm that recommends products based on their features and attributes, using the user's preferences as a guide. By analysing the product metadata and understanding the user's past interactions, content-based filtering can generate personalized recommendations that align with the user's age and gender preferences, ultimately enhancing the overall recommendation experience.

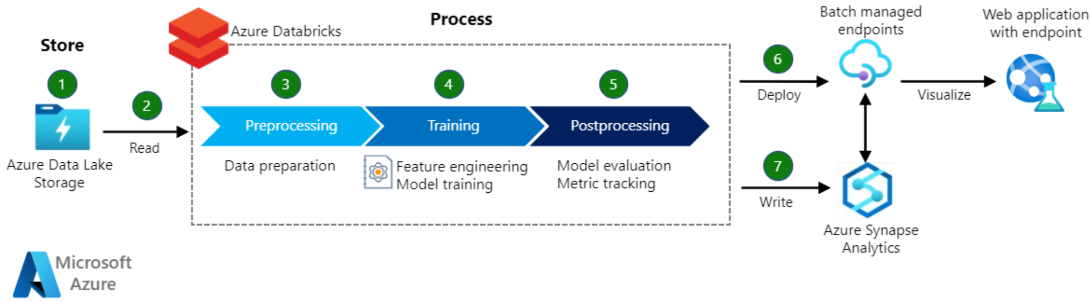


Figure 2.3 Content-based filtering model

2.2.3 Demographic-Based Filtering

An ML algorithm known as "demographic-based filtering" explicitly uses demographic data, such age and gender, to produce suggestions. This method examines user demographic profiles to find patterns and preferences specific to various age and gender groupings. The algorithm can provide product recommendations that are more likely to appeal to particular groups by recognising these features.

The first step in demographic-based filtering is gathering and examining user-provided demographic information. Age and gender details in this data offer insights into the demographic profile of the user. For instance, while registering for an account, an e-commerce platform may ask for information about your gender and age.

After gathering demographic information, the algorithm looks at patterns and preferences particular to certain age and gender groups. Within each demographic segment, it examines the previous interactions, purchases, and preferences of users. The programme can create relationships between demographic characteristics and product preferences by recognising similar patterns and behaviours. (Tommy, 2021).

For example, Amazon uses demographic-based filtering to recommend products to users based on their age and gender. By analyzing the shopping patterns of different demographic segments, Amazon tailors product recommendations to match the preferences of specific age and gender groups.

It is significant to highlight that hybrid models can be produced by combining demographic-based filtering with other recommendation methods like collaborative filtering or content-based filtering. These hybrid models can offer more precise and personalised recommendations that match the particular traits of each user segment by including demographic information into the overall recommendation process.

In summary, demographic-based filtering is a machine learning algorithm that focuses on using demographic data, such as age and gender, to produce suggestions. This method can make recommendations that are more likely to appeal to particular age and gender groups by comprehending the patterns and preferences associated with various demographics.

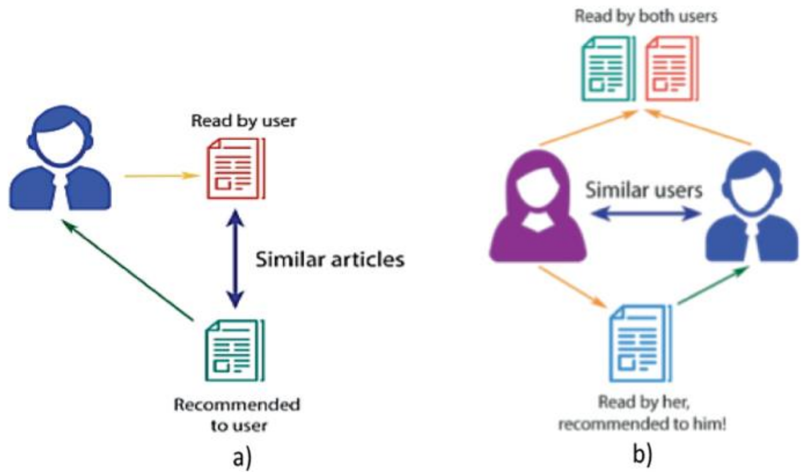


Figure 2.4 Demographic-based filtering model

2.3 Comparison of Existing System

Table 2.1 Comparison of Existing Machine Learning Algorithms

Criteria/ System	**Collaborative Filtering**	**Content-Based Filtering**	**Demographic-Based Filtering**	**Multi-task Cascaded Convolutional Networks (MTCNN)**
Scope	Focuses on analysing user behaviour and preferences to provide personalized recommendations	Recommends products based on their features and attributes.	Utilizes demographic information, such as age and gender, for recommendation	Focuses on facial recognition and age/gender recognition for product recommendations
Free or Paid version	Can be implemented in both free and paid recommendation systems.	Can be implemented in both free and paid recommendation systems.	Can be implemented in both free and paid recommendation systems.	Free
Approach used	Compares user preferences with similar users to suggest products.	Analyses product attributes and matches them with user preferences.	Considers demographic profiles and preferences of different user segments.	Utilizes deep learning-based facial recognition models for age and gender recognition.
Image Recognition	Does not directly incorporate image recognition capabilities.	Does not directly incorporate image recognition capabilities.	Does not directly incorporate image recognition capabilities.	Yes. Incorporates advanced image recognition capabilities for facial analysis.
Advertisement Analytics for Advertisers	Limited in providing targeted advertisement analytics.	Limited in providing targeted advertisement analytics.	Provides opportunities for targeted advertisement analytics.	Offers opportunities for targeted advertisement analytics based on demographic information.

Example System	Netflix uses collaborative filtering to recommend movies and TV shows.	Spotify uses content-based filtering to recommend songs and playlists.	Amazon uses demographic-based filtering to recommend products to users based on their age and gender.	An e-commerce platform using MTCNN for age and gender recognition in product recommendations.
Advantages	• Effective in providing personalized recommendations based on user behaviour. • Considers the preferences of similar users.	• Considers specific attributes and features of products. • Offers personalized recommendations based on user preferences.	• Tailors recommendations based on specific age and gender groups. • Provides targeted recommendations for different demographic segments.	• Provides accurate age and gender recognition from facial images. • Enables personalized recommendations based on recognized age and gender.
Disadvantages	• Does not explicitly incorporate demographic information like age and gender. • Limited in incorporating image recognition for recommendation	• May result in limited diversity in recommendation. • Does not explicitly incorporate demographic information.	• Relies heavily on accurate demographic information. • May overlook individual preferences within demographic groups.	• Requires high-quality facial images for accurate recognition. • May raise privacy concerns related to facial recognition technologies.

2.4 Summary

In conclusion, it can be shown from a comparison of machine learning algorithms for product recommendation that each method has advantages and disadvantages of its own. Personalised recommendations based on user behaviour are effectively provided by collaborative filtering, whereas content-based filtering takes into account product characteristics and attributes. Recommendations are tailored using demographic-based filtering based on particular age and gender demographics.

However, MTCNN (Multi-task Cascaded Convolutional Networks) stands out as the best method for product suggestion based on identified age and gender. MTCNN uses cutting-edge image recognition technology to precisely identify age and gender from facial photos. This improves the overall recommendation experience by enabling personalised recommendations that are in line with the user's recognised age and gender.

MTCNN clearly combines picture recognition and provides options for targeted ad analytics based on demographic data, in contrast to other algorithms. It offers a more thorough and precise grasp of the characteristics of the user, resulting in highly customised and pertinent product recommendations.

Although collaborative filtering, content-based filtering, and demographic-based filtering each have advantages of their own, it's possible that none of them explicitly incorporate picture recognition or provide the same level of individualised suggestions based on age and gender recognition as MTCNN.

Therefore, MTCNN emerges as the best machine learning strategy for product recommendation based on recognised age and gender, providing precise age and gender recognition from facial photos and enabling highly customised suggestions.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, the suitable approach or methodology will be chosen and described in-detail for the research for product recommendation system. There will also be information about the suggested model, structure, design, and data choices. The methodology helps us to develop the model in a professional way with complete documentation and data proof.

3.1.1 Multi-task Cascaded Convolutional Networks (MTCNN)

A framework called Multi-task Cascaded Convolutional Networks (MTCNN) was created as a method for both face alignment and detection. Convolutional networks are used in three steps of the process to identify faces and facial landmarks such the eyes, nose, and mouth.

The research suggests MTCNN as a method for combining both tasks (alignment and recognition) utilising multi-task learning. It uses a shallow Convolutional Neural Network (CNN) in the first step to generate candidate windows quickly. Through a more intricate CNN, the second step refines the suggested candidate windows. Finally, a third CNN, which is more complicated than the others, is used in the third stage to further refine the outcome and output face landmark positions. There are three stages of cascaded network as the first step is to take images and resize them to different types of scales to build a pyramid (Rongrong Jin, 2020).

I. Stage one - The Proposal Network (P-Net)

The Proposal Network is utilized to acquire possible windows and their bounding box regression vectors, which involves predicting the location of boxes for detecting pre-defined class objects, specifically faces. Overlapping regions are combined and refined, resulting in a reduced volume of candidate windows as the final output of this process as in Figure 3.1. (Gradilla, 2020).

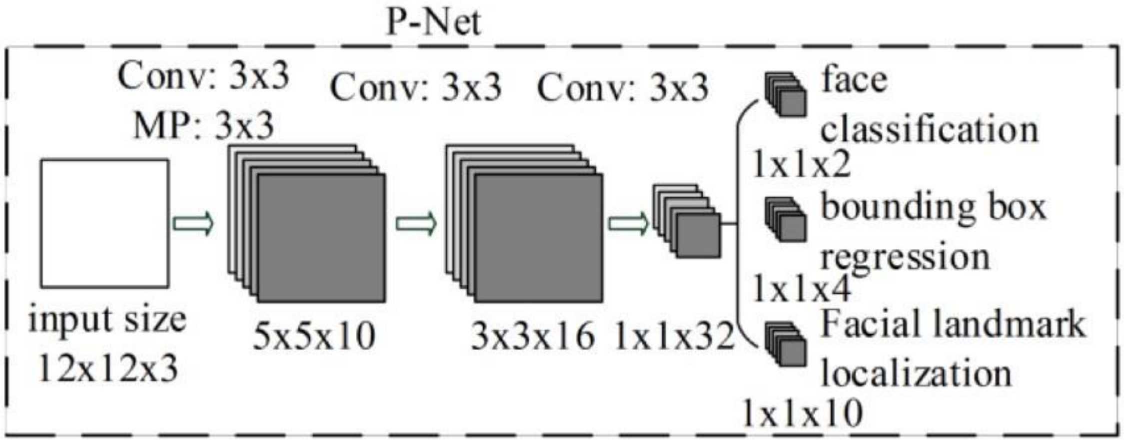


Figure 3.1 P-Net process from MTCNN paper (Gradilla, 2020)

II. Stage two - The Refine Network (R-Net)

The P-Net feeds the Refine Network with all candidates. Due to the presence of a dense layer at the last stage of the network architecture, this network is a CNN rather than an FCN like the one before. The R-Net uses non-maximum suppression (NMS) to combine overlapping candidates, performs calibration with bounding box regression, and further decreases the number of candidates. Depending on whether the input is a face or not, the R-Net produces a four-element vector that represents the bounding box for the face and a 10-element vector for the localization of facial landmarks as in Figure 3.2 (Gradilla, 2020).

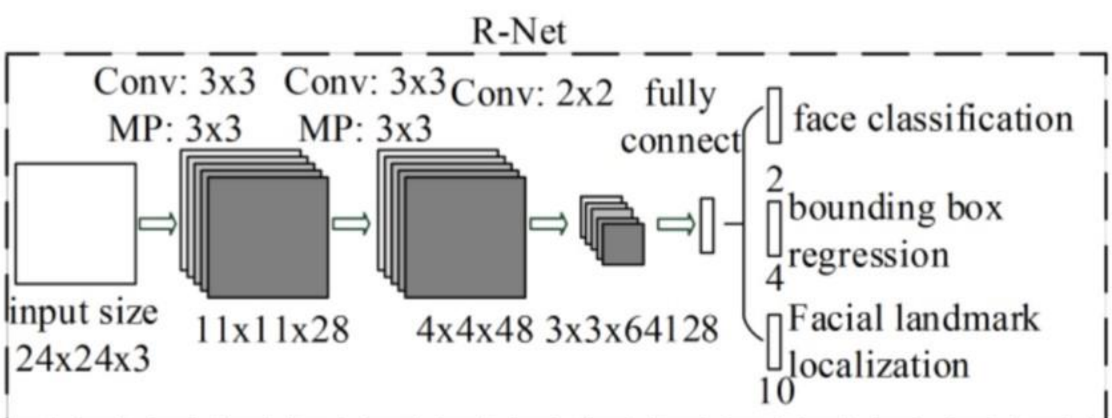


Figure 3.2 R-Net process from MTCNN paper (Gradilla, 2020)

III. Stage 3 - The Output Network (O-Net)

Similar to the R-Net, this stage seeks to characterise the face in greater depth and output the locations of the five facial landmarks, including the eyes, nose, and mouth as in Figure 3.3 (Gradilla, 2020).

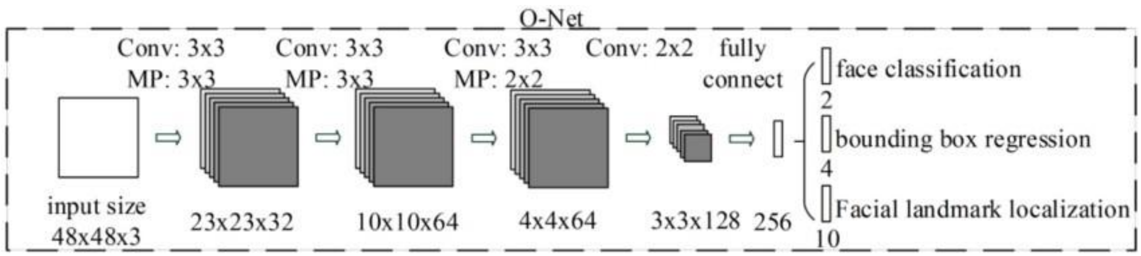


Figure 3.3 O-Net process from MTCNN paper (Gradilla, 2020)

There are three tasks of MTCNN which outputs face/non-face classification, bounding box regression, and facial landmark localization.

1. Face classification: This cross-entropy loss problem involves binary classification:

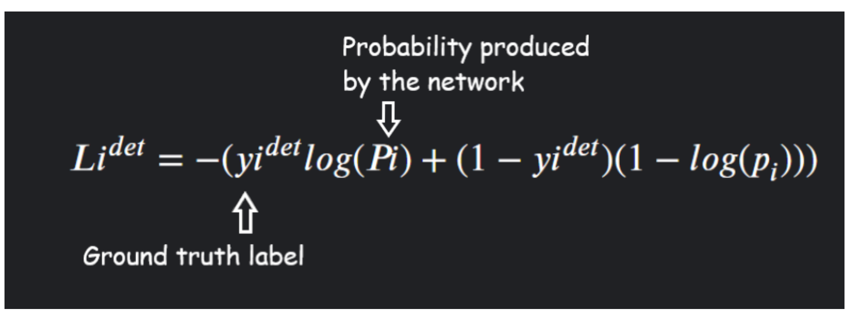


Figure 3.4 Cross-entropy loss calculation

2. Bounding box regression: A regression issue constitutes the learning aim. The offset between a candidate and the closest ground truth is calculated for each candidate window. For this challenge, Euclidean loss is used.

Ground truth coordinate

$$L_i^{box} = ||\hat{y}_i^{box} - y_i^{box}||_2^2$$

Target obtained from network

Figure 3.5 Bounding box and Euclidean loss calculation

3. Facial Landmark localization: The localization of face landmarks which are right eye, left eye, nose, right mouth corner and left mouth corner are modelled as a regression issue with Euclidean distance as the loss function.

$$Li^{landmark} = ||Yi^{landmark} - Yi^{landmark}||_2^2$$

Figure 3.6 Euclidean loss calculation

3.2 Research Framework

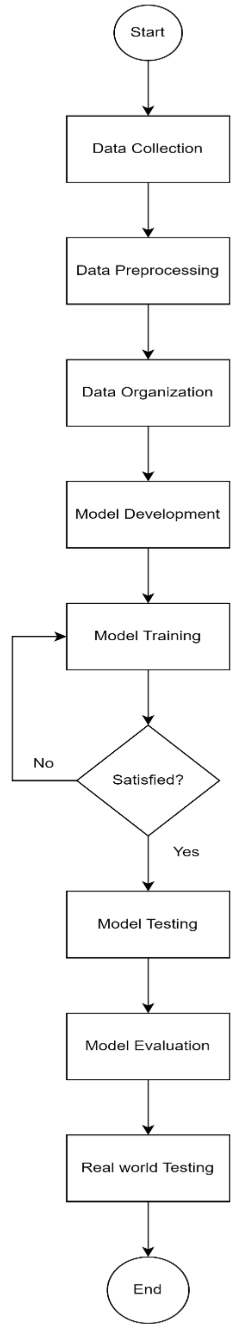


Figure 3.7 Flowchart of Model Development

The research framework used will be consists of data collection, data pre-processing, data organization, model development, model training, model testing, model evaluation and real-world testing.

I. Data Collection

The dataset of human face images will be collected from Kaggle website which is a website that provides various types of data for machine learning model training. The dataset of human faces that consists of all common creeds, races, age groups and profiles which sums up to 7.2K images. It also contains an excel sheet that contains the details of the images such as id, gender, class and age.

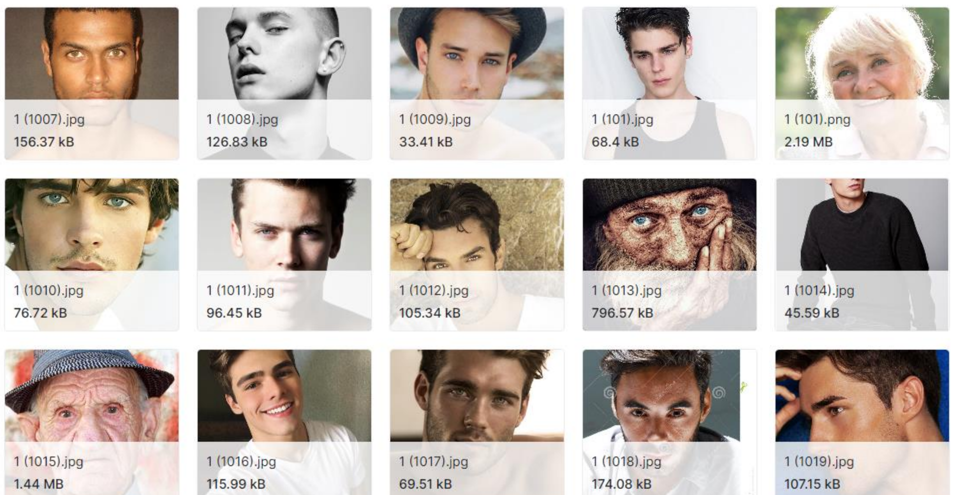


Figure 3.8 Human Face Images Dataset

	A	B	C	D
1	ID	Gender	Class	Age
2	377.jpg	Male	MIDDLE	25
3	17814.jpg	Male	YOUNG	12
4	21283.jpg	Male	MIDDLE	23
5	16496.jpg	Female	YOUNG	17
6	4487.jpg	Male	MIDDLE	26
7	6283.jpg	Female	MIDDLE	24
8	23495.jpg	Female	YOUNG	8
9	7100.jpg	Male	YOUNG	8
10	6028.jpg	Male	YOUNG	12

Figure 3.9 Excel sheet containing images details

II. Data Pre-processing

The images that was collected will be then pre-processed in 2 different ways, Firstly, the images will be resized to standard size which is 480 x 640 pixels to make it easier to load during training of model. Next, the images will be changed from coloured to greyscale. This helps to reduce the size of the image and computational complexity during image processing as colour does not play much role in image recognition.

III. Data Organization

400 images of pre-processed human images will be chosen at random which consists of young, middle, and old age faces. These images are then will be placed in a different folder for image training with the excel sheet data that have been sorted and filtered based on the chosen images.

IV. Model Development

The development of the model will be done using Visual Studio Code as the IDE and python programming language will be used to code the model. The model will use the data saved locally and will use webcam of laptop for real-time testing.

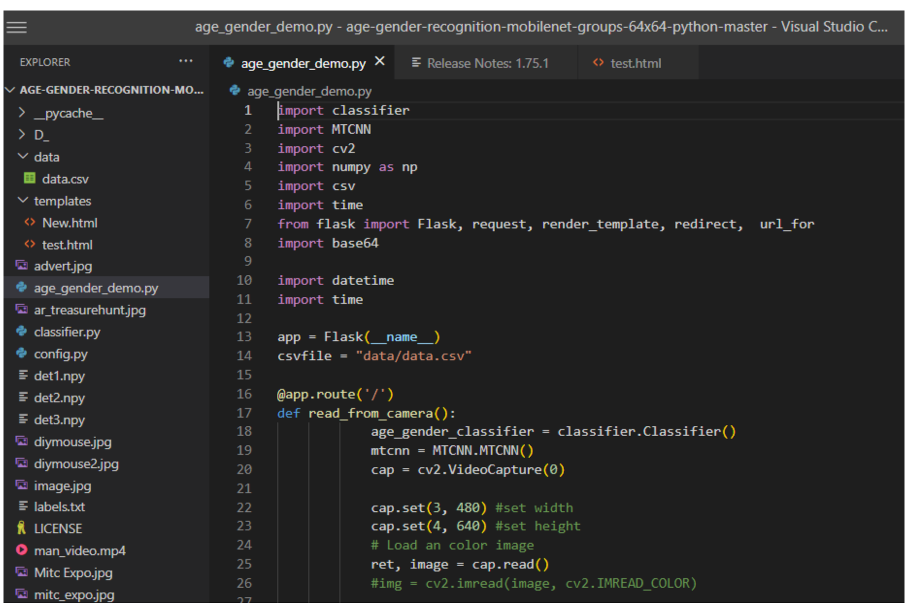


Figure 3.10 Visual Studio Code IDE for model development in Python

V. Model Training

The model training is done by segregating the dataset into 80% for training and remaining 20% for testing. The developed model will be run with the human images data set that has been prepared and the results of the gender and age classification reading will be recorded and saved in a new excel file for every training. The model will be configured until the accuracy of the prediction reaches 0.8. The product recommendation result will also be recorded and checked for accuracy. The training will be repeated until the targeted accuracy goal is reached.

VI. Model Testing

Once model training is done, the model will then be tested using webcam of laptop by integrating with OpenCV library which provides image reading feature to be further processed. The model then will be displayed with real human faces in front of the camera and the results and output of gender, age and product recommendations will be recorded in excel file to evaluation.

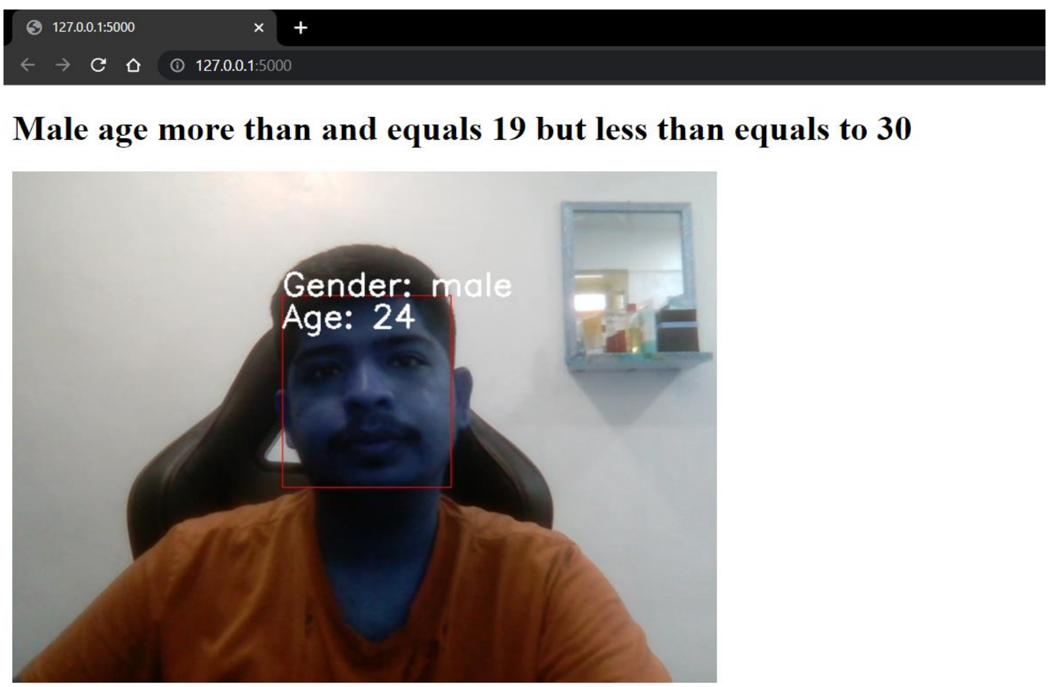


Figure 3.11 Model testing using webcam

VII. Model Evaluation

During evaluation, the recorded results and outputs from the model will be used to check for the accuracy, precision, recall and F1-Score for all gender and age predictions and product recommendations. The information such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) will be needed to calculate the matrices. The formula for accuracy, precision, recall and F1-Score are used as in figure 3.12.

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

$$Precision = \frac{T_p}{T_p + F_p}$$

$$Recall = \frac{T_p}{T_p + T_n}$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

Figure 3.12 Formulas for Model Evaluation

VIII. Real-world Testing

After appropriate evaluation and testing, the model will be then tested in real world scenario with people’s faces on a targeted area to check for it’s accuracy and effectiveness in predicting, recommending and attracting customers. These data will be recorded for calculating model effectiveness and marketability of the model.

3.2.1 Project Tools

Table 3.1 Project Tools

Software/Library	**Functionality**
Multi-task Cascaded Convolutional Networks (MTCNN)	For image recognition and alignment for further image processing.
OpenCV	A real-time computer vision used to capture images and processed.
Flask web application	Flask is used for developing web applications using python to show the output of the image processing.
Classifier	Classifiers are trained machine learning models used to detect specific objects or features within an image. These classifiers are created by training a machine learning model on a dataset of positive and negative examples of the object or feature being detected. The resulting model can then be used to detect the object or feature in new images.
Python NumPy and Pandas	For data pre-processing in python.
Python matplotlib	For Data visualization of process and output.

3.3 Research Requirement

3.3.1 Image Pre-processing

1. Image Resize

The dataset of images are resized to 480 x 640 pixels of width and height respectively to have standard size. This is done to reduce the size of the image and make it easier to load the image during image processing.

2. Image grayscale

Converting coloured images to grayscale helps to reduce the size, space and computational complexity. This is because for many objects, colour is not important to recognize and process an image. Grayscale images are good enough for face recognition as it will only find for face while detecting for the right eye, left eye, nose, right mouth corner and left mouth corner.

3.3.2 Input

The input of the model will be human face images which will be used to process and identify the 5 focal points which are right eye, left eye, nose, right mouth corner and left mouth corner. The human face images will be consisting of young, middle and old age faces.

3.3.3 Expected output

The model will process the human face and will classify and output the gender and age of the human face recognized and recommend products from DIY. The gender will be categorized into two categories which are male and female. For age, it is classified and grouped into different age groups which are Children (1 year to 12 years), Adolescents (13 years through 17 years), Young Adults (18 years or 30 years), Older Adults (31 years and older).

Table 3.2 Expected Accuracy and Precision for outputs

Task	**Accuracy**	**Precision**
Gender Classification	≈ 0.95	≈ 0.92
Age Classification	≈ 0.84	≈ 0.80
Product Recommendations	≈ 0.92	≈ 0.88

3.3.4 Process Description

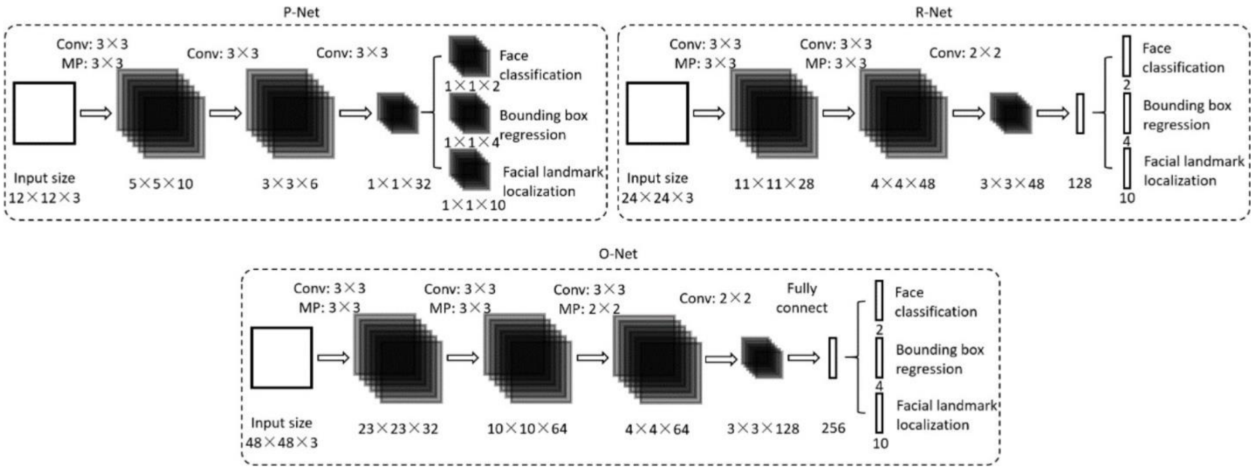


Figure 3.13 MTCNN Model

The model will be developed using Multi-task Cascaded Convolutional Networks (MTCNN) algorithm incorporated with Flask web application that uses OpenCV library that for image processing, to detect faces in a video stream from a camera and then uses a pre-trained classifier to predict the age and gender of the detected faces. The classifier is imported from a module called "classifier". The Flask library is used to route to web application to display the output of each reading and image processes. The video capture of object through webcam will be adjusted to 480x640 pixels and the face is read from the frame as object and return Boolean indicating if the frame was read successfully and the frame itself. It then converts the image from BGR to RGB format and passes it to the MTCNN object's detect() method to detect faces in the image. The MTCNN package returns a list of bounding boxes for each detected face. For each bounding box, the code extracts the x, y, width, and height of the box, and then uses the classifier's predict() method to predict the age and gender of the face within the bounding box. It then draws a rectangle around the bounding box and writes the age and gender predictions on the image. It then checks the gender and age and assign a number to a variable for product recommendation group based on the gender and age of the person in the image. In case no face is detected, or the gender or age is not found, the model sets gender and age to "not found" or "no object detected". Every result such as image id, predicted gender, age and age group and product recommended details will be recorded in excel sheet.

3.3.5 Constraints or Limitation

The model only recommends the products that exists in the database with metadata of the products specified for specific gender and age groups. The model can only read a human face at a time to maximise the accuracy of face recognition and age and gender reading. The model will search and read for human face for every 10 seconds in a loop. The output will be displayed on web view only and the image capture will be done using webcam of laptop.

3.4 Dataset

The dataset was taken from Kaggle for images of human faces and excel sheet containing images details. It is an unbiased dataset that have a thorough mix of all common creeds, races, age groups and profiles. 400 images are selected at random from 7.2k of images which are shown in figure 3.14 for 15 sample human images.

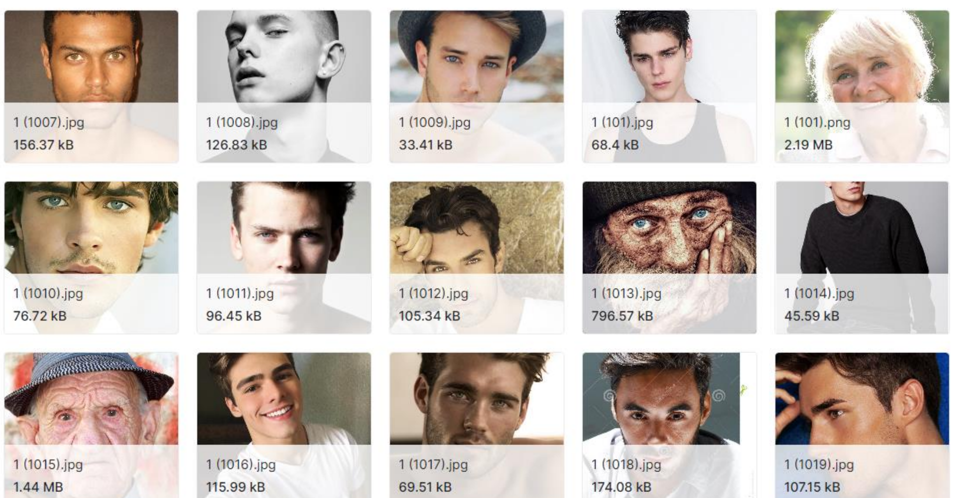


Figure 3.14 Human face images from Kaggle

	A	B	C	D
1	ID	Gender	Class	Age
2	377.jpg	Male	MIDDLE	25
3	17814.jpg	Male	YOUNG	12
4	21283.jpg	Male	MIDDLE	23
5	16496.jpg	Female	YOUNG	17
6	4487.jpg	Male	MIDDLE	26
7	6283.jpg	Female	MIDDLE	24
8	23495.jpg	Female	YOUNG	8
9	7100.jpg	Male	YOUNG	8
10	6028.jpg	Male	YOUNG	12
11	22617.jpg	Female	OLD	45
12	11177.jpg	Female	YOUNG	15
13	2462.jpg	Male	MIDDLE	24
14	24116.jpg	Male	MIDDLE	25
15	17689.jpg	Female	MIDDLE	25
16	728.jpg	Male	MIDDLE	24
17	3003.jpg	Male	MIDDLE	26
18	14408.jpg	Male	OLD	52
19	6679.jpg	Female	YOUNG	13
20	15152.jpg	Female	OLD	52

Figure 3.15 Excel data of images details from Kaggle

Figure 3.15 above is the excel sheet containing details of the images such as **ID** which represents the image id of each images name, **Gender** as the original gender of the image, **Class** which represents the age group and finally **Age** which gives the exact age of the face image.

3.5 Proof of Initial Concept

1. Image grayscale conversion

```
#get an image
img = read_img(df['file'][105],(255,255))

#gray
image_gray = gray_image(img)

fig, ax = plt.subplots(1, 2, figsize=(5, 5));
plt.suptitle('RESULT', x=0.5, y=0.8)
plt.tight_layout(1)

ax[0].set_title('ORIGINAL', fontsize=12)
ax[1].set_title('GRAY', fontsize=12)

ax[0].imshow(img/255);
ax[1].imshow(image_gray);
```

Figure 3.16 Code for Image conversion to grayscale

The code above in figure 3.16 is used to convert coloured images into grayscale to reduce the space and image processing complexity of model.

2. Face Recognition model

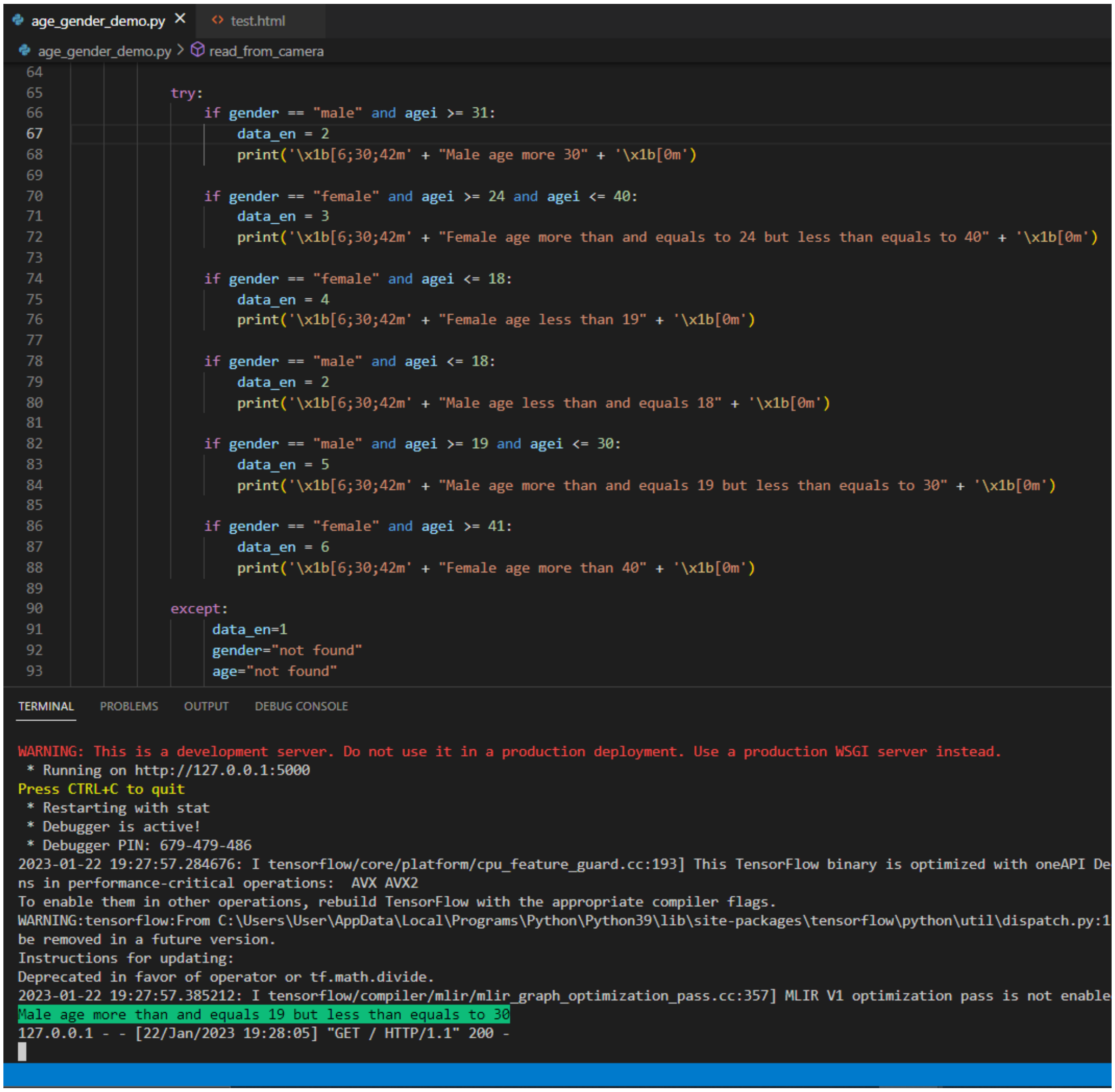


Figure 3.17 Code and output of image processing

The green highlighted text in figure 3.17 is the output generated using my face that predicts the gender and age range group.

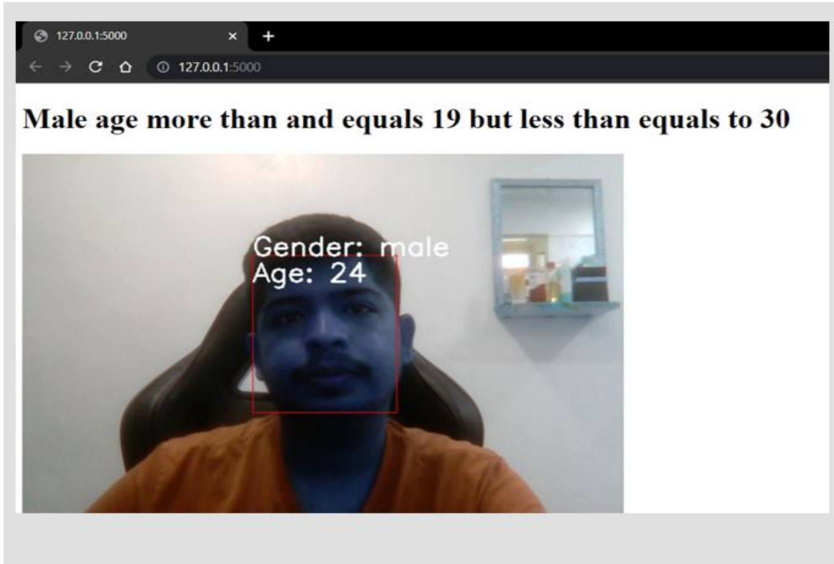


Figure 3.18 Output of gender and age recognition in web view

Figure 3.18 is the web view of the output of image processed which shows the gender and exact age predicted.

3. Product Recommendation

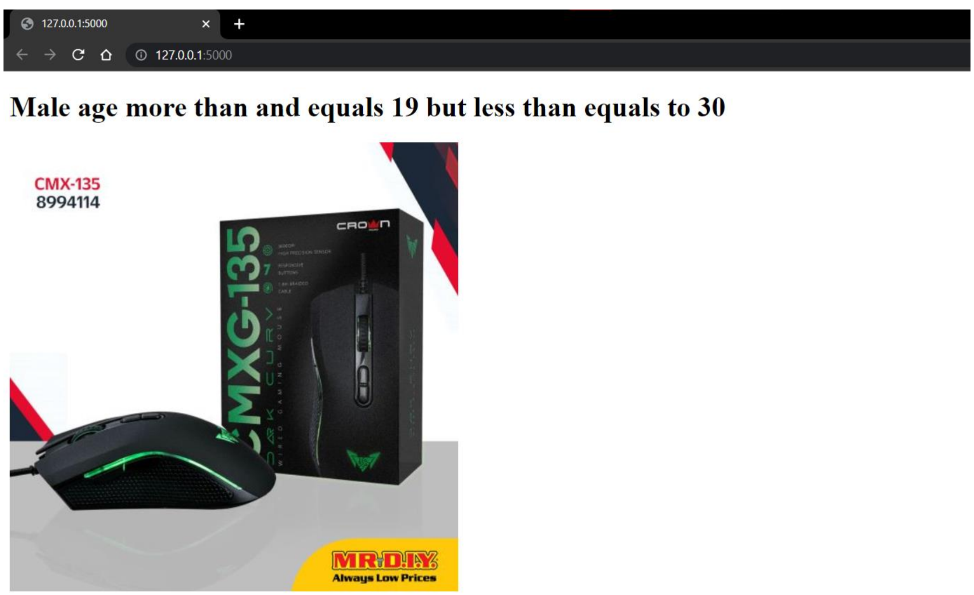


Figure 3.19 Output of product recommendation in web view

The output was opened on a browser and display the recommended product according to the gender and age category.

3.6 Testing/Validation Plan

3.6.1 Performance Testing:

1. **Identify suitable ai model:** Identify and test for appropriate AI Models that can predict gender and age of people.

2. **Performance metrics:** Identify the appropriate performance metrics to evaluate the model's accuracy and precision in detecting faces, predicting gender and age, and recommending products. Examples include accuracy, F1-score, precision, and recall (HE, 2021).

   i. **Accuracy:** The formula for accuracy is (number of correct predictions) / (total number of predictions). It is a measure of how well the model can predict the correct output.

   ii. **F1-Score:** The formula for F1-score is (2 * (precision * recall)) / (precision + recall). It is a measure of the trade-off between precision and recall.

   iii. **Precision:** The formula for precision is (number of true positives) / (number of true positives + number of false positives). It is a measure of how well the model can predict the correct output when it makes a prediction.

   iv. **Recall:** The formula for recall is (number of true positives) / (number of true positives + number of false negatives). It is a measure of how well the model can identify all relevant instances of the target class.

3. **Test scenarios:** Define test scenarios that simulate real-world conditions. This could include testing the model's performance on images with varying lighting conditions, different poses, and different backgrounds.

4. **Test automation:** Use test automation tools to run the performance tests and collect data on the model's performance. This will help to identify performance bottlenecks and improve overall efficiency.

5. **Test monitoring:** Monitor the model's performance during testing and identify any potential issues that may affect the model's accuracy and precision.

6. **Test reporting:** Prepare detailed test reports that summarize the model's performance, including any identified issues and recommended solutions.

7. **Test validation:** Validate the model's performance by testing it on a new set of images that were not used during the training process. Monitor and retraining: Regularly monitor the model's performance and retrain the model if necessary to ensure that it continues to perform well.

8. **Real-world testing:** Finally, test the model on real-world data to ensure that it is able to perform well in a real-world scenario.

3.7 Potential Use of Proposed Solution

The Product Recommendation System is a software solution for shops that have various types of products and items where it can narrow down the choices for customers by suggesting the optimum and precise products for them by recognizing the user's gender and age. For example, Mr. DIY shops are selling a variety of products and items in a single shop lot where this software can assist customers by advertising the products and suggesting the products for the customer.

Besides, this system has a centralized control center in web-based for clients to add new products, update existing product details, delete unwanted products, search, and view all their products in system and also produces reports and charts based on the engagement that the model received from customers. The client has full control of their product displays which gives them freedom to update as per their convenience. Moreover, the system also allows to control and adjust the product recommendation display format dynamically and precisely with the convenience of the client.

In conclusion, the client will be able to monetize this software completely as it will ease the job of a shopper. The recommended products will have the precise location mentioned which will also be a good navigator for users. This system will be able to change the game on marketing and product suggestion for shops. This system also can be enhanced in future where it also can be a smart advertiser for shopping malls by suggesting shops in malls and navigate the users to the precise location of the shop.

3.8 Gantt Chart

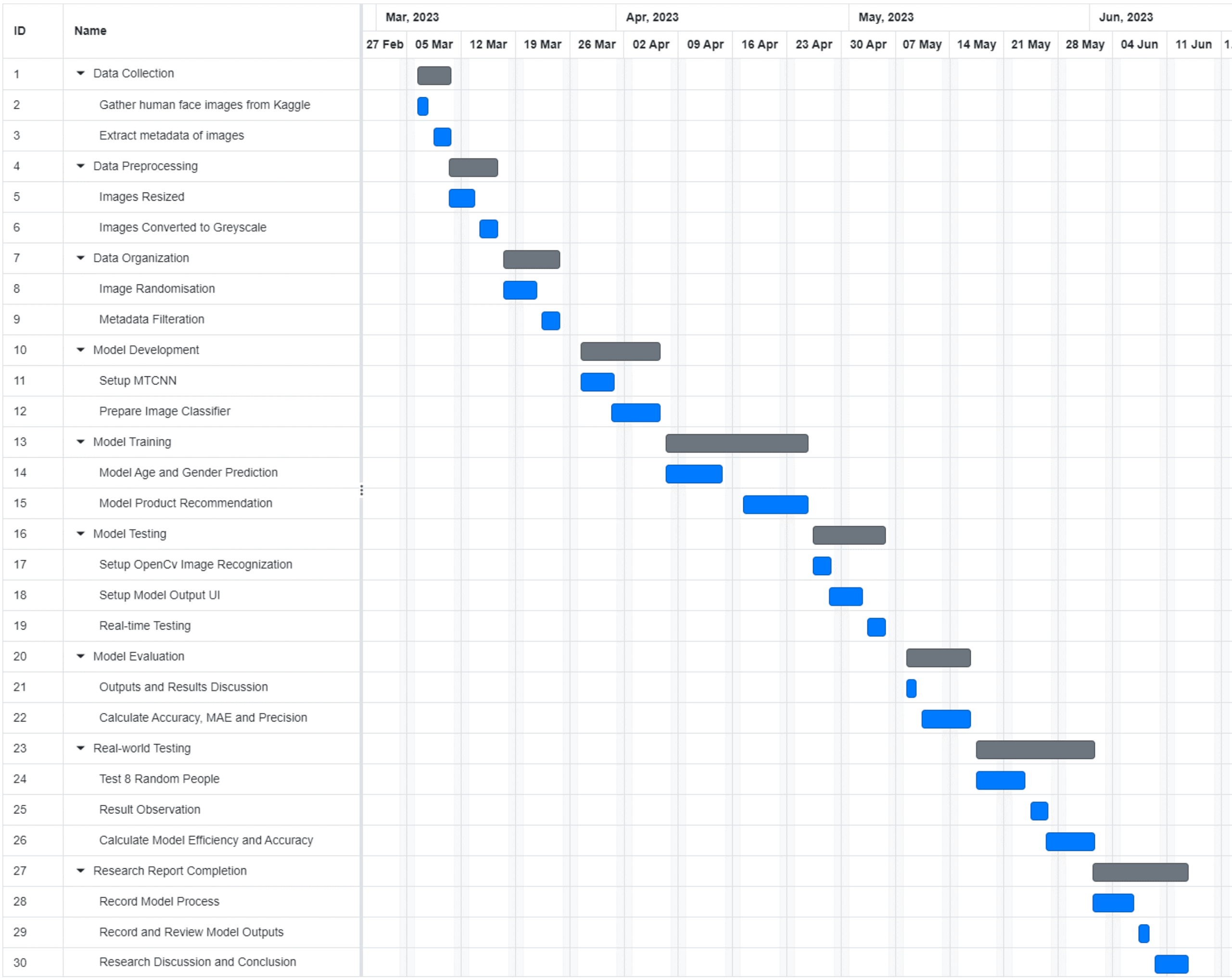


Figure 3.20 Gantt Chart

Chapter 4

IMPLEMENTATION, RESULT AND DISCUSSION

4.1 Input

4.1.1 Input of preprocessed face images

The human face images are collected and cropped to standard size of 480 x 640 pixels. This resizing is done to facilitate easier loading during the training of the model, as shown in Figure 4.1. The metadata of each image is written as the file name, following the format '15_0_0_20170103201301966.jpg.chip.jpg'. Underscores are used to separate different pieces of information within the filename. For example, '15' refers to the age of the image, '0' refers to the male gender, another '0' refers to the race, and finally, '20170103201301966' represents the date and time of the image. This unique identifier is used to recognize the images, as illustrated in Figure 4.2.

Figure 4.1 Image Dataset

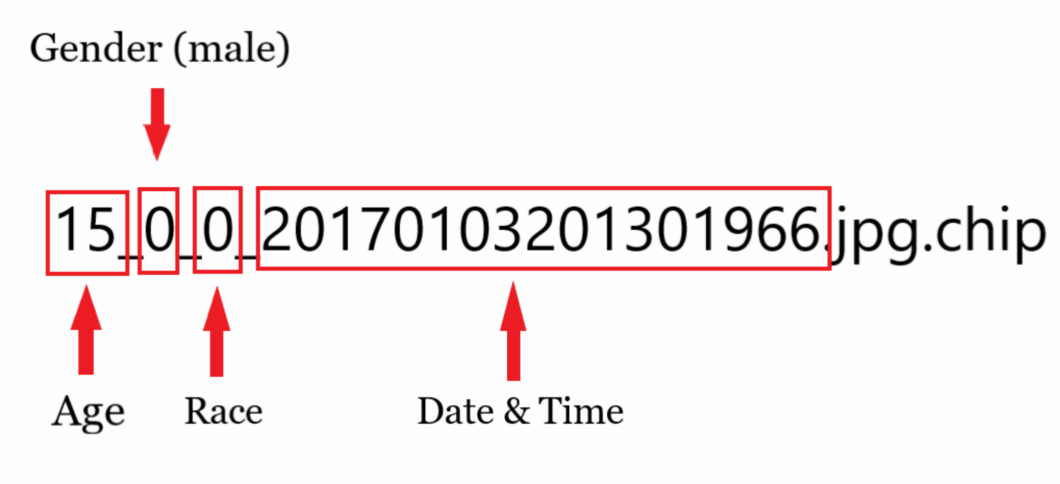


Figure 4.2 Image File Naming

Figures 4.3 are the sample cropped pictures which will then be converted to RGB (Red-Green-Blue).

Figure 4.3 Human Face Images

4.2 Output

The machine learning model will predict and label the age and gender detected in each individual image. These marked images then be saved locally. Figure 4.4 is the example output of the model. The output will also be saved in csv file with the id extracted from the image file name, predicted_age and predicted_gender as show in figure 4.5.

Figure 4.4 Output of AI Model

	A	B	C
1	id	predicted_age	predicted_gender
2	15_0_0_20170104013333801.jpg.chip.jpg	15	male
3	15_0_0_20170104225947233.jpg.chip.jpg	15	male
4	15_0_0_20170105183251055.jpg.chip.jpg	24	male
5	15_0_0_20170105183254311.jpg.chip.jpg	18	male
6	15_0_0_20170110223430616.jpg.chip.jpg	12	male
7	15_0_0_20170110224250144.jpg.chip.jpg	18	male
8	15_0_0_20170110224312647.jpg.chip.jpg	12	male
9	15_0_0_20170110224324459.jpg.chip.jpg	15	male
10	15_0_0_20170110225410802.jpg.chip.jpg	15	male
11	15_0_0_20170110225440579.jpg.chip.jpg	15	male
12	15_0_0_20170110225617650.jpg.chip.jpg	12	male
13	15_0_0_20170110225622776.jpg.chip.jpg	12	male
14	15_0_0_20170110225705232.jpg.chip.jpg	12	female
15	15_0_0_20170110231550866.jpg.chip.jpg	15	female
16	15_0_0_20170110232117349.jpg.chip.jpg	15	male
17	15_0_0_20170110232306381.jpg.chip.jpg	12	male
18	15_0_0_20170110232311158.jpg.chip.jpg	12	female
19	15_0_0_20170110232322390.jpg.chip.jpg	12	male
20	15_0_0_20170110232327328.jpg.chip.jpg	12	male
21	15_0_0_20170110232331351.jpg.chip.jpg	12	female
22	15_0_0_20170110232338801.jpg.chip.jpg	15	male
23	15_0_0_20170110232443234.jpg.chip.jpg	12	male
24	15_0_0_20170110232452356.jpg.chip.jpg	12	male
25	15_0_0_20170110232515682.jpg.chip.jpg	15	male
26	15_0_0_20170110232532949.jpg.chip.jpg	16	male
27	15_0_0_20170110232610061.jpg.chip.jpg	12	male
28	15_0_0_20170110232636744.jpg.chip.jpg	12	male
29	15_0_0_20170110232640357.jpg.chip.jpg	12	male

Figure 4.5 Output exported in CSV

4.3 Process Description

4.3.1 Colour conversion of face images from BGR to RGB

When using OpenCV in conjunction with other libraries or programmes that require RGB images, the image is frequently converted from BGR to RGB. It guarantees that the image is in the proper colour format for visualisation or further processing. Thus, the cropped images are then converted from BGR (Blue-Green-Red) to RGB (Red-Green-Blue) as shown in figures 4.6.

Figure 4.6 BGR to RGB converted images.

4.3.2 Image Region of Interest (ROI) Selection

The RGB images are then marked as shown in figures 4.7 with a rectangle to highlight or annotate a specific region of interest. Drawing rectangles on images is a common technique in computer vision and image processing. Here onwards, the model will predict the age and the gender of the face that is focused on each individual images.

Figure 4.7 Image Region of Interest sample

4.3.3 Age and Gender Prediction

The input image is initially subjected to the Multi-task Cascaded Convolutional Networks (MTCNN) object detection model in order to identify faces in the image. For each detected face, the algorithm retrieves the confidence score associated with the detection. The position and size of the face inside the image are then represented by the bounding box coordinates of the detected face.

To broaden the bounding box and maybe include more facial features, these bounding box coordinates are slightly modified. To facilitate future calculations, the altered coordinates are transformed to integers. The bounding box's individual values (x, y, width, and height) are then extracted.

The greatest value between the bounding box's width and height is determined to determine the size of the square region that will be extracted around the face. The top-left and bottom-right coordinates are then modified based on the extracted length to produce new coordinates that define a square zone around the face.

To ensure that the calculated coordinates do not exceed the boundaries of the image, they are constrained accordingly. Based on these modified coordinates, the region of interest (ROI) inside the image that corresponds to the recognised face is retrieved.

The extracted ROI is then passed to an age and gender classifier model for prediction. The age and gender of the person in the ROI are predicted by the model. The predicted age and gender information is combined into a single string.

The output of the classifier is utilized to extract the predicted age and gender. To clean up the age string, any non-numeric characters such as hyphens are removed. The subsequent step involves extracting the first two characters from the modified age string and converting them into an integer, which typically represents the expected age range.

4.3.4 Metadata Extraction

The dataset’s metadata are labelled and embedded as their image file name, formatted like [age]_[gender]_[race]_[date&time].jpg as in figure 4.8.

- [age] is an integer from 0 to 116, indicating the age.
- [gender] is either 0 (male) or 1 (female).
- [race] is an integer from 0 to 4, denoting White, Black, Asian, Indian, and Others (like Hispanic, Latino, Middle Eastern).
- [date&time] is in the format of yyyymmddHHMMSSFFF, showing the date and time an image was collected to UTKFace.

Underscores are used to divide each file name into a minimum of four parts before storing it. The person's age, gender, and a special picture identification can be determined from these components. The gender is standardized to "male" for 0 or "female" for 0. This extracted information is compiled into a list of dictionaries. The retrieved data is then used to generate a DataFrame, containing columns for the image ID, age, and gender. As a result, the metadata are formatted and organised in order to be compared with the predicted age and gender by the model.

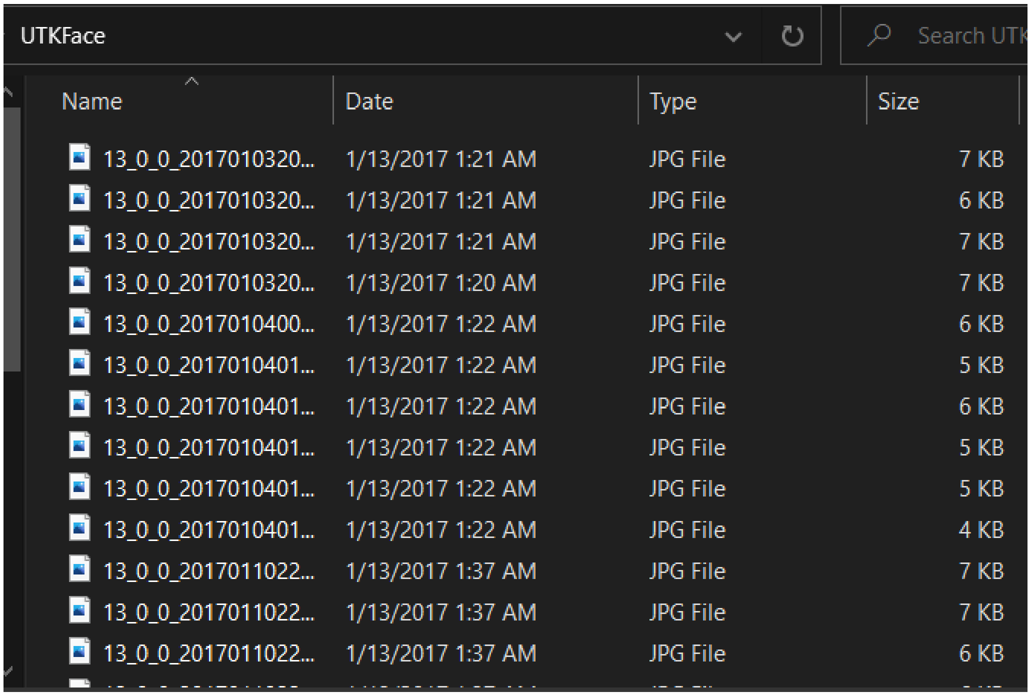


Figure 4.8 Dataset filename as metadata

4.3.5 Mean Absolute Error (MAE)

A popular evaluation statistic for age prediction models is mean absolute error (MAE). The average absolute difference between the predicted and actual age values is measured by this. The MAE is determined by taking the absolute difference between each predicted age value and its associated actual age value, averaging these differences across the dataset, and then calculating the difference in percentage terms. The formula for MAE is:

MAE = $(1/n) * \Sigma$ |predicted_age - actual_age|

Using MAE (Mean Absolute Error), we can measure the average magnitude of errors made by the prediction model in terms of absolute deviations from the true age. A lower MAE indicates a better model because it suggests that the predicted age values are, on average, closer to actual age values.

It is a suitable metric for evaluating the overall accuracy and performance of the age prediction model since it gives equal weight to overestimations and underestimations.

According to the current modal's Mean Absolute Error (MAE) for Age Prediction, which is 3.1977, the projected age values and actual age values diverge by around 3.2 years on average as in figure 4.9. This shows the degree of divergence or mistake in the model's age estimates. Since the predicted age values are on average closer to the actual age values, a model with a lower MAE is considered to be more accurate.

```
In [96]: from sklearn.metrics import mean_absolute_error
         merged_df = pd.merge(actual_df, predicted_df, on="id")

         # Calculate mean absolute error (MAE) for age prediction
         mae = mean_absolute_error(merged_df["age"], merged_df["predicted_age"])

         print("Mean Absolute Error (MAE) for Age Prediction:", mae)

         Mean Absolute Error (MAE) for Age Prediction: 3.197729698263316
```

Figure 4.9 Output of Mean Absolute Error (MAE) of Age prediction

4.3.6 Gender Prediction Accuracy

The accuracy of a gender prediction model is a metric used to assess how successfully the model predicts the gender of a given person. It aids in evaluating the accuracy and precision of the model's forecasts. By contrasting the projected gender values with the actual gender values in the dataset, the accuracy is determined. The percentage of accurate forecasts divided by the total number of guesses is the formula employed. In order to convert it to a percentage, multiply it by 100. We use accuracy to evaluate the gender prediction model's performance objectively and determine whether it is appropriate for use in practical applications.

In this case, the output value of Gender Prediction Accuracy: 96.84% indicates that the model predicted the gender correctly for approximately 96.84% of the cases in the dataset, suggesting a high level of accuracy in gender prediction as in figure 4.10. The formula for calculating accuracy in gender prediction is as follows:

Gender Accuracy = (Number of correct gender predictions) / (Total number of predictions) * 100

This formula calculates the ratio of correct predictions to the total number of predictions made by the model. The result is typically multiplied by 100 to express the accuracy as a percentage.

```
In [14]: #actual_df and predicted_df
predicted_df = dfp
actual_df = df_metadata
merged_df = pd.merge(actual_df, predicted_df, on="id")

# Calculate gender prediction accuracy
gender_accuracy = (merged_df["gender"] == merged_df["predicted_gender"]).mean()

print("Gender Prediction Accuracy: {:.2%}".format(gender_accuracy))
```

```
Gender Prediction Accuracy: 96.84%
```

Figure 4.10 Output of Gender Accuracy Calculation

4.4 Constraints and limitations

There are plenty of constraints and limitations faced during the model training for age and gender recognition.

1. Image Quality: The poor image quality, such as low resolution, blur, or noise, from the dataset made it challenging for the AI model to extract relevant features for age and gender prediction.

2. Occlusion and Feature Extraction: The watermarks covering the face of the images obstruct crucial facial features that the model relies on during age and gender prediction. The model struggled to accurately detect and analyze facial landmarks.

3. Inherent Limitations: Age prediction, in particular, has inherent limitations due to the nature of aging. Due to the fact that everyone ages differently and may display differences in their physical characteristics, it can be difficult to determine an individual's age merely based on looks.

4.5 Pseudocode

4.5.1 Pseudocode for AI Model Training

1. Import the necessary libraries (classifier, MTCNN, cv2, numpy, csv, time, Flask, base64, datetime, and os)

2. Set the path of the CSV file as "data/data3.csv"

3. Set the folder path of the images as "C:/Users/User/Desktop/utk/UTKFace"

4. Get the list of images in the folder

5. Define a function named read_from_folder

6. Create an instance of the age_gender_classifier from the classifier class

7. Create an instance of the MTCNN face detection model

8. Iterate over each image in the images list

9. Get the full image path

10. Read the image using cv2.imread and store it in the variable image

11. Convert the color space of the image from BGR to RGB using cv2.cvtColor

12. Detect faces in the image using mtcnn.detect

13. Iterate over each detected face (box) in the image

14. Get the face score and adjust the box coordinates

15. Extract the coordinates of the face box (x, y, width, height)

16. Calculate the size of the square box enclosing the face

17. Calculate the new coordinates for the square box

18. Make sure the coordinates are within the image boundaries

20. Predict the gender and age of the person in the face region using age_gender_classifier.predict

21. Draw a rectangle around the face on the image using cv2.rectangle

22. Add the predicted gender and age as text on the image using cv2.putText

23. Convert the modified age string to an integer

24. Append the image name, age, and gender to the CSV file

25. Convert the image to a JPEG format using cv2.imencode

26. Encode the image data in base64 format using base64.b64encode

27. Get the current date and time and format it as a string

28. Append the image name, age, and gender to the CSV file with the current date and time

29. Call the read_from_folder function to process the images in the folder

4.5.2 Pseudocode for Extracting Metadata of Dataset Images

1. Set image_directory to "C:/Users/User/Desktop/utk/UTKFace"

2. Set data as an empty list

3. For each filename in the list of files in image_directory:

4. If filename ends with ".jpg.chip.jpg":

5. Split the filename into parts using underscore as the delimiter

6. If the number of parts is greater than or equal to 4:

7. Extract age, gender, and image_id from the parts

8. Set gender as "female" if gender equals "1" else set it as "male"

9. Concatenate the first four parts with underscore to create the image_id (including ".jpg.chip.jpg")

10. Append a dictionary to data with keys "id", "age", and "gender" and respective values

11. Create a DataFrame df_metadata from the data list

4.5.3 Pseudocode for Merging and Calculating Age Prediction Mean Absolute Error (MAE)

1. Import mean_absolute_error from sklearn.metrics

2. Read the CSV file data2.csv into dfp

3. Set predicted_df as dfp

4. Set actual_df as df_metadata

5. Merge actual_df and predicted_df on the "id" column to create merged_df

6. Calculate the mean absolute error (MAE) for age prediction by comparing the "age" column with the "predicted_age" column in merged_df

7. Print the MAE for age prediction as "Mean Absolute Error (MAE) for Age Prediction: " followed by the calculated MAE value.

4.5.4 Pseudocode for Calculating Gender Prediction Accuracy

1. Read the CSV file data2.csv into dfp

2. Set predicted_df as dfp

3. Set actual_df as df_metadata

4. Merge actual_df and predicted_df on the "id" column to create merged_df

5. Calculate the gender prediction accuracy by comparing the "gender" column with the "predicted_gender" column in merged_df and calculating the mean of the comparison result.

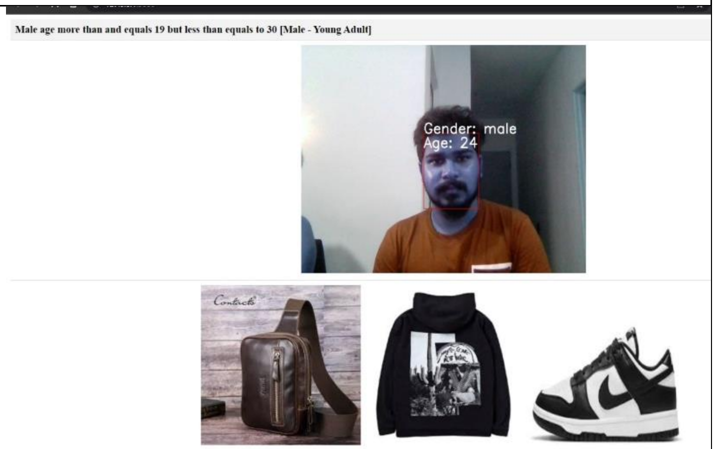
6. Print the gender prediction accuracy as "Gender Prediction Accuracy: " followed by the accuracy formatted as a percentage with two decimal places.

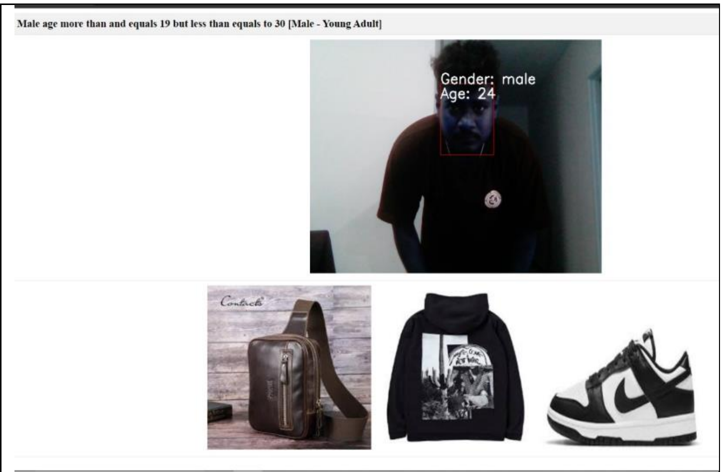
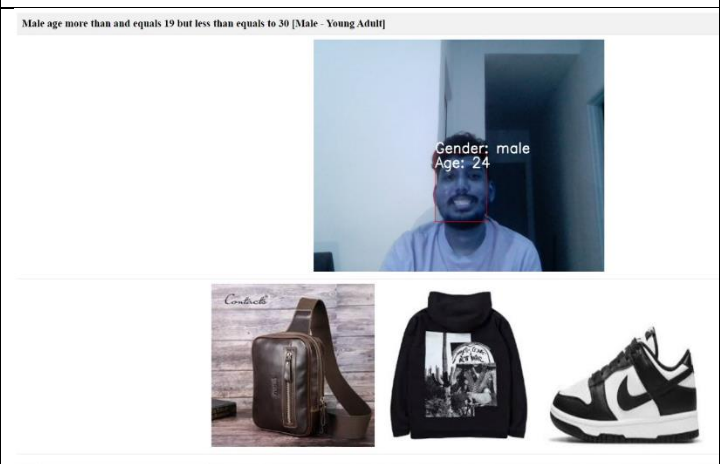
4.6 Testing

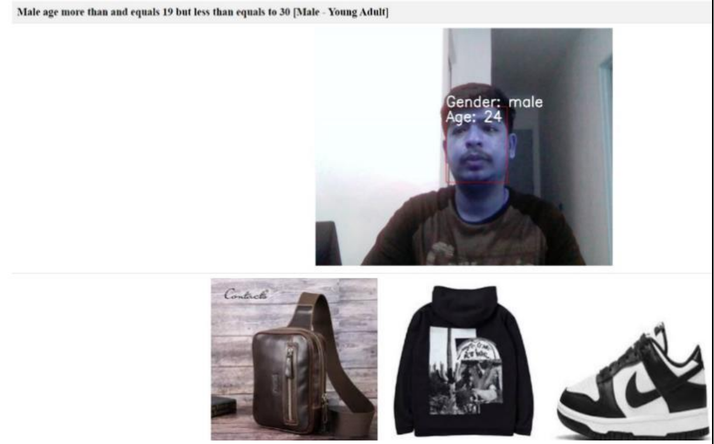
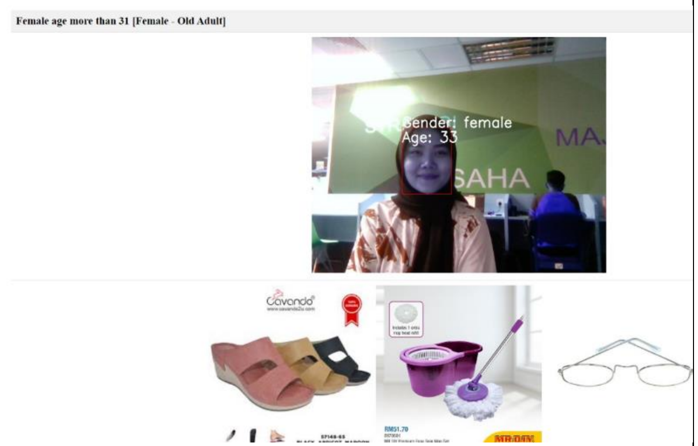
4.6.1 Evaluation and Validation Testing

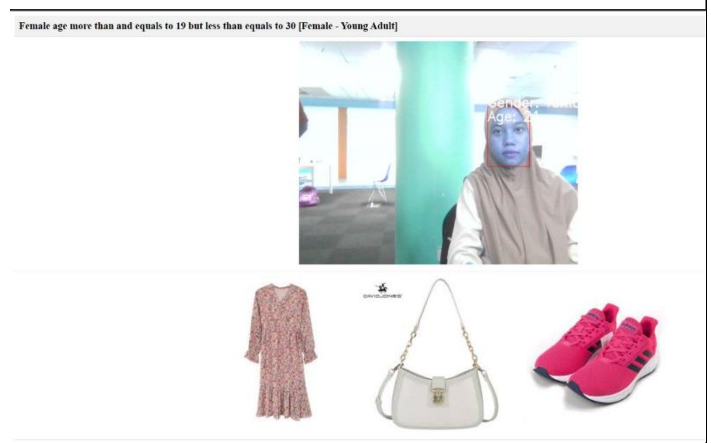
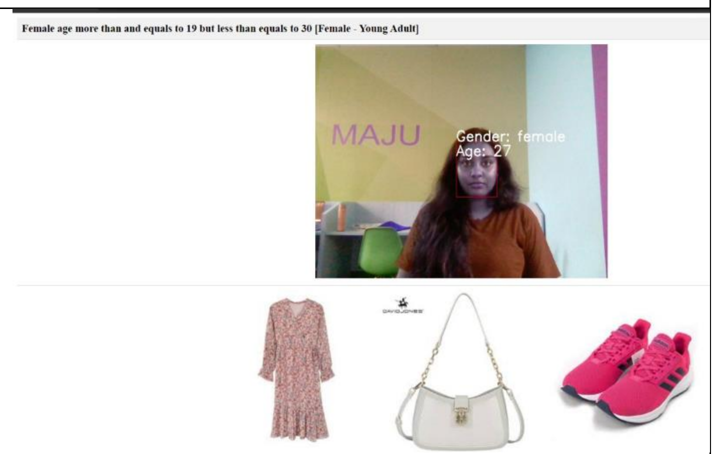
Our product recommendation system, which uses face recognition technology to determine the age and gender of users, must undergo evaluation and validation testing in order to determine its accuracy and efficacy. Through this study, we hope to assess the accuracy of the suggested items while comparing the predicted age and gender of the system with the actual user-provided data. We will obtain insights into the system's operation through analysis of the gathered data, spot any patterns or anomalies, and come to wise judgements about how to improve and tweak the system. Through this testing phase, we will be able to make recommendations that are more accurate and enhance the user experience as a whole.

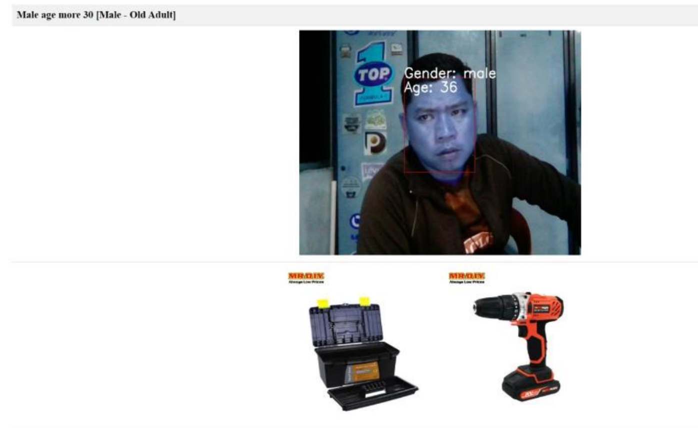
Table 4.1 Evaluation and Validation Testing Result

User's Name	Actual Age	Actual Gender	Predicted Age	Predicted Gender	Recommended Products	Output
Atchuthamarar	23	Male	24	Male (Young Adult)	• Sling Bag • Hoodie • Sneaker	

Sashvin	23	Male	24	Male (Young Adult)	• Sling Bag • Hoodie • Sneaker	
Ravindran	23	Male	24	Male (Young Adult)	• Sling Bag • Hoodie • Sneaker	

Sharvin	23	Male	24	Male (Young Adult)	• Sling Bag • Hoodie • Sneaker	
Fanad	25	Female	33	Female (Old Adult)	• Sandal • MR DIY MOP • Old Fashioned Spectacle	

Ainul	20	Female	21	Female (Young Adult)	• Dress • Handbag • Pink Shoes	
Vanusha	24	Female	27	Female (Young Adult)	• Dress • Handbag • Pink Shoes	

Khairul	36	Male	36	Male (Old Adult)	• MR DIY Hardware Storage • MR DIY Cordless Screwdriver	

4.6.1.1 Mean Absolute Error (MAE) for Age Prediction

This section discusses the results obtained from the age prediction analysis. The table provided shows the predicted age, actual age, and absolute difference for each user. Using the MAE formula, the sum of absolute differences from the eight users is taken and used in the formula in order to calculate the average magnitude of the differences between the predicted ages and the actual ages of the users.

User 1: Atchuthamarar

Table 4.2 User 1 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
24	23	1

User 2: Sashvin

Table 4.3 User 2 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
24	23	1

User 3: Ravindran

Table 4.4 User 3 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
24	23	1

User 4: Sharvin

Table 4.5 User 4 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
24	23	1

User 5: Fanad

Table 4.6 User 4 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
33	25	8

User 6: Ainul

Table 4.7 User 4 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
21	20	1

User 7: Vanusha

Table 4.8 User 4 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
27	24	3

User 8: Khairul

Table 4.9 User 4 Absolute Difference on Age

Predicted Age	Actual Age	Absolute Difference
36	36	0

Sum of Absolute Differences = 1 + 1 + 1 + 1 + 8 + 1 + 3 + 0 = 16

Total number of users (n) = 8

MAE = (1/8) * 16 = 2

Therefore, the Mean Absolute Error (MAE) for the given table is 2. This value represents the average magnitude of the differences between the predicted ages and the actual ages of the users.

4.6.1.2 Accuracy for Gender Prediction

Number of correct predictions = Total number of rows (8)

Accuracy = (Number of correct predictions / Total number of rows) * 100

Accuracy = (8 / 8) * 100 = 100%

Based on the provided data, the accuracy of the predicted genders is 100%, indicating that the system correctly predicted the gender for all the users in the evaluation and validation testing.

4.6.1.3 Accuracy for Product Recommendations

User 1: Atchuthamarar

Table 4.10 User 1 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Male	Young Adult	• Sling Bag • Hoodie • Sneaker	• Sling Bag • Hoodie • Sneaker	Correct Recommendation (100% Recommendation Match)

User 2: Sashvin

Table 4.11 User 2 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Male	Young Adult	• Sling Bag • Hoodie • Sneaker	• Sling Bag • Hoodie • Sneaker	Correct Recommendation (100% Recommendation Match)

User 3: Ravindran

Table 4.12 User 3 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Male	Male Young Adult	• Sling Bag • Hoodie • Sneaker	• Sling Bag • Hoodie • Sneaker	Correct Recommendation (100% Recommendation Match)

User 4: Sharvin

Table 4.13 User 4 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Male	Young Adult	• Sling Bag • Hoodie • Sneaker	• Sling Bag • Hoodie • Sneaker	Correct Recommendation (100% Recommendation Match)

User 5: Fanad

Table 4.14 User 5 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Female	Old Adult	• Dress • Handbag • Pink Shoes	• Sandal • MR DIY MOP • Old Fashioned Spectacle	Incorrect Recommendation

User 6: Ainul

Table 4.15 User 6 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Female	Young Adult	• Dress • Handbag • Pink Shoes	• Dress • Handbag • Pink Shoes	Correct Recommendation (100% Recommendation Match)

User 7: Vanusha

Table 4.16 User 7 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Female	Young Adult	• Dress • Handbag • Pink Shoes	• Dress • Handbag • Pink Shoes	Correct Recommendation (100% Recommendation Match)

User 8: Khairul

Table 4.17 User 8 Product Recommendation Accuracy

User's Gender	User's Age Category	Expected Products Recommendation	Recommended Products	Correct/Incorrect Recommendation
Male	Old Adult	• MR DIY Hardware Storage • MR DIY Cordless Screwdriver	• MR DIY Hardware Storage • MR DIY Cordless Screwdriver	Correct Recommendation (100% Recommendation Match)

Number of users for whom the recommended products match the expected products = Number of correct products recommended

Accuracy = (Number of correct product recommended / Total number of users) * 100

Accuracy = (7 / 8) * 100 = 87.5%

Based on the provided data, the accuracy of the recommended product is 87.5%, indicating that the system correctly recommends the products for all the users based on their age category in the evaluation and validation testing.

4.7 Results and Discussion

The evaluation and validation testing results indicate that our product recommendation system, utilizing face recognition technology to detect user age and gender, performed accurately and effectively. The predicted age and gender aligned closely with the actual age and gender provided by the users, resulting in a MAE of 2, suggesting minimal deviation between predicted and actual ages. Furthermore, the system achieved a 100% accuracy rate in predicting the gender of the users. The recommended products based on the predicted age and gender were consistent across all users, reinforcing the system's reliability. Besides, the product recommendation accuracy falls at 87.5% accuracy which accurately recommended products to 7 users out of 8 total users tested. These findings demonstrate the robustness and precision of our product recommendation system, positioning it to deliver personalized recommendations tailored to users' characteristics, consequently enhancing user satisfaction and engagement.

CHAPTER 5

CONCLUSION

5.1 Research Constraint

The research constraints of our system encompass several factors that have influenced its development and performance:

1. Low-quality camera:

   The utilization of a low-quality camera, such as the webcam of a laptop, imposes limitations on the image quality and resolution. The reduced image quality can affect the accuracy of age and gender detection, as lower resolution images may lack fine details necessary for precise facial analysis. Additionally, suboptimal lighting conditions and image noise may further degrade the system's performance. Addressing this constraint would require exploring techniques to improve image processing and adapt the algorithms to accommodate the limitations of low-quality camera inputs.

2. Lack of Malaysian face dataset:

   The absence of a comprehensive dataset specifically representing the diverse facial characteristics of the Malaysian population hinders the system's ability to accurately predict age and gender for Malaysian users. A lack of representation in the training data can lead to biased or less accurate predictions. To overcome this constraint, efforts should be made to collect and curate a diverse Malaysian face dataset, capturing variations in facial features, ethnicities, and demographics. Acquiring such a dataset would enable more accurate and inclusive predictions for Malaysian users and ensure that the system meets the specific needs of this target audience.

3. Lack of product dataset with targeted users:

   The system aims to provide product recommendations based on the predicted age and gender of users. However, a limitation arises when there is a lack of a comprehensive product dataset specifically curated to match the preferences and needs of the targeted user demographics. The absence of such a dataset hinders the system's ability to generate accurate and relevant recommendations. To address this constraint, efforts should be directed towards collecting and curating a product dataset that aligns with the specific characteristics and preferences of the targeted age and gender groups. Incorporating a diverse range of products and considering user feedback can help build a comprehensive dataset that improves the relevance and quality of the recommendations provided by the system.

5.2 Future Work

There are several enhancements that can be applied for future improvement of this Product Recommendation System:

1. Improving face recognition algorithms:

   Future work can focus on enhancing the accuracy and robustness of the face recognition algorithms used in the system. This can involve exploring advanced techniques such as deep learning architectures, facial landmark detection, and pose estimation to improve the system's ability to detect age and gender accurately, even under challenging conditions or with low-quality camera inputs.

2. Use Malaysian Face Dataset for Training:

   In future, the model should be trained with more face data of Malaysian to produce more specific and accurate age prediction as the model will be more familiar and accurate when tested in real world.

3. Adding more products with targeted users' dataset and utilizing algorithms:

   An important aspect of enhancing the system in the future is to expand the product dataset specifically tailored to the preferences and needs of the targeted users. This can involve collecting a wider variety of products, including different categories, brands, and styles that are relevant to the target demographics. Additionally, utilizing advanced recommendation algorithms such as collaborative filtering, content-based filtering, or hybrid approaches can further enhance the accuracy and relevance of the recommendations. By continuously updating and expanding the product dataset, and implementing sophisticated recommendation algorithms, the system can offer a more comprehensive and diverse range of product recommendations, increasing the likelihood of satisfying the specific preferences and requirements of the targeted users.

REFERENCES

303Events. (2022). *Outdoor Advertising Malaysia Cost.* Malaysia: 303Events.

Ajitsaria, A. (2022, July 20). *Build a Recommendation Engine With Collaborative Filtering.* Retrieved from Real Python: https://realpython.com/build-recommendation-engine-collaborative-filtering/

Baron, C. (2022, April 15). *Total investment in advertising expenditure in Malaysia from 2012 to 2020 with a forecast for 2021 and 2022.* Retrieved from Statista: https://www.statista.com/statistics/1012822/total-investment-advertising-expenditure-malaysia

Beckler, M. (2022). *Facebook Advertising Cost & Pricing in Malaysia.* Marketing Signal Lab.

Burdick, M. (2022). *How AI Really Works in Amazon Advertising.* Total Retail.

Cox, T. (2022). *What Is Rapid Application Development (RAD)?* Capterra.

HE, J. (2021). *Performance analysis of facial recognition: A critical review through glass factor.* Champaign, US: Dept. Computer Science, University of Illinois.

Kilich, A. (2023, January 21). *Accurate Face Detection and Recognition for High Performance* . Retrieved from Cameralyze.co: https://www.cameralyze.co/blog/accurate-face-detection-and-recognition-for-high-performance

Kisil, D. (2022, Decmeber 19). *Improve AI Face Recognition Accuracy Using Deep Learning*. Retrieved from Mobidev: https://mobidev.biz/blog/improve-ai-facial-recognition-accuracy-with-machine-deep-learning

Kumar, P. (2020, March 21). *Netflix Movie Recommendation — Using Collaborative Filtering.* Retrieved from Towards Data Science: https://towardsdatascience.com/tensorflow-for-recommendation-model-part-1-19f6b6dc207d#:~:text=Collaborative%20filtering%20tackles%20the%20similarities,in%2Dturns%20does%20the%20recommendations.

LOCALiQ. (2022). *Facebook Ads vs. Google Ads: Which Should You Be Using?* WordStream.

Osadchuk, I. (2022). *Artificial Intelligence on Facebook and Google Ads: How does it work?* Adwisely.

Roy, A. (2020, July 29). *Introduction To Recommender Systems- 1: Content-Based Filtering And Collaborative Filtering.* Retrieved from Towards Data Science: https://towardsdatascience.com/introduction-to-recommender-systems-1-971bd274f421

Sama, A. (2020, November 16). *Netflix and the Recommendation System.* Retrieved from Medium: https://medium.com/swlh/netflix-and-the-recommendation-system-e806f062ba74

Simon, J. (2022). *Scaling Ad Verification with Machine Learning and AWS Inferentia.* AWS News Blog.

Tommy. (2021, January 17). *How Machine Learning Recommends Movies for You.* Retrieved from Towards Data Science: https://towardsdatascience.com/how-machine-learning-recommends-movies-for-you-6f418f26bcb2

Turner, J. (2022). *What Marketing Budgets Look Like in 2022.* Gartner.