TITLE OF THE PROJECT

BY

**LAST NAME** , Other Names

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DEPARTMENT OF THE CANDIDATE

BAZE UNIVERSITY

ABUJA

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Development of an Age and Gender Classification System Using Deep Learning

project Submitted in Partial Fulfilment of the Requirement

for the Degree of

B. Sc.

In

Computer Science

By

**Cisse**, Nafisah Hassan

To

The Department of Computer Science

Baze University, Abuja

SEPTEMBER, 2024

**DECLARATION**

This is to certify that this project entitled “Development of an Age and Gender Classification System Using Deep Learning”, which is submitted by **Nafissah Cisse** in partial fulfilment of the requirement for the award of degree for B.Sc. in Computer Science to the Department of Computer Science, Baze University Abuja, Nigeria, comprises of only my original work and due acknowledgement has been made in the text to all other materials used.

Date: Date Month Year Name of Student:

**APPROVED BY** ……………………………

**Head**

Department of Computer Science

**CERTIFICATION**

This is to certify that this project entitled “**Development of an Age and Gender Classification System Using Deep Learning”**, which is submitted by **Nafisah Hassan Cisse** in partial fulfilment of the requirement for the award of degree for B.Sc. in Computer Science to the Department of Computer Science, Baze University Abuja, Nigeria is a record of the candidate’s own work carried out by the candidate under my/our supervision. The matter embodied in this project is original and has not been submitted for the award of any other degree.

Date: Supervisor: Name

**APPROVAL**

This is to certify that the research work, Dental Management System and the subsequent preparation by Nafisah Hassan Cisse with BU/22A/IT/6218 has been approved by the Department of Computer Science, Faculty of Computing and Applied Science, Baze University, Abuja, Nigeria.

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External Examiner Date/Sign

**DEDICATION**

This project is dedicated to my family, who only continue to enhance and drive me to be better. I would like to thank to my parents for their endless sacrifices and belief in my qualities. I also dedicate this work to my friends, who were constant motivation and companionship in these most difficult moments. Furthermore, I give thanks to God for giving and granting me the guidance, perseverance and grace to finish this project.

# ABSTRACT

An automated age and gender classification system developed using deep learning is a major step forward in the domains of computer vision and artificial intelligence. In this project, I use Convolutional Neural Network (CNNs) to classify age and gender from facial images at high accuracy. The system is advanced to train in complex facial features in a robust manner through modern datasets like IMDB-WIKI, Adience and were trained using deep learning techniques to ensure robustness against variation in illumination, pose and expression. Several architectural improvements are highlighted in the research and include incorporating attention mechanisms in the focus on the facial regions. We demonstrate that traditional machine learning methods are greatly outperformed by the results for the age and gender classification tasks and have a very high level of accuracy. We believe this system has the potential to be used in personalized marketing, biometric security, and user experience personalization. The system is also developed responsibly with respect to ethical considerations including privacy and data biases.

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**LIST OF ABBREVIATIONS**

CPU Central Processing Unit

ERD Entity Relationship Diagram

IT Information Technology

# CHAPTER 1: INTRODUCTION

* 1. **Overview**

Detecting age and gender is a significant application within computer vision that has gained traction in recent years. This task presents challenges that necessitate advanced machine learning algorithms for accurately determining a person's age and gender from an image. The goal of this project is to create a deep learning model capable of predicting a person's age and gender based on a provided image using a Python CNN. The project consists of multiple phases, beginning with assembling a substantial dataset of labelled images. Each image in the dataset is annotated with the corresponding age and gender of the individual depicted. The dataset undergoes pre-processing to standardize size and colour while eliminating any extraneous background noise. After pre-processing, the images are input into a deep learning model employing a Convolutional Neural Network (CNN) architecture. CNN is a neural network type that excels in image processing tasks. It is composed of several layers, which include convolutional layers, pooling layers, and fully connected layers. The convolutional layers within the CNN are tasked with identifying various features in the images, such as edges, shapes, and patterns. The model's performance is assessed using a test set of images to evaluate its accuracy. Techniques such as regularization, dropout, and data augmentation are employed to enhance the model's effectiveness. Regularization helps to mitigate overfitting, dropout prevents neurons from co-adapting, and data augmentation generates additional training data by introducing noise, rotation, and scaling to existing images. In the end, the model is deployed as an application accessible via a web interface or mobile application.

* 1. **Background and Motivation**

The goal of the age and gender detection project utilizing Python CNN is to create an advanced computer vision application capable of accurately estimating a person's age and gender from an image. This initiative has many practical uses across different sectors, including security, entertainment, and social media analysis. In security applications, age and gender detection can enhance surveillance camera operations. By evaluating the age and gender of individuals nearby, the security system can pinpoint potential threats and alert security personnel if necessary. For instance, if the system identifies a group of teenagers lingering in a restricted zone, it can set off an alarm and inform security staff to take action. In the realm of entertainment, age and gender detection can tailor content to fit the user’s demographic. For example, a video streaming platform can utilize this technology to suggest age and gender-appropriate content. Likewise, game developers can adjust gameplay according to the user's age and gender. In social media analysis, age and gender detection can be employed to collect demographic information for marketing and research objectives. By analyzing the age and gender of social media participants, companies are able to create focused marketing strategies and understand consumer behavior better.

Additionally, this detection technology can find applications in healthcare, such as monitoring the well-being of older adults. By evaluating the age and gender in a healthcare context, the application can recognize possible health issues and alert medical professionals. The advancement of age and gender detection through Python CNN also aids in the broader domain of computer vision and deep learning. Enhancing the accuracy of the model can lead researchers to innovate new techniques and algorithms for other image processing applications. Furthermore, the prevalence of large datasets and computational resources has facilitated the development of advanced models for age and gender detection. The project can make use of established datasets, such as the IMDB-WIKI dataset, for model training and development. It can also employ open-source deep learning frameworks like TensorFlow and Keras for model implementation and evaluation.

Another driving factor behind this project is the rising need for computer vision applications across multiple industries. With a growing abundance of data and computing power, creating and deploying sophisticated image processing models has become more feasible. Age and gender detection using Python CNN stands out as a noteworthy application with widespread practical implications in various sectors.

* 1. **Problem Statement**

Determining age and gender is a prevalent issue in computer vision that entails estimating a person's age and gender from images or videos. This challenge has numerous applications across various sectors, including marketing, security, and healthcare. Age and gender detection can help evaluate customer demographics, oversee security in public areas, and identify medical conditions that impact different age and gender groups differently. However, achieving precise age and gender detection proves difficult due to factors like lighting variations, different poses, facial expressions, and significant diversity in appearances among individuals of the same age and gender. Thus, the aim of this project is to create a deep learning model that can effectively predict a person’s age and gender from an image or video by employing data augmentation techniques to enhance the size and variety of the training dataset.

* 1. **Aim and Objectives**

The goal of age and gender detection is to create a machine learning model that can reliably estimate a person's age and gender based on images or videos. The main aims of this objective are:

1. Enhancing accuracy: The foremost aim of age and gender detection is to build a model that can predict age and gender with precision. Achieving this requires training the model on a varied dataset and fine-tuning it with suitable loss functions and evaluation criteria.

2. Boosting efficiency: Another goal of age and gender detection is to create a model that can deliver predictions swiftly and effectively. This entails optimizing the model's architecture, data preparation methods, and hyper parameters to allow for real-time predictions.

3. Strengthening generalization: Models for age and gender detection should perform well on previously unseen data. This necessitates careful selection of training and testing datasets, alongside employing techniques like data augmentation and regularization to avoid overfitting.

4. Facilitating real-world applications: The overarching goal of age and gender detection is to design a model that can be applied in practical scenarios, such as in security systems, market research, and entertainment. This requires the model to be scalable, reliable, and capable of managing various types of input data and situations.

* 1. **Significance of the Project**

As real-world applications continue to grow, daily life has also evolved, prompting researchers to take a greater interest in soft biometrics to bridge communication gaps between people and machines. Soft biometrics encompass traits such as age, gender, ethnicity, height, and facial dimensions. Unlike machines, the human brain excels at recognizing patterns.

Consequently, the objective is to leverage technology to replicate the human brain's capability to ascertain an individual's age and gender. This challenge can be addressed by creating an algorithm that can accurately identify a person's age and gender. The information regarding age and gender is obtained through analyzing the individual's facial features. The resulting output will indicate the person's age and gender, which can be used for facial recognition and surveillance, image retrieval system, demographic profiling, human computer interaction and customized advertisement systems.

* 1. **Project Risks Assessment**

| **Risk** | **Description** | **Impact** | **Likelihood** | **Mitigation Strategy** |
| --- | --- | --- | --- | --- |
| Data Privacy Concerns | A discussion of the ethical issues raised by the use of facial images includes privacy and consent. All data collection has to be ensured to be handled securely and the privacy of the individuals who were collected data have to be looked after. | High | Medium | Implementing protocols to protect secure data storage and processing data for user information. Anonymizing data, obtaining informed consent from participants. |
| Biases in the Dataset | If the training dataset isn’t diverse enough, and the model is not trained well on that, it can create biases which might lead to inaccurate predictions for underrepresented groups. Such discrimination against some demographics could lead to failure of the project objectives. | High | Medium | Making a real effort to build a broad range of demographics in the training set, in an attempt to minimize biases. |
| Technical Challenges in Model Integration | Technical challenges may exist when integrating the deep learning model into an application that is easy to use, but more especially when performing at real time. The issue here is that it will take careful planning and execution. | High | High | Conducting Thorough Testing and Validation |
| Regulatory Compliance | Noncompliance with local and global regulations regarding AI and data utilization. | High | High | Using updated applicable laws and industry guidelines concerning AI and data utilization. |

* 1. **Scope/Project Organization**

This project centers on creating a system for age and gender classification utilizing deep learning techniques, specifically aimed at analyzing facial images. It surpasses conventional classification approaches by employing advanced Convolutional Neural Networks (CNNs) and incorporating attention mechanisms to improve accuracy and resilience. By effectively categorizing age and gender, the system aspires to enhance applications in personalized marketing, user engagement, and security systems, ensuring a more customized experience for users.

The structure of the rest of this project report is organized as follows: Chapter Two (2) offers a literature review and an overview of relevant work in the domain of age and gender classification. Chapter Three (3) outlines the methodology and strategy used to develop the classification system, including choices regarding datasets, model architecture, and training processes. Chapter Four (4) discusses the implementation and testing of the system, presenting performance metrics and evaluation outcomes. Lastly, Chapter Five (5) wraps up the report with a recap of the findings, limitations, and suggestions for future improvements.

# CHAPTER 2: LITERATURE REVIEW

# **2.1 Introduction**

The literature review section aims to offer a detailed summary of the current understanding and research concerning the creation of a classification system for age and gender using deep learning approaches. This section will investigate the historical development of classification systems, looking at early techniques that relied on manual feature extraction and conventional machine learning methods. It will also highlight key advancements in deep learning, especially the use of Convolutional Neural Networks (CNNs) and attention mechanisms for age and gender classification. Additionally, the section will pinpoint gaps and shortcomings in existing research, including concerns about dataset bias and ethical issues. Through a thorough analysis of the literature, this study intends to enhance existing knowledge and contribute to developing a precise and ethically sound age and gender classification system.

**2.2 Historical Overview**

The evolution of systems for classifying age and gender can be traced back to the beginnings of machine learning, when researchers primarily utilized manually crafted features and conventional statistical techniques. Early efforts in gender classification typically used simple classifiers like support vector machines (SVMs) and decision trees, which achieved limited accuracy due to the complex nature of human characteristics and the variability found in datasets. The advent of deep learning, especially convolutional neural networks (CNNs), brought about a significant transformation in this area. CNNs showed exceptional ability to automatically learn hierarchical features from raw data, resulting in substantial improvements in classification accuracy.

The pioneering research by Krizhevsky et al. (2012), which introduced AlexNet, highlighted the promise of deep learning for image classification tasks. This breakthrough spurred a surge of research aimed at utilizing deep learning architectures for a variety of applications, including age and gender classification. Later developments in network architectures, such as VGGNet and GoogLeNet, further advanced the field by creating deeper and more intricate models capable of identifying complex patterns in data. The introduction of residual networks (ResNets) by He et al. in 2015 was particularly significant, as it proved that deeper networks could deliver enhanced performance without encountering the vanishing gradient problem.

As deep learning methods gained popularity, researchers began to investigate their relevance to age and gender classification tasks. The creation of large-scale datasets, like the Adience dataset, offered a valuable asset for training and assessing classification models. This dataset, which consists of images of faces annotated with age and gender data, has become a standard for evaluating the efficacy of various algorithms. The shift from traditional machine learning techniques to deep learning frameworks has not only improved classification accuracy but has also broadened the range of applications, paving the way for multimodal approaches that combine multiple data sources.

**2.3 Related Work**

In recent years, there has been a tremendous interest in age and gender classification because, thanks largely to the use of deep learning techniques and the presence of large scale data, the task has become tractable. Researchers have looked at architecture, methodology and approach to increase accuracy and robustness of classification systems. This section reviews recent contributions to the field, with an emphasis on how methods differ and what implications they have for real world applications.

The work of Girsang and Nugraha (2022) offers an in-depth analysis of age classification utilizing deep learning techniques, with a particular emphasis on the facial images of cinema patrons. The research underscores the importance of automated systems for sorting individuals into age categories, essential for customizing content in an increasingly digital film environment. Through the use of various deep learning models and fine-tuning hyperparameters, the authors showcase substantial improvements in classification accuracy, thereby offering valuable contributions to the ongoing conversation about age and gender classification through deep learning methods.

The study by Ali and Angelov (2017) lays a crucial groundwork for creating age and gender classification systems utilizing deep learning methods, particularly in the context of analyzing human behavior. Their pioneering application of transfer learning and a pretrained deep convolutional neural network (CNN) for extracting features marks a notable enhancement in achieving high levels of classification accuracy, which is essential for use in security and surveillance settings. This research not only enhances the technical approaches within the field but also highlights the significance of reliable datasets, like GAFace, in improving the dependability of automated systems for identifying unusual behaviors based on demographic characteristics.

Another study by Abinaya et al. (2020) offers an in-depth analysis of age and gender classification through deep learning methods, particularly emphasizing the recognition of facial images. By using features from Local Binary Pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM), the authors present a strong approach for differentiating between various age categories and genders, utilizing advanced Convolutional Neural Networks (CNN) and its adaptations. This research not only adds to the biometrics field but also highlights the effectiveness of deep learning in improving identity recognition systems, thereby closely aligning with the aims of developing models for age and gender classification.

Wahlang et al. (2022) offers an in-depth examination of deep learning models aimed at classifying age and gender, highlighting how the integration of these demographic factors can improve accuracy in classification. By utilizing a range of models, such as Convolutional Neural Networks (CNNs) alongside traditional approaches like Support Vector Machines (SVM), the research demonstrates the potency of sophisticated deep learning methods in handling intricate data, thus providing valuable contributions to the domains of computer science and medical imaging.

Gupta & Nain (2022) presents an in-depth examination of both single and multi-attribute methods for estimating facial gender and age, emphasizing the importance of these technologies in areas such as consumer profiling and security. Their evaluation of traditional and deep learning techniques not only outlines the advantages and disadvantages of current models but also provides important insights for future research paths in age and gender classification. This foundational piece is essential for grasping the development and possible future innovations in deep learning techniques for demographic profiling.

Cole & Franke (2017) offers a thorough summary of the progress made in neuroimaging and deep learning techniques aimed at predicting brain age, a key factor in comprehending individual variations in the aging process of the brain. By highlighting the capability of deep learning methods to reveal intricate connections within extensive datasets, this research contributes to the creation of classification systems for age and gender that utilize similar computational strategies. Moreover, the examination of multimodal neuroimaging underscores the significance of merging various data sources, which is vital for improving the accuracy and dependability of models used for age and gender classification.

The study by Agbo-Ajala and Viriri (2020) offers an in-depth analysis of progress in age and gender classification through deep learning methods, particularly Convolutional Neural Networks (CNNs). The authors point out the drawbacks of conventional techniques when it comes to processing the complexities of raw facial images and introduce an innovative two-level CNN architecture that significantly improves classification accuracy. Their experimental findings reveal a substantial enhancement compared to earlier benchmarks, highlighting the effectiveness of deep learning strategies in practical applications of facial analysis.

The research conducted by Rothe et al. in 2016 makes a significant contribution to age and gender classification by presenting an innovative deep learning framework that estimates both actual and perceived age from facial images without depending on facial landmarks. Their creation of the IMDB-WIKI dataset, the largest publicly accessible dataset for this area, improves the availability of labeled data crucial for training effective convolutional neural networks (CNNs), specifically using the VGG-16 architecture. This study not only tackles the enduring problem of age estimation but also leads the way in investigating apparent age, thus broadening the potential applications of deep learning in facial analysis.

The work by Hassan et al. (2023) offers an extensive review of how deep learning algorithms can be utilized to estimate biological traits such as age and gender through the examination of fundus images. This research emphasizes the proficiency of cutting-edge DL techniques in providing precise classifications, thus enriching the larger conversation surrounding the convergence of computer vision and biological trait assessment. By concentrating on retinal imagery, the authors highlight the potential of deep learning to improve diagnostic capabilities in medical imaging, which is essential for creating reliable systems for age and gender classification.

The study by Kwaśny & Hemmerling (2021) offers an in-depth investigation of the techniques used for estimating gender and age through speech analysis, emphasizing the efficacy of Deep Neural Networks (DNNs) in these applications. Their analysis of x-vector and d-vector frameworks highlights the capabilities of advanced neural network architectures to extract detailed features from speech signals, thus improving the precision of classification systems. This research makes a notable contribution to the field of age and gender classification by illustrating how DNNs can effectively process complex auditory information for demographic assessment.

Another work by Inácio et al. (2021) extensively investigates the use of deep learning techniques for classifying age and gender through video analysis. The authors present a strong framework that combines face detection and tracking with cutting-edge neural network models, specifically EfficientNet, to improve the precision of demographic classification in real-time applications. Their research highlights the capability of deep learning methods to tackle issues related to people counting, particularly in situations prompted by public health challenges, thus making a significant contribution to the conversation on automated demographic assessment in surveillance systems.

The work by Benkaddour (2021) offers an in-depth analysis of how convolutional neural networks (CNN) can be utilized for classifying age and gender, emphasizing the notable progress made through deep learning methods. By concentrating on the automated extraction of features from facial images, the research shows that CNNs can surpass traditional approaches, thus highlighting the revolutionary influence of deep learning in computer vision and pattern recognition. This study represents a crucial addition to the existing literature, showcasing the effectiveness of CNNs in improving the precision of demographic predictions from visual data.

**Challenges in Age and Gender Classification**

Despite the advancements in deep learning, age and gender classification systems still face several challenges:

1. Dataset Bias: Unfortunately, many of the data has been biased towards certain ethnicities, age groups, and genders and as a result the models perform poorly on underrepresented groups. To address bias, additional training data needs to be more diverse and algorithms that stabilize bias created must be developed.
2. Uncontrolled Environments: Real world images are often contentious and include occlusions (such as sunglasses or hats), varying lighting conditions, or variable facial poses. CNNs are better than traditional methods at handling these variations, but in the extremes, CNNs fail.
3. Age Estimation Complexity: Age is more difficult to predict than gender, because age is continuous and facel features overlap widely with age. One model, a 25 year old or a 30 year old may not look that different, so it’s hard to estimate a person’s age to a fine granularity.
4. Privacy and Ethical Concerns: Controversially, age and gender classification systems deteriorate privacy as well as make it possible to misuse public surveillance and marketing. These systems need ethical guidelines in their usage.

**2.4 Comparative Analysis**

| **Authors** | **Methodology** | **Strength** | **Weakness** |
| --- | --- | --- | --- |
| Levi & Hassner (2015) | | CNN architecture for age and gender classification | | --- | | |  | | --- |  | High accuracy; established baseline for CNNs. | | --- |  |  | | --- | | | Limited to specific datasets; requires more diversity. | | --- | |
| Rothe et al. (2018) | Transfer learning on IMDB-WIKI dataset | Large dataset; robust model performance. | May not generalize well to other contexts. |
| Kumar et al. (2021) | Dual attention mechanism with CNN | Improved accuracy through attention mechanisms. | Complex architecture may require extensive training. |
| Chen et al. (2019) | Enhanced Deep Residual Network | Architectural innovations enhance performance. | Potential overfitting; requires careful validation. |
| Yin et al. (2021) | EfficientNet with transfer learning | Efficient model with low computational cost. | Dependence on large labeled datasets. |
| Gonzalez et al. (2020) | Multi-branch CNN for facial region analysis | Focus on critical facial regions improves results. | Requires significant computational resources. |
| Girsang & Nugraha (2022) | Deep learning for moviegoer age classification | Addresses content personalization in digital media. | Limited scope beyond the film industry. |
| Zhang et al. (2021) | Spatial and channel attention in CNN | Dynamic focus on salient features enhances accuracy. | Complexity may hinder real-time applications. |
| Li et al. (2022) | Multi-task learning for age, gender, and ethnicity | Joint learning improves model generalization. | May lead to model bias without diverse data. |
| Gao et al. (2023) | Multi-task learning for age, gender, and emotion | Comprehensive analysis of multiple attributes. | Requires large-scale data for effectiveness. |
| Takahashi et al. (2020) | Transfer learning with VGGFace | Utilizes existing models effectively. | Potential for overfitting without regularization. |
| Binns et al. (2020) | Bias analysis in datasets | Identifies significant dataset biases. | Needs comprehensive evaluation of biases. |
| Barocas & Selbst (2016) | Fairness in machine learning | Advocates for ethical AI deployment. | Ethical considerations often overlooked. |

**2.4 Summary**

The advancement of age and gender classification systems through deep learning is a vibrant and fast-developing area. The shift from conventional machine learning methods to deep learning frameworks has greatly improved classification precision and expanded application possibilities. As researchers delve into innovative architectures, multimodal strategies, and transfer learning methods, the opportunities for further progress in this field appear encouraging.

In summary, the review of existing literature highlights the critical role of deep learning in transforming age and gender classification. Future studies should aim to optimize algorithms, broaden datasets, and consider ethical issues related to the use of biometric information. As this area continues to progress, the incorporation of deep learning techniques will certainly be pivotal in defining the future of age and gender classification systems.

In the next chapter, we will discuss the exact needs and design concern in developing an age and gender classification system using deep learning.

## 

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