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Theme

Deep Learning-Based Facial Age Estimation as a Foundation for Parental Control Systems

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Acknowledgment

All praise is due to Allah, for no effort is ever completed nor any journey fulfilled except by His grace. O Allah, to You belongs all praise—from the depths of my heart to Your glorious Throne— praise that matches Your countless blessings and reflects Your infinite generosity.

I dedicate this work to those for whom gifts and words will never be enough, to those whose prayers lit my life and brightened paths I once thought dark, to those whose support brought me to where I am today: my beloved parents.
To my brothers and sisters, who supported me through every step, never withholding their encouragement, and in whose eyes I always saw pride and belief.
To my dear friends and companions, with whom I shared every moment of joy and challenge, and who left beautiful marks on my journey.
To all my esteemed professors and everyone who contributed to this work, to those who nurtured me academically, opened the doors of knowledge, and generously offered their guidance and wisdom.
To all of you... I dedicate this humble work with gratitude, appreciation, and deep respect.

Summary

This thesis explores the development of an AI-based system to estimate a child's age from facial images, as a foundation for adaptive parental control solutions on smart devices. Motivated by the growing use of digital platforms among children and the associated risks of inappropriate content, the study aims to implement the first essential step: facial age estimation using deep learning. A convolutional neural network is trained and evaluated using a labeled dataset, and its performance is analyzed based on accuracy and mean absolute error. The findings demonstrate that deep learning can provide reliable age estimation, which may support future systems in classifying and regulating content based on user age. The results serve as a stepping stone toward intelligent, age-aware safety tools for children in digital environments.
Keywords: Artificial Intelligence, Deep Learning, Age Estimation, Face Analysis, Smart Devices, Parental Control, Child Safety.

Résumé

Ce mémoire explore le développement d'un système basé sur l'intelligence artificielle pour estimer l'âge d'un enfant à partir d'images faciales, en tant que base pour des solutions adaptatives de contrôle parental sur les appareils intelligents. Face à l'utilisation croissante des plateformes numériques par les enfants et aux risques associés à l'exposition à des contenus inappropriés, cette étude vise à mettre en œuvre la première étape essentielle : l'estimation de l'âge à l'aide de techniques d'apprentissage profond. Un réseau de neurones convolutifs est entraîné et évalué à l'aide d'un ensemble de données annotées, et ses performances sont analysées en termes de précision et d'erreur absolue moyenne. Les résultats démontrent que l'apprentissage profond peut fournir une estimation fiable de l'âge, ce qui pourrait soutenir les futurs systèmes capables de classer et de réguler les contenus numériques selon l'âge de l'utilisateur. Cette recherche constitue une étape initiale vers des outils intelligents de protection adaptés aux enfants dans les environnements numériques.
Mots-clés : Intelligence Artificielle, Apprentissage Profond, Estimation de l'âge, Analyse Faciale, Appareils Intelligents, Contrôle Parental, Protection de l'Enfant.

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General Introduction

Introduction

As technology continues to evolve rapidly, smart devices such as smartphones and tablets have become essential tools in everyday life. Children are among the most active users, engaging with these technologies for learning, entertainment, and communication. This trend intensified during the COVID-19 pandemic, as digital platforms became primary channels for education and interaction. As a result, children's daily exposure to screens has significantly increased, often extending into various domains beyond learning, such as social media and online entertainment. However, this growing reliance on electronic devices is not without consequences. Research has highlighted negative effects on children's sleep quality, concentration, and academic performance, as well as a decline in direct social interactions. Additionally, many children are exposed to harmful or inappropriate online content, raising serious concerns about their mental and emotional well-being. These challenges underscore the importance of developing smart systems that can support parents in managing their children's digital engagement effectively and safely. To respond to these concerns, this study focuses on the initial step of developing an intelligent system that analyzes facial images to estimate a child's age using deep learning techniques. Since many digital platforms categorize and restrict content based on age, accurate age estimation plays a vital role in automatically adapting content access to be age-appropriate. The proposed approach lays the foundation for future intelligent parental control solutions that can dynamically adjust digital experiences based on the user's estimated age. This thesis is organized into three main chapters. Chapter One explores the impact of smart devices on children and the importance of monitoring. Chapter Two presents the technical background of artificial intelligence and deep learning in the context of age estimation. Chapter Three discusses the experimental phase, focusing on the implementation and evaluation of the face-based age estimation model.

Chapter1:The Impact of Smart Devices on Children

Chapter 1

The Impact of Smart Devices on Children

Introduction

In the midst of rapid technological advancement, smart devices have become widely prevalent in society, integrating seamlessly into our daily lives. With this widespread adoption, children have become one of the most active age groups interacting with these devices, whether through smartphones, tablets, or wearable gadgets. In this chapter, we will explore a comprehensive definition of smart devices and their historical evolution, their types and uses by children, the pros and cons of this usage, and the importance of monitoring children's use of these devices through applications and artificial intelligence.

1.1 Introduction to Smart Devices

Smart devices are autonomous computing devices capable of connecting with other devices wirelessly or through wired connections to exchange collected and processed data. These devices are characterized by interactive interfaces that facilitate human use and automation, enabling them to perform specific tasks automatically without human intervention [1].

When discussing smart devices, it is essential to address the intelligent systems that distinguish them, which include:

- **Integration**: How smart devices integrate into a single system to function cohesively.
- **Data Management**: Collecting data from various sources and analyzing it to improve system performance.
- **Environmental Interaction**: How intelligent systems interact with the surrounding environment to achieve specific goals [2].

1.2 Types of Smart Devices

Smart devices are classified into several types, including:

- **Smart Home Devices**: Such as smart refrigerators.
- **Wearable Devices**: Such as smartwatches and smart glasses.
- **Industrial Devices**: Such as sensors.
- **Medical Devices**: Such as implantable devices [1].

- **Smartphones**: the IBM Simon, was launched in 1994, combining phone functions with a personal digital assistant. Later, phones like the Palm Treo and BlackBerry emerged. In 2007, the iPhone introduced a touchscreen interface and third-party applications, marking a significant turning point. This was followed in 2008 by the introduction of the Android operating system, which expanded the reach of smartphones and made them accessible to everyone [3].
- **Smart Computers and Tablets**: Tablets were initially a technological revolution, combining the features of smartphones and computers [4]. This technology began in the 1960s with devices like the RAND Tablet, and in the 1990s, devices such as the Apple Newton emerged, which relied on touchscreens [5]. In 2010, the launch of the Apple iPad was considered a major turning point in the history of tablets, thanks to its large screen, advanced operating system, and seamless user experience. Following this, many companies, such as Samsung and Microsoft, entered the market with tablets running different operating systems like Android [4].

Figure 1.1: Types of Smart Devices

1.3 Pros and Cons of Smart Device Usage by Children

The use of smart devices by children has become increasingly common in modern society. While these devices offer numerous benefits, they also come with potential drawbacks. Below is an overview of the advantages and disadvantages of children's use of smart devices, based on the sources provided.

1.3.1 Pros (Advantages)

1. **Enhanced Learning Opportunities**:
   - Smart devices provide interactive and engaging platforms for learning. For example, educational apps and games can help children improve their language skills, problem-solving abilities, and creativity [6].
   - Contextual gaming approaches, as discussed in the study by [6], have been shown to improve grammar learning performance among students, making learning more enjoyable and effective.
2. **Convenience and Accessibility**:
   - Smart devices offer quick access to information and educational resources, allowing children to learn at their own pace and explore topics of interest [7].
   - They also provide a platform for children to connect with educational content outside the classroom, enhancing their overall learning experience.
3. **Social Connectivity**:

- Smart devices enable children to stay connected with friends and family through social media platforms and messaging apps. This can help them build and maintain relationships, even when physically apart [8].
- For children who struggle with face-to-face interactions, smart devices can offer a less intimidating way to communicate and express themselves.

4. **Entertainment and Creativity**:
   - Smart devices provide a wide range of entertainment options, such as games, videos, and music, which can be both fun and educational [9].
   - They also allow children to explore their creativity through apps that support drawing, music composition, and storytelling.

1.3.2 Cons (Disadvantages)

1. **Health Concerns**:
   - Excessive use of smart devices can lead to physical health issues, such as eye strain, obesity due to sedentary behavior, and sleep disturbances caused by blue light exposure [8].
   - The constant connectivity and notifications can also contribute to stress and anxiety, particularly in younger children [9].
2. **Psychological and Social Risks**:
   - Overuse of smart devices can lead to addiction, where children become overly reliant on these devices for entertainment and social interaction [7].
   - Social media platforms can expose children to cyberbullying and inappropriate content, which can negatively impact their mental health and self-esteem [8].
3. **Impact on Academic Performance**:
   - While smart devices can enhance learning, excessive use for non-educational purposes (e.g., gaming or social media) can distract children from their studies and negatively affect their academic performance [8].
   - Parents often worry that smart devices may become a source of distraction rather than a tool for learning.
4. **Reduced Face-to-Face Interaction**:
   - Over-reliance on smart devices can reduce children's opportunities for face-to-face social interactions, which are crucial for developing social skills and emotional intelligence [7].
   - This can lead to feelings of isolation and hinder the development of meaningful relationships.

1.4 The Importance of Monitoring Children's Use of Smart Devices

With the increasing use of smart devices among children, monitoring their usage has become essential to ensure their healthy and balanced development. Statistics show a significant rise in the use of mobile devices among children; for example, in the United States, the percentage of children under 8 years old using mobile devices increased from 38% in 2011 to 84% in 2017 [10]. Additionally, 98% of households in Slovenia have access to the internet [10]. This surge in usage highlights the importance of adult supervision in guiding children's interactions with technology. Recent studies have further emphasized the risks associated with excessive screen time. For instance, research indicates that 60% of working children in industrial settings suffer from smartphone addiction, which is closely linked to excessive internet usage

[11]. This addiction not only affects their mental health but also has physical consequences. A study on the effects of smartphone addiction on children's lung function found that 30% of children with smartphone addiction experience respiratory issues, likely due to prolonged sedentary behavior and poor posture while using devices [12]. Furthermore, a study conducted during the COVID-19 pandemic in Iran revealed that 40% of children experienced musculoskeletal discomfort due to increased smartphone usage, with common issues including neck pain, back pain, and wrist strain [13]. The study also highlighted that the pandemic led to significant changes in children's patterns of smartphone use, with many spending more than 6 hours daily on their devices for both educational and recreational purposes [13]. The American Academy of Pediatrics (AAP) recommends reducing screen time for children under 8 years old, emphasizing active supervision rather than setting strict time limits (e.g., two hours per day) [14]. Effective monitoring helps protect children from potential risks, such as exposure to inappropriate content, cyberbullying, and excessive use that may lead to physical and mental health issues. Furthermore, parents and educators can utilize parental control tools and establish clear rules to ensure children use smart devices responsibly and safely, while encouraging them to engage in physical and social activities to achieve a healthy balance between digital and real-life experiences.

1.5 The Role of Applications and Artificial Intelligence in Monitoring Children

Parental control applications have become essential tools for ensuring children's online safety. These applications allow parents to monitor and manage their children's digital activities, such as screen time, app usage, and access to inappropriate content [15]. However, excessive monitoring can lead to a sense of mistrust and invasion of privacy among children, as they may perceive these tools as punitive rather than protective [16]. To address this, it is crucial to design parental control solutions that promote open communication between parents and children, allowing children to understand the reasons behind the restrictions and feel involved in the process [17]. The integration of artificial intelligence (AI) into these applications has significantly enhanced their capabilities. AI-based tools, such as wearable sensors and mobile apps, are increasingly used to track children's behavior, sleep patterns, and online activities in real-time, providing parents and professionals with actionable insights [18]. These technologies enable early detection of developmental delays, disruptive behaviors, and online risks, such as cyberbullying and inappropriate content [19]. However, the use of AI in child monitoring raises concerns about privacy, data security, and the potential for over-surveillance, which may impact children's sense of autonomy and trust [20]. Studies highlight the importance of balancing safety with privacy, ensuring that AI tools are transparent, ethical, and designed with input from both parents and children [21]. Furthermore, while AI can augment traditional parenting and therapeutic approaches, such as Parent-Child Interaction Therapy (PCIT), its effectiveness depends on the quality of data and the avoidance of algorithmic biases [18]. Overall, the combination of parental control applications and AI offers promising solutions for child monitoring, but their implementation must prioritize ethical considerations, user acceptance, and the well-being of children [15, 21]. To illustrate the practical applications of these technologies, the table below provides examples of popular parental control applications, categorizing them according to their use of AI. These examples demonstrate how technology can support parents in effectively monitoring their children:

App	Description	Evaluation	Smartphone Reviews	Tablet Reviews	Uses AI
ABCmouse [53]	This app provides interactive educational activities for children.	4.2 stars	57.7K	33.8K	Yes
Digital Wellbeing [54]	Provides phone usage statistics and enables screen time limitation without intelligent analysis.	4.4 stars	12.6K	581	No
Find My Kids [55]	This app offers features such as geolocation tracking, listening to the child's surroundings, and sending alerts when the child leaves a pre-defined safe zone.	4.6 stars	1.72M	13.5K	Yes
Flipd [56]	Use of other applications is prohibited for a specified period.	3.3 stars	5.85K	166	No
Kids Place [57]	An app that allows parents to block apps and control device usage.	4.3 stars	34.4K	12.3K	No
Life360 [58]	This app is used to track the locations of family members in real time.	4.6 stars	2.04M	17.1K	Yes
Qustodio [59]	Used to monitor children's online activity.	3.5 stars	48.6K	5.1K	Yes

Table 1.1: Popular Parental Control Applications and Their Use of AI (Sorted by Reference Order)

1.6 Ethical and Legal Challenges in Using AI for Child Monitoring Applications

The use of artificial intelligence (AI) in child monitoring applications raises significant ethical and legal challenges. Below is a summary of these challenges and recommendations to address them:

- **Privacy Concerns**: Children often feel that excessive surveillance violates their privacy [20]. Clear privacy policies and child-controlled monitoring levels are recommended [15].
- **Balance Between Protection and Surveillance**: Applications should avoid being perceived as punitive tools and instead focus on enhancing protection without restricting autonomy [16].
- **Compliance with Laws**: Many applications fail to comply with data protection laws like GDPR or COPPA, risking children's data security [22]. Regular legal reviews are essential.
- **Children's Digital Rights**: Monitoring without consent can violate children's digital rights [23]. Applications should include consent mechanisms for children.
- **Security Risks**: Vulnerabilities in applications can lead to data breaches [22]. Regular security updates and penetration testing are crucial.

- **Data Quality**: Inaccurate or insufficient data can hinder effective decision-making [15]. Advanced algorithms should be used to improve data quality.
- **Ethical Design**: Applications should prioritize ethics, involving children and parents in the design process to meet their needs [16].
- **Transparency**: Clear explanations of data collection and usage should be provided to users [23].
- **Continuous Review**: Regular evaluations by independent ethics committees are necessary to ensure compliance with ethical and legal standards [22].

Conclusion

smart devices have become an integral part of children's lives in the modern era. These devices offer unprecedented educational and entertainment opportunities that enhance children's creativity and social skills. However, excessive or uncontrolled use of these devices can lead to health and psychological risks, such as addiction, cyberbullying, and negative impacts on academic performance. Therefore, monitoring children's use of smart devices is crucial to ensure a healthy balance between benefits and risks. Parental control applications can play a pivotal role in achieving this balance. By providing effective tools to track children's activities, set screen time limits, and protect them from inappropriate content, these applications help create a safe digital environment. With recent advancements in artificial intelligence, these tools have become smarter and more capable of analyzing data accurately, enhancing their effectiveness in monitoring. In the next chapter, we will delve deeper into the role of artificial intelligence and how it can be used to develop effective applications for monitoring children. We will explore advanced techniques such as age estimation, which is one of the promising solutions to ensure children are protected from inappropriate content based on their age group. We will also discuss how to practically implement these technologies to maximize their potential in enhancing children's digital safety..

Chapter 2: Age Estimation Using Deep Learning

Chapter 2

Age Estimation Using Deep Learning

Introduction

With the increasing prevalence of smart gadgets among young users, the demand for improved methods to safeguard them from online dangers has also risen. Recently, sophisticated AI technologies have come to the forefront, enhancing parental control applications, with age estimation standing out as one of the key automated elements. The technical underpinnings of age estimate systems are presented in this chapter, along with important problems and their fixes. These range from basic ideas in artificial intelligence to state-of-the-art deep learning models for face feature analysis.

2.1 Artificial Intelligence (AI) Concept

2.1.1 What is Artificial Intelligence?

Artificial Intelligence represents a segment of computer science dedicated to creating systems that can execute functions usually necessitating human intellect, including learning, evaluation, and judgment[24]. AI is regarded as a groundbreaking accomplishment in software development, anticipated to emerge as a crucial component of all forthcoming applications in the coming years and decades [25]. AI plays a vital role in refining decision-making, as smart systems depend on systematic approaches to gather and interpret data rationally, rather than depending on speculation or gut feelings, thus increasing the effectiveness and precision of choices [26].

2.1.2 How Artificial Intelligence Works?

Artificial Intelligence (AI) systems function through a series of coordinated processes that mimic human cognitive abilities by adhering to essential stages. The initial stage involves **information processing**, where AI employs machine learning algorithms to analyze data and utilizes artificial neural networks that are designed to reflect the structure of the human brain. Following this, **self-learning** allows AI to detect patterns and relationships within extensive datasets, continually improving its performance through feedback mechanisms. During the **decision-making** phase, AI produces predictions, classifications, and adaptive responses based on its trained models, enabling it to adapt to new information. The intricate operational framework of AI consists of four main steps:

1. **Data collection**, which involves gathering textual, visual, or numerical inputs;
2. **Pattern identification**, which reveals hidden relationships within the data;
3. **Output generation**, resulting in decisions, forecasts, or classifications; and
4. **Continuous learning**, which enhances performance with each cycle.

The fundamental principles of AI encompass pattern recognition in data, computational models inspired by biological systems, and processes of iterative refinement. [27]

2.1.3 Advantages and Disadvantages of Artificial Intelligence

Advantages of AI

- 24/7 operation capability without fatigue
- Faster processing speeds than humans
- Lower operational costs
- Automation of routine tasks
- Reduced human resource requirements
- Predictive capabilities
- High accuracy in repetitive tasks [28]
- Personalized learning experiences
- Identification of individual knowledge gaps
- Customized learning paths based on performance
- Improved student engagement
- Automated grading and assessments [29]

Disadvantages of AI

- High initial development costs
- Need for specialized technical expertise
- Infrastructure requirements
- Job displacement concerns
- Ethical dilemmas
- Lack of creativity and human intuition
- Difficulty handling unexpected situations
- Risk of over-dependence[28]

2.1.4 Types of Artificial Intelligence

Based on its capabilities, artificial intelligence can be classified into a number of categories, the most significant of which are:

Artificial Narrow Intelligence (ANI) is a weak AI that executes specific tasks within a confined scope, such as recommendation systems and voice assistants. It lacks general consciousness and comprehension beyond its specific training, but excels in repetitive tasks .

General AI (AGI) aims to emulate human cognitive capabilities across various fields, requiring advancements in self-supervised learning, contextual awareness, and cognitive adaptability [30, 31]. Super AI (ASI) is a theoretical form of AI that surpasses human intelligence across all measurable dimensions, encompassing superior computational abilities, creativity, emotional intelligence, and social capabilities. While ASI is still a theoretical idea, it sparks philosophical discussions about machine consciousness and the existential threats posed by superintelligent systems [30].

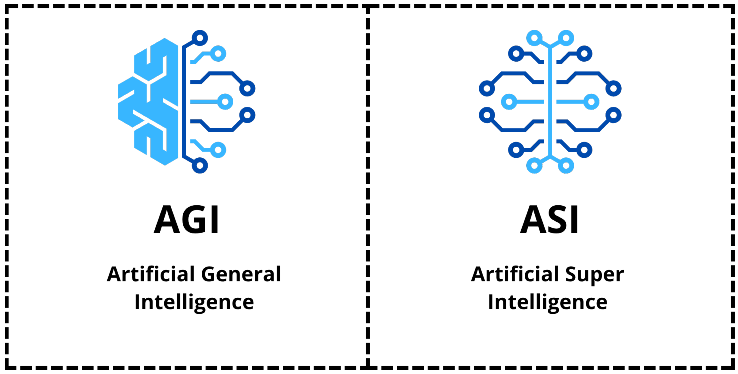

Figure 2.1: Types of Artificial Intelligence

2.1.5 Machine Learning (ML)

ML was defined in 1959 by Arthur Samuel who stated that it is "the field of study that gives computers the ability to learn without being explicitly programmed." [32].

2.1.6 How Machine Learning Works?

The first step in any core machine-learning process is data collection, where relevant information is collected and its quality is checked. It is especially important to use the most representative data in order to avoid unintentional bias[33]. The next step is the model training step, where the correct algorithm is selected according to the specific nature of the problem followed by a process that iteratively optimizes the model parameters. These algorithms differ based on the learning type being applied [34]. The next is the model evaluation step, where model testing occurs on data that were unseen and not encountered during the training phase while assessing its prediction accuracy and generalization capability. The evaluation metrics change depending on the nature of the task [35].

2.1.7 Types of Machine Learning

Supervised Learning

In supervised learning, the goal is to learn a function that is a mapping from both inputs to outputs based on a set of example input-output pairs. Supervised learning requires a fully labeled dataset, meaning that each training example is accompanied by the correct label or answer, and so the algorithm learns by comparing its predictions (outputs) to the known outputs (labels) and then makes some adjustments[34].

Unsupervised Learning

Unsupervised learning refers to the method of examining unlabeled data with no provided output types. The system studies the fundamental arrangement of the data using techniques including clustering, dimensionality reduction, etc, identifying previously unknown patterns, or clusters that were not previously understood. This approach is considered useful for exploratory data analysis and feature extraction[36].

Reinforcement Learning

Reinforcement learning is a set-up in which an agent learns to make decisions by taking actions and receiving rewards or penalties from the environment. Unlike other approaches, it does not require datasets with labels, but learns through trial-and-error interactions, and optimizes its behavior to maximize cumulative reward over time. Reinforcement learning has been applied successfully in game playing, and in robotic control systems.[35].

Semi-supervised Learning

Semi-supervised learning employs a combination of both labeled (or annotated) data and unlabeled data during the training process, usually resulting in a small set of labeled data and a large pool of unlabeled examples. This hybrid approach is particularly useful due to the high costs and/or a long time involved in obtaining fully labeled training data because it can provide good performance while substantially decreasing annotation costs. [37].

Transfer Learning

Transfer learning allows knowledge gained in solving one problem to be applied to a different but related problem. Instead of learning from scratch, the model will utilize parameters already learned from a source task. The transfer learning framework will utilize fewer training data and compute power for the new target task. Transfer learning is a major foundation of deep learning applications.[38].

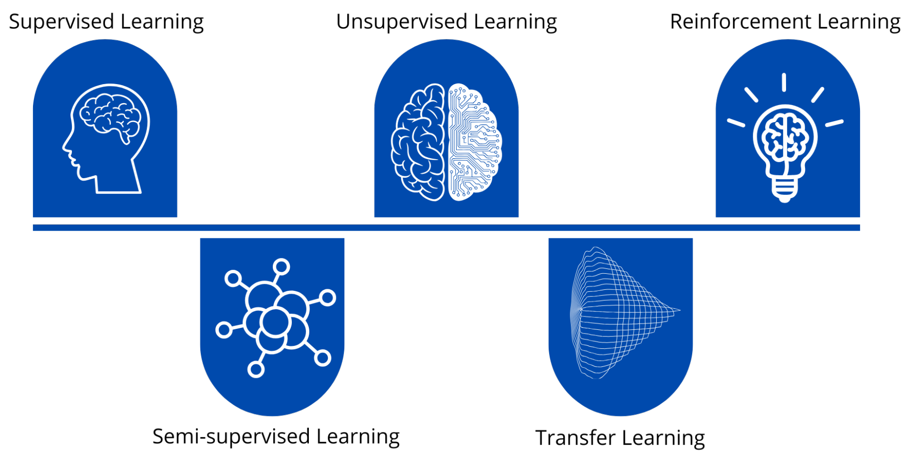

Figure 2.2: Types of Machine Learning

2.1.8 Deep Learning (DL)

Deep Learning is a sophisticated method in the realm of machine learning which formulates models that are made to learn from data through a number of layers of representation - each layer having a unique level of abstraction. This method is fundamentally dependent on artificial neural networks (ANNs), where the first few layers are used to learn basic features, while higher layers are used to learn more complex concepts from the previous layers' basic features. The hierarchical organization aligns simple details with more abstract concepts, reusing the same limited basic features to construct unlimited advanced concepts and ideas [39].

2.1.9 Types of Deep Learning

Convolutional Neural Networks (CNNs)

is a type of Deep Learning algorithm designed to process images. It can analyze an input image, assign learnable weights and biases to different elements or objects within the image, and distinguish between them. Unlike traditional classification methods, CNNs require minimal pre-processing. In older techniques, filters had to be manually designed, but CNNs can automatically learn these filters and features through sufficient training.[40]

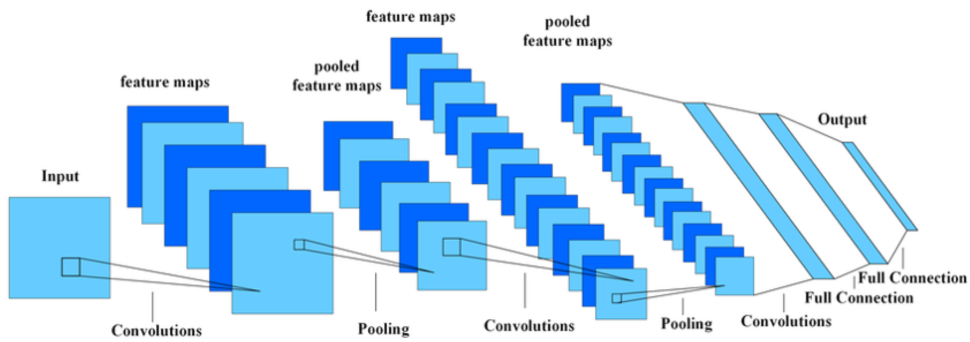

Figure 2.3: Convolutional Neural Networks
[60]

A number of well-known Convolutional Neural Network (CNN) architectures have been developed to improve efficiency and performance in deep learning applications. Among the most notable are VGG-16, ResNet50, and MobileNet. VGG-16, proposed by Simonyan et al., is a convolutional neural network consisting of thirteen convolutional layers followed by three fully connected layers, continuing the use of ReLU activation as introduced in AlexNet [41]. ResNet50, or Residual Network, is a deep neural network comprising 50 weight layers, designed primarily to address the issue of low classification accuracy found in shallow networks [42]. MobileNet, on the other hand, is based on a streamlined architecture that utilizes depth-wise separable convolutions to construct lightweight and efficient deep neural networks, making it particularly suitable for mobile and embedded vision applications [43].

Recurrent Neural Networks (RNNs)

RNNs have the advantage of monitoring sequences of data by means of internal memory, making them appropriate for use with time-series and natural language processing (NLP) data. Advanced forms such as LSTMs mitigate the vanishing gradient problem through their gating mechanisms. RNNs perform well in applications that utilize temporal context, such as speech recognition and text generation.[44].

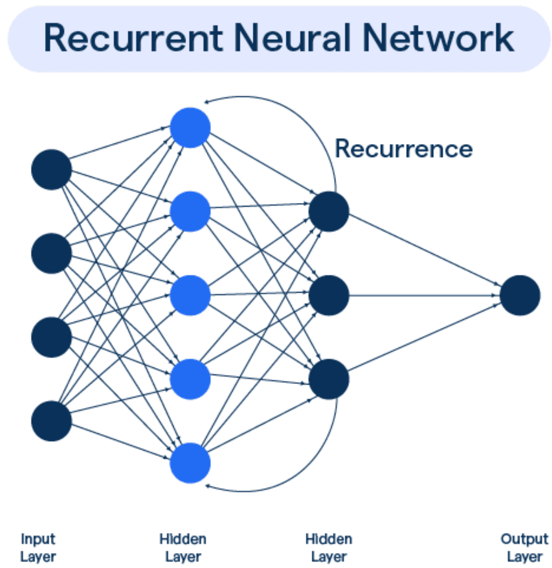

Figure 2.4: Recurrent Neural Networks
[63]

Transformer Networks

The use of self-attention in transformers allows them to process sequences simultaneously while capturing long-distance dependencies effectively. The transformer architecture serves as the foundation for many modern language models. The importance of transformers derives from their scalability and flexibility.[45].

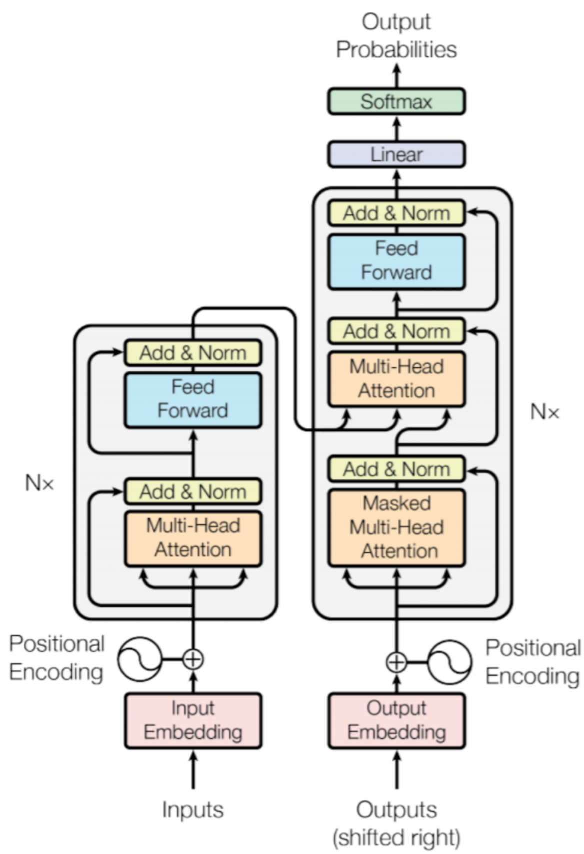

Figure 2.5: Transformer Networks
[61]

Generative Adversarial Networks (GANs)

GANs utilize either two opposing networks: a generator and discriminator - in an adversarial framework. This proved to be effective in creating realistic synthetic data. Applications of this capability include image generation, data augmentation, and art generation. [44].

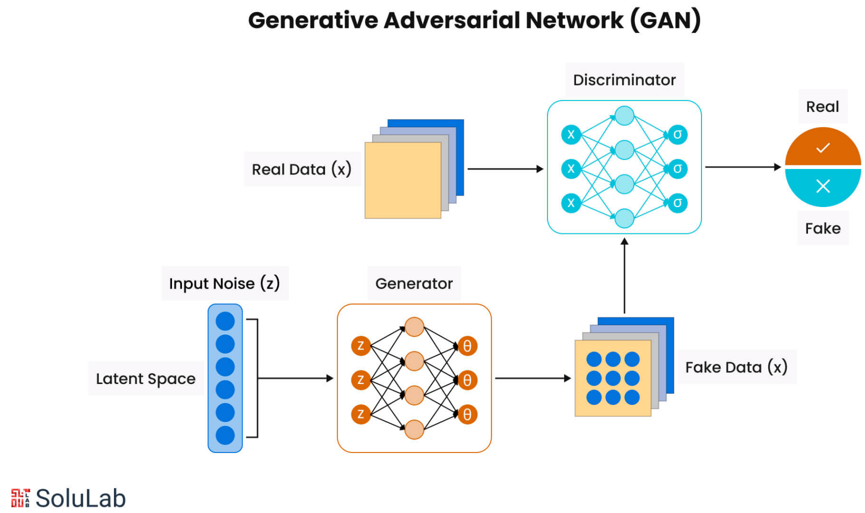

Figure 2.6: Generative Adversarial Networks
[62]

2.1.10 Emerging Architectures

Graph Neural Networks

Graph Neural Networks (GNNs) are specialized networks that understand non-Euclidean graph data, making predictions at scale, and are valuable in molecular modeling and social network analysis.[45].

Hybrid Architectures

Hybrid architectures combine various neural network paradigms, such as Vision Transformers, multimodal networks, and Neural Ordinary Differential Equations, expanding deep learning's capabilities.[44].

2.1.11 How Deep Learning Works

Deep learning systems analyze data through several layers of artificial neural networks, with each layer mapping input data into a more abstract representation [45]. The fundamental operating principles are:

Hierarchical Feature Learning

- Data is processed through multiple non-linear functions
- Early layer neurons are able to detect simple patterns (edges, textures)
- Layers deeper in the network combine patterns present in the previous layers into complex features[44]

Neural Network Architecture

- Composed of layers of artificial neurons connected to one another
- Each connection possesses weights that may be adjusted
- Activation functions are what add non-linearity [45]

Training Process

- Adjust weights based on backpropagation algorithm
- Loss function is minimized through gradient descent
- Requires large labeled datasets [44]

Common Architectures

- CNNs are used for spatial data (i.e. an image)
- RNNs are used for sequential data (i.e. text, speech)
- Transformers are used for tasks that rely on attention [45]

2.1.12 Importance of deep learning

The TIDL framework research indicates that deep learning is now a natural fit for embedded systems based on:

Edge Computing Capabilities

- Allows for real-time inference without needing the cloud
- Decreases latency for time-sensitive applications
- Processing the data locally at 5W of power consumption

Industrial Applications

- Predictive maintenance using vibration analysis
- Visual inspection for quality control on manufacturing lines
- Autonomous navigation for mobile robots

Architectural Innovations

The TIDL framework illustrates:

- 8-bit quantization of CNN models
- Fusion of layer techniques to optimize memory
- Multiple network topology support:
  - CNNs for vision tasks
  - RNNs for temporal data
  - Custom operator support [46]

2.2 Gender Recognition Definition

The practice of determining a person's gender using computer vision methods based on their behavior, appearance, and other characteristics is known as gender recognition. It can be used in a number of domains, including demographic statistics, biometrics, and human-computer interaction. [47]

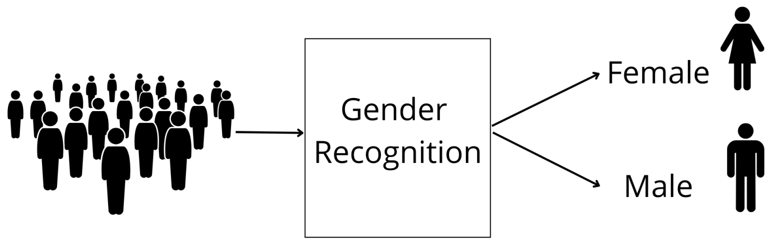

Figure 2.7: Gender Recognition

2.3 Age Detection Definition

Age is a key facial feature that promotes and/or inhibits communication. Age is similar to culture, beliefs, experience, and language in that it influences how we communicate and how others understand a message [48]. The human face expresses information about identity, age, gender, emotion, and ethnicity. As a demographic attribute, it also serves as a soft biometric trait for human recognition. Improving the ability of machines to recognize and even assess various aspects of faces (such as age) in real time can improve the interaction between humans and computers [49].Today, because of increasing online usage, users spend much of their time navigating e-commerce sites, reading about sports, news, and entertainment, and commenting on social media articulating their opinions and feelings about those topics. Analyzing those comments can provide significant information about user satisfaction that is valuable for service providers and product vendors [48]. Age estimation - predicting someone's age from a face image - has been a longstanding and difficult problem in computer vision, with applications for precision advertising, smart surveillance, and face retrieval and recognition. The challenges are in part due to the fact that faces may be photographed of individuals of different ethnicities and races, at different poses, in poor lighting conditions, and with or without makeup. Even humans can only inspect the face and provide an approximate age estimation. [50].

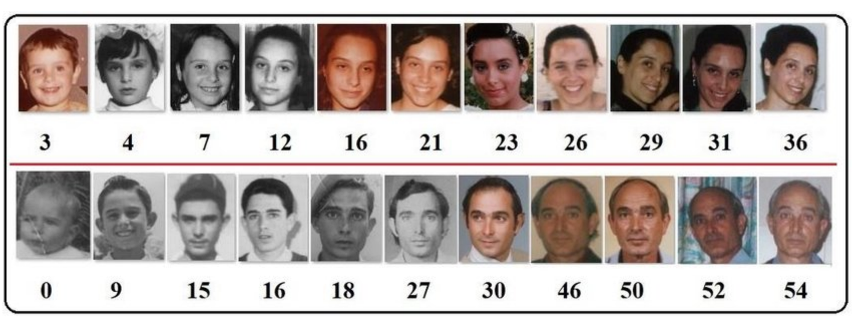

Figure 2.8: Age Detection
[64]

2.4 Advantages and Challenges of Age Estimation Using AI and Deep Learning

Deep learning techniques are effective in predicting age using facial data due to their adaptability to environmental conditions (e.g., lighting and image noise) and the use of age-weighted sampling techniques to address data imbalance [50, 39]. However, several challenges persist. Imbalanced data may lead to over- or under-representation of certain age groups [51], and facial expression variability can significantly reduce accuracy, with estimation errors reaching up to 10.98 MAE in some cases [50]. Additionally, ethnic and gender differences impact model performance [48]. The use of short and spontaneous data—such as social media content—adds further complexity, particularly due to irrelevant features like hashtags and mentions [48]. Finally, traditional metrics like Mean Absolute Error (MAE) do not sufficiently reflect error distribution, prompting the adoption of alternative metrics such as Cumulative Corrective Scores (CCS) [51].

Building on the previously discussed advantages and challenges of age estimation using AI and deep learning, we now present the practical phases that were implemented and evaluated in this research to develop and assess an age and gender prediction system.

2.5 Stages of Age Detection

The methodology of this research follows a structured pipeline for accurate age and gender prediction from facial images, composed of four key stages: data collection, data processing, model design, and model training.

Data Collection

The UTKFace dataset is a large-scale face dataset with a long age span, ranging from 0 to 116 years old. This dataset consists of over 20,000 face images annotated for age, gender, and ethnicity [52]. The images are huge in variations of pose, facial expressions, illumination, occlusions, resolution, and others. This dataset can be used for various tasks, such as face detection, age estimation, age progression/regression, landmark localization, and suchlike.

Data Processing

he preprocessing steps applied to the dataset include converting grayscale images to a three-channel RGB format to ensure compatibility with certain pre-trained models, as well as resizing all images to a fixed dimension for uniformity and consistency.

Model Design

Two types of deep learning architectures were utilized for age and gender prediction:

- **Custom CNN:** A convolutional neural network designed specifically for this task, consisting of multiple `Conv2D` layers with `BatchNormalization` and `LeakyReLU` activation functions.
- **Transfer Learning Models:** Pre-trained architectures including **VGG16, ResNet50, and MobileNetV2**, where the base layers were frozen, and additional custom layers were added for classification and regression tasks.

Model Training

The models were trained with 30 epochs and a batch size of 32. The activation functions used were sigmoid for gender classification, which produces a binary output (male/female), and ReLU for age prediction, a regression task. The Adam optimizer was employed with a learning rate of 0.0001. For loss functions, binary cross-entropy was used for gender classification, while Mean Absolute Error (MAE) was applied for age estimation. Although techniques like Early Stopping or Regularization were not explicitly implemented, they could be beneficial in improving model generalization and preventing overfitting.

Evaluation Metrics

A fundamental indicator for classification jobs is Accuracy (ACC), which indicates the ratio of cases accurately categorized by the model. This metric is presented in Equation 1. Moreover, Mean Absolute Error (MAE) is a conventional metric for regression tasks, quantifying the average absolute discrepancy between the model's predictions and the actual data. The Mean Absolute Error (MAE) is computed utilizing Equation 2.

$$ACC = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Samples}} \tag{2.1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2.2}$$

Model performance is evaluated based on Gender classification accuracy data and Mean Absolute Error (MAE) for age prediction on the testing data.

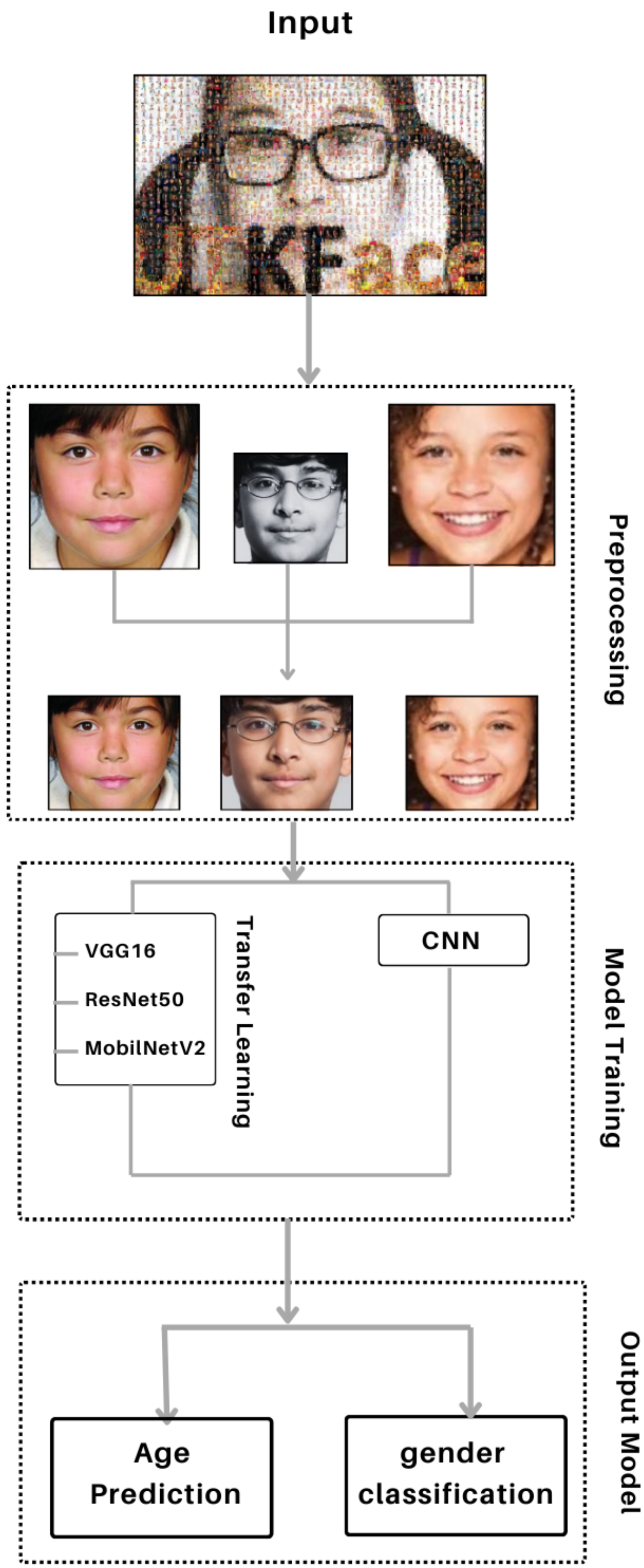

Figure 2.9: Workflow of Age and Gender Prediction Model

Conclusion

This chapter concluded with outlining the theoretical underpinnings of age estimate methods based on artificial intelligence. By creating a thorough model to handle the study's main issue, with a focus on accuracy enhancement and challenge resolution, the following chapter will move into actual implementation.

Results And Discussion

Chapter 3

Results And Discussion

Introduction

After addressing the theoretical aspect in the previous chapters, this chapter discusses the experimental results, model performance, system architecture, and practical application of the model within a web interface.

3.1 Work Environment

To develop and execute this project, the following hardware and software environment was used:

- **Device:** Dell Laptop
- **Processor:** Intel(R) Core(TM) i5-8350U CPU @ 1.70GHz (up to 1.90GHz)
- **RAM:** 16 GB (15.9 GB usable)
- **Operating System:** Windows 11 Professional

For training and evaluating the deep learning models, Google Colab was used. It provides a cloud-based development environment with access to powerful GPU acceleration, which significantly reduces training time and enhances performance.

3.2 Programming Tools

3.2.1 Python

Python is an interpreted, high-level, and dynamically typed programming language. It offers rich support for rapid development thanks to its simple syntax, extensive standard libraries, and large ecosystem. Python encourages code reusability through modules and packages, and its readability helps reduce maintenance overhead. It is the backbone of this project, enabling efficient implementation of both the model and the application interface.

3.2.2 Libraries Used

- **TensorFlow:** An open-source machine learning platform that supports training and inference of deep neural networks. It was used to build, train, and deploy the deep learning model for age and gender estimation.
- **Keras:** A high-level neural network API running on top of TensorFlow. It simplifies the model building and training process through its modular architecture and easy-to-use interface.

- **OpenCV:** A widely used library for real-time computer vision. In this project, it was employed for face detection using the Haar Cascade classifier.
- **PIL (Pillow):** A Python imaging library used for loading, processing, and manipulating images.
- **NumPy:** A core library for numerical computing in Python. It provides support for large, multi-dimensional arrays and matrices, which is essential for handling image data.
- **Streamlit:** A lightweight, open-source Python framework used to create interactive web applications for machine learning and data science. It enables users to easily upload images and view predictions directly in the browser.

3.2.3 Development Environment

The code was written and tested using:

- **Visual Studio Code:** A powerful and customizable source code editor.
- **Jupyter Notebook:** An interactive computing environment ideal for writing and debugging machine learning code in Python.

Results and Discussion

3.3 Results

Model Performance Comparison

The performance of different models for both gender classification and age prediction tasks is summarized in Table 1. The table includes training and validation metrics such as loss, accuracy, and Mean Absolute Error (MAE).

Performance	**Transfer Learning**			**CNN**
	VGG16	**ResNet50**	**MobileNet**	
age out loss	5.6900	6.3211	2.4443	9.0805
age out mae	5.6907	6.3216	2.4454	9.0842
gender out accuracy	0.6145	0.5170	0.8592	0.9696
gender out loss	0.6693	0.7374	0.3416	0.1548
loss	6.3598	7.0589	2.7871	9.2390
val age out loss	3.1858	3.0966	3.2066	5.1298
val age out mae	3.1790	3.0930	3.2218	5.2884
val gender out accuracy	0.7069	0.4080	0.8333	0.6897
val gender out loss	0.6299	0.7017	0.4102	0.5993
val loss	3.8043	3.7947	3.6105	5.8783

Table 3.1: Model Performance Comparison

Visualization of Results

Figure 3.1 illustrates the accuracy of different models for gender classification across training and validation datasets. The figure highlights the superior performance of MobileNetV2 and the overfitting issue observed in Custom CNN.

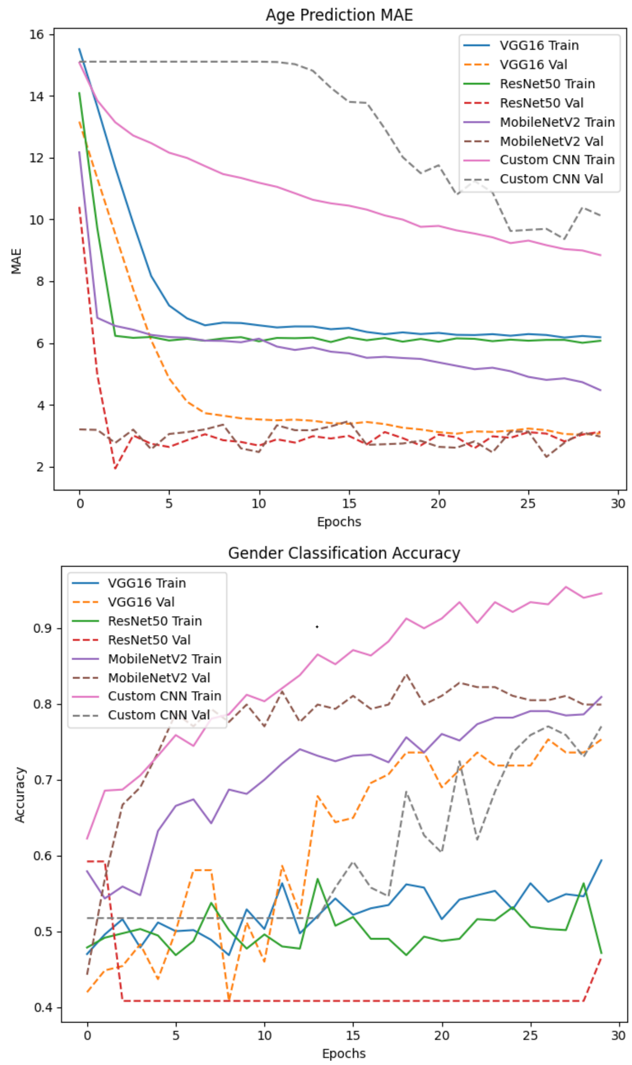

Figure 3.1: Classification and prediction results

3.4 Discussion

3.4.1 Gender Classification

MobileNetV2 achieved the highest training accuracy of 0.8592 and validation accuracy of 0.8333, indicating robust performance. Custom CNN showed the highest training accuracy of 0.9696 but a lower validation accuracy of 0.6897, suggesting potential overfitting. VGG16 and ResNet50 demonstrated lower accuracy compared to the other models.

3.4.2 Age Prediction

MobileNetV2 achieved the lowest Mean Absolute Error (MAE) of 2.4454 on training data and 3.2218 on validation data, indicating the best performance among the models. Custom CNN showed the highest MAE of 9.0842 on training data and 5.2884 on validation data, suggesting poor performance. VGG16 and ResNet50 demonstrated moderate performance.

3.4.3 Loss Analysis

The loss values for both training and validation datasets are consistent with the accuracy and MAE results. MobileNetV2 achieved the lowest loss values, indicating better generalization. Custom CNN, despite achieving low training loss, showed higher validation loss, further confirming overfitting.

3.4.4 Model Selection

After conducting a comprehensive comparison of different models for gender classification and age estimation tasks, MobileNetV2 was identified as the best-performing model based on accuracy, mean absolute error (MAE), and loss values. It demonstrated strong generalization capabilities and avoided overfitting, unlike some other models.

Based on these results, the MobileNetV2 model was selected for deployment in a practical application designed to perform real-time age and gender detection from face images.

The next step was to implement this model within an application, which required establishing a suitable work environment and programming tools to facilitate development and deployment.

3.5 Model Architecture

The deep learning model used for age and gender estimation is based on a transfer learning approach utilizing the **EfficientNetB0** architecture as a feature extractor. The model processes facial images that are initially grayscale, resized to 128×128 pixels, and then converted to RGB format by repeating the grayscale channel three times, resulting in an input shape of $(128, 128, 3)$.

The architecture is composed of the following components:

- **Input Layer:** Accepts RGB images with a shape of $(128, 128, 3)$.
- **Base Model:** Used as a pretrained convolutional feature extractor with `include_top=False` and `weights='imagenet'`. All layers in the base model are frozen during training to retain the learned representations.
- **Global Average Pooling Layer:** Applies global average pooling to reduce the spatial dimensions of the feature maps and produce a compact feature vector.
- **Fully Connected Layer:** A dense layer with 256 neurons and `ReLU` activation is used to learn high-level representations from the extracted features.
- **Dropout Layer:** A dropout rate of 0.5 is applied to the dense layer to prevent overfitting.
- **Output Layers:**
  - gender_out: A dense layer with 1 neuron and `sigmoid` activation function used for binary gender classification.
  - age_out: A dense layer with 1 neuron and `ReLU` activation function used for age regression.

The model is compiled using the `Adam` optimizer with a learning rate of 0.0001. The loss function is defined as a combination of:

- `binary_crossentropy` for the gender classification output.

- `mean absolute error (MAE)` for the age regression output.

Evaluation metrics include:

- `accuracy` for the gender classification task.
- `MAE` (Mean Absolute Error) for the age estimation task.

This dual-output architecture enables the model to simultaneously perform both age and gender prediction efficiently using transfer learning from the EfficientNetB0 backbone.

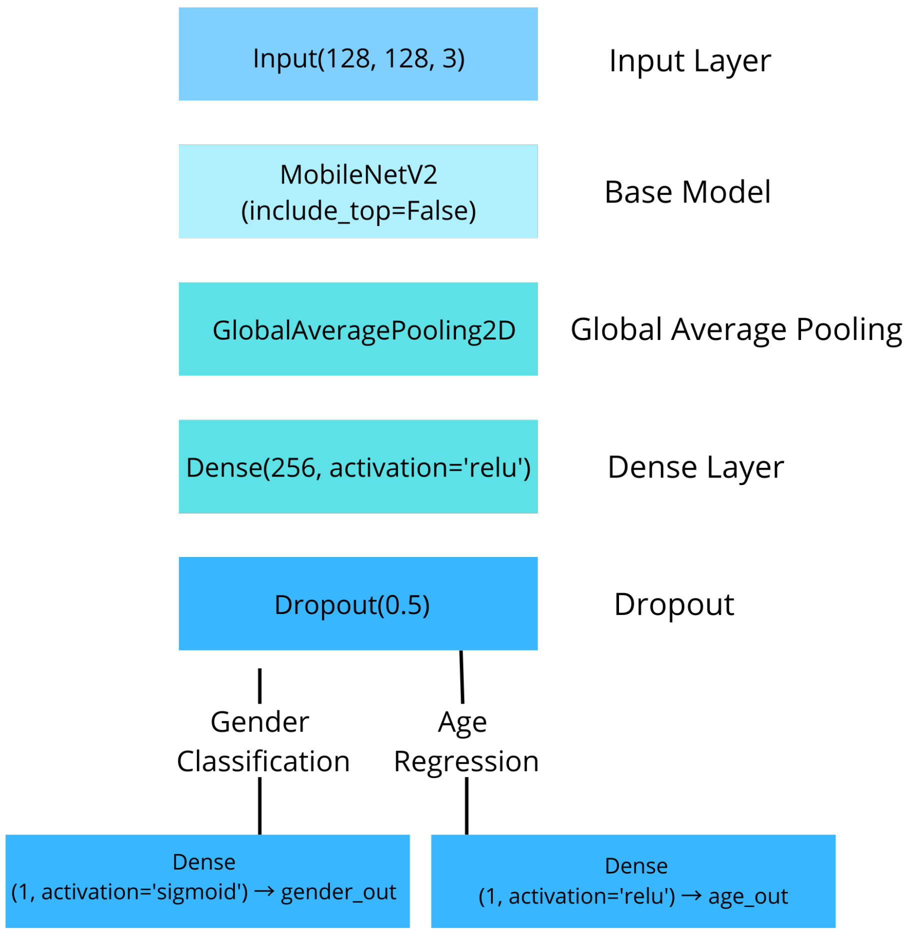

Figure 3.2: Model Architecture

3.6 Application

This application allows you to upload an image containing one or more faces. It then uses a deep learning model (saved in `.h5` format) to estimate the age and gender of each detected face in the image. The results are displayed in a clear and organized manner above the image, including the gender probability (showing the likelihood of the face being male or female).

Interface:

This image shows the main interface of the application, where the user can upload a face image for analysis. The interface features a clear title, "Age and Gender Prediction from Face Image," and a simple sidebar with a mode selection, currently offering a single option.

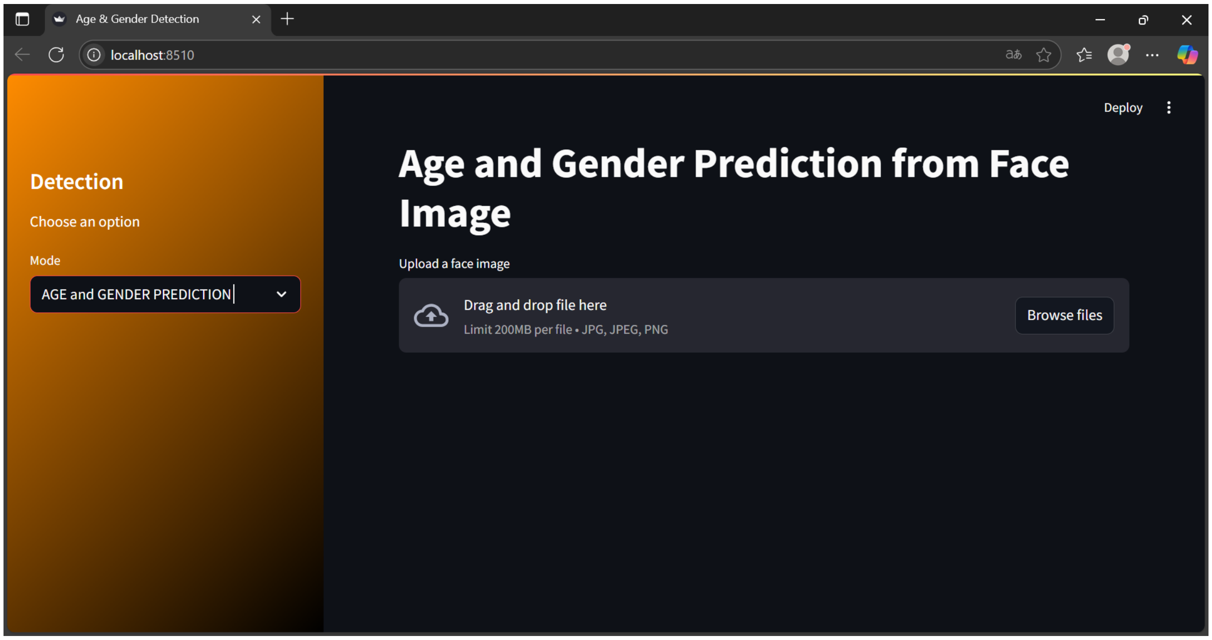

Figure 3.3: Interface1

This image demonstrates how the interface adapts when the browser window is resized to a smaller size. The application maintains a clean and readable layout, making it suitable for smaller screens or mobile devices while preserving the clarity of texts and key elements.

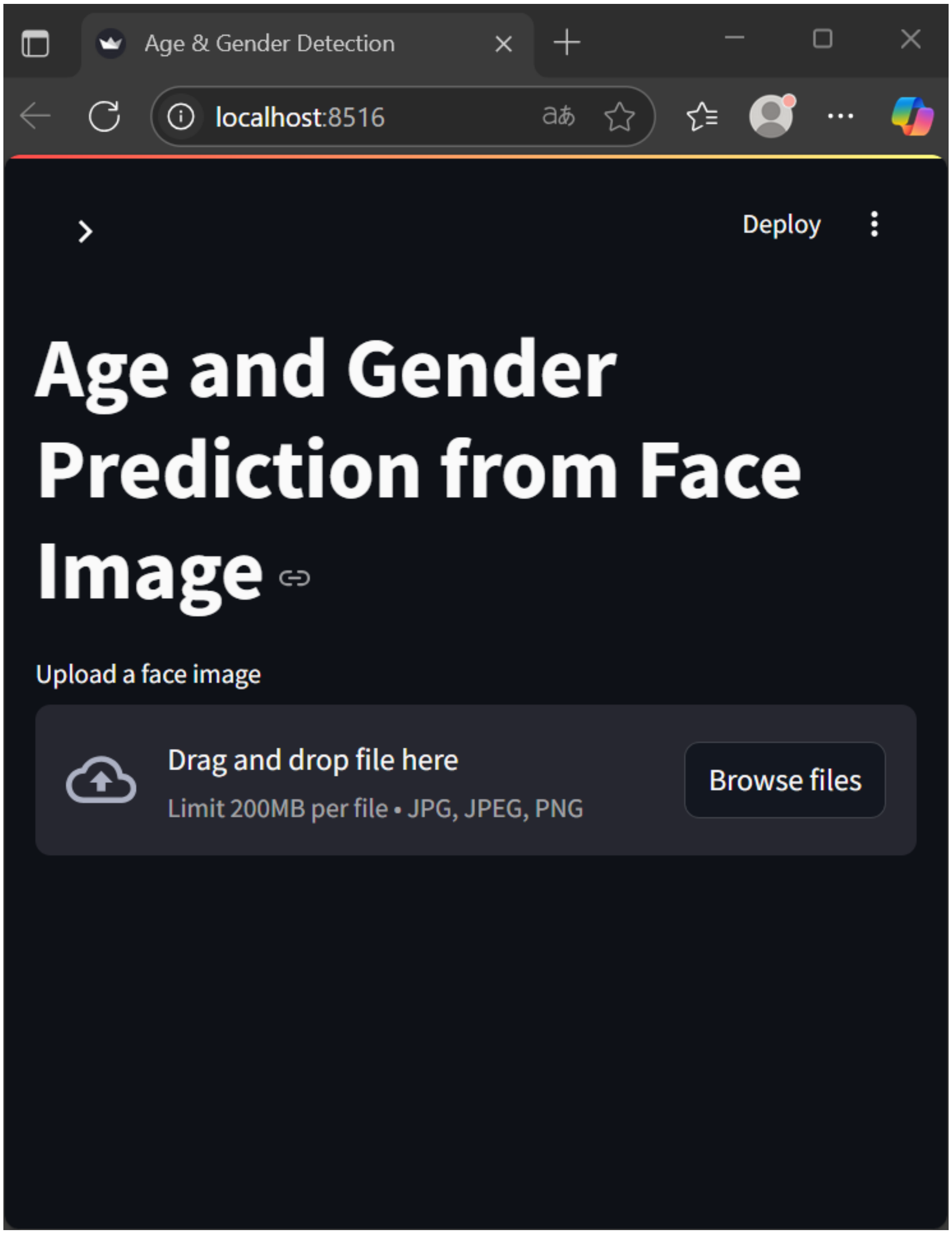

Figure 3.4: Interface2

A face image has been uploaded, and the application starts detecting faces within the image using the Haar Cascade face detector. The detected face regions are processed for prediction.

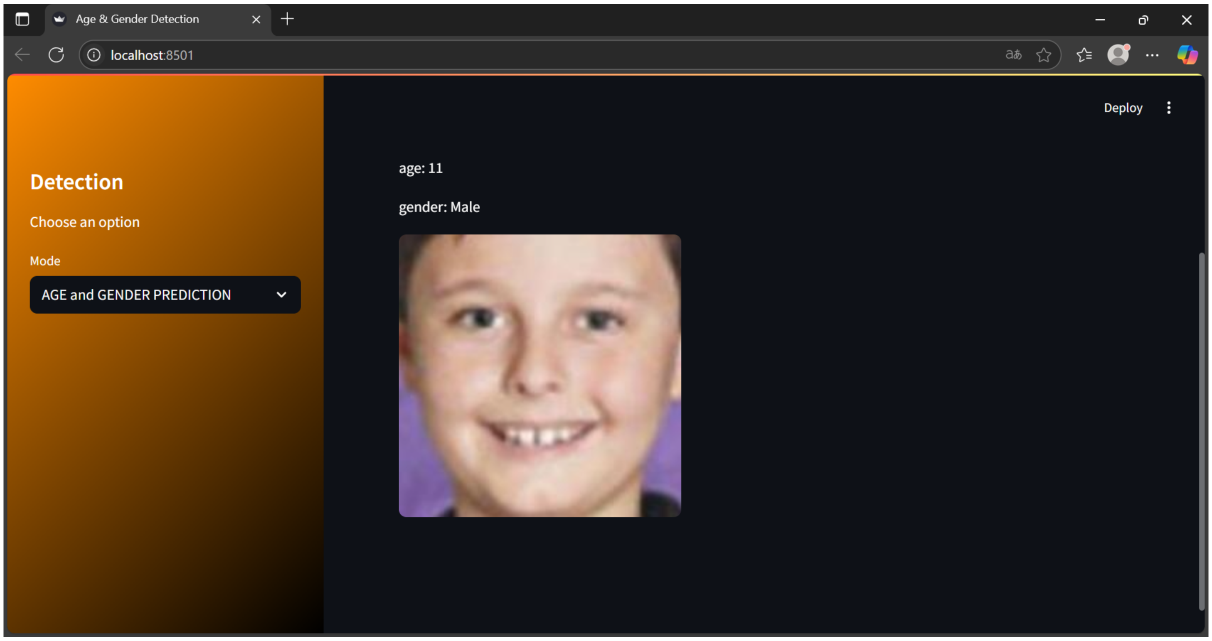

Figure 3.5: Load image1

The prediction results appear after the image analysis, showing the estimated age and classified gender (male or female) for each detected face. The results are displayed clearly as text above the image.

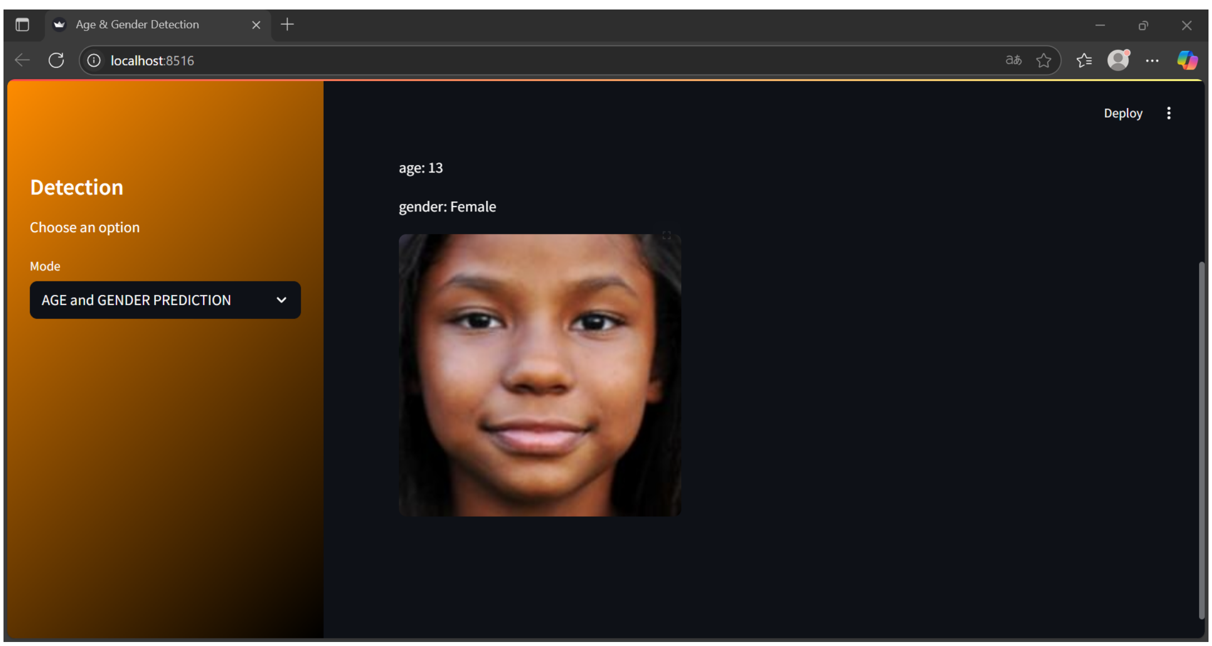

Figure 3.6: Load image2

3.7 Conclusion

This chapter provided a detailed evaluation of various deep learning models applied to the task of age and gender estimation from facial images. Among the tested architectures, MobileNetV2 demonstrated superior performance in both classification and regression tasks, achieving high accuracy in gender classification and low MAE in age prediction. The model's efficiency and lightweight structure made it suitable for real-time applications. To demonstrate practical deployment, the model was integrated into a user-friendly web application built with Streamlit, enabling interactive analysis and prediction based on uploaded images. These results confirm the effectiveness of transfer learning and the potential of deploying deep learning solutions in accessible web platforms.

Conclusion

Conclusion

In conclusion, this thesis offers a meaningful and timely contribution to the growing field of child safety in the digital age, particularly with regard to the use of smart devices. By designing and implementing an intelligent system based on artificial intelligence and deep learning, the study has successfully demonstrated the potential of modern technologies to address one of the most pressing concerns facing parents and educators today. The integration of facial analysis to estimate age and adapt digital content accordingly reflects an innovative and practical approach to strengthening parental control mechanisms. The research has achieved its objectives by combining theoretical analysis with hands-on implementation, resulting in a model that is not only accurate but also viable for real-world applications. The effectiveness of the proposed system, as demonstrated through rigorous evaluation and testing, supports the notion that AI-driven solutions can be both efficient and user-centered. Nonetheless, the work also highlights several challenges that remain, such as improving model precision, enhancing adaptability to diverse user profiles, and ensuring full compliance with ethical and legal standards, especially concerning privacy and data protection. This study serves as a foundation for further exploration and development in this domain. It opens the door to future research on more adaptive and intelligent systems that can better understand and respond to children's needs in digital environments. Moreover, it underscores the importance of multidisciplinary collaboration—bringing together expertise from computer science, psychology, education, and law—to build solutions that are not only technically sound but also socially responsible. It is our hope that the findings and methodologies presented here will inspire continued innovation aimed at creating safer, smarter digital experiences for children. By doing so, we move one step closer to ensuring that technology serves as a tool for growth, learning, and protection—rather than a source of harm or risk—in the lives of young users.

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