A DEEP LEARNING APPROACH FOR FACIAL DETECTION IN TARGETED BILLBOARD ADVERTISING

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ABSTRACT

Deep learning has significantly changed industries by facilitating the development of more intelligent and adaptive systems, with applications especially in advertising. Facial detection using deep learning in advertising offers the potential for highly personalised and effective marketing by leveraging real-time consumer demographics. This research explores a deep learning-based facial detection system for targeted advertising, aiming to enhance consumer engagement by delivering personalized advertisements. The research focuses on addressing key difficulties including lack of audience-targeted delivery, real-time implementation challenges and model accuracy difficulties. This system utilises sophisticated deep learning algorithm using Convolutional Neural Network (CNN) to identify and examine human faces, enabling advertisers to customise their content according to demographic variables including age and gender. The system has two modules which are the Realtime Module and the Dataset Evaluation Module. The system employs Multi-task Cascaded Convolutional Networks (MTCNN) for face detection in the DeepFace model, processes webcam photos, predicts age and gender, and maps relevant advertisements accordingly. The evaluation process encompasses real-time performance analysis and testing using the Wikipedia dataset, evaluating the accuracy, precision, recall, F1-score, and confusion matrices. The system's capacity to provide targeted advertising not only enhances user experience but also greatly enhances consumer engagement. Results indicate that the Realtime Module attains an accuracy of 70% in age prediction and 90% in gender prediction, whereas the Dataset Evaluation Module achieves an accuracy of 74% for age prediction and 90% for gender prediction, hence enhancing advertisement relevance. The study indicates that using facial recognition technologies in advertising tactics can transform conventional advertising methods, providing real-time, adaptive solutions customised for diverse audiences.

Keywords: Facial Detection, Targeted Advertising, Consumer Engagement, Deep Learning, Convolutional Neural Network (CNN).

ABSTRAK

Pembelajaran mendalam telah mengubah industri secara signifikan dengan memudahkan pembangunan sistem yang lebih pintar dan adaptif, terutamanya dalam bidang pengiklanan. Pengenalpastian wajah menggunakan pembelajaran mendalam dalam pengiklanan menawarkan potensi untuk pemasaran yang sangat diperibadikan dan berkesan dengan memanfaatkan data demografi pengguna secara masa nyata. Kajian ini meneroka sistem pengenalpastian wajah berasaskan pembelajaran mendalam untuk pengiklanan sasaran, dengan tujuan meningkatkan penglibatan pengguna melalui penyampaian iklan yang diperibadikan. Penyelidikan ini memberi tumpuan kepada mengatasi cabaran utama seperti kekurangan penghantaran yang disasarkan kepada penonton, cabaran pelaksanaan masa nyata, dan kesukaran ketepatan model. Sistem ini menggunakan algoritma pembelajaran mendalam yang canggih dengan rangkaian neural konvolusi (CNN) untuk mengenal pasti dan menganalisis wajah manusia, membolehkan pengiklan menyesuaikan kandungan mereka berdasarkan pemboleh ubah demografi seperti umur dan jantina. Sistem ini terdiri daripada dua modul utama, iaitu Modul Masa Nyata dan Modul Penilaian Dataset. Sistem ini menggunakan Rangkaian Neural Konvolusi Pelbagai Tugas (MTCNN) untuk pengesanan wajah dalam model DeepFace, memproses foto daripada kamera web, meramalkan umur dan jantina, serta memetakan iklan yang berkaitan dengan sewajarnya. Proses penilaian merangkumi analisis prestasi masa nyata dan ujian menggunakan set data Wikipedia, menilai ketepatan, kepekaan, kebolehpercayaan, skor F1, dan matriks kekeliruan. Keupayaan sistem untuk menyediakan pengiklanan sasaran bukan sahaja meningkatkan pengalaman pengguna tetapi juga secara signifikan meningkatkan penglibatan pengguna. Keputusan menunjukkan bahawa Modul Masa Nyata mencapai ketepatan 70% dalam peramalan umur dan 90% dalam peramalan jantina, manakala Modul Penilaian Dataset mencapai ketepatan 74% untuk peramalan umur dan 90% untuk peramalan jantina, sekali gus meningkatkan relevansi pengiklanan. Kajian ini menunjukkan bahawa penggunaan teknologi pengecaman wajah dalam strategi pengiklanan boleh mengubah kaedah pengiklanan konvensional, menyediakan penyelesaian adaptif masa nyata yang diperibadikan untuk pelbagai khalayak.

Kata kunci: Pengenalpastian Wajah, Pengiklanan Tertumpu, Penglibatan Pengguna, Pembelajaran Mendalam, Rangkaian Neural Konvolusi (CNN).

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CHAPTER 1: INTRODUCTION

This chapter discusses the research background, research problem statement, research questions, research objectives and research significance.

1.1 Research Background

Facial identification technique has become a potent tool for focused advertising, with the potential to transform how businesses interact with customers. Advertisers can enhance their content customisation by utilising artificial intelligence and machine learning algorithms. This allows them to tailor their material to specific audience segments based on demographic data like age and gender, resulting in more effective audience engagement.

Researchers have recently concentrated on optimising facial detection technology to precisely identify age and gender across various populations. Research has investigated the creation of sophisticated biometric system models using advanced neural network architecture. These models are trained on extensive datasets of facial photos and have shown remarkable accuracy in detecting face spoofing, determining age and gender, and classifying facial expressions (Kumar et al., 2022). In addition, empirical studies have examined the effects of customised advertising that uses age and gender recognition. These studies have found that such targeted advertising leads to increased consumer engagement and higher conversion rates compared to generic advertisements (Yu et al., 2019).

The objective of this research is to overcome key challenges in targeted advertising, including the lack of audience-targeted delivery, real-time implementation challenges, and model accuracy limitations. This is achieved by developing a facial detection system that can accurately distinguish among different age groups and genders. Additionally, a limited-scale investigation will be carried out to examine the influence of focused marketing on customer conduct.

1.2 Research Scope

The research focusses on the development and technical evaluation of a facial detection system specifically for targeted advertising. The scope includes the application of advanced deep learning methodologies, specifically Convolutional Neural Networks (CNNs) and Multi-task Cascaded Convolutional Neural Networks (MTCNN)—to precisely ascertain age and gender from facial photos. The system has two modules: a Real-Time Module for processing live camera feeds and a Dataset Evaluation Module for comprehensive testing utilising the Wikipedia dataset.

The research highlights the attainment of high accuracy in demographic classification by optimizing the system's performance. Comprehensive evaluation measures, including accuracy, precision, recall, F1-score, and confusion matrices, are utilised to evaluate the system's capability in differentiating across several age groups and genders. This research targets the enhancement of advertisement targeting accuracy, hence increasing the relevance of advertisements for various demographic groupings. It is important to note that while the system is designed to enhance advertisement relevance through improved demographic detection, this study does not directly measure consumer involvement, purchasing behaviour, or overall satisfaction. Instead, the research provides a robust technical framework that can serve as the foundation for future studies incorporating user feedback and behavioural analysis to further evaluate the impact of targeted advertising on consumer engagement. Figure 1.1 shows the scope of the research.

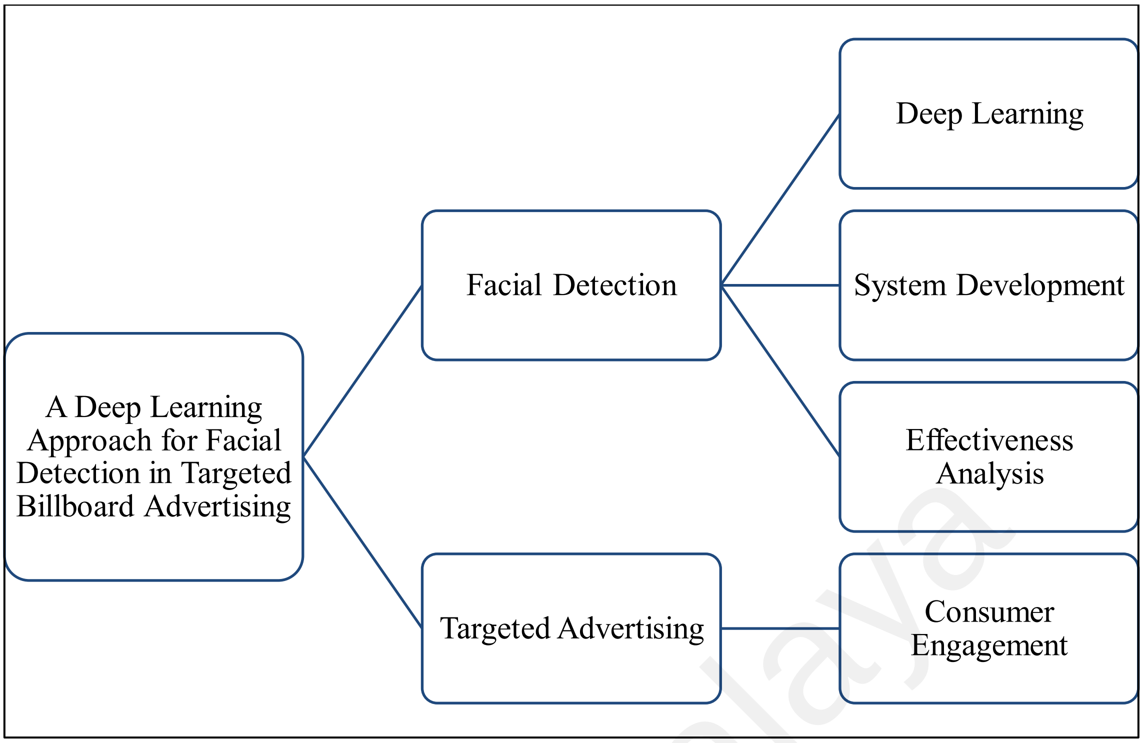

Figure 1.1: Research Scope

1.3 Research Problem Statement

Conventional advertising techniques are progressively encountering difficulties in sustaining relevance and effectively engaging consumers. Studies have indicated that such methods, which lack the ability to tailor content to specific demographic groups, result in lower engagement rates and wasted advertising resources. Non-targeted advertisements frequently fail to engage audience interest, resulting in reduced customer contact and ineffective marketing strategies (Yu et al., 2019). Moreover, the ineffectiveness of conventional advertising spending, as substantial segments of the audience may deem the content irrelevant, hence diminishing the return on investment for businesses (Kim et al., 2021). Conventional methods are static and incapable of adjusting to fluctuating audience choices or real-time circumstances, this constrains their capacity to engage viewers successfully (Moraru & Cărbune, 2021). These constraints highlight the pressing necessity for innovative solutions such as AI-driven face identification systems, which (Wang & Deng, 2021) propose can markedly enhance the accuracy of targeted advertising, thus addressing the shortcomings of conventional methods.

1.4 Research Questions

1. How do recent research studies utilise facial detection techniques for age and gender recognition?
2. What methods can be employed to develop a facial detection system capable of accurately distinguishing between different age groups and genders?
3. How does the developed facial detection system perform in accurately identifying age groups and genders for targeted advertising?

1.5 Research Objectives

1. To investigate the facial detection techniques for age and gender recognition used in advertisement.
2. To develop a facial detection system that can distinguish between different age groups and genders.
3. To analyse the effectiveness of the developed system for targeted advertising.

1.6 Research Significance

This research investigates the use of facial identification technologies in targeted advertising strategies, aiming to address the urgent requirement for a more efficient marketing approach. The project intends to improve the effectiveness of commercials by specifically targeting age and gender recognition, resulting in higher levels of consumer engagement and conversion rates. Table 1.1 provides an overview of the significant contributions of the research, including enhanced advertising effectiveness, framework for targeted advertising, advancements in marketing technology and system performance.

Table 1.1: Research Contribution

No.	Contributions	Descriptions
1.	Enhanced Advertising Effectiveness	This research offers valuable insights into the effective utilisation of facial identification technologies for targeted advertising, leading to enhanced relevance and engagement.
2.	Framework for Targeted Advertising	This research established a robust technical framework that could support future integration of personalised advertising strategies by aligning accurate demographic predictions with relevant advertisements.
3.	Advancements in Marketing Technology	The research findings have the potential to influence the development of marketing technology, leading to the creation of new tactics and tools for personalised advertising.
4.	System Performance	This research exhibited the technical effectiveness of the system by attaining an accuracy of 70–74% for age prediction and 90% for gender prediction in both real-time and dataset evaluation modules.

1.7 Summary

This chapter introduces the background, problem statement, objectives, and significance of the study. It emphasises how facial recognition technologies, driven by deep learning, may enhance targeted advertising by identifying age and gender. Conventional advertising techniques are less effective in capturing customer attention, but AI-based facial recognition technologies can augment personalisation, hence enhancing consumer engagement. The chapter indicates that the research concentrates on deep learning methodologies to accurately predict age and gender in real-time for targeted advertising purposes. It elucidates the need to establish a robust technological framework for advertisement relevance while highlighting that the research prioritises technical performance over direct consumer engagement measurements.

CHAPTER 2: LITERATURE REVIEW

Advertising is characterised as communication initiated by a brand with the intent to influence individuals. It seeks to affect consumer behaviour by fostering awareness and moulding perceptions of products or services (Upadhyay, 2024). It is intrinsically compelling, crafted to persuade audiences to rely on and utilise the advertised goods or services (Kamu et al., 2024). Targeted advertising allows companies to concentrate their marketing strategies on consumers who are more inclined to be interested in their products while minimising ineffective advertising directed at disinterested audiences (Ponomareva et al., 2024). This accuracy improves the pertinence of advertisements for consumers, offering a more tailored experience (Karandin, 2024). Targeted advertising utilises customer data to customise advertisements, perhaps enhancing click-through rates considerably. Nonetheless, the most effective targeting does not invariably optimise ad network income, indicating a need for equilibrium between targeting accuracy and revenue production (Rafieian & Yoganarasimhan, 2020).

Facial recognition technology in advertising entails the acquisition of photographs or video streams to identify facial characteristics, subsequently analysed to ascertain qualities such as age, gender, and emotional state. This data is utilised to customise advertisements according to the viewer's profile, hence augmenting the relevancy and effectiveness of the commercials (Jayantibhai & Nachappa, 2024). The field of facial recognition technology has experienced significant progress in recent years, mostly due to the widespread use of deep learning methods and the growing need for real-time applications in diverse fields. Despite its scientific progress, facial recognition technology has also sparked considerable issues over efficiency and real-time recognition. The purpose of this literature review is to present a thorough summary of the current research in these important topic areas, including insights into the current level of understanding, research methods used, and potential directions for further investigation.

2.1 Overview of Machine Learning and Deep Learning

Machine learning and deep learning are essential to the advancement of facial recognition systems. Machine learning techniques, like Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP), are frequently employed for classification tasks in facial recognition systems (Hamou & Chelali, 2024). Deep learning, especially via Convolutional Neural Networks (CNNs), has markedly progressed the domain by facilitating the extraction of high-level information from facial photos, essential for precise recognition (Thanathamathee et al., 2023). Deep learning is a distinct subset of machine learning that uses artificial neural networks with multiple layers to represent intricate patterns in data. It is very proficient in applications like speech recognition, computer vision, and natural language processing, frequently exceeding the performance of conventional machine learning models (Mishra & Gupta, 2016). Deep learning models may learn from extensive datasets, rendering them appropriate for high-dimensional data processing (Dong et al., 2021).

2.2 Facial Recognition with Deep Learning

Facial recognition with deep learning has emerged as a crucial research domain, markedly enhancing the functionality of biometric devices. This method utilises deep learning to autonomously learn and extract significant features from unprocessed facial data, resulting in enhanced accuracy and practical usability. Deep learning has revolutionized facial recognition by providing hierarchical architectures that enhance feature extraction and representation. This has resulted in major advances in state-of-the-art performance and the development of strong real-world applications (Yao, 2024).

Techniques including DeepFace have been important in this transformation since 2014, setting new milestones in the area (Wang & Deng, 2021). Diverse network architectures and loss functions have been suggested to enhance deep facial recognition systems. These include advancements in algorithm designs that address specific issues such as pose, age, illumination, and expression changes (Fuad et al., 2021). In conclusion, deep learning has markedly enhanced facial recognition technology, providing superior accuracy and application. Nonetheless, obstacles such as data bias, privacy concerns, and environmental fluctuations persist, directing future research towards the development of more resilient and equitable systems.

2.3 Challenges for Conventional Billboard Advertising

Conventional billboard advertising encounters substantial obstacles in properly reaching target audiences, resulting in resource wastage and diminished impact. Conventional billboards typically lack audience-targeting capabilities, leading to useless advertising and inefficient reach for advertisers. The authors tackle this issue by introducing a data-driven framework for targeted billboard advertising that utilises vehicle trajectory data to analyse audience mobility patterns and determine appropriate locations and timings for ad placement. Their model enhances targeting efficiency by aligning billboard display hours and locations with the travel intents of proximate users, hence optimising advertising impact in outdoor environments (Wang et al., 2020).

Additionally, conventional billboards present unchanging content that fails to align with the evolving preferences of surrounding viewers, resulting in diminished engagement levels. The authors offer an Interest-Based Adaptive Billboard Content Management system that enables billboards to adjust in real-time according to the preferences of adjacent pedestrians. By gathering user preferences via a mobile application, the billboard adaptively alters its displayed material according to the predominant interests of nearby individuals, so providing a more engaging and pertinent advertising experience (Moraru & Cărbune, 2021).

The efficacy of conventional billboard advertisements is challenging to quantify in comparison to digital advertising, constraining insights into audience involvement. The authors in the Data-driven Targeted Advertising Recommendation System for Outdoor Billboards bridge this gap by creating a targeted influence model that assesses advertising efficacy based on user mobility and location. The system's optimisation techniques improve budget allocation by maximising advertising effectiveness and minimising wasted exposure, underscoring the need for data-driven models for accurate, measurable targeting (Wang et al., 2022).

Collectively, these studies highlight the difficulties associated with conventional billboard advertising namely, restricted targeting, unchanging content, and absence of quantifiable impact while reinforcing the necessity for flexible, data-informed solutions. These findings are essential for examining how facial identification technology, together with deep learning, can provide a more advanced and adaptive method for targeted advertising that addresses these limitations.

2.4 Utilisation of Deep Learning Techniques

Convolutional neural networks (CNNs), a type of deep learning technique, have become widely recognised and important in many fields, such as facial recognition and analysis. Multiple research projects have proven the efficacy of deep learning in tackling intricate challenges related to facial recognition technology.

(Kumar et al., 2022) propose a complex neural network structure for biometric systems, which integrates advanced deep learning techniques to achieve precise face detection and classification of many attributes such as age, gender, facial expression, and identification of face spoofing. This demonstrates the adaptability and strength of deep learning methods in tackling complex problems in the field of biometrics.

(Wang & Deng, 2021) present a thorough review of DeepFace recognition methodologies, delineating the progression of face recognition algorithms, loss functions, and network structures. Their survey emphasises the substantial advancements in deep learning-based face recognition systems, especially in face identification, alignment, and feature representation, attaining human-level performance on demanding benchmarks such as Labelled Faces in the Wild (LFW). The paper highlights the significance of network architecture and the use of loss functions in enhancing recognition accuracy in unconstrained settings. This study significantly enhances comprehension of the scalability and resilience of facial recognition systems.

In addition, an AI-driven targeted advertising system that incorporates multiple deep learning techniques, such as facial recognition, age estimate, gender recognition, and object detection is proposed (Yu et al., 2019). Through the utilisation of deep learning, the system strives to provide more tailored and impactful advertising content to specific audiences, hence improving advertising effectiveness and pertinence.

In summary, the use of deep learning methods in these studies highlights their efficacy in tackling intricate issues related to facial identification and analysis. These issues encompass biometric security, targeted advertising, and customer behaviour analysis.

2.5 Efficiency and Lightweight Models

When developing facial recognition systems, it is important to prioritise efficiency and lightweight models. This is especially important for applications that need to use resources efficiently and can only be deployed on devices with limited processing capabilities. Two studies especially address this topic, highlighting the significance of optimising the complexity of models and processing requirements while yet achieving high levels of performance.

(Rahman et al., 2020) proposed a lightweight methodology for age and gender estimation utilising facial images, emphasising efficiency via the Viola-Jones algorithm for real-time face detection, regions of interest (ROI) processing to diminish computational complexity, and Naïve Bayes classifiers for categorisation. This architecture attains minimal computational expense and energy efficiency, rendering it appropriate for real-time applications on limited devices. The model's simplicity results in compromises regarding accuracy and flexibility when compared with contemporary deep learning techniques such as CNNs, which are proficient at managing varied datasets and intricate variations.

In another paper, a lightweight CNN architecture for age group recognition in smart digital advertising platforms is proposed (Priadana et al., 2023). The architecture integrates innovative components to enhance feature extraction and map quality, while also ensuring efficiency and competitive performance. The suggested architecture utilises Residual Mini Multi-level (RM2L) and Deep Lite Attention (DELA) modules to properly predict the age group of the audience's face in real-time on CPU devices. These improvements emphasise the significance of creating lightweight models customised for certain application domains, such as advertising and audience profiling, to guarantee fast implementation and optimal performance in contexts with limited resources.

2.6 Consideration of Real-time Recognition

Applications that necessitate fast reactions or feedback, such as advertising recommender systems and customer behaviour research, rely on real-time recognition capabilities. Multiple studies have concentrated on creating facial recognition systems that can process and analyse facial data in real-time.

(Kim et al., 2021) have presented a CNN-based system for recommending advertisements. This system utilises real-time user face recognition to deliver personalised advertising content. Using advanced deep learning techniques and analysing facial expressions in real-time, the system can constantly adjust to user preferences and provide timely advertising content that is appropriate to the user.

(Lu et al., 2021) have developed a real-time recognition system that uses deep learning algorithms to accurately identify human emotions, age, and gender at a low cost. The system employs convolutional neural networks to do facial identification and emotion detection, allowing for real-time analysis of facial cues to recognise emotions, age, and gender.

These studies emphasise the significance of real-time recognition capabilities in many applications, emphasising the requirement for efficient algorithms and computational architectures that can analyse facial input in real-time while upholding accuracy and dependability.

2.7 Research Themes

The research papers can be grouped into four main themes based on their common areas of focus. Figure 2.1 shows the four main themes of the review.

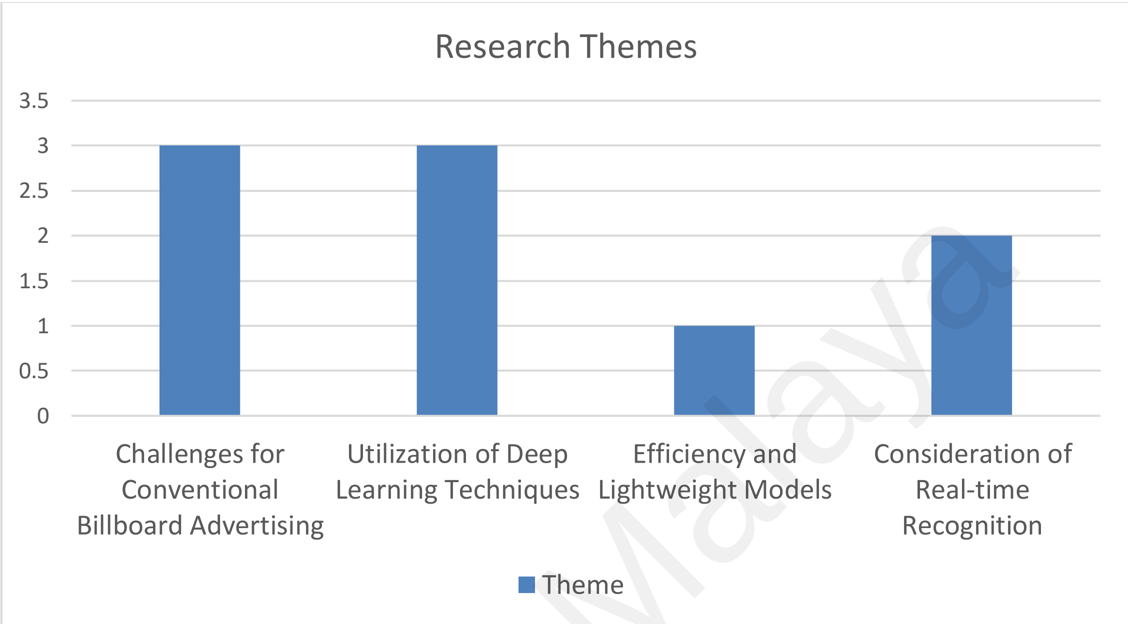

Figure 2.1: Research Themes

1. Challenges for Conventional Billboard Advertising

   Conventional billboard advertising fails to engage target audiences effectively due to its absence of audience-targeting features and static content, leading to resource wastage and diminished effectiveness. These billboards are unable to tailor their content to the tastes of surrounding viewers, hence diminishing ad relevancy and engagement. Moreover, traditional billboards provide restricted insights into advertising efficacy, impeding the assessment of audience involvement. These problems highlight the necessity for adaptable, data-informed solutions that facilitate targeted, dynamic content and quantifiable advertising effectiveness.

2. Utilisation of Deep Learning Techniques

   This element involves the investigation and application of deep learning techniques, namely convolutional neural networks (CNNs), for different functions within facial recognition systems. Deep learning has become a potent tool for managing intricate tasks like facial detection, age estimation, gender categorization, emotion recognition, and facial attribute recognition. Deep learning has exceptional efficacy of approaches in tackling complex issues in facial recognition. These techniques provide superior accuracy and consistent performance across many tasks.

3. Efficiency and Lightweight Models

   This element specifically emphasises the creation of effective and low-weight models for facial recognition systems, with a special focus on using them on devices with limited resources and in real-time applications. Efficient models are crucial for maximising computational resources and guaranteeing rapid and responsive performance, particularly in applications that demand real-time processing or deployment on devices with restricted computing capabilities.

4. Consideration of Real-time Recognition

   Real-time recognition capabilities are essential for applications that necessitate fast answers or feedback, such as advertising recommender systems, customer behaviour analysis, and public security surveillance. This feature highlights the need for face recognition systems that can collect and analyse facial data in real-time, allowing for quick decision-making and response in fast-paced scenarios.

In summary, although all four aspects are crucial for the progress of facial recognition technology, the theme of “Utilisation of Deep Learning Techniques” and “Challenges for

Conventional Billboard Advertising” has the highest number of papers. This popularity arises from the innovative influence of deep learning techniques, which have been extensively embraced for their remarkable capacity to address diverse issues in facial detection systems. Deep learning algorithms provide exceptional accuracy in recognising, analysing, and interpreting facial data, establishing them as a fundamental element for advancement in this domain. Likewise, tackling the issues with conventional billboard advertising has attracted considerable focus due to the urgent demand for dynamic, targeted, and quantifiable advertising solutions to improve engagement and resource efficiency. Consequently, these two themes signify crucial domains propelling progress in facial detection and its practical implementations.

2.8 Evaluation Metrics

Table 2.1 shows the evaluation metrics of the findings.

Table 2.1: Evaluation Metrics

Author	Facial Detection	Targeted Advertising	Consumer Engagement	Deep Learning	CNN	Accuracy
Kim et al. (2021)	✓	✓	✓	✓	✓	✓
Kumar et al. (2022)	✓			✓	✓	✓
Lu et al. (2021)	✓			✓	✓	✓
Moraru & Cărbune (2021)		✓	✓			
Priadana et al. (2023)	✓	✓	✓	✓	✓	✓
Rahman et al. (2020)	✓					
Wang et al. (2022)		✓				
Wang et al. (2020)		✓	✓			
Wang & Deng (2021)	✓			✓	✓	✓
Yu et al. (2019)	✓	✓	✓	✓	✓	✓
Total Percentage	70%	60%	50%	60%	60%	60%

Table 2.1 evaluates the contributions and focus areas of the 10 cited research by classifying their key components. Each row represents a study, and each column delineates a significant aspect. The metrics encompass Facial Detection, Targeted Advertising, Consumer Engagement, Deep Learning, CNN and Accuracy, illustrating the diverse aspects of the research. The table depicts that the highest percentage, in

comparison to others in the research paper, indicates that the primary emphasis of this study will be on facial detection.

Facial detection is a crucial element addressed in numerous studies, utilising ways to recognise facial traits for subsequent tasks. Research by Kim et al. (2021), Kumar et al. (2022), Lu et al. (2021), Priadana et al. (2023), Rahman et al. (2020) and Yu et al. (2019) extensively examines this domain for applications including emotion analysis, age classification, and gender identification. Wang & Deng (2021) also incorporate facial detection into their review of DeepFace model paper. Facial detection obtained 70% indicates that seven out of the ten examined papers incorporated face detection as a fundamental element of their research which is also the highest among the 10 papers.

Targeted Advertising explores the utilisation of these technologies in personalised marketing which obtained also 60% signifies that 6 out of the 10 studies examined targeted advertising. Research by Kim et al. (2021), Moraru & Cărbune (2021), Priadana et al. (2023), Wang et al. (2022), Wang et al., (2020) and Yu et al. (2019) employs facial detection to adapt advertisements in real-time according to demographic or behavioural indicators, with the objective of improving the relevance and effectiveness of billboards or digital commercials.

Consumer Engagement emphasises strategies to assess and enhance audience participation, with 50% of the studies prioritising consumer participation in their methodology. Moraru & Cărbune (2021) modify billboard material in real-time to align with pedestrian preferences. Research by Kim et al. (2021), Priadana et al. (2023), Wang et al. (2020) and Yu et al. (2019) also explores in terms of consumer engagement. These tactics seek to enhance advertising efficacy through the personalisation of content to foster improved viewer engagement.

Deep Learning serves as a common foundation for all studies, utilising sophisticated neural networks for diverse facial recognition challenges, with 60% of the research reviewed mentioned. Convolutional Neural Networks (CNNs), U-Net topologies, and various other frameworks are extensively employed. For example, Kim et al. (2021) utilise CNNs for real-time facial expression detection, whilst Priadana et al. (2023) concentrate on efficient CNN-based models for age classification. Additionally, Kumar et al. (2022)

Deep learning techniques are fundamental to all the papers, facilitating accurate and adaptive recognition systems with also 60% of the studies including deep learning. Kim et al. (2021) utilise convolutional neural networks (CNNs) for feature extraction in expression and behavioural analysis. Kumar et al. (2022) integrate U-Net and AlexNet designs for enhanced biometric systems, whilst Lu et al. (2021) utilise CNNs in conjunction with pre-processing techniques to improve recognition efficacy. Priadana et al. (2023) and Wang & Deng (2021) illustrate the efficacy of deep learning in improving age group categorisation and large-scale facial recognition systems, respectively. Yu et al. (2019) employ machine learning and computer vision technology to enhance advertising flexibility.

Convolutional Neural Networks (CNNs) are often utilised in these investigations, with 60% of the examined research incorporating CNNs. Kim et al. (2021) utilise CNNs for real-time facial expression recognition, whereas Priadana et al. (2023) and Lu et al. (2021) exploit CNN architectures for the recognition of emotion, age, and gender, prioritising efficiency. Kumar et al. (2022), Wang & Deng (2021) and Yu et al. (2019) also employ CNN in their systems. Convolutional Neural Networks (CNNs) are distinguished by their adaptability in feature extraction, establishing them as fundamental in facial recognition applications.

Accuracy quantifies the precision attained by models in facial detection and identification tasks which also obtain 60% from the reviewed studies encompassing accuracy. Studies such as Kumar et al. (2022) and Priadana et al. (2023) emphasise high accuracy rates, reporting competitive outcomes in benchmarks for emotion, age, and gender recognition. Likewise, Lu et al. (2022) attain notable accuracy rates, underscoring the dependability of their methodology.

The evaluation table classifies the contributions of each work to facial detection, advertising, and technological improvements. It underscores the variety of methodologies, with several studies concentrating on real-time adaptability and speed, whereas others prioritise accuracy or targeted advertising applications. This detailed analysis illustrates the facial detection (70%) is widely used to overcome the problem on targeted advertising.

2.9 Research Gap

The research gap included a lack of audience-targeted delivery, privacy preservation, generalization across datasets and demographics, real-time implementation challenges, model accuracy difficulties, bias and fairness, scalability and efficiency and robustness to environmental variability. Figure 2.2 shows the research gap and the related research gap to this research. This research will concentrate on improving the lack of audience-targeted delivery, real-time implementation challenges and accuracy and reliability in dynamic environments which are related to the research. These areas are crucial for the efficient implementation of facial detection technologies for targeted advertising.

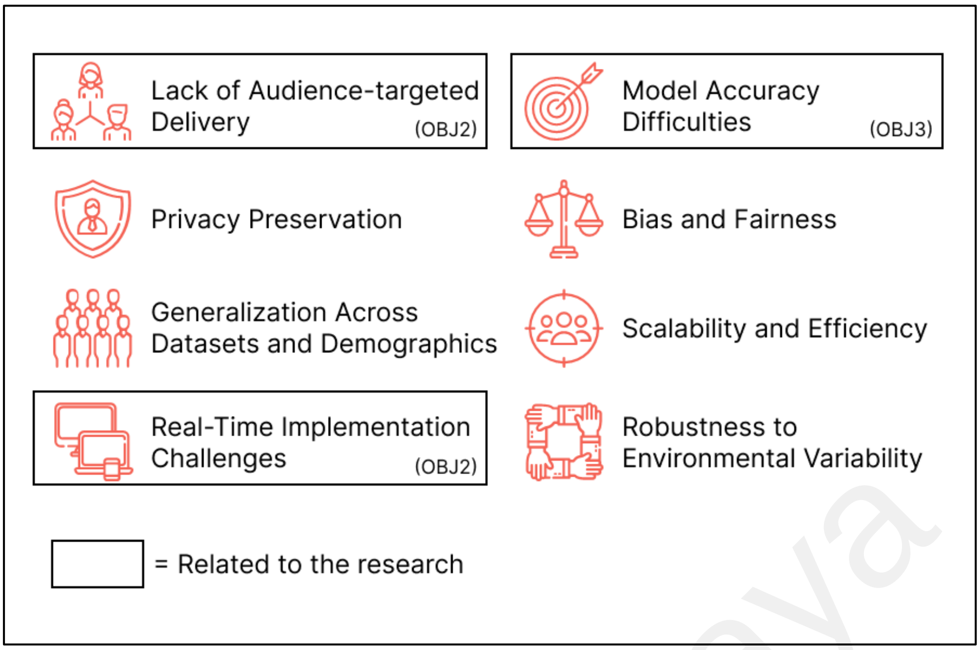

Figure 2.2: Research Gap

A major constraint of conventional billboard advertising is the lack of audience-targeted delivery, resulting in generic content display and diminished engagement. Conventional billboards cannot dynamically modify their content according to the particular interests or demographics of surrounding viewers, leading to lost opportunities for meaningful engagement (Moraru & Cărbune, 2021). Although recent research has proposed data-driven methodologies to enhance targeting through vehicle trajectory data and adaptive content management systems, existing systems continue to face challenges in accurately customising material for the immediate audience (Wang et al., 2020). This gap highlights the necessity for sophisticated targeting methods, including facial recognition and deep learning, which can provide personalised, real-time advertising that adjusts to audience traits in a responsive fashion.

Privacy is widely emphasised in numerous studies on facial recognition technologies. The acquisition, storage, and utilisation of biometric information without explicit agreement might give rise to substantial ethical and legal apprehensions (Kumar et al., 2022). To tackle these privacy concerns, it is necessary to devise strategies that guarantee clear and open data handling while giving utmost importance to safeguarding individual privacy. Research should prioritise the development of resilient privacy-preserving methods that can be effortlessly incorporated into facial detection systems utilised for targeted advertising.

Multiple research studies acknowledge the difficulty of applying facial detection and identification systems to various datasets and demographic groupings (Lu et al., 2021). Contemporary models frequently exhibit strong performance on particular datasets but encounter difficulties when faced with diverse real-world populations (Priadana et al., 2023). Research could explore methods to improve the generalizability of these systems, guaranteeing their consistent performance across diverse demographics and in various circumstances. This may entail generating more heterogeneous training datasets and designing algorithms that can adjust to novel and different inputs.

The real-time application of facial detection systems poses significant computational and technical obstacles. Real-time image processing requires substantial computational capacity and optimal memory utilisation (Priadana et al., 2023). The research could concentrate on enhancing algorithms and system designs to achieve real-time performance without compromising accuracy. This entails investigating methods such as model compression, hardware acceleration, and efficient data management to guarantee the system functions well in real-time situations.

Existing face detection systems frequently encounter difficulties in maintaining continuously high accuracy, especially in the precise identification of varied faces in age groups. Despite developments in deep learning enhancing performance, there is still a necessity for more resilient methods to optimise detecting capabilities. My research reduces this gap by employing sophisticated pre-processing techniques and optimising deep learning models to improve the system's accuracy in recognising diverse faces.

The literature emphasises the significant concerns regarding potential biases in facial detection and identification systems, specifically in relation to gender, age, and racial prejudices (Rahman et al., 2020). These biases can result in mistakes and unjust treatment of specific demographic cohorts. Conducting research to reduce these biases is crucial in order to guarantee that facial detection algorithms are just and impartial. This may involve the creation of methods to identify and rectify biases, as well as the integration of fairness measurements in the assessment of these systems.

Scalability and efficiency are crucial for implementing facial detection systems, as they must be able to handle huge numbers of users and process substantial amounts of data (Priadana et al., 2023). Research could investigate scalable systems and efficient algorithms capable of handling higher workloads without sacrificing performance. These could involve strategies like as distributed computing, parallel processing, and the creation of efficient models that can run effectively on low-end hardware.

Facial detection systems can be greatly influenced by environmental elements such as lighting conditions, background clutter, and camera angles, which can have a considerable impact on their performance (Lu et al., 2021). Research should prioritise improving the resilience of these systems to handle such fluctuation. This may entail the creation of algorithms that are less susceptible to variations in illumination, capable of accurately differentiating faces from complex backgrounds, and maintaining consistent accuracy regardless of camera angles. Enhancing the system's resilience will guarantee consistent and dependable operation in varied and frequently uncertain environments.

To address the research gap in the lack of audience-targeted delivery and real-time implementation challenges, the solutions are being formulated in Objective 2, which is to develop a facial detection system that can distinguish between different age groups and genders. Moreover, model accuracy difficulties are being addressed in Objective 3, which is to analyse the effectiveness of the developed system for targeted advertising. These domains are critical to the effective application of facial recognition technology for targeted advertising.

Furthermore, addressing the existing constraint of audience-targeted delivery is crucial to enhance the system's performance in accurate demographic targeting, a vital element for applications of targeted advertising. This improvement would facilitate more tailored and effective advertising techniques. Furthermore, tackling the practical difficulties in implementing the system in real-time will guarantee its efficient operation and prompt responsiveness. Ensuring model accuracy will guarantee consistent performance despite fluctuating conditions. Ultimately, the project intends to enhance the effectiveness and dependability of facial identification systems for targeted advertising through the application of deep learning techniques.

2.10 Summary

This chapter combines existing research on targeted advertising, facial recognition technology, and their integration to tackle issues in conventional billboard advertising. It commences by delineating targeted advertising as a data-driven methodology aimed at augmenting consumer relevance, while also considering revenue implications. The discussion transitions to facial recognition technology, highlighting its function in assessing demographic characteristics via deep learning, namely Convolutional Neural Networks (CNNs), which have transformed feature extraction and precision in biometric systems.

Conventional billboard advertising faces significant issues, including static material, inadequate audience targeting, and unquantifiable impact. Proposed solutions include adaptive content systems and data-driven frameworks utilising mobility patterns. The chapter highlights the supremacy of deep learning methodologies (e.g., CNNs, DeepFace) in facilitating real-time facial detection, age and gender classification, and emotion analysis, which are essential for dynamic advertising.

Efficient and lightweight models are examined to mitigate computational limitations, guaranteeing real-time performance on resource-constrained devices. Research themes highlight deep learning and billboard problems as pivotal, underscoring their transformational promise and ongoing deficiencies. Evaluation metrics indicate a predominant emphasis on facial detection (70% of research), while targeted advertising, CNNs, and accuracy each account for 60%.

The chapter finishes by identifying research gaps, such as real-time implementation, precision in audience targeting, and model correctness in dynamic contexts. The identified gaps shape the current study's objectives: to create a robust facial identification system for demographic targeting, to optimise real-time performance, and to improve accuracy, thereby aligning theoretical breakthroughs with actual advertising implementations.

CHAPTER 3: METHODOLOGY

This chapter outlines the comprehensive approach utilised to achieve the study's aims, focussing on the development, implementation, and evaluation of a facial detection system designed for targeted advertising. The chapter includes a SMART diagram, research design, module flowchart, pipeline overview, system development and architecture, description of the dataset, ad mapping and display ads process and also evaluation metrics.

3.1 SMART Model

The research methodology employs the SMART model to develop a facial detection system for targeted advertising, emphasising specific, measurable, achievable, relevant, and time-bound objectives. The process commences with the establishment of explicit objectives, which include investigating detection techniques and developing a system to distinguish age and gender. Essential phases encompass conducting literature research, adapting the DeepFace model, and evaluating performance through metrics from the sckit-learn library. The process aims to guarantee relevance and practicality, incorporating milestones to monitor progress and adjust to developments in facial detection technology. Figure 3.1 shows the SMART diagram for this research.

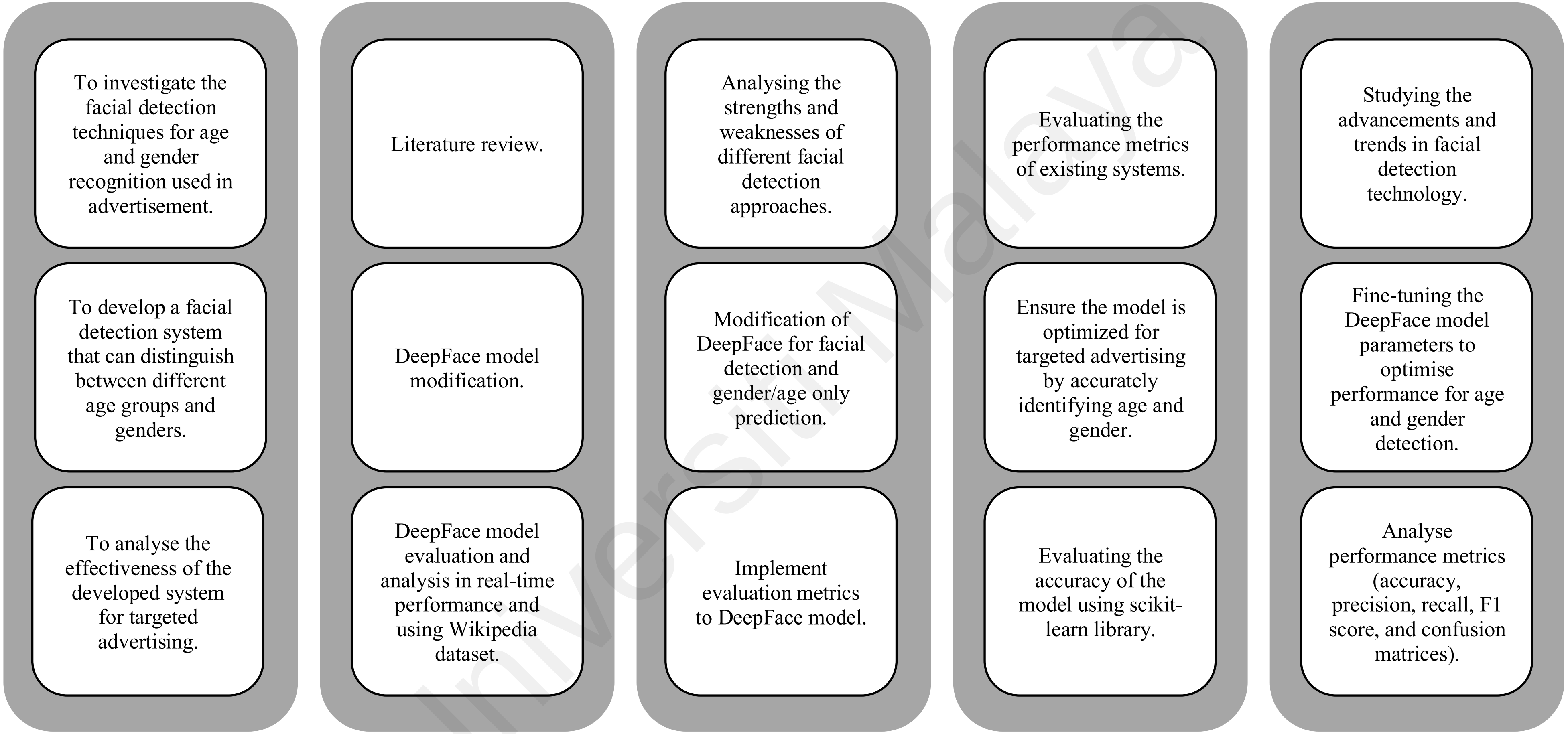

Figure 3.1: SMART Diagram

3.2 Research Design

This study utilises a mixed-methods strategy to comprehensively investigate its three primary objectives. In order to examine the facial detection methods employed in recent studies, a qualitative analysis was conducted on the literature on facial detection technology, which corresponds to Objective 1. In addition, the DeepFace library is utilised to develop a facial recognition system capable of differentiating between various age groups and genders, coinciding with Objective 2, which involves a quantitative study. Objective 3 involves assessing the effectiveness of the established system for targeted advertising. This is done by conducting evaluation and analysis for both the real-time advertisements display module and Wikipedia dataset evaluation modules using evaluation metrics from the scikit-learn library. The evaluation and analysis are quantitative analysis.

The research aims to gain a comprehensive understanding of practical insights for the application of facial identification technologies in advertising contexts through the integration of quantitative and qualitative methodologies. The research design is presented in Table 3.1.

Table 3.1: Research Design

Aspect	Objective 1	Objective 2	Objective 3
Research Design	Qualitative	Quantitative	Quantitative
Research Question	How do recent research studies utilize facial detection techniques for age and gender recognition?	What methods can be employed to develop a facial detection system capable of accurately distinguishing between different age groups and genders?	How does the developed facial detection system perform in accurately identifying age groups and genders for targeted advertising?
Research Objective	To investigate the facial detection techniques for age and gender recognition used in advertisement.	To develop a facial detection system that can distinguish between different age groups and genders.	To analyse the effectiveness of the developed system for targeted advertising.
Method	Qualitative analysis	Quantitative analysis	Quantitative analysis
Description	Conducting a comprehensive analysis of existing literature to identify and understand different facial detection approaches and conventional advertising problems in recent studies.	The DeepFace library is modified to create and execute a facial detection system detecting age groups and gender only.	Utilising quantitative analysis to assess the real-time performance of the facial detection system and also evaluate using a labelled dataset.
Tool/Software/ Techniques	Literature review, qualitative data analysis techniques.	DeepFace library, Multi-task Cascaded Convolutional Networks (MTCNN) for face detection, Python for development.	Python libraries such as Scikit-learn for evaluation metrics.
Analysis	Qualitative data analysis to identify strengths and weaknesses of different facial detection approaches	System testing and debugging, ensuring robust performance.	Quantitative evaluation using metrics like accuracy, precision, recall, and F1-score, confusion matrix.

3.3 System Development

The project aimed to develop a real-time facial analysis system that customises adverts according to the user's detected age group and gender. The development approach encompassed multiple steps, including environment setup, image capture and pre-processing, facial feature analysis, and the presentation of personalised advertisements.

3.3.1 System Development Flow Diagram

The system development follows the Agile methodology, guaranteeing an iterative and adaptable approach to system improvement. Agile approaches have numerous benefits, such as heightened project efficiency, improved communication and collaboration, and more stakeholder satisfaction. These approaches are especially efficacious in dynamic and uncertain contexts, where they promote ongoing enhancement and client satisfaction. Agile methodologies enhance product quality, increase the frequency of software releases, and optimise defect handling (Natarajan & Pichai, 2024). The procedure is segmented into several sprints, each concentrating on essential capabilities including system setup and preliminary testing, facial detection and demographic classification, advertisement mapping and display module, system evaluation and final testing. Figure 3.2 shows the system development flow diagram using agile methodology.

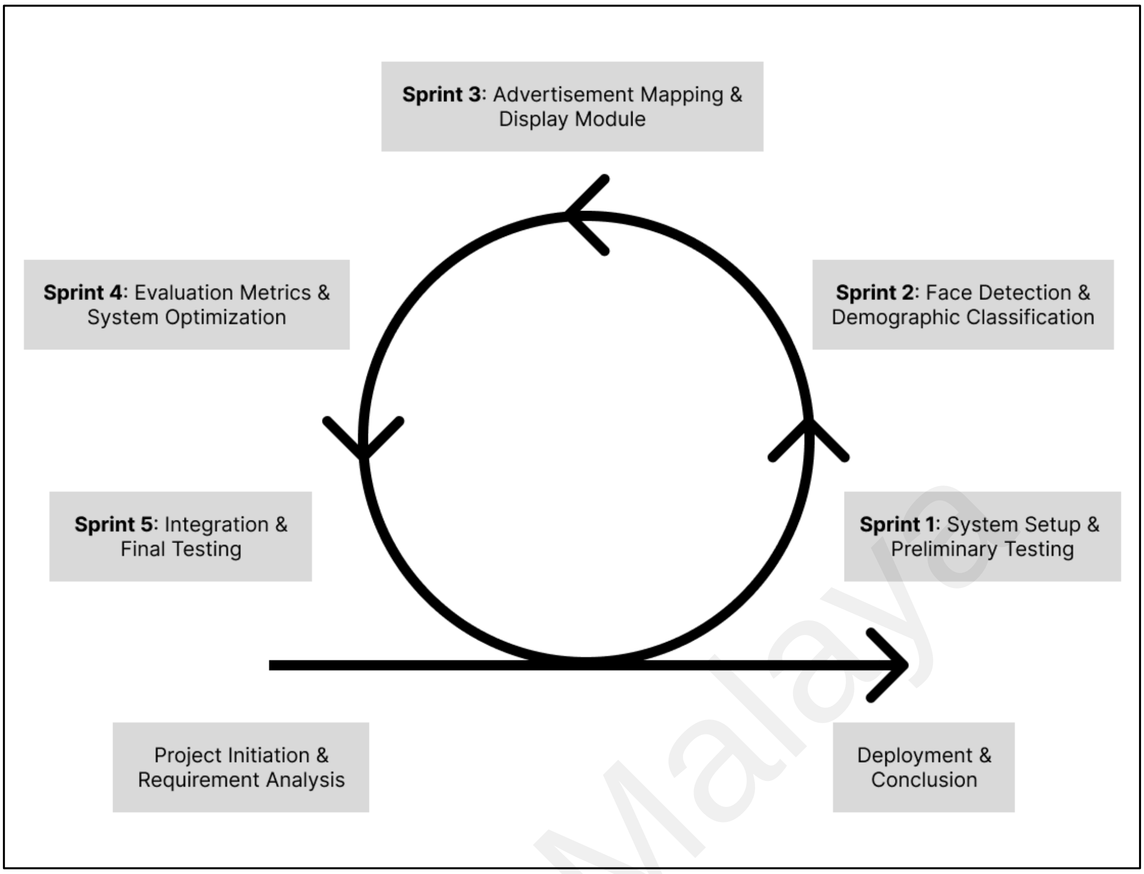

Figure 3.2: System Development Flow Diagram using Agile Methodology

The project commences with Project Initiation and Requirement Analysis, during which the objectives and scope of the system are delineated. Critical problems, including real-time processing, precision, and user engagement, are recognised to inform development. This phase entails establishing an Agile development plan, facilitating iterative advancement via several sprints.

During Sprint 1 System Setup & Preliminary Testing, the development environment is configured utilising Google Colab and requisite Python libraries to facilitate access to cloud resources and connection with Google Drive for file storage. The project utilised external tools such as JavaScript to interface with the webcam and take real-time photographs directly from the browser. During the preprocessing stage, the acquired image resolution is configured to half that of the original video feed to decrease processing time while preserving adequate detail for facial analysis. Essential libraries, including DeepFace for facial recognition, MTCNN for image processing, and Matplotlib/Seaborn for result visualisation, were utilised during the development process. DeepFace, a pre-trained deep learning library for facial identification and analysis, was incorporated into the system to discern essential facial characteristics such as age and gender. The system uses the MTCNN face detection model for initial facial detection, and early evaluations are performed using sample photos, thereafter conducting the analysis. MTCNN was chosen due to its high accuracy in detecting faces, even in challenging scenarios such as varying lighting conditions and dense facial arrangements. Its multi-task framework efficiently combines face detection with landmark localization, ensuring reliable inputs for the DeepFace analysis (Amirgaliyev et al., 2021). The sprint culminates in a review to collect input and enhance the implementation.

Sprint 2 emphasises Face Detection and Demographic Classification. The deep learning model is optimised for real-time facial identification. Since DeepFace will output all the age, gender, facial expressions (including angry, fear, neutral, sad, disgust, happy and surprise) and race (including Asian, White, Middle Eastern, Indian, Latino and Black) predictions, the system is further modified to incorporate age and gender classification only to fit the research objectives. The algorithm classifies the individual into demographic categories (child, teen, adult, or senior) based on expected age and gender and identifies the person as male or female. These classifications are employed to choose a suitable advertisement from the available selections. Optimisation initiatives focus on enhancing processing speed and accuracy. The identified age and gender information is corroborated with a preliminary dataset prior to the sprint's completion, which includes a review and additional adjustments.

Upon the system's successful detection of facial demographics, Sprint 3 will implement the Advertisement Mapping & Display Module. A logical system is employed to choose adverts based on identified demographic characteristics, guaranteeing a tailored advertising experience. Upon establishing the age group and gender, the algorithm selects an advertisement customised to the individual's demographic profile. In the absence of facial detection, the system defaults to random advertising. Advertisements are classified into four demographic categories: child (<13 years), teen (13–19 years), adult (20–49 years), and senior (≥50 years), with distinct possibilities for males and females. The chosen commercial is presented alongside pertinent information, like age, gender, and the corresponding ad group. This guarantees that the user encounters an advertisement pertinent to their demographic profile. Moreover, fallback techniques are intended to present random advertisements when no face is identified. This sprint is subject to review and testing to guarantee flawless integration with the detection system.

Sprint 4 encompasses Evaluation Metrics and System Optimisation to assess system performance. Diverse evaluation criteria, including accuracy, precision, recall, F1-score, and confusion matrices, are employed to evaluate the system's accuracy. The Wikipedia dataset is utilised for comprehensive testing, and optimisations of deep learning models are conducted to improve accuracy and real-time processing performance. The sprint culminates in the assessment and enhancement of the evaluation system.

During Sprint 5: Integration & Final Testing, all developed components are completely merged into a cohesive system. Thorough real-time testing with actual users is performed to assess the system's precision and latency. Debugging and enhancements are conducted according to test outcomes, guaranteeing a reliable and efficient system prior to release.

The system ultimately progresses to the Deployment and Conclusion phase. The system is implemented for practical testing, and user input is gathered to assess its efficacy in targeted advertising. The conclusive project report is finished, detailing findings and performance outcomes. The project's success is evaluated based on enhancements in advertisement engagement, precision, and system responsiveness.

Adopting an Agile methodology ensures a flexible development process, facilitating ongoing enhancements and iterative adjustments informed by real-time input. This methodology guarantees that the facial detection system achieves its goals of augmenting targeted advertising, enhancing consumer interaction, and refining marketing strategies.

3.4 Real-time Operation and Dataset Evaluation Modules

There are a total of two modules in the system which are the Real-Time Ad Display Module and Dataset Evaluation Modules. The system functions in real-time, perpetually gathering photographs from the webcam and analysing the outcomes to modify the displayed advertisement accordingly. The procedure is perpetuated endlessly until the user chooses to terminate the system. The system can also be assessed using an image dataset, enabling performance evaluations based on accuracy, precision, recall, F1-score and confusion matrix for both real-time operation and dataset evaluation module. This assessment measures and is able to compare the performance of facial analysis in accurately predicting age groups and gender while optimising the system for enhanced performance.

3.4.1 Real-Time Ad Display Module

Figure 3.3 shows the process dynamically acquires user images, evaluates their demographic characteristics and displays the targeted advertisements.

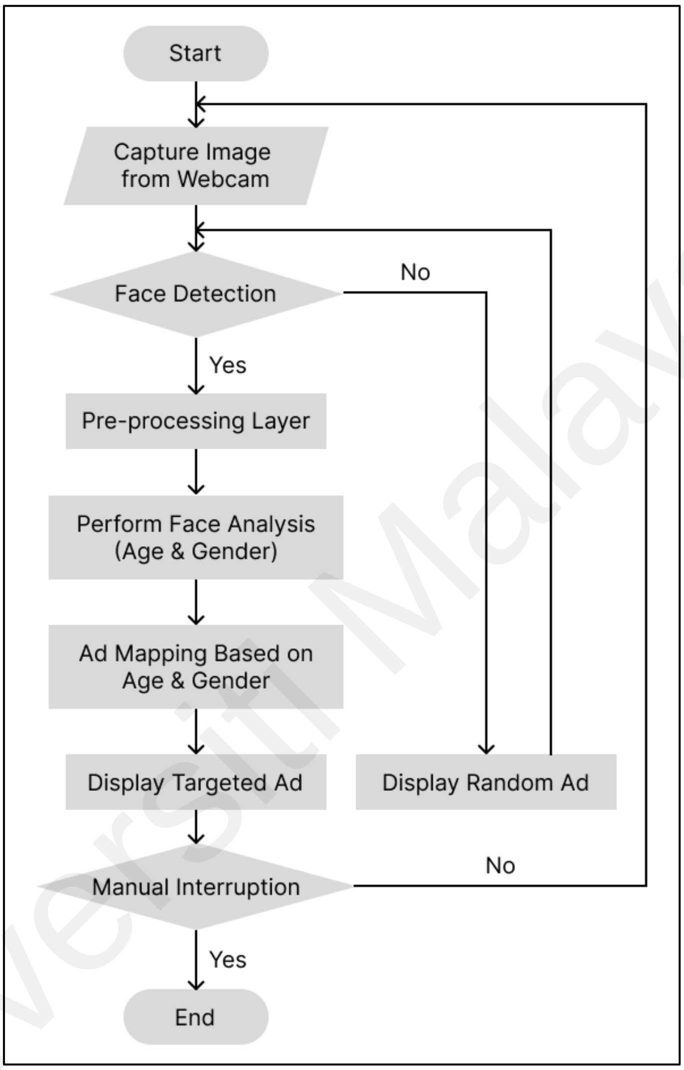

Figure 3.3: Real-Time Advertisements Display Flowchart

The flowchart illustrates the Real-Time Advertisements Display System, detailing the dynamic procedure for displaying advertisements according to a user's demographics (age and gender) or utilising random advertisements when targeting is impractical. The system initiates by activating its components, acquiring an image from the webcam, and identifying the face within the image. A pre-processing layer of cropping and resizing the image capture is also applied. Subsequently, facial analysis is conducted utilising DeepFace to ascertain the user's age and gender. According to these predictions, the system assigns the user to an appropriate advertisement category, such as targeting younger demographics with video game advertisements or older users with health-related products. In the event that the predictions are unclear, a random advertisement is presented. The ad display procedure permits manual interruption to maintain flexibility. The cycle terminates when the advertisement is displayed or manually terminated, prepared for reinitiation for the subsequent user. This efficient method integrates precise advertisement distribution with flexibility, improving user interaction and system resilience.

3.4.2 Wikipedia Dataset Evaluation Metrics Module

Figure 3.4 shows the evaluation procedure entails utilising the Wikipedia dataset, scrutinising each image, and contrasting prediction with the ground truth to calculate metrics.

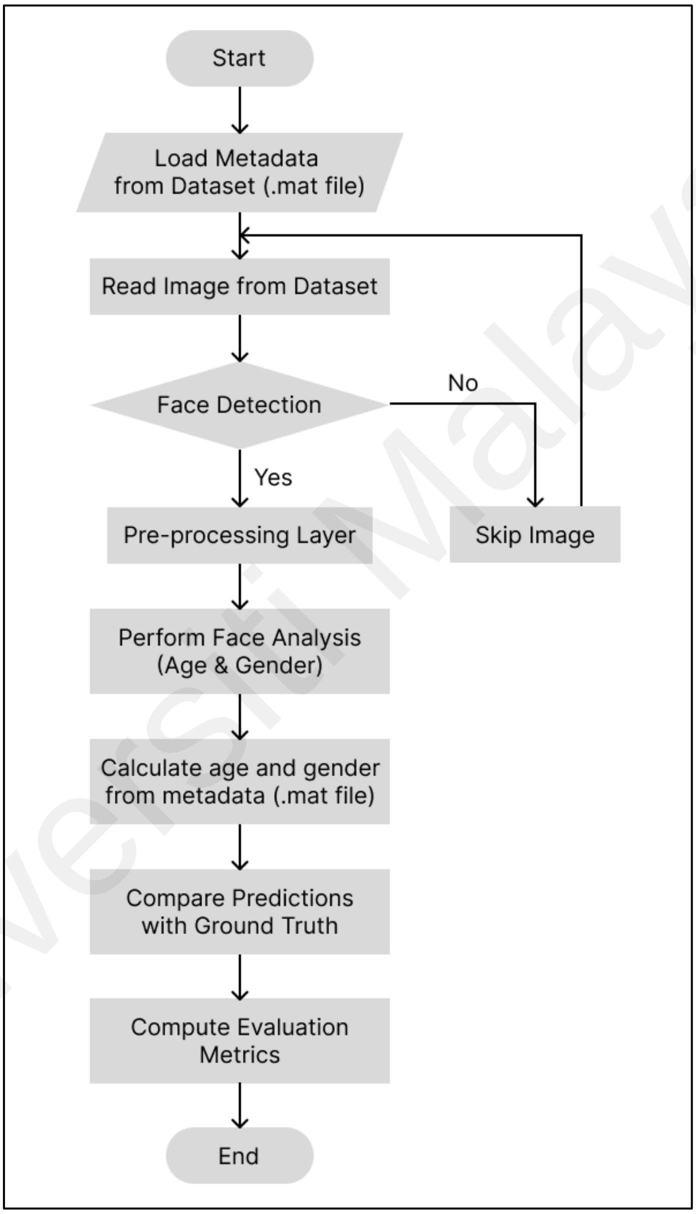

Figure 3.4: Evaluation Process Flowchart

The evaluation process flowchart outlines the procedures implemented to evaluate the accuracy of the system in predicting age and gender from facial photos. The procedure commences with the acquisition of the test dataset, which is either obtained in real-time or sourced from an external dataset. Images from this dataset are analysed using a facial detection model, such as MTCNN, to identify and extract faces. Furthermore, the images undergo pre-processing for cropping and resizing. The identified faces are subsequently evaluated via a deep learning model to ascertain their age and gender. The anticipated outcomes are compared with the ground truth values in the dataset metadata, facilitating the calculation of evaluation metrics, including accuracy, precision, recall, F1-score and confusion matrix for both age and gender predictions. This assessment gauges the system's dependability and identifies opportunities for enhancing its performance. The process concludes once all test cases have been evaluated and their respective conclusions documented for subsequent discussion.

3.5 Pipeline Overview

The system's operation is structured into distinct stages. The source code snippets of all layers are depicted in Appendix B.

1. Input Layer: Acquires photos using a webcam (for real-time application) or analyses dataset images for evaluation.
2. Pre-processing Layer: Aligns, scales, and prepares pictures for subsequent analysis.
3. Analysis Layer: Employs MTCNN for facial detection and DeepFace for the extraction of demographic attributes.
4. Classification Layer: Links identified attributes (age and gender) with established categories including child, teen, adult and senior age groups also male and female for gender group.
5. Output Layer: Presents a specific advertisement or assesses system accuracy.
6. Evaluation Layer: Assesses system performance by criteria like accuracy, precision, recall, F1-score and confusion matrix.

3.6 Pre-processing Layer

Pre-processing is an essential phase prior to inputting data into a deep learning model, particularly for tasks such as age and gender prediction. The following are the pre-processing procedures commonly employed in facial recognition and classification tasks.

The first step involves obtaining an image from the webcam through JavaScript executed within the browser. To enhance speed and decrease processing time, the acquired image is collected at half the resolution of the video stream. This is accomplished by configuring the canvas width and height to 50% of the video's dimensions.

```
canvas.width = video.videoWidth / 2;
canvas.height = video.videoHeight / 2;
```

The image is resized to a uniform dimension of 224x224 pixels. This size is selected because numerous image classification and deep learning models, especially those utilised for facial analysis such as DeepFace, require images to be of a consistent dimension. Resizing the image guarantees that the model can process it without facing mistakes associated with differing input dimensions.

```
resized_img = cv2.resize(img, (224, 224))
```

Gaussian blurring is executed on the scaled image utilising a 3x3 kernel. This process mitigates high-frequency noise in the image, which can disrupt the precision of facial detection and analysis. Gaussian blurring boosts the robustness of future analysis by smoothing the image, enabling the deep learning model to concentrate on crucial facial traits without distraction from pixel-level noise.

```
blurred_img = cv2.GaussianBlur(resized_img, (3, 3), 0.5)
```

Collectively, these pre-processing procedures enhance the quality and uniformity of the input photos, enabling the facial analysis DeepFace model to generate more precise predictions concerning age, gender, and other characteristics. By downsizing, lowering resolution, and smoothing the image, the model can recognise and analyse facial features with more precision.

3.7 Analysis Layer

The analysis layer focusses on processing input data to identify facial features and extract essential demographic attributes, including age and gender. This layer assesses several facial detection methodologies to determine the most appropriate strategy for the targeted advertising system. The objective of comparing detectors is to achieve a balance of detecting accuracy, computing efficiency, and adaptability to various real-world situations. This section also examines the DeepFace network architecture which is utilised to assess the age and gender of identified faces.

3.7.1 Face Detectors

OpenCV, Dlib, SSD (Single Shot Multibox Detector), MTCNN (Multi-Task Cascaded Convolutional Neural Networks), and RetinaFace are prominent and widely used frameworks for face detection in computer vision.

OpenCV provides various face detection techniques, such as the Haar Cascade and Single Shot Multibox Detector (SSD). The Haar Cascade is recognised for its rapid performance on CPU-based systems, however, it exhibits limitations in accuracy, particularly in difficult settings such as diverse head orientations, lighting variations, and occlusions. The SSD algorithm in OpenCV outperforms Haar Cascade, attaining approximately 80% accuracy under difficult conditions, akin to Dlib CNN (Majeed et al., 2021). Nonetheless, OpenCV techniques typically encounter challenges like as missing and incorrect detections (Zhang et al., 2020).

Dlib offers a CNN-based face detector that excels in accuracy, particularly under tough settings such as occlusions and diverse emotions (Zhang et al., 2020). It is optimised for GPU-based systems, hence improving its performance relative to CPU-based implementations (Majeed et al., 2021). Dlib’s face detection is resilient and may significantly enhance detection sensitivity and identification accuracy in comparison to OpenCV.

SSD is acknowledged for its balance between speed and accuracy, making it appropriate for real-time applications (Tariyal et al., 2024). It has comparable performance to Dlib under demanding situations, with approximately 80% accuracy. SSD effectively mitigates over-detection and misdetection, while it may not exceed MTCNN and Dlib in accuracy for prediction. Facial landmarks are points of interest on the face, such as the eyes, nose, mouth, and chin. SSD lacks support for face landmarks and relies on OpenCV's eye detection module for alignment (Chan et al., 2022).

MTCNN exhibits exceptional accuracy, especially in identifying facial landmarks, and demonstrates effective performance in real-world data scenarios (Hofer et al., 2021). It is more appropriate for GPU-based systems, providing enhanced accuracy compared to CPU-based techniques such as Haar Cascade (Majeed et al., 2021). MTCNN is known for its resilience in managing occlusions and intricate facial expressions (Hofer et al., 2021).

RetinaFace is recognised for its exceptional effectiveness in real-world impact identification tasks, surpassing competing detectors such as OpenCV and Dlib in pre-processing difficulties (Raut & Kulkarni, 2022). It is especially effective in situations including occlusions and diverse facial expressions, rendering it an excellent option for applications necessitating high levels of accuracy (Moqbel & Parameswaran, 2022). RetinaFace models provide effective compromises for face detection and recognition, providing excellent accuracy while sacrificing speed. Furthermore, it necessitates substantial computational power. Consequently, RetinaFace is the least efficient face detector relative to others (Sydor et al., 2024).

MTCNN was selected for this study due to its exceptional accuracy and adaptability in real-world applications. It excels in identifying face landmarks and effectively addresses various obstacles, such as occlusions and complex facial expressions, which are essential for the targeted advertising system. Its capacity to equilibrate detection accuracy with computational efficiency renders it an exemplary contender for this inquiry. Moreover, its compatibility with GPU-based systems guarantees improved performance, essential for deploying deep learning models in dynamic environments. MTCNN provides a strong combination of accuracy, robustness, and adaptability compared to other detectors, fitting effectively with the research aims.

3.7.2 DeepFace Network Architecture

The DeepFace architecture, developed for facial recognition, integrates multiple deep learning methodologies, particularly convolutional neural networks (CNNs), to extract information from facial images. This description delineates the principal layers and their functions within the VGG-Face model architecture. The VGG-Face model has demonstrated enhanced performance in age and gender classification relative to other models like AlexNet and task-specific models such as GilNet. This suggests that transferring a deep CNN model from a related domain can substantially improve classification accuracy (Gyawali et al., 2020). Figure 3.5 depicts the network architecture of the DeepFace VGG-Face Model.

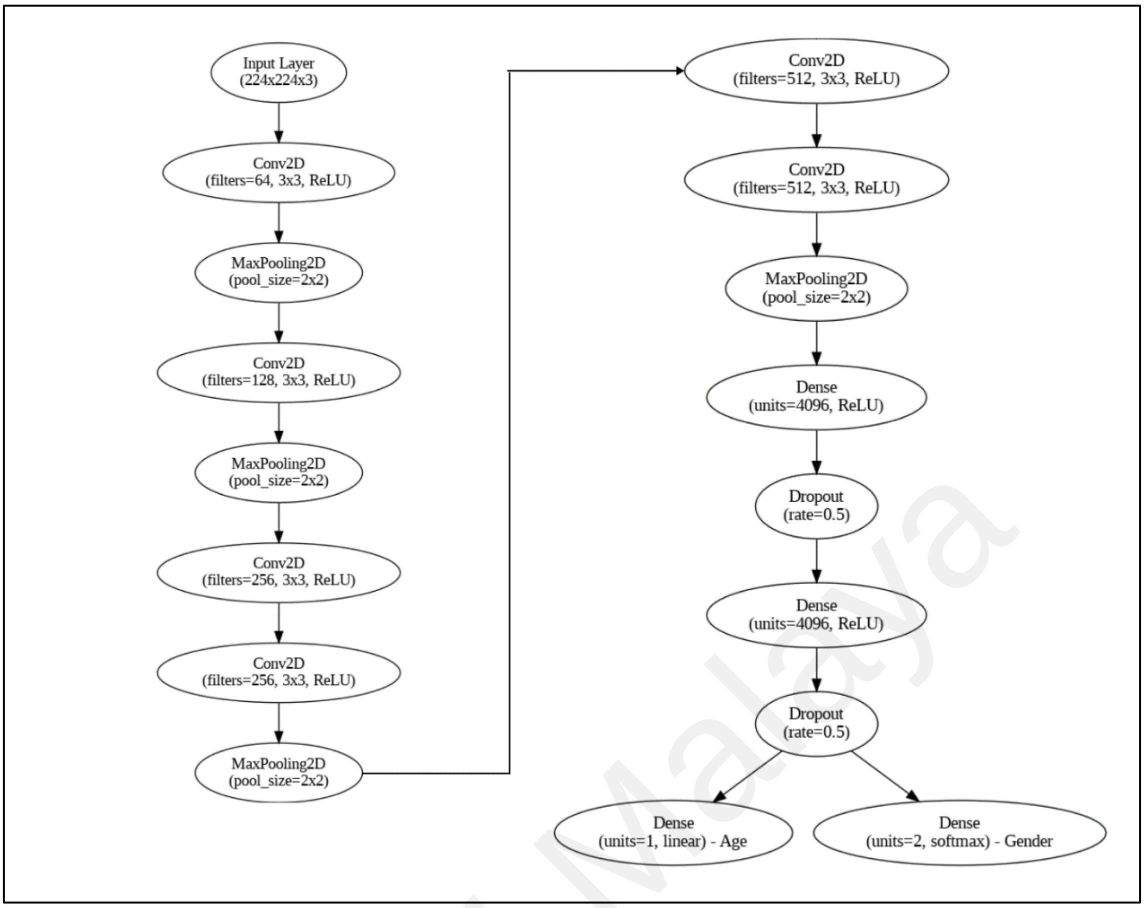

Figure 3.5: DeepFace Network Architecture

3.7.3 Input Layer

The input layer of the model is configured to accept images of 224×224×3, with 224 indicating both the height and width and 3 denoting the three RGB channels. This layer is tasked with acquiring the unprocessed image input and transmitting it over the network for feature extraction. The dimensions of 224×224 are frequently employed as they are compatible with the DeepFace architecture, which was initially trained on images of this size.

3.7.4 Convolutional Blocks

Convolutional Block 1: Conv2D (filters=64, kernel_size=3x3, activation=ReLU): The initial convolutional block employs a sequence of 3x3 convolutional filters on the input picture, yielding 64 feature maps. These feature maps denote fundamental characteristics, including edges and textures. The ReLU activation function is utilised post-convolution to incorporate non-linearity, enabling the model to discern intricate patterns within the data.

MaxPooling2D (pool_size=2x2): This pooling layer diminishes the spatial dimensions of the feature maps, thereby downsampling the data while preserving just the most salient features. The 2x2 pooling process aids in diminishing computational demands and mitigating overfitting.

The initial convolutional block extracts fundamental information from the image, including edges and textures, which are crucial for establishing a preliminary comprehension of the face.

Convolutional Block 2: Conv2D (filters=128, kernel_size=3x3, activation=ReLU): The second convolutional block utilises 128 convolutional filters on the output from the preceding block. This layer catches intricate patterns and structures from the image. With an increase in the number of filters, the model gains the ability to learn more abstract and advanced features.

MaxPooling2D (pool_size=2x2): This layer, akin to the initial pooling layer, diminishes the spatial dimensions, facilitating the downsampling of feature maps and decreasing computing complexity.

This block collects intermediate traits, including facial elements such as eyes, nose, and mouth, which are crucial for face identification and recognition.

Convolutional Block 3: Conv2D (filters=256, kernel_size=3x3, activation=ReLU): In this segment, 256 filters are utilised to enhance the extracted features. This block identifies intricate patterns essential for comprehending the nuanced aspects of the face, including the configuration and location of facial features.

A second convolutional layer, Conv2D (filters=256, kernel_size=3x3, activation=ReLU), is employed consecutively to enhance the depth of feature extraction. This also augments the model's capacity to discern complex facial features.

MaxPooling2D (pool_size=2x2): Max-pooling is employed to diminish the dimensions of the feature maps, preserving just the most essential information for subsequent layers.

The third block improves the network's capacity to collect complex facial characteristics, which is crucial for differentiating between various faces.

Convolutional Block 4: Conv2D (filters=512, kernel_size=3x3, activation=ReLU): At this juncture, the model employs 512 filters to extract increasingly intricate information. The filters assist in recognising intricate patterns, including textural differences and subtle nuances of facial features that differentiate individuals.

A second convolutional layer with 512 filters, a kernel size of 3x3, and ReLU activation is employed to enhance the extracted features, yielding greater insights into the distinctive characteristics of the face.

MaxPooling2D (pool_size=2x2): Similar to previous applications, max-pooling facilitates the downsampling of feature maps, emphasising the most pertinent aspects for ultimate decision-making.

This block is crucial for acquiring intricate, advanced facial characteristics, aiding the network in differentiating between faces with nuanced distinctions.

3.7.5 Fully Connected Layers

Dense layer (units=4096, activation function=ReLU): Subsequent to the convolutional layers, the recovered features are flattened and sent through a fully connected layer including 4096 neurones. This thick layer integrates all retrieved information to create a high-dimensional representation of the input face. The ReLU activation function enables the model to discern more intricate links among the features.

Dropout (rate=0.5): Dropout is utilised to mitigate overfitting by randomly deactivating a proportion of input units to 0 during the training process. This compels the model to acquire more resilient properties that do not excessively depend on any individual neurone.

A fully linked layer including 4096 neurones, utilising the ReLU activation function, substantially enhances the feature representations. This layer encapsulates elevated abstractions of the input image.

A second dropout layer (rate=0.5) is used to mitigate the danger of overfitting by preventing the model from memorising the training data.

These layers are essential for integrating the characteristics derived from the convolutional layers into a final, concise representation of the face that is appropriate for classification or regression.

3.7.6 Output Layer

Dense (units=1, activation='linear') for Age Prediction (Regression): The initial output layer comprises a fully linked layer including a solitary neurone and a linear activation function. This layer is utilised for predicting continuous variables, such as age. The linear activation function is suitable in this context due to the regression nature of the ageing task.

Dense layer (units=2, activation='softmax') for gender classification. The secondary output layer is utilised for gender prediction. The system has two neurones (one for male and one for female) and employs the softmax activation function, suitable for multi-class classification applications. The softmax function guarantees that the output values represent probabilities that total to 1.

Modifying the output layer to exclusively predict age and gender enhances the system's computational efficiency since it eliminates the need to compute extraneous information such as facial expressions and race, which are irrelevant to the targeted advertising system. This efficient method decreases processing duration, simplifies model intricacy, and improves inference velocity, rendering it appropriate for real-time application in advertising displays. The architecture guarantees precise mapping of identified demographic traits to personalised adverts, enhancing engagement and relevance in targeted marketing.

The optimised output layer, in conjunction with MTCNN for face detection and DeepFace's feature extraction pipeline, guarantees excellent accuracy in age and gender classification, rendering it an effective tool for intelligent advertising solutions.

The DeepFace model, utilising the VGG16 architecture, adeptly integrates deep convolutional layers for feature extraction with fully connected layers for decision-making. The convolutional blocks extract facial features ranging from low to high levels, whereas the fully connected layers amalgamate these features into a high-dimensional representation utilised for both regression (age prediction) and classification (gender prediction). Employing dropout layers aids in regularising the model, mitigating overfitting, and enhancing generalisation. The model is engineered to manage intricate tasks, including age and gender prediction, by utilising deep learning methodologies in facial recognition.

3.8 Ad Mapping and Display Ads

The Ad Mapping process entails correlating the model's results, including age and gender estimates, with suitable advertisements. The model's predictions are essential for customising ad selection. According to these predictions, various sorts of advertisements can be directed at certain demographic segments.

Upon processing the facial image with the model, predictions are generated for attributes such as age and gender. Advertisements are generally classified by target demographics. Advertisements can be classified according to age brackets including child (<13 years), teen (13–19 years), adult (20–49 years), and senior (≥50 years).

Moreover, advertisements tailored to a specific gender (e.g., gadget items for men or cosmetics for women) might be chosen based on gender prediction. There are a total of 11 sample advertisements used in this research. Figure 3.6 depicts the sample advertisements utilised in this investigation. Advertisements for boys' toys targeting male children, girls' toys for female children, clothing for male teenagers, and clothing for female teenagers. The advertisement for gadget sales targets adult males, cosmetics products are aimed at adult females, health products are directed towards senior males, and medical services are specifically focused on senior females. The figure additionally displays three random advertisements, ensuring that in the absence of face detection, the system cycles through all advertisements, including the random ones. For instance, the model could predict the age as 25 and the gender as male. Once predictions are generated the system can utilise them to retrieve relevant advertisements from an ad database, in this case, it will display gadget sales advertisement.

Figure 3.6: Sample Advertisements

Figure 3.7 shows the process of ad mapping and displaying. In the first image, the billboard is displaying a random ad since no one is in range of the camera. Then, the second image shows the zoomed in image of the camera on top of the billboard display screen. Image 3 below depicts that a male senior (aged 50 and above) is detected. Hence, the billboard in Image 4 displays a health products ad as the targeted advertisement.

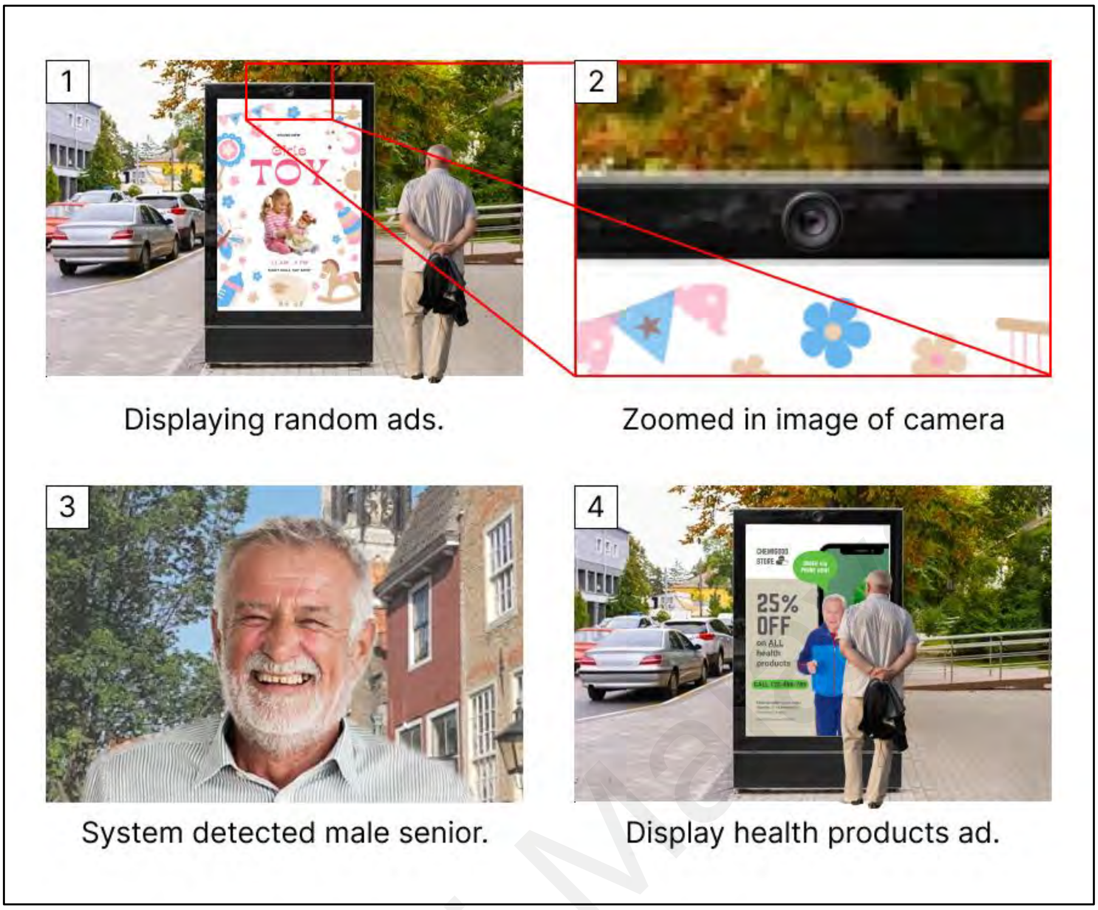

Figure 3.7: Process of Ad Mapping and Displaying

The system selects the most appropriate advertisement based on the user's demographic characteristics and presents it to the user. This constitutes a sort of personalised advertising, wherein the advertisement is customised according to the anticipated attributes derived from the facial detection model.

The Ad Mapping and Display Ads process utilises predictions from the deep learning model, such as age and gender, to curate and deliver personalised adverts to users, exemplifying a prevalent application in targeted advertising technologies.

3.9 Dataset Description

There total of 3 types of datasets from IMDB-WIKI including IMDB, WIKI, and IMDB-WIKI (combined). The dataset was introduced in 2016 with no major update after its initial release. The Wikipedia image dataset from IMDB-WIKI is frequently utilised for age and gender prediction applications. The reason Wikipedia is chosen for this research as the dataset is because the dataset covers worldwide faces and also the IMDB dataset primarily focuses on actors and actresses, so it contains a narrower demographic compared to the Wikipedia dataset (Rothe et al., 2018). Table 3.2 shows the description of the Wikipedia dataset, including its contents and applications in facial analysis.

Table 3.2: Dataset Description

Aspect	Description
Images	The dataset contains facial images of individuals, which can be used to predict age and gender.
Metadata (.mat File)	The dataset includes several attributes in structured data about each individual.
Date of Birth (dob)	The birth year of the individual.
Photo Taken (photo_taken)	The year the photo was taken.
Gender	The gender of the individual. Gender labels (1 for male, 0 for female).
Full Path	The relative path to the image file in the dataset.

In the Wikipedia dataset, the date of birth (dob) is expressed as the total number of days since January 1, 0000. To determine an individual's age, the system must transform the data from days to years. Dividing the date of birth value by 365 yields an approximation of the individual's age in years.

```
age = photo_taken_year - (dob_in_days // 365)
```

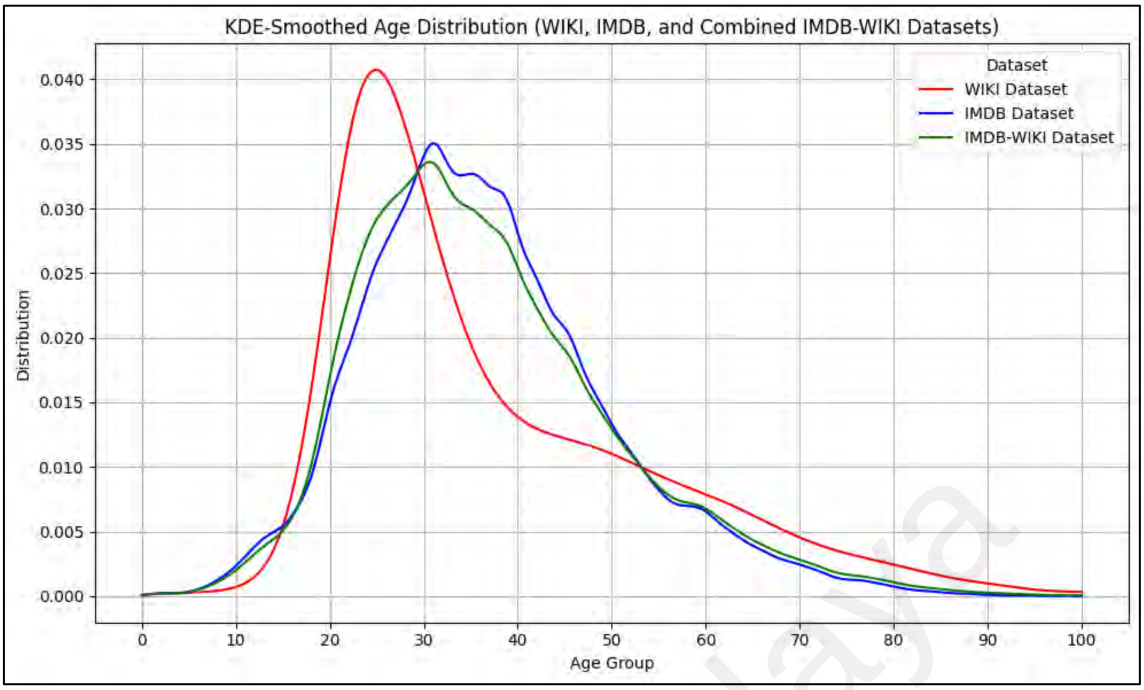

Figure 3.8: IMDB-WIKI Dataset Age Distribution (Rothe et al., 2018)

Figure 3.8 illustrates the graph of the age distribution of individuals in the WIKI, IMDB, and combined IMDB-WIKI datasets with Kernel Density Estimation (KDE) smoothing. KDE is a statistical technique that offers a smooth, continuous representation of a dataset's underlying distribution, facilitating the visualization and analysis of patterns in contrast to conventional histograms. This method is very effective for detecting patterns in datasets with disparate sample sizes or sparse data points in specific ranges.

The graph indicates that the WIKI dataset (red line) has a significant peak in the 20-30 age range, implying that the bulk of facial photos in this dataset depict younger persons. The WIKI dataset demonstrates a lengthy tail for older ages, signifying a more extensive representation of older demographics in contrast to the IMDB dataset. In contrast, the IMDB dataset (blue line) exhibits a comparable peak between 20 and 30 years but displays a more restricted distribution for older ages, indicating a scarcity of photos featuring elderly adults.

The combined IMDB-WIKI dataset (green line) has a distribution pattern that closely resembles that of the IMDB dataset. This similarity is anticipated, considering the approximately 8:1 ratio of photos from IMDB to WIKI in the combined dataset. The properties of the IMDB dataset predominantly govern the combined distribution, with a minor influence from the WIKI dataset.

The application of KDE smoothing in this research is essential for improving visualization. In contrast to histograms, which categorize data into distinct bins and may exhibit a jagged appearance, Kernel Density Estimation (KDE) generates a smooth curve that diminishes noise and emphasizes fundamental trends. This approach facilitates the precise identification of biases or imbalances within datasets. The differences in the distributions underscore the WIKI dataset's more extensive representation of older age demographics in contrast to IMDB, which is biased towards younger individuals.

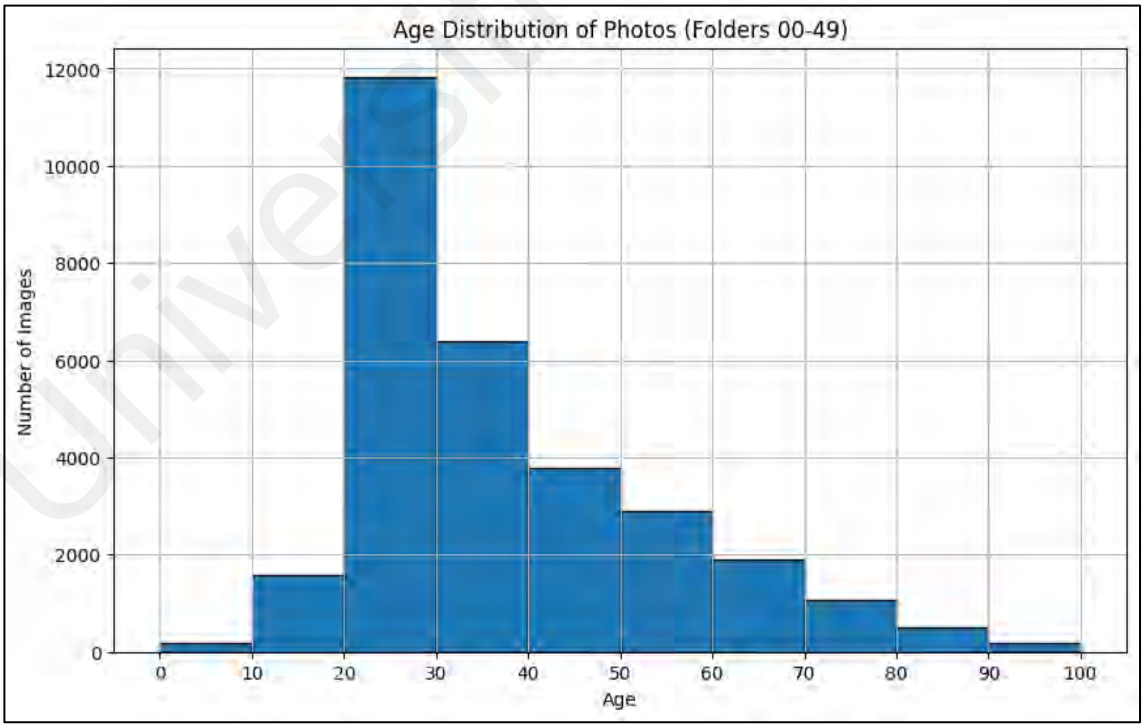

Figure 3.9: Wikipedia Dataset Age Distribution

Table 3.3: Total Images per Age Group from Metadata (.mat File)

Age Group	Total Images
0-10	97
11-20	2177
21-30	11122
31-40	5438
41-50	3479
51-60	2617
61-70	1687
71-80	950
81-90	419
91-100	149
Total	28135

Figure 3.9 depicts the histogram of the age distribution of facial images from the WIKI dataset, concentrating on photographs contained in folders from 00 to 49. There is a total of 31146 images in the folders from 00 to 49 but there are only 28135 of them contain valid faces which concludes that 3011 images do not include any sort of facial information as indicated in the metadata (.mat file). Furthermore, this group comprises persons aged 0 to 100, predominantly featuring images of those in the 20-30 age range. Table 3.3 shows the total images per age group of the selected dataset. An analysis of the dataset indicates that there are 11122 images for individuals aged 21-30, rendering it the most predominant age group. Subsequently, there are 5,438 images for the age group 31-40 and 3479 images for the age group 41-50. The distribution persists in its fall with advancing age, yielding merely 419 images for those aged 81-90 and 149 images for those aged 91-100. The collection comprises 97 photos for the age group 0-10 and 2,177 images for the age group 11-20.

The choice to process solely folders 00-49, rather than the entire dataset (folders 00-99), was intentional and driven by practical considerations. Utilizing half of the dataset markedly decreases processing time, facilitating faster dataset preparation cycles. This is especially beneficial in the first phases of research when frequent troubleshooting and model enhancement are required. Additionally, restricting the dataset to 50 folders necessitates reduced memory usage, which is essential for computers with hardware limitations. This decrease in processing demand mitigates the risk of system crashing or slowdowns resulting from the resource-intensive processes of facial detection and recognition.

Moreover, choosing folders 00-49 preserves a representative framework of the dataset's age distribution. The selected subset maintains the prevailing trends, notably the significant prevalence of photos within the 20-30 age demographic, which mirrors the attributes of the entire dataset. This guarantees the validity of the study and model development while conserving resources. The scope may be broadened to encompass all folders (00-99) in subsequent phases to enhance the model's resilience and generalisation.

3.10 Evaluation Metrics

This section is essential for assessing the model's performance. Following the model's predictions, such as estimating a person's age and gender from a facial image, it is crucial to evaluate the accuracy of these predictions against the actual ground truth values. This procedure often entails comparing the model's output with the actual values, computing errors, and employing metrics to assess the model's precision.

3.10.1 Compare Predictions with Ground Truth

The predicted values are compared with the actual values (ground truth) for each sample in the test dataset. This assists in assessing the accuracy of the model's predictions. For age prediction (Regression), the model generates a predicted age. The ground truth represents the true age of the individual depicted in the photograph. For gender prediction (Classification), the model produces a predicted category. The ground truth refers to the individual's true gender.

3.10.2 Compute Evaluation Metrics

The evaluation metrics for classification tasks, including age and gender prediction, enable a quantifiable assessment of a model's performance in the real-time module and using the dataset. These metrics facilitate the comprehension of the model's accuracy in differentiating age groups or genders.

3.10.2.1 Accuracy

Accuracy is a frequently employed evaluation metric. It denotes the ratio of accurate predictions to the total predictions made.

$$Accuracy = \frac{\text{Number of Correct Predictions}}{Total\ Number\ of\ Predictions} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

TP = True Positives (correctly predicted positive cases)

TN = True Negatives (correctly predicted negative cases)

FP = False Positives (incorrectly predicted as positive)

FN = False Negatives (incorrectly predicted as negative)

In the code, accuracy_score from scikit-learn library is used to calculate accuracy for both age and gender predictions.

3.10.2.2 Precision

Precision measures the proportion of examples predicted as a specific class (positive) that genuinely belong to that class. It is often referred to as the positive predictive value.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Where:

TP = True Positives

FP = False Positives

Precision indicates the reliability of our favourable predictions. A high precision indicates that when the model predicts a good outcome (e.g., a specific age group or gender), it is likely to be accurate.

Precision is computed in the code utilising precision_score from scikit-learn for both age and gender, employing average='weighted' for multi-class metrics (age groups) and average='binary' for binary classification (gender).

3.10.2.3 Recall

Recall refers to the model's capacity to accurately identify all positive instances (true instances of the class). It is also referred to as Sensitivity or True Positive Rate.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Where:

TP = True Positives

FN = False Negatives

Recall indicates the number of actual positives that the model successfully identifies. A high recall indicates that the model accurately identifies the majority of true positives. Recall is calculated in the code using recall_score from scikit-learn, employing average='weighted' for age (multi-class) and average='binary' for gender (binary).

3.10.2.4 F1-Score

The F1-score represents the harmonic mean of precision and recall. It integrates precision and recall into a singular metric, equilibrating the trade-off between the two. The F1-score is especially beneficial for imbalanced datasets since it helps prevent the deceptive implications of high accuracy resulting from the predominance of a single class.

$$\mathrm{F1 - Score} = \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

The F1-score is advantageous for achieving a balance between precision and recall, particularly when one metric is prioritised over the other. The F1-score is calculated via the f1_score function from scikit-learn.

3.10.2.5 Confusion Matrix

A confusion matrix is a table representation utilised to clarify the performance of a classification model, defining the quantity of accurate and erroneous predictions categorised by class. It encompasses the subsequent terms:

The age predicted involves several categories: child, teen, adult, and senior. The confusion matrix will be a square matrix with dimensions reflecting the number of age categories. Table 3.4 illustrates the age confusion matrix.

Table 3.4: Age Confusion Matrix

True \ Predicted	Child	Teen	Adult	Senior
Child	TP_{child}	$FP_{child,teen}$	$FP_{child,adult}$	$FP_{child,senior}$
Teen	$FP_{teen,child}$	TP_{teen}	$FP_{teen,adult}$	$FP_{teen,senior}$
Adult	$FP_{adult,child}$	$FP_{adult,teen}$	TP_{adult}	$FP_{adult,senior}$
Senior	$FP_{senior,child}$	$FP_{senior,teen}$	$FP_{senior,adult}$	TP_{senior}

The diagonal numbers (TP) denote the accurately categorised occurrences for each class (age group), whereas the off-diagonal values (FP) indicate misclassifications.

Table 3.5 shows the confusion matrix for gender with only two classes (male and female).

Table 3.5: Gender Confusion Matrix

True \ Predicted	Male	Female
Male	TP_{male}	$FP_{male,female}$
Female	$FP_{female,male}$	TP_{female}

The diagonal signifies accurate predictions (True Positives), while the off-diagonal components denote misclassifications.

Conclusively, utilising these evaluation measures provides a comprehensive insight into the model's performance. Accuracy provides a general assessment, whereas precision, recall, and F1-score offer more nuanced insights into the model's performance, especially on its management of imbalanced classes. The confusion matrix visibly delineates regions where the model errs, such as misclassifying specific age groups or genders, which might inform subsequent enhancements.

3.11 Summary

This chapter delineates the research technique by employing a mixed methods approach to examine facial identification systems for advertising purposes. The document outlines the system development process, commencing with environment configuration, gathering images, and pre-processing, succeeded by demographic projections via DeepFace. The system incorporates tailored advertisement mapping, guaranteeing real-time responsiveness and user-specific relevance. Extensive evaluation metrics from scikit-learn library are utilised to assess the system's accuracy in age and gender prediction. Utilising the Wikipedia dataset, the methodology guarantees comprehensive insights into the possibility of targeted advertising. The chapter finishes with a comprehensive summary of pipeline phases, demonstrating an integrated strategy for enhancing facial identification in advertising.

CHAPTER 4: RESULT AND DISCUSSION

This chapter outlines the evaluation outcomes of the age and gender prediction model assessed on a dataset of 31,146 images. Key performance metrics, including accuracy, precision, recall, F1-score and confusion matrix are analysed. The findings are analysed comprehensively, emphasising the model's advantages and limitations.

4.1 Modules Results

There are two modules: the real-time advertisement display module and the assessment with dataset module. Both modules are assessed using evaluation metrics that involve accuracy, precision, recall, F1-score, and confusion matrix, and the results are compared between the two modules.

4.1.1 Real-Time Advertisements Display Module Results

The model undergoes a 20-person real-time ad display module between the ages of 1 to 100 years old. The process real-time advertisements display module can be seen in Appendix A. Figure 4.1 depicts the photo of the person from Person 1 to Person 20. Table 4.1 shows the result of the person's actual age and gender and also predicted age and gender and the displayed advertisement.

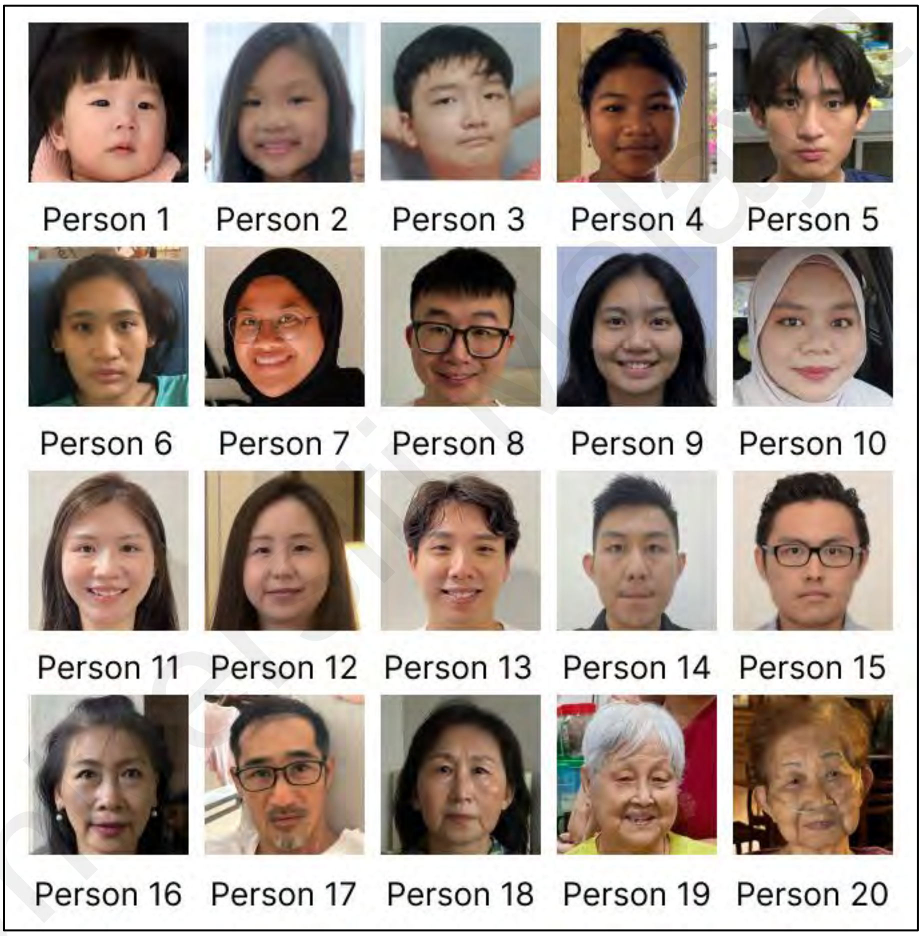

Figure 4.1: Photos of All 20 Individuals

Table 4.1: Actual and Predicted Values for Age and Gender

Person	Actual		Predicted		Results		Ads Display	Ads
	Age	Gender	Age	Gender	Age	Gender		
Person 1	2	Female	28	Female	✗	✓	Cosmetics Products Ad	✗
Person 2	9	Female	26	Female	✗	✓	Cosmetics Products Ad	✗
Person 3	13	Male	27	Male	✗	✓	Gadget Sale Ad	✗
Person 4	18	Female	29	Female	✗	✓	Cosmetics Products Ad	✗
Person 5	20	Male	27	Male	✓	✓	Gadget Sale Ad	✓
Person 6	23	Female	26	Female	✓	✓	Cosmetics Products Ad	✓
Person 7	23	Female	27	Male	✓	✗	Gadget Sale Ad	✗
Person 8	25	Male	27	Male	✓	✓	Gadget Sale Ad	✓
Person 9	25	Female	28	Female	✓	✓	Cosmetics Products Ad	✓
Person 10	25	Female	27	Female	✓	✓	Cosmetics Products Ad	✓
Person 11	26	Female	27	Female	✓	✓	Cosmetics Products Ad	✓
Person 12	30	Female	30	Female	✓	✓	Cosmetics Products Ad	✓
Person 13	32	Male	33	Male	✓	✓	Gadget Sale Ad	✓
Person 14	33	Male	32	Male	✓	✓	Gadget Sale Ad	✓
Person 15	39	Male	33	Male	✓	✓	Gadget Sale Ad	✓
Person 16	52	Female	49	Female	✗	✓	Cosmetics Products Ad	✗
Person 17	56	Male	44	Male	✗	✓	Gadget Sale Ad	✗
Person 18	59	Female	55	Female	✓	✓	Medical Service for Female Senior Ad	✓

Table 4.1: Actual and Predicted Values for Age and Gender (Continue)

Person 19	78	Female	54	Female	✓	✓	Medical Service for Female Senior Ad	✓
Person 20	93	Female	51	Male	✓	✗	Health Products Ad	✗

The table summarises actual and predicted values for age and gender among 20 individuals. If the predicted age is in the age categories: Child (0–12 years), Teen (13–20 years), Adult (21–49 years), and Senior (50+ years) same as the actual age it is considered as correct. In age prediction, a significant discrepancy exists between actual and anticipated values, especially at the extremes of the age range. Younger individuals, such as Person 1 (age 2), Person 2 (age 9), and Person 3 (age 13), were significantly misclassified, with predicted ages spanning from 26 to 29 years, resulting in advertisements targeted at adults, which is incorrect. In contrast, older individuals, including Person 19 (age 78) and Person 20 (age 93), were undervalued, with predicted ages of 54 and 51, respectively. Nevertheless, they remain within the same age group of 50 years and above, displaying advertisements for the senior population. Persons 16 and 17 are near the threshold of classification, with actual ages of 52 and 56, yielding predicted ages of 49 and 44, respectively, which approximate the age of 50, so triggering display advertisements targeted at adults. For persons aged 25–39, predictions were more aligned with actual values, demonstrating greater consistency, and displaying correct advertisement for the targeted age group.

The performance of gender prediction is summarised, demonstrating predominantly accurate outcomes. The model accurately predicts the gender of the individual wearing a shawl, as demonstrated by the results for Person 10; however, it incorrectly identifies

Person 7 as male, which should be female. This happens because of less pre-trained dataset with people in a shawl in the model. Nonetheless, Person 20, whose gender was also incorrectly predicted.

Table 4.2 and Table 4.3 show the real-time age group evaluation metrics and real-time gender evaluation metrics respectively. On the contrary, Figure 4.2 depicts the graph of evaluation metrics for real-time age and gender prediction.

Table 4.2: Real-time Age Group Evaluation Metrics

Evaluation Metrics	Scores
Age Accuracy	70.00%
Age Precision	60.59%
Age Recall	70.00%
Age F1-Score	61.96%

Table 4.3: Real-time Gender Evaluation Metrics

Evaluation Metrics	Scores
Gender Accuracy	90.00%
Gender Precision	77.78%
Gender Recall	100.00%
Gender F1-Score	87.50%

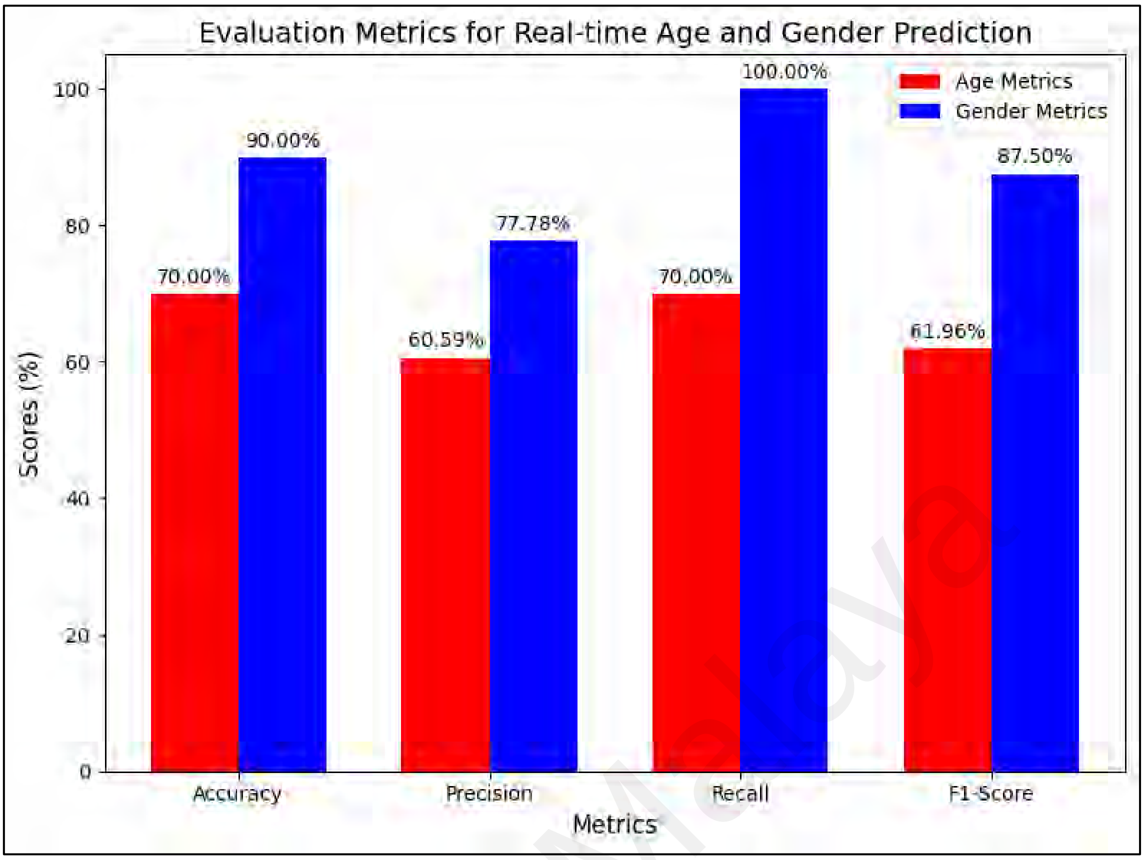

Figure 4.2: Graph of Evaluation Metrics for Real-Time Age and Gender Prediction

The evaluation of the model for real-time age and gender prediction highlights its strengths and weaknesses. The model attained an accuracy of 70.00% in age prediction, indicating it accurately classified the age group for 70.00% of the samples. This demonstrates a competent capacity to categorise persons into their appropriate age categories, however there is potential for additional improvement. The accuracy of age prediction was 60.59%, indicating that merely 60.59% of predictions for a certain age group were accurate. This comparatively diminished precision suggests potential misclassifications, maybe arising from overlapping face characteristics across age groups or inadequate training data for certain demographics. The recall for age prediction was 70.00%, indicating that 70.00% of real age group cases were successfully identified, whereas 30.00% were overlooked. The F1-score, an average of precision and recall, was 61.96%, indicating the model's modest efficacy in balancing the trade-offs between accurately identifying age groups and minimising false positives.

The model had significantly better results in gender prediction. It attained an accuracy of 90.00%, signifying a substantial degree of reliability in accurately predicting gender for 90.00% of the samples. This illustrates the model's robustness in gender classification tasks. The precision for gender classification was 77.78%, indicating that around 78.00% of predictions for a certain gender were correct, with potential misclassifications arising from ambiguous face traits or imbalanced training data. The recall for gender prediction was an impressive 100.00%, indicating that the model accurately identified all true instances of gender in the dataset without any omissions. This remarkable recall performance underscores the model's ability to identify all pertinent gender situations. The F1-score for gender was 87.50%, highlighting the robust equilibrium between precision and recall, hence confirming the dependability of gender predictions.

The bar chart associated with these data visually illustrates the model's performance metrics for predicting age and gender. It distinctly underscores the gap between the two tasks, indicating that the model excels in gender categorisation while significantly faltering in age group predictions. The markedly elevated results for gender prediction measures indicate the model's robustness in this area, either attributable to more pronounced visual signals or superior dataset representation for gender relative to age. The modest scores for age prediction indicate potential improvements, such as augmenting the training dataset to more accurately reflect all age demographics or utilising more sophisticated feature extraction methods to discern nuanced face ageing characteristics.

Although the model exhibits robust performance in gender categorisation, its moderate accuracy and F1-score in age prediction underscore the necessity for optimisation.

Mitigating issues such as feature overlap among age groups, dataset bias, and differences in image quality may enhance age group classification in subsequent iterations. The bar graph visually underscores these findings, acting as a crucial instrument for informing further model development and training methodologies.

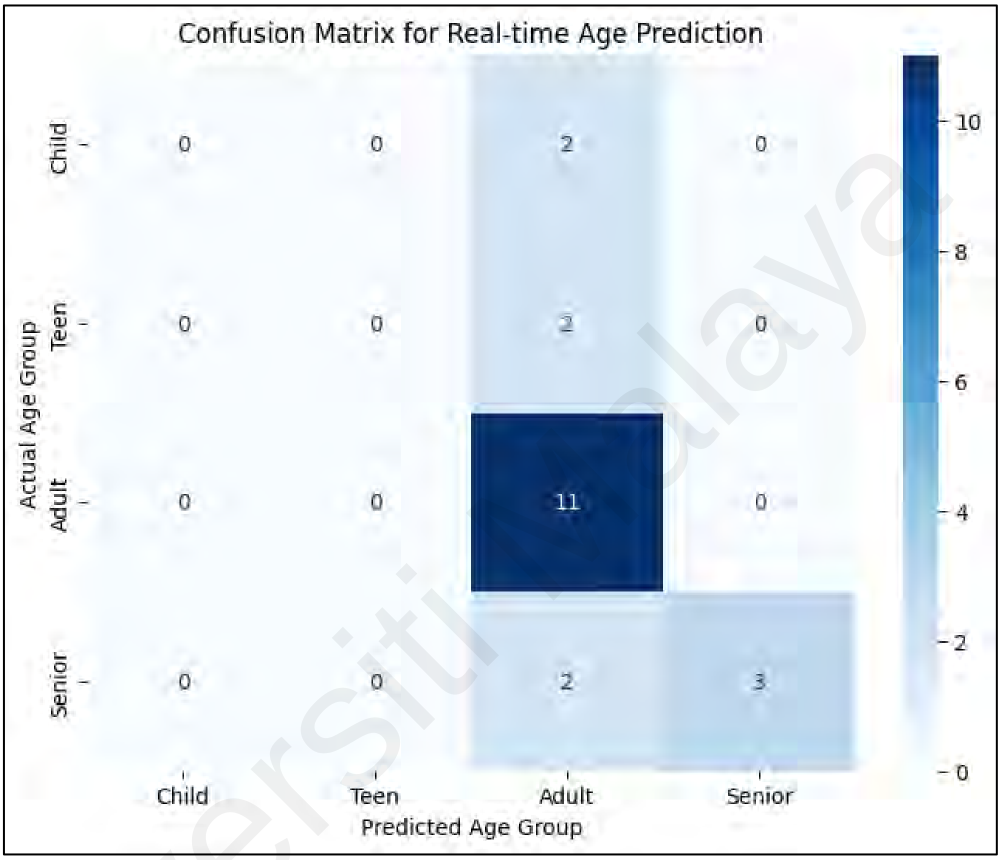

Figure 4.3: Confusion Matrix for Real-time Age Prediction

Figure 4.3 depicts the confusion matrix, demonstrating the performance of the real-time age prediction across four specified age categories: Child (0–12 years), Teen (13–20 years), Adult (21–49 years), and Senior (50+ years). The model has robust performance in the Adult category, accurately predicting 11 out of 15 participants. Nonetheless, it has difficulties with other age demographics, especially Children and Teens, where all predictions were inaccurate. Misclassifications predominantly arose when younger individuals (child and teen) were categorised as adults. In the Senior category, 3 out of 5 predictions were accurate, while 2 were incorrectly classed as Adult.

This suggests that the system excels in mid-range age demographics but has difficulties at the extremes, maybe due to insufficient balanced training data or the complexities of recognising facial ageing characteristics (Bao et al., 2023).

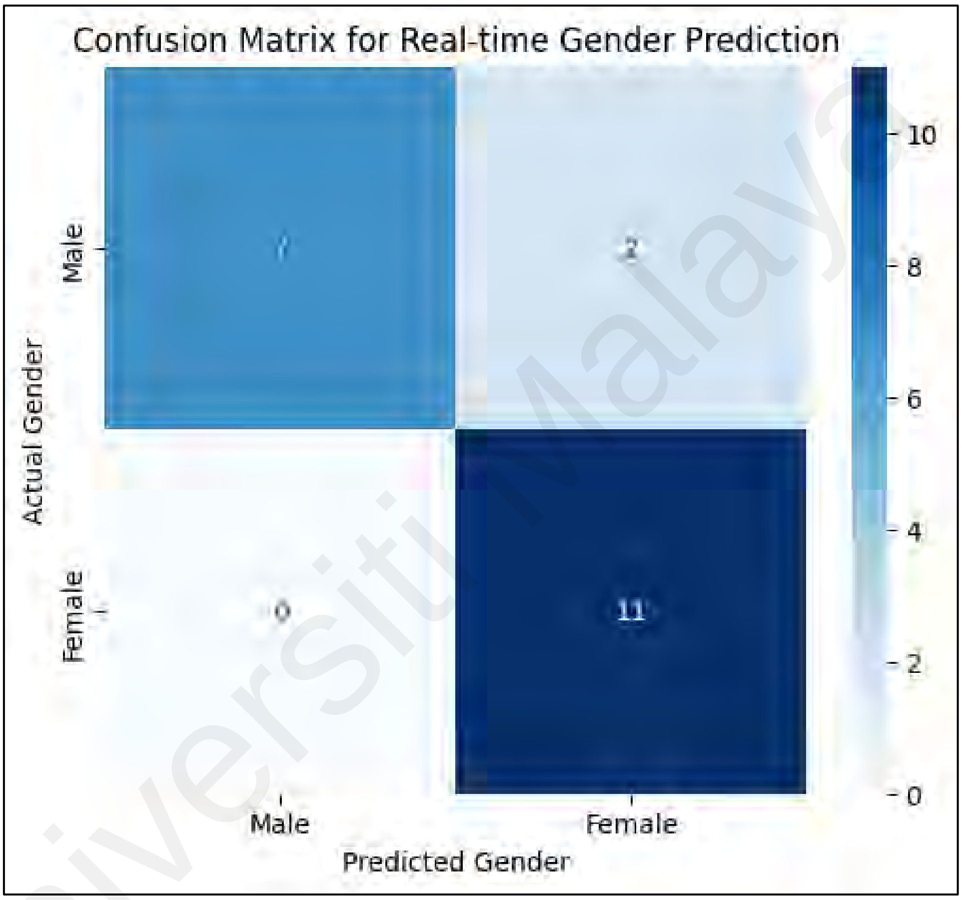

Figure 4.4: Confusion Matrix for Real-time Gender Prediction

Figure 4.4 shows the accuracy of real-time gender prediction demonstrated by a confusion matrix. The matrix compares the model's predictions with the actual gender of the test data. Out of 20 cases, the model accurately recognised all 7 males and 11 of 13 females. This reflects an accuracy of 100% for males and 84.6% for females. The model committed a total of two errors which are two females were incorrectly classified as males.

The gender prediction results exhibit considerable accuracy, however they also suggest a potential for enhancement. The inaccuracies may stem from factors such as indistinct facial features, diverse haircuts, or overlapping traits between genders that impede the model's capacity for precise differentiation (Jebaseeli, 2020).

The analysis underscores the advantages and limitations of the real-time facial detection method. Although the gender classification produces favourable outcomes, with a majority of predictions accurate, the age prediction necessitates enhancement, especially for extreme age brackets. These findings underscore the necessity for a balanced dataset that sufficiently reflects various age demographics and genders. Additional improvements, including model fine-tuning and the incorporation of a broader spectrum of training data, can enhance the system's overall performance, particularly in practical applications such as targeted advertising.

4.1.2 Evaluation with Wikipedia Dataset Module Results

The model was validated using a Wikipedia dataset from folder 00 to 49 of 31146 images, of which 28135 were identified as valid facial images according to the metadata (.mat file). Ultimately, only 22229 images were successfully detected and analysed for classification, with performance assessed on two main tasks: age classification and gender classification. Despite a loss of 5906 images (21.00%) with no faces detected, 22229 images (79.00%) have been successfully processed from the total of 28135 valid face images. This loss is minor, as some images within the 28135 are unclear and 79.00% is still the majority of the images. Table 4.4 shows the Wikipedia dataset age group evaluation metrics and Table 4.5 depicts the Wikipedia dataset gender evaluation metrics which both included accuracy, precision, recall and F1-score of each classification.

Moreover, Figure 4.5 illustrates Wikipedia dataset evaluation metrics for age and gender prediction in a bar graph.

Table 4.4: Wikipedia Dataset Age Group Evaluation Metrics

Evaluation Metrics	Scores
Age Accuracy	74.00%
Age Precision	78.00%
Age Recall	74.00%
Age F1-Score	66.00%

Table 4.5: Wikipedia Dataset Gender Evaluation Metrics

Evaluation Metrics	Scores
Gender Accuracy	90.00%
Gender Precision	90.00%
Gender Recall	98.00%
Gender F1-Score	94.00%

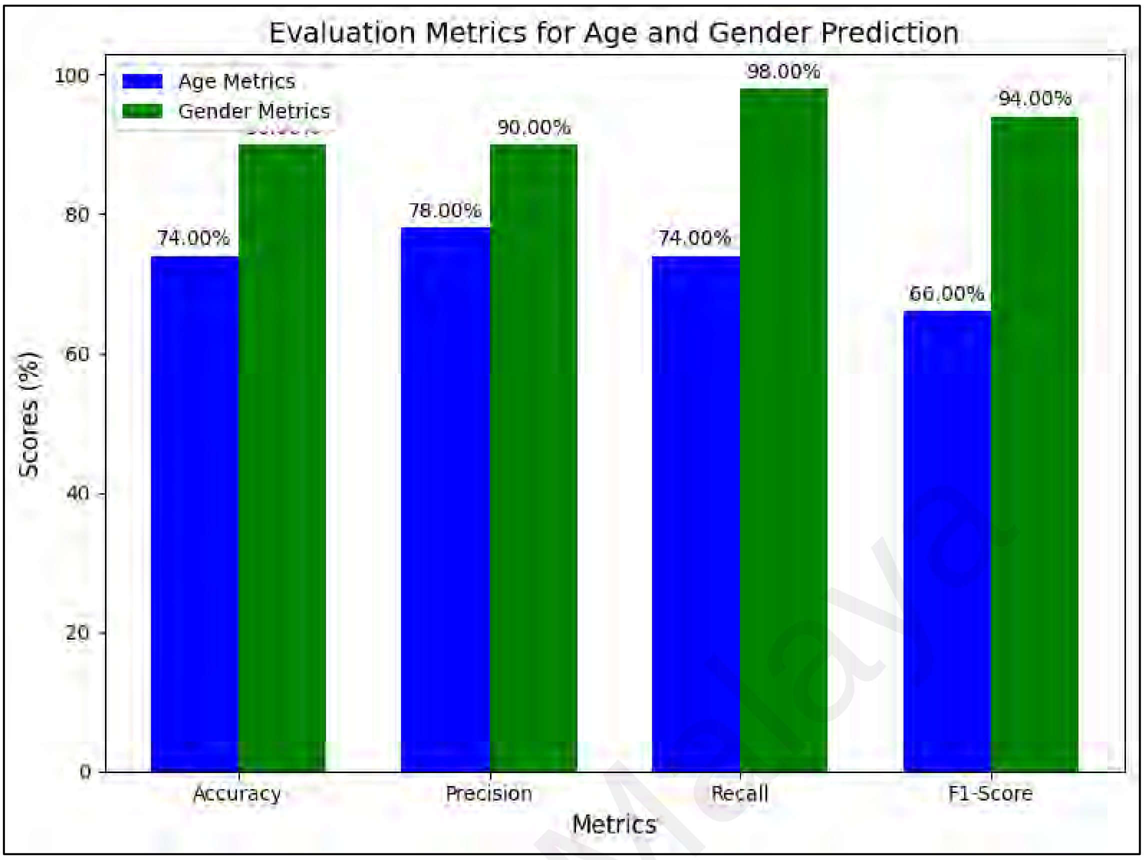

Figure 4.5: Graph of Wikipedia Dataset Evaluation Metrics for Age and Gender Prediction

The model attained an accuracy of 74.00% in age prediction, indicating it accurately classified the age group for 74.00% of the test samples. This demonstrates a good capacity to categorise persons accurately by age, however there remains potential for enhancement. The precision for age was documented at 78.00%, indicating that 78.00% of the cases classified within a specific age category were accurate. This indicates that the model's predictions for a certain age group are typically precise. The recall score of 74.00% indicates that the model accurately identified 74.00% of the actual age group instances in the dataset while failing to recognise 26.00% of them. The F1-score, which balances precision and recall, was 66.00%, signifying that although the model's age prediction is somewhat accurate, the balance between precision and recall is imperfect, involving certain compromises between accurately estimating age and missing certain instances.

Conversely, the gender prediction measures were more favourable. The model attained an accuracy of 90.00%, indicating it accurately predicted gender for 90.00% of the test samples. This result is robust, signifying substantial reliability in gender classification. The precision for gender identification was 90.00%, indicating that the model's predictions were correct 90.00% of the time. The recall score for gender was remarkably high at 98.00%, signifying that the model accurately predicted 98.00% of the actual gender instances, with only a minor fraction missed. The F1-score for gender was 94.00%, indicating robust precision and recall, which suggests the model reliably predicts gender.

On the other hand, the bar chart provides a distinct visual comparison of the model's performance in predicting age and gender, illustrating the accuracy, precision, recall, and F1-scores for each category. The bar graph indicates that the model excels in gender prediction compared to age prediction.

The model's performance measures for age prediction are rather moderate. The model accurately predicted the age group for more than two-thirds of the samples with an accuracy of 74.00%. A precision of 78.00% signifies that when the model predicted an age group, it was typically accurate, albeit with some inaccuracies. The recall score of 74.00% indicates that the model overlooked a quarter of the age occurrences, resulting in a diminished F1-score of 66.00%, signifying the potential for enhancement in age prediction, especially in reconciling the trade-off between precision and recall.

Conversely, the model attained significantly superior outcomes for gender prediction. An accuracy of 90.00% indicates that the model is exceptionally dependable in gender classification. The precision and recall for gender are also elevated, with precision at 90.00% and recall at 98.00%, indicating that the model not only generates accurate predictions but also infrequently overlooks any gender cases. The elevated F1-score of 94.00% underscores the model's efficacy in gender prediction with negligible errors.

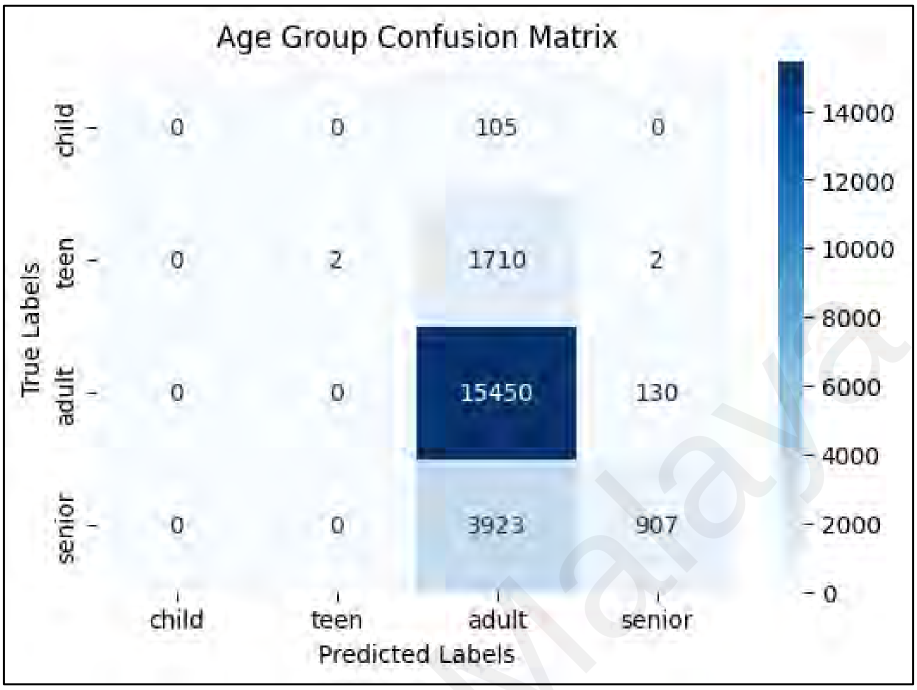

Figure 4.6: Wikipedia Dataset Age Group Confusion Matrix

Figure 4.6 illustrates the Wikipedia dataset age group confusion matrix of the classification of four age categories: child, teen, adult, and senior. The model demonstrates exceptional proficiency in predicting the adult group, with 15450 accurate predictions. The actual labels are shown on the y-axis, whereas the predicted labels are indicated on the x-axis. The matrix indicates that the predominant number of samples is categorised as adults, with 15450 predictions accurately identified. A substantial number of senior labels, 907, were likewise predicted with accuracy. Nevertheless, there are significant misclassifications, including 105 child samples erroneously categorised as adults and 130 adult samples inaccurately classed as seniors. Furthermore, a limited number of teens were incorrectly categorised into other classifications.

The confusion matrix indicates that the model excels in the adult category, presumably because of the greater dataset size for this group, which offers the model more training data and enhances generalisation. Conversely, child and teen experience under-representation, as seen by their reduced true label counts and elevated misclassification rates. The dataset's imbalance immediately affects the model's capacity to reliably differentiate minority age groups.

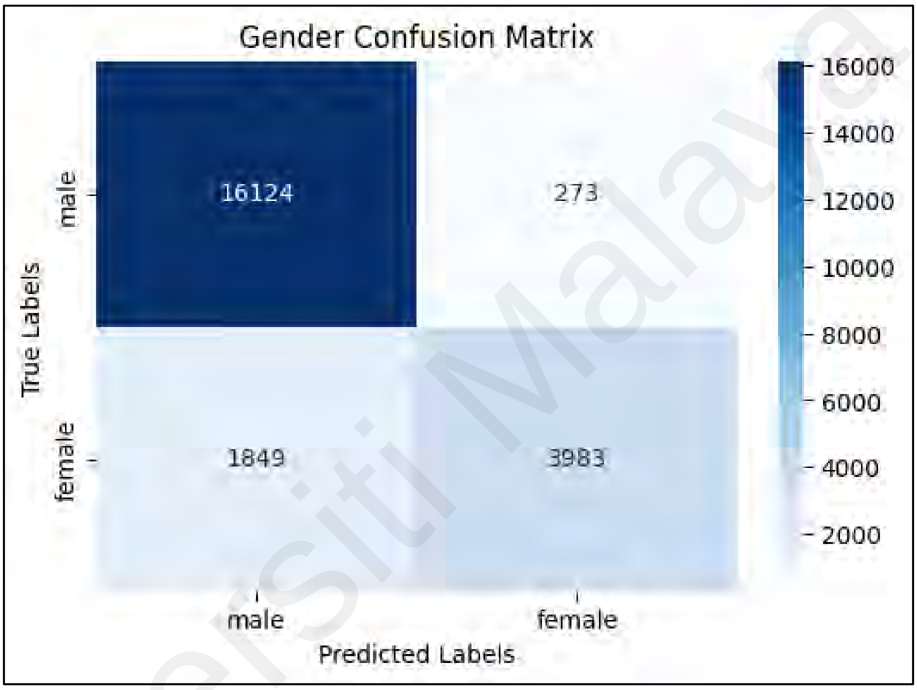

Figure 4.7: Wikipedia Dataset Gender Confusion Matrix

Figure 4.7 shows the Wikipedia dataset gender confusion matrix assesses the model's proficiency in categorising genders (male and female). The matrix indicates that 16124 male samples were correctly identified as male, whereas 3983 female samples were accurately categorised as female. The model erroneously classified 273 male samples as female and misidentified 1849 female samples as male.

The results indicate that the model exhibits greater predictive accuracy for male samples compared to female samples. This mismatch may result from dataset imbalance, wherein male images predominate, facilitating superior generalisation for this gender. Furthermore, certain female facial characteristics could match those of males in some instances, therefore elevating the likelihood of misclassification.

Both confusion matrices underscore the significance of balanced datasets for model training. The excellent accuracy in age prediction for adults underscores the significance of dataset size, but the inadequate performance for under-represented groups such as child and teen illustrate the necessity for more diverse data collecting. The gender confusion matrix suggests a possible dataset imbalance that favours males, hence distorting the model's predictive performance.

To enhance future outcomes, augmentation of the dataset with more samples from under-represented age groups and genders should address the imbalance. Furthermore, supplementing under-represented categories with synthetic data or employing sophisticated methods such as transfer learning could improve the model's overall efficacy.

4.1.3 Modules Result Comparison

The real-time model for age prediction attained an accuracy of 70.00%, slightly below the 74.00% accuracy of the evaluation using the Wikipedia dataset. This signifies a minor reduction in the model's performance to accurately categorise age groups in real-time environments, potentially due to low pre-trained datasets or image quality. The precision of the predictions for age in real-time (60.59%) is much lower than the Wikipedia dataset's 78.00%, indicating diminished confidence in accurate predictions for a particular age group. Correspondingly, the recall decreased to 70.00% from 74.00%, indicating a diminished ability to recognise true age group occurrences. The F1-score, which reconciles precision and recall, decreased to 61.96% in real-time from 66.00% using the Wikipedia dataset, signifying that trade-offs in predictive accuracy are increasingly evident in real-world contexts.

The model exhibits better accuracy and consistency in gender prediction between real-time data and the Wikipedia dataset findings. The model attained a commendable accuracy of 90.00% in real-time, corresponding with the Wikipedia dataset. The precision for gender prediction is 77.78% in real-time, contrasted with 90.00% in the Wikipedia dataset, indicating a marginal reduction in accuracy for real-time gender identification. The recall for gender prediction is remarkably high at 100.00% in real-time, surpassing the 98.00% recall observed in the Wikipedia dataset. This indicates that the model is proficient in identifying all gender instances in real-time data. The real-time F1-score is 87.50%, marginally behind the Wikipedia dataset's 94.00%, confirming the model's overall reliability in gender classification, despite small trade-offs.

The confusion matrices offer enhanced insights. The evaluation confusion matrix of the Wikipedia dataset underscores the model's proficiency in accurately detecting "Adult" age groups within a substantial dataset while revealing considerable misclassifications in the "Senior" and "Child" categories. Significantly, no occurrences of "Child" were accurately categorised, indicating a possible problem with the training data or feature representation for this category. Conversely, the real-time confusion matrix, derived from a reduced sample size, indicates a more erratic performance. Although it illustrates the model's capacity to accurately categorise certain "Senior" occurrences, the limited sample size and lack of proper "Child" predictions highlight difficulties in generalising the model to practical applications. Furthermore, the model exhibits a bias towards predicting the "Adult" class in both matrices, indicating a possible dataset imbalance or feature overlap among age groups.

The real-time matrix for gender prediction indicates a pronounced bias in accurately identifying males, whilst the misclassification rates for females are marginally elevated. This may indicate an imbalance in the training data or feature representation for female occurrences. On the other hand, the Wikipedia dataset exhibits more balanced metrics among genders.

In conclusion, although the model's performance regarding gender is consistently strong in real-time, its age prediction abilities demonstrate a significant decline, highlighting the difficulties at the low pre-trained dataset in younger and older demographics and the necessity for more refinement for practical use.

4.2 Existing Models Comparison

Table 4.4 depicts the comparison of existing models with the proposed method.

Table 4.6: Comparison with Existing Models

Models	Age Accuracy	Gender Accuracy
VGG + Modified Cross-Entropy Loss (MCE) (Lin & Lin, 2021)	51.81%	84.95%
VGG16 (Tsai & Lin, 2023)	55.63%	87.37%
Caffe Framework (Nada et al., 2020)	57.00%	82.24%
CNN Model (Thaneeshan et al., 2022)	57.60%	84.20%
ConvNeXt (Tsai & Lin, 2023)	57.66%	90.28%
Multi-task CNN Model (Vu et al., 2019)	66.80% ± 1.00%	87.10% ± 0.70%
Proposed Method (Real-time Module)	70.00%	90.00%
Proposed Method (Wikipedia Dataset)	74.00%	90.00%

The comparison of the proposed method with other existing models demonstrates substantial enhancements in both age and gender accuracy. The proposed method using the real-time module attained 70.00% age accuracy and 90.00% gender accuracy while for Wikipedia dataset obtained 74.00% age accuracy and also 90.00% gender accuracy, surpassing models like ConvNeXt (57.66% age accuracy, 90.28% gender accuracy) and the Multi-task CNN Model (66.8% ± 1.0 age accuracy, 87.1% ± 0.7 gender accuracy). The VGG + Modified Cross-Entropy Loss model and CNN Model underperformed, with age accuracies of 51.81% and 57.60%, respectively. The real-time module has a smaller and less diverse test set, leading to a less robust evaluation. The consistent data in the Wikipedia dataset ensures that the model's performance is evaluated under optimal conditions, naturally resulting in higher accuracy (Altabeiri et al., 2023).

The proposed method showed significant robustness in age estimate tasks, showing a considerable enhancement compared to other models. In gender detection, although the accuracy of 90.00% for both real-time module and using the Wikipedia dataset are comparable to ConvNeXt's 90.28%, the simplicity of the DeepFace implementation and its applicability across tasks enhance its overall attractiveness. The findings underscore the effectiveness of employing MTCNN for facial identification and the DeepFace analysis module for feature extraction and prediction.

4.3 Consumer Engagement

Incorporating sophisticated facial detection and analysis models into advertising systems significantly improves customer engagement by facilitating the distribution of personalised and relevant content. Facial detection and analysis are crucial for comprehending consumer preferences and behaviours. By anticipating user preferences and interests, organisations can develop precisely focused advertisements that resonate more profoundly with their audience, enhancing engagement and increasing conversion rates. Recognising customer preferences enables advertisements to correspond with user expectations, hence enhancing their relevance and personalisation (Liu et al., 2022).

Deep learning techniques, exemplified by contemporary face identification algorithms, markedly enhance the capacity to identify a user's age and gender. By customising advertisements to align with these demographics, businesses may increase relevance and acceptance among users, hence improving engagement. Precise systems that recognise appearance facilitate a deeper connection between the consumer and the promotional material (Moreno-Armendáriz et al., 2023).

Advanced deep learning models from DeepFace, provide the accurate identification of user characteristics including gender and age. This increased accuracy enables businesses to provide tailored advertisements to the most suitable audience segments. By targeting certain demographic or psychographic segments, advertisers can enhance the efficacy of their efforts, resulting in elevated engagement and improved click-through rates (Zhang, 2024).

Real-time observation of user responses by facial recognition enhances engagement. Systems that assess facial expressions and attention levels facilitate dynamic and adaptable advertising. An advertisement can modify its tone, style, or substance in real time according to consumer responses, leading to a more interactive and personalised experience. This adaptability enhances the significance and efficacy of advertisements (Yolcu et al., 2020).

Accurate gender classification and demographic identification are essential elements of personalised advertising tactics. By customising content for distinct consumer segments, firms can improve the user experience. Targeting advertisements to correspond with the preferences of various age groups or genders enhances engagement and cultivates a sense of relevancy. This method has demonstrated an increase in engagement rates and consumer satisfaction (Jayantibhai & Nachappa, 2024).

Ultimately, accurate facial and behavioural analysis enhances advertising return on investment considerably. By minimising resource wastage and guaranteeing that campaigns target the appropriate demographic, firms can enhance their marketing strategy. Conveying the appropriate message to the correct audience at the optimal moment reduces inefficiencies and amplifies the overall effectiveness of advertising campaigns. This accuracy enhances instant engagement metrics and fortifies long-term consumer loyalty (El-Hajj & Pavlova, 2024).

Collectively, enhancing model accuracy and utilising real-time data analysis enables businesses to cultivate a more engaging and personalised consumer experience. This enhances immediate engagement metrics while also cultivating long-term loyalty and brand engagement.

4.4 Summary

This chapter thoroughly examined the performance of the DeepFace modified method, including real-time advertisement testing, evaluation outcomes, comparisons with other leading models and also consumer engagement improvement. The suggested method demonstrated exceptional performance, attaining superior accuracy rates in age and gender prediction relative to current models.

The real-time ad display module results exhibited practical applicability, with gender prediction displaying significant consistency and dependability. Despite slight issues in age group categorisation, especially in anticipating boundary situations, the overall performance demonstrates the method's viability for practical applications.

The evaluation metrics validated the model's resilience, demonstrating high precision and recall scores for gender prediction. In comparison to other existing models, the DeepFace modified method excelled in age accuracy and maintained strong competitiveness in gender detection accuracy.

In conclusion, the suggested methodology represents a substantial advancement in the field of facial recognition for age and gender estimates. The results demonstrate its appropriateness for use in real-world situations, and the enhancements in accuracy underscore the efficacy of the selected methodology. Higher accuracy of the model can improve consumer engagement further highlighting its practical value in targeted advertising. Future endeavours may concentrate on refining the model for atypical scenarios in age prediction and enhancing computing efficiency for real-time applications.

CHAPTER 5: CONCLUSION

This chapter summarises the findings and contributions of this research. It offers a thorough overview of the primary results and their implication, emphasising the system's benefits and possibilities. This chapter addresses the limitations faced throughout the study and suggests future enhancements to improve the system's performance and applicability. Furthermore, it examines the wider implications of the research, including recommendations for practical application and ethical considerations. The chapter finishes the study by focussing on its overall significance and proposing a framework for the advancement of AI-driven targeted advertising.

5.1 Conclusion

This study introduces a deep learning approach for facial detection in targeted billboard advertising, providing notable improvements in the personalisation and optimisation of digital marketing. Table 5.1 depicts the research objectives and its methodology.

Table 5.1: Research Objectives and Methodology

No.	Research Objectives	Methodology
1.	To investigate the facial detection techniques for age and gender recognition used in advertisement.	The research conducted a comprehensive analysis of existing literature to identify and understand facial detection techniques used in recent research.
2.	To develop a facial detection system that can distinguish between different age groups and genders.	The system employs advanced deep learning algorithms, DeepFace to accurately recognise and classify facial attributes, including age and gender, facilitating targeted advertisement delivery.
3.	To analyse the effectiveness of the developed system for targeted advertising.	The research analyses performance metrics such as accuracy, precision, recall, F1-score, and confusion matrices for both the real-time advertisements display module and evaluation with the Wikipedia dataset module.

In order to investigate the facial detection techniques for age and gender recognition used in advertisement, the research conducted a comprehensive analysis of existing literature to identify and understand facial detection techniques used in recent research. To develop a facial detection system that can distinguish between different age groups and genders, the system employs an advanced deep learning algorithm, DeepFace to accurately recognise and classify facial attributes, including age and gender, facilitating targeted advertisement delivery. To analyse the effectiveness of the developed system for targeted advertising, the research analyses performance metrics such as accuracy, precision, recall, F1-score, and confusion metrics for both the real-time advertisements display module and evaluation with the Wikipedia dataset module. Hence, all the objectives of this research are fulfilled.

AI-driven personalisation in advertising results in heightened customer engagement, higher return on investment (ROI), and augmented sales and brand perception (Agarwal et al., 2023). The main advantage of the suggested system is its capacity to integrate advanced artificial intelligence with practical advertising applications. This connection guarantees that advertisements target their targeted audience, providing a more engaging and relevant experience. Furthermore, the system exhibits adaptability to diverse contexts, showcasing scalability and robustness for advertising distribution platforms.

The study provides multiple contributions to the field. In addition to technological breakthroughs, it facilitates greater investigation into ethical AI applications in targeted advertising. This study presents a framework that utilises enhanced facial detection to optimise targeted advertising by ensuring advertisement relevance based on demographic attributes. Moreover, the technology demonstrates the capacity of deep learning to revolutionise conventional advertising techniques, facilitating advancements in other AI-driven sectors.

Despite its merits, the study faced limitations. A significant problem was the dependence on limited trained datasets, which affected the model's capacity to generalise across varied populations and extreme age ranges. Furthermore, the system's processing requirements pose challenges for the evaluation of huge datasets on low-resource devices. Ethical considerations, such as privacy issues and the possible abuse of facial recognition technologies, were significant hurdles, highlighting the necessity for responsible application.

To rectify the identified problems, multiple improvements are proposed. Initially, integrating a broader and more varied dataset to be trained and fine-tuned in the model will enhance the system's capacity to generalise among distinct user groups (Zhang & Bao, 2022). Secondly, the use of edge computing can enable the evaluation of huge datasets in this case able to run all the folders from the Wikipedia dataset (folder 00 to 99) on resource-constrained devices, enhancing system accessibility, efficiency and memory performance (Cecilia et al., 2020). Third, the incorporation of privacy-preserving methodologies, such as federated learning and secure data encryption, would safeguard user data, thereby enhancing trust and ensuring adherence to data protection standards (Wang et al., 2024).

The research ultimately defines prospects for future advancement. Engaging with industry stakeholders facilitates the practical testing and enhancement of the system, assuring its applicability to real-world scenarios. Developing a thorough ethical framework can mitigate privacy and fairness issues, fostering appropriate AI use in advertising. Regular model upgrades utilising current data and ongoing learning processes will ensure the system's efficacy under dynamic market situations.

This study underscores the benefits and possibilities of employing deep learning for targeted advertising, providing a scalable, accurate, and personalised approach to address contemporary marketing needs. Despite existing limitations, the suggested future enhancements and ethical concerns will facilitate the system's enhanced applicability and influence. This research acts as a foundation for developing intelligent, accountable, and efficient advertising systems that advantage both consumers and advertisers.

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