RESEARCH ARTICLE

RSP Science Hub

International Research Journal on Advanced Science Hub
2582-4376
www.rspsciencehub.com
Vol. 07, Issue 02 February

Check for updates

http://dx.doi.org/10.47392/IRJASH.2025.012

Real-Time Gender and Age Detection Using Visual and Vocal Cues

Malavika.M [1], *Afrin Dinusha.J* [2], *Mr. Shenbagharaman A* [3], *Dr. B. Shunmugapriya* [4]

[1,2]*Student, Dept of Computer Science and Engineering, National Engineering College, Kovilpatti, India.*

[3]*Assistant Professor, Dept of Computer Science and Engineering, National Engineering College Kovilpatti, India.*

[4]*Assistant Professor (Sr. grade) Dept of Computer Science and Engineering National Engineering College, Kovilpatti, India.*

Emails: *sraman@nec.edu.in*[1], *2112067@nec.edu.in*[2], *2112049@nec.edu.in*[3], *bsp@nec.edu.in*[4]

Article history

Received: 27 January 2025
Accepted: 05 February 2025
Published: 22 February 2025

Keywords:

Real-time webcam feeds, Face detection ,Speech features, Deep Neural Network (DNNs), Convolutional Neural Networks (CNNs), OpenCV.

Abstract

This study describes a comprehensive multi-modal system that uses voice signals, real-time webcam feeds, and facial photos as three different input modalities for gender and age detection. Convolutional Neural Networks (CNNs) are used for image-based detection in order to extract face traits, categorize gender, and estimate age. For face detection and picture pre-processing, Open CV is included, guaranteeing that the model can handle a range of lighting situations, facial expressions, and occlusions. Deep Neural Networks (DNNs) are used in voice-based identification to evaluate speech features including pitch, tone, and rhythm, which serve as important markers of age and gender. Because it was trained on a wide range of voice sample datasets, the system is resilient to variations in ambient noise, accents, and languages. The webcam-based input continually detects gender and estimates age from live facial data using a real-time processing pipeline that combines CNN and video stream analysis. This results in dynamic and accurate findings even in difficult circumstances. Every modality is intended to work in concert with the others to provide a flexible and adaptable solution. A thorough evaluation of the system's performance reveals great accuracy for each of the three input types. This multi-input architecture is a flexible tool with real-world applications that could be used in a variety of industries, such as security, tailored marketing, human- computer interaction, and assistive technology for people with impairments. Subsequent research endeavours will centre on including other modalities, like behavioural inputs, and optimizing the model to achieve even quicker processing speeds. The integration of different inputs allows the system to be highly adaptive and expandable, delivering personalized user experiences. To provide a more complete picture of users, the suggested framework can potentially be expanded to include additional demographic predictions, like ethnicity and emotion recognition. This work is an important advancement in the disciplines of artificial intelligence (AI) and human-computer interaction because it helps to build intelligent systems that can function effectively in real-time, multi-environment settings.

1. Introduction

Modern artificial intelligence (AI) systems must be able to determine gender and age. These systems are essential for many applications, including security, personalized services, and human-computer interaction. Advances in artificial intelligence and deep learning have made it possible to use more sophisticated multimodal techniques. Traditionally, methods have mostly concentrated on single-modal inputs, such as facial photographs. This work presents an integrated system for age and gender detection that combines spoken signals, real-time camera feeds, and facial photos. The system is able to extract and combine diverse information from these various inputs by employing Convolutional Neural Networks (CNNs) for image-based classification and Deep Neural Networks (DNNs) for voice-based analysis. While OpenCV is utilized for efficient image processing and face detection, real-time video stream analysis allows for the real-time prediction of gender and age. Incorporating these modalities strengthens the system against variations in speech characteristics, facial traits, and environmental conditions while increasing its accuracy and adaptability. This integrated approach not only provides a more thorough understanding of user demographics, but it also opens up new possibilities in areas like security, targeted marketing, and assistive technologies. Additionally, the system can utilize the benefits of each modality to compensate for the limitations of the other by integrating several inputs. For example, in low-light conditions, voice input can still provide precise information. This multi-modal framework creates more accurate and responsive models by surpassing the capabilities of traditional AI systems.

2. Related Works

[1] In order to improve applications in security, surveillance, and social media, the project investigates deep learning methods for age and gender detection using facial photos. Accurate predictions are the goal. [2] Using a large labeled dataset, the study creates a CNN-based method for autonomous age and gender prediction from facial photos, focusing on precise estimation and effective feature learning. [3] With an emphasis on deep learning, data fusion, and bias reduction, this article examines several age and gender detection methods. Important conclusions emphasize CNN's accuracy, with the goal of enhancing detection systems' precision and impartiality. [4] With an emphasis on accuracy and data analysis, this research uses deep learning techniques to construct an age and gender detector. The objective is to monitor and assess performance outcomes in order to improve everyday applications. [5] This study proposes a CNN model for multi-label gender and age estimation, achieving 84.20% accuracy for gender and 57.60% for age, with a focus on visualizing key facial landmarks for clarity. [6] The investigation develops a DCNN-based approach for gender and age prediction, including third gender classification, achieving 96.2% accuracy. The focus is on improving machine learning's reliability in facial recognition tasks. [7] This system leverages surveys age and gender prediction from facial images, emphasizing computer vision techniques. Key findings indicate that facial features provide significant data for enhancing prediction accuracy across various approaches. [8] This work introduces a CNN-based mathematical approach for age and gender prediction from facial images, achieving high accuracy with over 20,000 annotated images, emphasizing minimal pre-processing and effective feaure extraction [9] By optimizing an existing model trained on the UTKFace dataset, this study presents a DCNN- based method for age and gender detection that outperforms conventional techniques in terms of accuracy and efficiency. [10] In order to improve face recognition technology for use in forensics and security, this article examines the classification of age and gender in facial photos using deep CNNs and transfer learning, assessing several architectures. [11] A hybrid classical-quantum neural network-based quantum machine learning method for gender classification is presented in this investigation. It surpasses previous performance standards and shows better accuracy on face image datasets. [12] This system uses convolutional neural networks to estimate age and predict gender. It validates three different architectures on the IMDB and WIKI datasets, showing notable gains in accuracy and performance. [13] This work introduces recent advancements in gender and age prediction using deep learning and computer vision, discussing ethical concerns, challenges, and future research directions to enhance transparency and address data bias. 14] This study uses VGG16 and attention

mechanisms to offer a deep learning method for multimodal age, gender, and ethnicity recognition, which achieves 82% accuracy for age, 95.31% for gender, and 98.44% for race.[15] This approach develops a real-time system using convolutional neural networks to detect faces, classify genders, and predict ages from live camera streams, achieving 85% accuracy for security and age restriction applications.[16] This research aims to generate automatic image captions using a dense attention model combining CNN and RNN, achieving an average BLEU score of 51.77 for improved image annotation. [17] The project implements gender and age group acoustical models' performance on unrelated audio data, aiming to enhance early predator detection in minors' chats, primarily using English-speaking datasets. [18] The goal of this project is to create an algorithm that can effectively identify age and gender from facial photos utilizing HAAR cascade and deep convolutional neural networks, even with sparse input. [19] This system leverages a novel technique for classifying speaker attributes such as age, gender, and emotion. Accuracy rates for age and gender classification are 79.57% and 93.26%, respectively, while emotion detection is 98%.[20] This research focuses on developing an age and gender recognition system using deep learning by detecting faces, preprocessing images, and extracting features, emphasizing the importance of facial characteristics in various applications.[21] This study develops a gender and age classification framework using Deep Belief Networks and Shifted Filter Responses, achieving 98% and 99% accuracy, highlighting the challenges of automatic gender identification from facial images.[22] This work proposes a deep learning algorithm for age group and gender detection from face images, achieving 91-99% accuracy for gender and 58-85% for age across benchmark datasets.[23] This novel approach explores gender estimation based on human gait using Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), aiming for high accuracy and low computational cost through various architectures and hyperparameters. [24] This investigation presents a lightweight deep CNN model for real-time age and gender prediction, achieving 48.59% accuracy for age and 80.76% for gender using a diverse dataset of 18,728 images.[25] This paper proposes a motion detection technique for CCTV data storage, utilizing Haar cascades for face detection and Inception V3 for gender classification, achieving 97.4% accuracy in real- time predictions.[26] This novel approach introduces a balanced face image dataset with 108,501 images across seven race groups, improving classification accuracy for diverse races and demonstrating consistent performance across gender and age in face analytics.[27] This work presents a multi-layer, multi-channel attentive network for gender and age recognition, achieving higher accuracy than mainstream models while reducing size to under 0.5 m, making it suitable for mobile applications. [28] This system leverages ECA-EfficientNetB4, improving age estimation and gender recognition accuracy with an MAE of 4.55 years and 93.62% accuracy, leveraging the ECA attention mechanism and cross-entropy loss function. [29] This study explores age and gender determination from facial portraits using pre-trained CNN models (VGG16, ResNet50, SE-ResNet50), providing benchmarks and best practices for effective feature extraction on the VGGFace2 dataset. [30] This approach investigates deep learning models ResNet152V2 and VGG16 for age and gender prediction from facial images, achieving 89.84% accuracy by integrating both models into a unified predictive framework.

2.1. Redesigned CNN for Gender and Age Detection

The proposed age and gender identification model, which leverages CNN architectures and OpenCV's robust detection and classification powers, is examined in this article. The model's tuning, picture augmentation, and improved processing techniques are among the enhancements. The success of the model is assessed using real-time video and image inputs.

2.2. CNN

Convolutional neural networks (CNN) are crucial for detecting gender and age from images and audio data. CNNs excel at automatically extracting relevant features, such as facial characteristics in images and frequency patterns in audio. The architecture consists of convolutional layers that identify local patterns, enabling the model to recognize edges, textures, and facial features. Additionally, pooling layers reduce the spatial dimensions of the data, enhancing computational efficiency while retaining essential information, Figure 1 shows Structure of CNN.

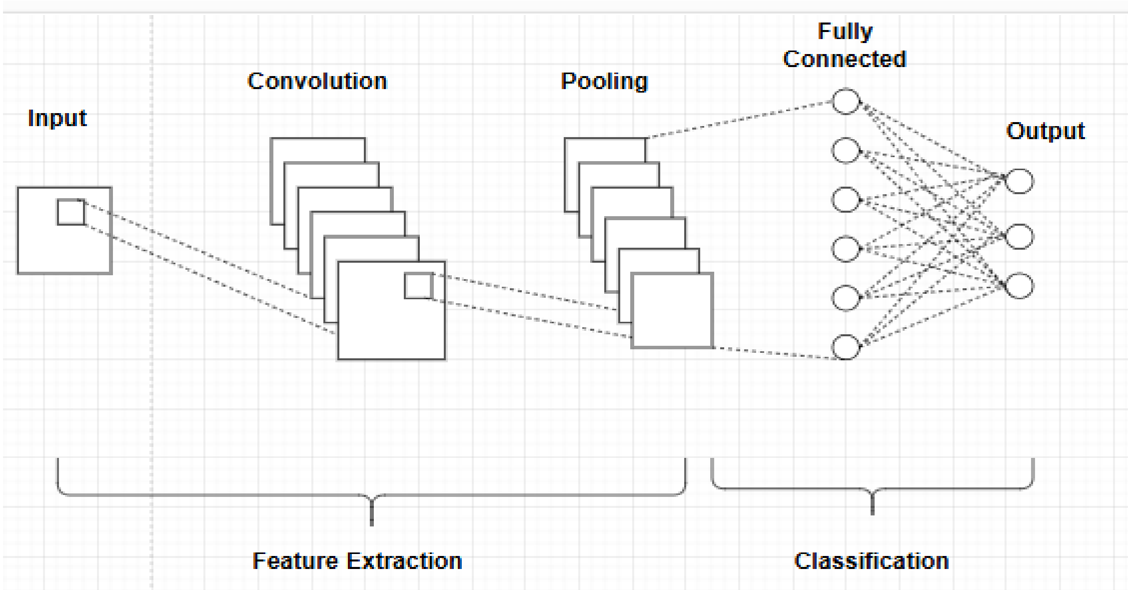

Figure 1 Structure of CNN

3. Proposed Work

3.1. Architectural Diagram

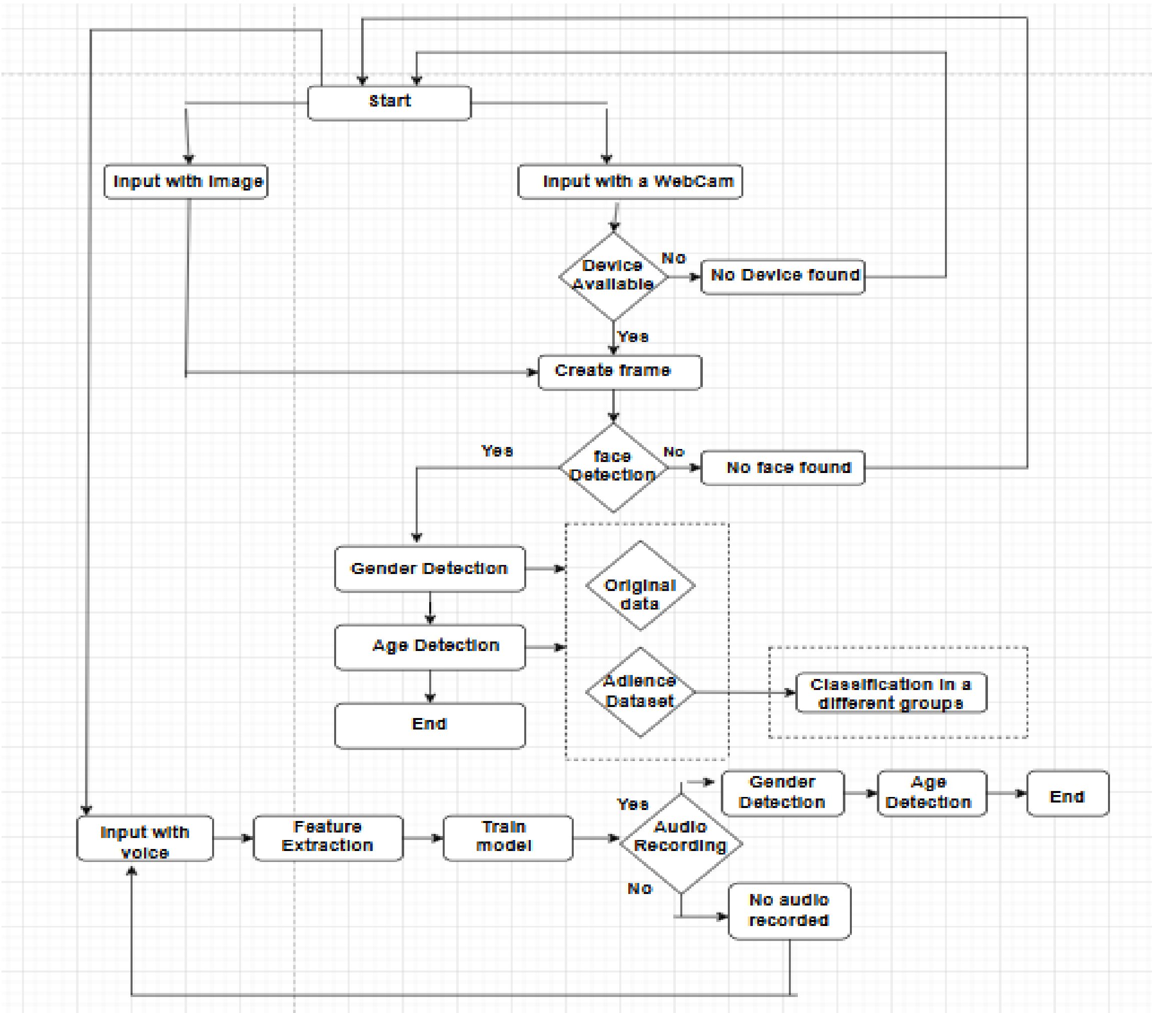

Figure 2 Visual Representation

3.2. Proposed Methodology

Three major modules comprise the proposed system for age and gender detection: voice-based, image-based, and webcam-based real-time input. For the purpose of feature extraction and classification, each module makes use of convolutional neural networks (CNNs), which are tailored to handle the particular type of input data (audio or image). The implementation details and architecture for each module are explained below:

3.2.1. Image-Based Input Module

In this module, the system takes facial images as input to predict gender and age. A CNN model trained on the Adience dataset—which includes photos labeled with gender (male/female) and age (in ranges like 0-2, 4-6, etc.) is applied to the preprocessed input images. Multiple convolutional layers, pooling layers, and a fully linked layer for classification make up the CNN architecture.

3.2.2. Input Image Pre-Processing

The model's performance is enhanced by normalizing and resizing the input photos to a specific resolution (such as 256x256). The application of data augmentation techniques, including brightness alteration, flipping, and rotation, improves generalization.

3.2.3. Model Architecture

Input Layer: Receives the input image, which is preprocessed (resized to 64x64 pixels, converted to grayscale, and normalized).

Convolutional Layers: Several convolutional layers are applied to extract features such as edges, textures, and patterns from the input imagesThere is a ReLU activation function after each layer.

Pooling Layers: Following convolutional layers, max- pooling layers are employed to downsample the input while maintaining important information by reducing the spatial dimensions of the feature maps.

Fully Connected Layer: The feature maps are flattened and sent to a fully connected (dense) layer following a number of convolutional and pooling processes.

Output Layer: The image is classified into one of the preset age and gender groups using a softmax activation function.

3.2.4. Model Training and Testing

Training data made up 80% of the dataset, while testing data made up 20%. Horizontal flipping and random cropping are two data augmentation strategies that were used to increase the model's generalization. Figure 3 Image Based Input Module Output

3.3. Output

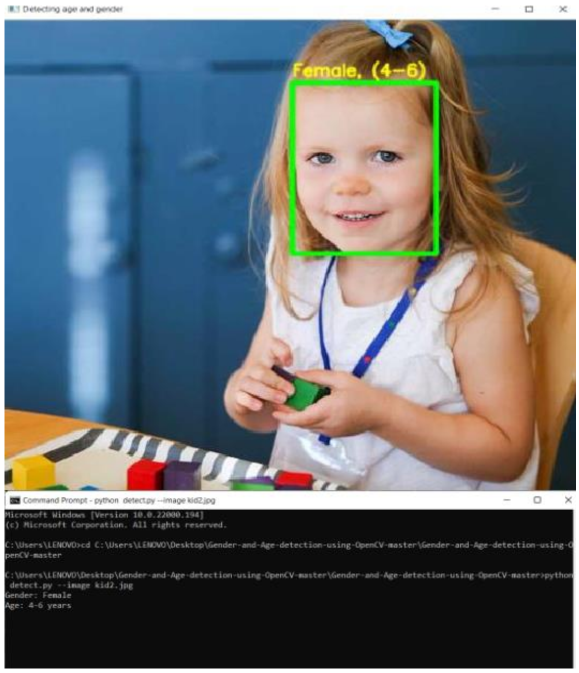

Figure 3 Image Based Input Module Output

3.4. Webcam-based Real-time Input Module

The second module is a real-time gender and age classification system implemented using OpenCV for face detection and the pre-trained CNN model from the image- based module for classification. This system captures input from the webcam and applies the trained CNN model to classify the face in real-time.

3.4.1. Face Detection

We used OpenCV's Haar Cascade Classifier to detect faces in real-time from the webcam feed. The Haar Cascade model quickly detects and localizes facial regions.

3.4.2. Pre-Processing

Once a face is detected, the region of interest (ROI) is cropped, resized to 64x64 pixels, and passed through the same preprocessing pipeline (grayscale conversion and normalization) as in the image-based module.

3.4.3. Real Time Prediction

The preprocessed ROI is passed through the pre-trained CNN model, which outputs the predicted gender and age class. Figure 4 shows Real Time Webcam Based Input Module Output, Figure 5 shows Real Time Voice Based Input Module Output

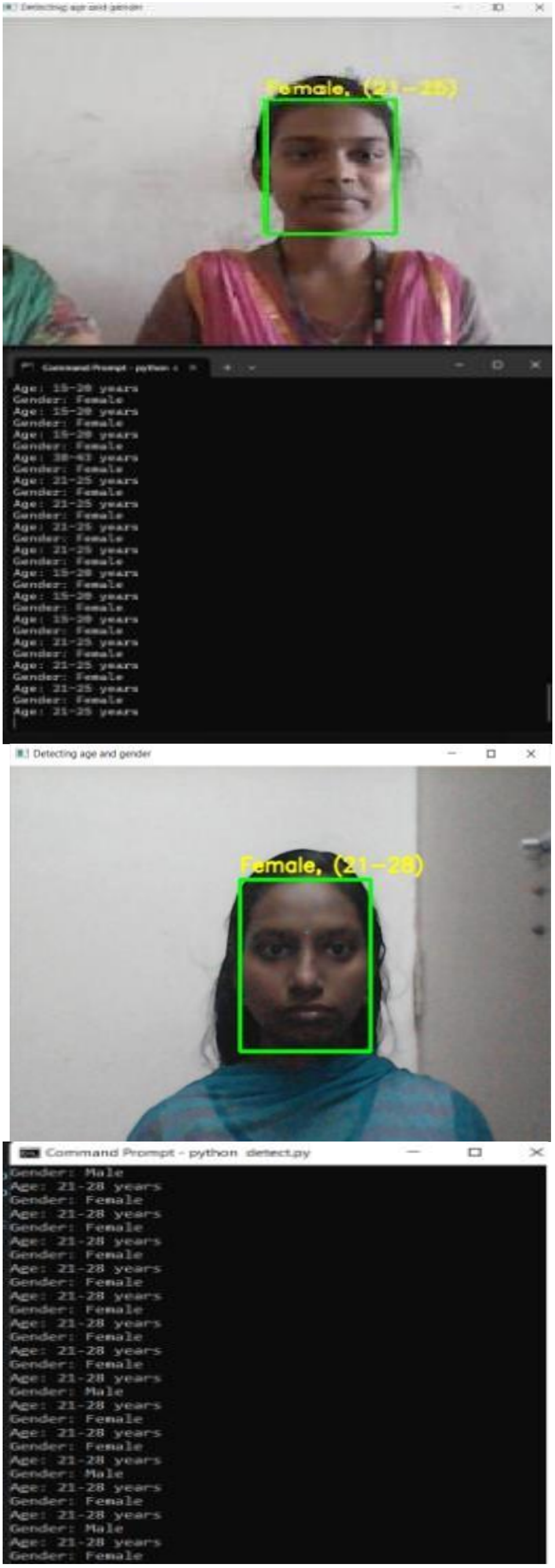

Figure 4 Real Time Webcam Based Input Module Output

3.5. Voice-Based Input

The third module of the system focuses on gender and age detection from audio inputs. We leveraged statistical features extracted from the Mozilla Common Voice dataset to train a CNN-based model that predicts gender and age from speech.

3.5.1. Pre-Processing

The Mozilla Common Voice dataset consists of audio samples labelled with gender and age. From these audio samples, we extracted statistical features such as MFCCs (mel frequency cépstral coefficients), pitch, and spectral contrast. The extracted features were organized into a feature matrix, which serves as input to the CNN model.

3.5.2. CNN Architecture

Convolutional Layers: These layers apply filters to the feature matrix, learning patterns that correspond to gender and age cues in speech. Pooling Layers: Max-pooling is applied to down sample the feature maps. Fully Connected Layer: The convolutional layers' output is compressed and routed through thick layers.

3.5.3. Model Training

Training data made up 70% of the dataset, while testing data made up 30%. Using the Adam optimizer and categorical cross- entropy as the loss function, the CNN model was trained.

3.5.4. Real Time Prediction

For real-time voice input, the system records speech using a microphone, pre-processes the audio to extract the necessary features (MFCCs), and feeds them into the trained model for prediction.

3.6. Output

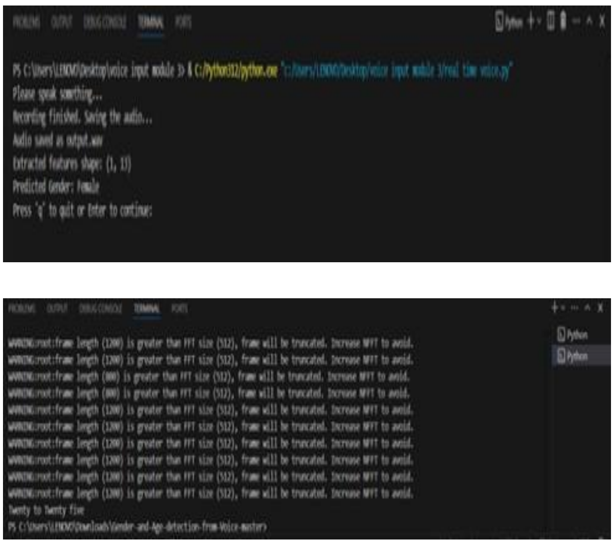

Figure 5 Real Time Voice Based Input Module Output

After the model has been developed, its performance is assessed using the validation and test sets.

4. Important Metrics Consist of

Numerous evaluation criteria, including accuracy, precision, recall, and F1 score, were used to gauge the models' performance. The proportion of predictions that the model properly classifies is known as accuracy. Important metrics that evaluate the model's performance in several categories are precision, recall, and F1-score. A confusion matrix shows the model's classification findings in detail, pointing out regions where it works well and pointing out possible misclassifications. Table 1 shows Classifications

Table 1 Classifications

Model	Accuracy	Precision	Recall	F1 Score
CNN (Gender Images)	94.6%	93.5%	94.2%	93.8%
CNN (Age - Images)	82.4%	80.0%	81.5%	80.7%
CNN (Gender - Voice)	92.0%	91.0%	92.5%	91.7%
CNN (Age - Voice)	75.3%	74.5%	75.0%	74.7%

5. Utilization

The age and gender detection models that have been trained are made to be included in real-time systems for a variety of uses. These models can be applied in a variety of sectors where demographic data and tailored experiences are crucial, such as retail, security, and customer service. The models in real-time systems are implemented in software platforms that can interpret real-time data via voice input, camera feeds, or photographs.

6. Dataset

To build an accurate gender and age detection system, we carefully prepared and structured our dataset. The data was divided into training, validation, and testing sets to make sure the models were tested on unseen data and could generalize well. We used the Adience dataset for detecting gender and age from images and the Mozilla Common Voice dataset for predicting the same from audio inputs. Before feeding the data into the models, we performed preprocessing steps to improve the quality. For images, this included enhancing resolution, resizing them to a standard size, and normalizing the pixel values. For audio, we cleaned and standardized the sound quality. These steps were essential to ensure consistency across all inputs and avoid overfitting, which happens when models perform well on training data but fail with new data For feature extraction, we used Convolutional Neural Networks (CNNs), specifically models like VGG and ResNet, which are known for their strong performance in image tasks. We also leveraged transfer learning to improve accuracy, allowing our models to benefit from the knowledge gained in other tasks. The models were trained using the cross-entropy loss function, which is ideal for classification problems, and we used optimization algorithms such as Adam and SGD to fine-tune the model parameters.

Conclusion

In summary, the development of a reliable gender and age detection model leveraging advanced machine learning techniques has significantly enhanced our understanding of human demographics through both visual and auditory inputs. This system underscores the importance of accurately predicting gender and age to facilitate personalized interactions in various applications, such as marketing, security, and social services. By employing convolutional neural networks (CNNs) for both image and voice data, our approach achieves the necessary speed and precision for real-time analysis, adapting seamlessly to diverse input conditions. Applications that need demographic information could see an improvement in user experience and operational efficiency if these approaches are successfully integrated.This study demonstrates how utilizing state-of-the-art advancements in machine learning and audio-visual processing can drive transformative changes in the way demographic data is collected and analyzed. The development, evaluation, and refinement of the detection models were streamlined through the use of high-level neural network APIs, ensuring a swift and effective deployment process. Ultimately, our project aims to push the boundaries of gender and age detection technologies, highlighting the critical role of innovation in enhancing societal understanding and interaction.

References

[1]. Saxena, P. Singh, and S. Narayan Singh, Gender and Age Detection Using Deep Learning," 2021 11th International Conference on Cloud Computing, Data

Science & Engineering (Confluence), Noida, India, 2021,pp. 719-724.

[2]. R. Singla and G. Singh, “Age and Gender Detection using Deep Learning,”; 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA), Pune, India, 2023, pp. 1-6

[3]. K. Deepanshi, K. Gupta and R. Sendhil, “Review on Age and Gender Detection: Diverse approach and Algorithmic Insights,” 2023 6th International Conference on Recent Trends in Advance Computing (ICRTAC), Chennai, India,2023, pp. 672-677

[4]. G. Priyanka, K. N. Latha, P. S. Prakash and K. Madhavi, “Gender and Age Prediction Using Deep Learning,” 2022 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), Bhubaneswar, India, 2022, pp. 1-6

[5]. R. Thaneeshan, K. Thanikasalam and A. Pinidiyaarachchi, “Gender and Age Estimation From Facial Images using Deep Learning,” 2022 7th International Conference on Information Technology Research (ICITR), Moratuwa, Sri Lanka, 2022, pp. 1-6

[6]. N. Shanthi, P. Yuvasri, S. Vaishnavi and P. Vidhya, "Gender and Age Detection using Deep Convolutional Neural Networks," 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2022, pp. 951-956

[7]. J. S. Hiremath, S. B. Patil and P. S. Patil, "Human Age and Gender Prediction using Machine Learning Algorithm," 2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkur, Karnataka, India, 2021, pp. 1-5

[8]. A. Ghildiyal, S. Sharma, I. Verma, and U. Marhatta, "Age and Gender Predictions Using Artificial Intelligence Algorithms," 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS), Thoothukudi, India, 2020, pp. 371-375.

[9]. T. P. Kancharlapalli and P. Dwivedi, "A Novel Approach for Age and Gender Detection using Deep Convolution Neural Network," 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2023, pp. 873-878

[10]. S. Naaz, H. Pandey, and C. Lakshmi, "Deep learning- based age and gender detection using facial images," 2024 International Conference on Advances in Computing, Communication, and Applied Informatics (ACCAI), Chennai, India, 2024, pp. 1-11.

[11]. M. Praveena, K. G. Srinija, and A. Meghana, "Perception of Age and Gender Detection by Using Hierarchical Deep Learning Architecture through Vision," 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2022, pp. 133-140.

[12]. M. K. Benkaddour, S. Lahlali, and M. Trabelsi, "Human Age and Gender Classification using Convolutional Neural Network," 2020 2nd International Workshop on Human- Centric Smart Environments for Health and Well-Being (IHSH), Boumerdes, Algeria, 2021, pp. 215-220.

[13]. K. Verma, S. Shah, S. Gupta, and S. Roy, "Age and Gender Prediction using Deep Learning Framework," 2023 5th International Conference on Advances in Computing, Communication Control, and Networking (ICAC3N), Greater Noida, India, 2023, pp. 613-617.

[14]. M. Ragul and S. Veluchamy, "Deep Transfer Learning Empowered Facial Features Based on Age, Gender, and Ethnicity Prediction System," 2024 5th International Conference on Innovative Trends in Information Technology (ICITIIT), Kottayam, India, 2024, pp. 1-6

[15]. A. Mustafa and K. Meehan, "Gender Classification and Age Prediction using CNN and ResNet in Real-Time," 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI), Sakheer, Bahrain, 2020, pp. 1-6.

[16]. B. Jain, K. Doshi, and P. Dwivedi, "Hybrid CNN-RNN Model for Accurate Image Captioning with Age and Gender

Detection," 2023 2nd International Conference on Automation, Computing, and Renewable Systems (ICACRS), Pudukkottai, India, 2023, pp. 568-573.

[17]. R. Haluška, M. Popovič, M. Pleva, and M. Frohman, "Detection of Gender and Age Category from Speech," 2023 World Symposium on Digital Intelligence for Systems and Machines (DISA), Košice, Slovakia, 2023, pp. 72-77.

[18]. D. D. Prasad, K. V. Subba Rami Reddy, N. Akash, K. Dakshayani, N. Jessica, and C. R. Krishna, "Identification of Gender and Age using Classification and Convolutional Networks," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 1-6.

[19]. Y. Karbhari, V. Patil, P. Shinde, and S. Kamble, "Age, Gender, and Emotion Recognition by Speech Spectrograms Using Feature Learning," 2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 2023, pp. 466-44.

[20]. A.R. S. and V. R. V., "Age & Gender Recognition Using Deep Learning," 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT), Kannur, India, 2022, pp. 386-390.

[21]. M. Patel and U. Singh, "Age and Gender Recognition using Deep Learning Technique," 2023 3rd International Conference on Smart Data Intelligence (ICSMDI), Trichy, India, 2023, pp. 238-245

[22]. Z. Khan, M. A. Khan, A. Wahab, and U. Musharaf, "GADNN: Gender and Age Detector Neural Network," 2023, 18th International Conference on Emerging Technologies (ICET), Peshawar, Pakistan, 2023, pp. 299-304.

[23]. A.R. S. Alrashed and T. Inan, "Age And Gender Detection By Face Segmentation And Modefied CNN Algorithm," 2023 5th International Congress on Human-Computer Interaction, Optimization, and Robotic Applications (HORA), Istanbul, Turkiye, 2023, pp. 1-7.

[24]. M. N. Islam Opu, T. K. Koly, A. Das, and A. Dey, "A Lightweight Deep Convolutional Neural Network Model for Real-Time Age and Gender Prediction," 2020 Third International Conference on Advances in Electronics, Computers, and Communications (ICAECC), Bengaluru, India, 2020, pp. 1-6.

[25]. R. Thangaraj, P. Pandiyan, T. Pavithra, V. K. Manavalasundaram, R. Sivaramakrishnan, and V. K. Kaliappan, "Deep learning-based real-time face detection and gender classification using OpenCV and Inception v3," 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing, and Automation (ICAECA), Coimbatore, India, 2021, pp. 1-5

[26]. K. Kärkkäinen and J. Joo, "FairFace: Face Attribute Dataset for Balanced Race, Gender, and Age for Bias Measurement and Mitigation," 2021 IEEE Winter Conference on Applications of Computer Vision (WACV), Waikoloa, HI, USA, 2021, pp. 1547-1557

[27]. J. Chen, H. Yu, and Y. Kang, "A Multi-Layer Multi- Channel Attentive Network for Gender and Age Recognition," ICASSP 2021—2021 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Toronto, ON, Canada, 2021, pp. 4135-4139.

[28]. X. Shi, G. Chen, J. Kan, F. Dong, and K. Chen, "A New Try for Age Estimation and Gender Recognition Based on EfficientNetB4," 2023 2nd International Conference on Computing, Communication, Perception, and Quantum Technology (CCPQT), Xiamen, China, 2023, pp. 216-221.

[29]. B. S. Chowdary, V. N. Subhadra, and S. Kavitha, "Age and Gender Detection to Detect the Manipulated Images Using CNN," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 1187-1192.

[30]. S. Prasher, L. Nelson, and D. Arumugam, "Deep Learning Models for Age and Gender Prediction Using Facial Images," 2024 5th International Conference for Emerging Technology (INCET), Belgaum, India, 2024, pp. 1-5.