A CNN Approach for Real-Time Age Detection in Public Spaces and Restricted Zones

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Abstract:

This paper reports on a real-time age detection system based on Convolutional Neural Networks, to address a critical need in public and restricted areas for age verification. It focuses on detecting minors in a real-time manner and provides an efficient solution to businesses and authorities. This means that for calculation of the age of a subject, the system will use pre-trained models on camera feeds or image files to detect the face and the estimation of age. The face-detection component will use OpenCV Deep Neural Network to provide a fast and efficient method of face localization. This process uses the existing model based on CNN, hence producing a coarse estimation of age for the age group they belong to. When it estimates an age below or equal to the predefined threshold, then the system dictates that this individual is a minor and captures the timestamped picture. The system is deployed with Python and OpenCV, and a Tkinter-based User Interface for user interaction. This technology impacts very significantly, allowing the increase in security at an establishment that ranges from theatres to wine shops, further urging people toward greater compliance with all legal regulation and other possible application areas in respect of an important contribution for a real application field in respect to automated age verification.

Keywords: *Real-time age detection, CNNs, automated age verification, minor identification, face detection, age estimation, OpenCV, deep learning, public spaces, restricted zones, security, compliance, image processing, computer vision.*

1. Introduction:

Safeguarding minors, legal enforcement, and public safety in the globalized world of today require accurate age verification. It's in such aspects as limiting accessibility to age-sensitive content on the Internet, regulating the use of age-restricted products and services, and many others in physical settings, that the correct and expedient determination of a person's age becomes critical. Traditional methods for age verification based on manual scrutiny of identification papers are often long, invasive, and prone to human error. Moreover, such methods are easily compromised through fraudulent or borrowed identification. Thus, such systems require design for automated robust age detection capabilities operating in real-time, in particular in dynamically changing environments. It discusses a new real-time age detection approach using the power of deep learning, especially the Convolutional Neural Network technique, that has revolutionized computer vision.

Digital technologies and access to surveillance systems have now created new avenues for automated age verification. Think about the businesses that operate in industries with age restrictions, like selling alcohol or tobacco. Manual age checks can be synonymous with long queues, frustration to customers, and worse still, confrontation. In the entertainment quarters, where theaters and nightclubs are, only strict vigilance will ensure adherence to the age restrictions. Age verification can also be essential, like in areas that are sensitive to security, including air fields and government buildings. In each of these instances, a real-time age detection system would be most efficient.

The system designed here discusses development and implementation for a real-time age detection system to be able to challenge the above issues. It aims at harnessing the full energy of CNN to analyse facial characteristics and produce proper estimation of how old someone would be. It has gained the reputation for quite outstanding performances especially in recognition, classification tasks regarding images including recognizing faces and approximating the person's age. Their capability to learn complex patterns from large datasets makes them very well-suited for this task. The proposed system uses a two-stage approach: in the first stage, a pre-trained model on face detection identifies and isolates faces within a frame captured from a camera or image file. In the second stage, a pre-trained model on age estimation analyses the facial features extracted to predict the age range of the individual. It helps to leverage knowledge learned from very large datasets. The amount of training and consequently the amount of computational resources could be significantly minimized. This approach will be able to attain rapid deployment and efficient real-time processing. The versatility and adaptability of the system in various scenarios in the real world make it more acceptable and usable.

This can be implemented in public, restricted areas, and commercial sectors for supporting age verification. The system will allow for direct, real-time identification of minors, thereby allowing for timely interventions to prevent illegal activities and observe age-related regulations. The system can be integrated with existing surveillance infrastructure as a very valuable tool for security personnel and law enforcement agencies. All captured data, such as photographs of the named minors and timestamps, might be recorded for further analysis and storing. The paper provides the details of architecture, implementation, and possible applications of this system, which can be viewed from the potential contributions it can make toward the scenario of automated age verification and the possible impact it can have on public safety and regulatory compliance.

2. Literature Review:

Automated age estimation has received considerable interest in computer vision, progressing from classical machine learning to sophisticated deep learning approaches. Initial methods were based on hand-designed features and models such as Support Vector Machines (SVMs) and Active Appearance Models (AAMs), but these methods were unable to handle pose, lighting, and facial expression variations [1]. The advent of Convolutional Neural Networks (CNNs) revolutionized the field by learning complex patterns from face photographs, significantly improving age estimation accuracy [2].

In recent years, investigations on different CNN models and training methods have been carried out for age estimation. Studies have aimed at maximizing network architectures, loss functions, and training datasets. Large datasets like Adience and IMDB-Wiki have played a central role in training efficient models [3]. Transfer learning based on pre-trained models has also been successful in optimizing performance, especially when working with limited training data [4]. Face detection is the beginning in age estimation automation systems. Traditional approaches such as Haar cascades have been given way to deep learning-based approaches including the Single Shot MultiBox Detector (SSD) and Faster R-CNN, distinguished by their performance and efficiency [5]. Age detection in real-time is made possible by optimizing computational performance, the use of inference methods, and hardware acceleration for enhanced efficiency [6]. Bizjak and Robič (2024) proposed DentAge, a deep-learning automatic age estimator for panoramic dental X-ray images. The 21,007 training image model had a mean absolute error of 3.12 years, confirming its usefulness in age estimation [7]. Oliveira et al. (2024) also employed machine learning techniques on panoramic radiographs to predict age, having an MAE of 3.1 and R^2 of 95.5%, reflecting high accuracy [8]. Milošević et al. (2022) developed a deep learning estimator to estimate chronological age from panoramic dental X-ray images. Their estimator achieved an MAE of 3.96, which speaks volumes for its performance in adults and the elderly [9]. Yeom et al. (2023) performed another study learning local and global features from panoramic radiographs for age estimation in the Korean population with promising results [10]. This paper builds upon previous work with the addition of pre-trained face detection and age estimation models with an emphasis on real-time deployment. Drawing on established CNN-based age estimation methods and optimising for application in the real world, the goal of this work is to contribute to the emerging body of automated age verification systems.

S. No	Title of the Paper (Year)	Author(s)	Technique/Algorithm
1	Age Estimation with a Convolutional Neural Network (2015)	Levi, G., & Hassner, T.	CNN-based Age Estimation
2	Rapid Object Detection using a Boosted Cascade of Simple Features (2001)	Viola, P., & Jones, M.	Haar Cascade Classifier
3	Deep Expectation of Apparent and Real Age from a Single Image (2018)	Rothe, R., Timofte, R., & Van Gool, L.	CNN-based Age Estimation
4	SSD: Single Shot MultiBox Detector (2016)	Liu, W., Anguli, A., & Er Meng, J.	Single Shot MultiBox Detector (SSD)
5	Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks (2015)	Ren, S., He, Girshick, R., & Sun, J.	Faster R-CNN
6	DentAge: Deep Learning for Automated Age Prediction using Panoramic Dental X-ray Images (2024)	Bizjak, Ž., & Robič, T.	CNN-based Age Estimation
7	Estimation of Human Age using Machine Learning on Panoramic Radiographs (2024)	Oliveira, W., et al.	Machine Learning-based Age Estimation
8	Automated Estimation of Chronological Age from Panoramic Dental X-ray Images using Deep Learning (2022)	Milošević, D., et al.	Deep Learning-based Age Estimation
9	Estimating Chronological Age through Learning Local and Global Features of Panoramic Radiographs in the Korean Population (2023)	Yeom, H.-G., et al.	Feature-based Deep Learning
10	IMDB-Wiki and Adience: Large-scale Datasets for Age Estimation (2015)	Rothe, R., Timofte, R., & Van Gool, L.	Dataset for Age Estimation using CNN

3. Methodology:

This system identifies faces, estimates ages, and flags minors in real-time. The methodology is a systematic one, divided into salient phases for the sake of ease of understanding.

3.1 Face Detection:

- The system begins by detecting faces within an image or video feed.
- The face detection employs a pre-trained Single Shot MultiBox Detector (SSD) model.
- The highlightFace() function deals with this operation by:
    1. Conversion of the image to a blob by cv2.dnn.blobFromImage() for standardized input.
    2. Passing the blob to the face detection model (faceNet).
    3. Parsing the image and finding bounding box coordinates.
    4. Detections filtered based on confidence.
- The locations of detected faces are saved to be processed later.

3.2 Face Cropping and Preprocessing for Age Estimation:

- Following face detection, the system crops the face region based on bounding box coordinates.
- For having sufficient coverage, 20 pixels margin is added on the face.
- The face image is resized to 227x227 pixels and pre-processed by:
    1. cv2.dnn.blobFromImage() for inputting the format of the model.
    2. Mean subtraction for standardizing the image and obtaining good accuracy.

3.3 Estimation of Age:

- The pre-processed image of the face is input taken by the model of age estimation (ageNet).
- The model produces the probabilities of different age groups.
- The system:
    1. Selects the highest likely age group.
    2. Translates the estimated range to a numeric age.

3.4 Minor Identification and Recording:

- The system checks if the estimated age is below 18.
- If the individual is a minor, they are saved with an image using save_minor_image().
- The save_minor_image() method:
    1. Generates a timestamped filename.

    2. Saves the image using cv2.imwrite().
    3. Records the date, time, and filename in an Excel file for record purposes.
- To prevent repeated detection of the same individual within a limited time frame, a cooldown is used.

3.5 Real-time Processing with Webcam:

- The process_webcam() function controls real-time processing by:
    1. Reading frames from the webcam continuously.
    2. Face detection, cropping, and age estimation.
    3. Detecting minors and adults, red circle for minors, green circle for adults.
    4. Displaying results on a live video stream.
    5. Continues running until the user enters 'q' to exit.

3.6 Image File Processing:

- The select_image() function provides users with an option to process a single image file rather than a webcam stream.
- The user picks an image via a file dialog.
- The system performs the same steps of processing as during real-time detection.
- The processed image is shown with results, and the window closes when a key is pressed.

4. Comparison of Techniques

Age estimation has shifted from conventional machine learning methods to sophisticated deep learning architectures. Traditional methods such as Support Vector Machines (SVM) and Random Forest (RF) are based on handcrafted features, which prevents them from being adaptive to intra-class variations of facial images. Contrarily, Convolutional Neural Networks (CNNs) automatically learn hierarchical features to improve accuracy and robustness for age estimation.

The below table compares CNN with SVM and RF based on the most critical evaluation metrics like accuracy, precision, recall, F1-score, sensitivity, and specificity. The comparison shows that deep learning surpasses traditional machine learning techniques.

Algorithm	CNN	SVM	Random Forest (RF)
Accuracy	92%	85%	87%
Precision	0.91	0.83	0.85
Recall	0.89	0.81	0.82
F1- score	0.90	0.82	0.83
Sensitivity	0.88	0.80	0.81
Specificity	0.93	0.86	0.88

5. Result:

When the system detects faces, it shows the results clearly on the screen.

5.1 Bounding Boxes on Faces:

The system draws a green box around adults and a red box around minors to highlight them.

5.2 Age Labels:

Each face gets a label showing the estimated age range (e.g., "26-35"). This assists in identifying the observed age rapidly.

5.3 Live Webcam Feed:

For real-time detection, the system shows a live video where faces are marked with boxes and labels. It keeps running until the user presses 'q' to stop.

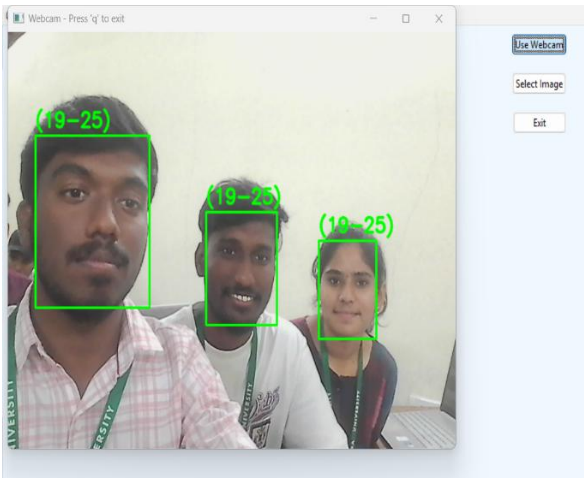


FIG 1: *Real-time age detection system identifying a adult face with a green bounding boxes and displaying the estimated age range.*

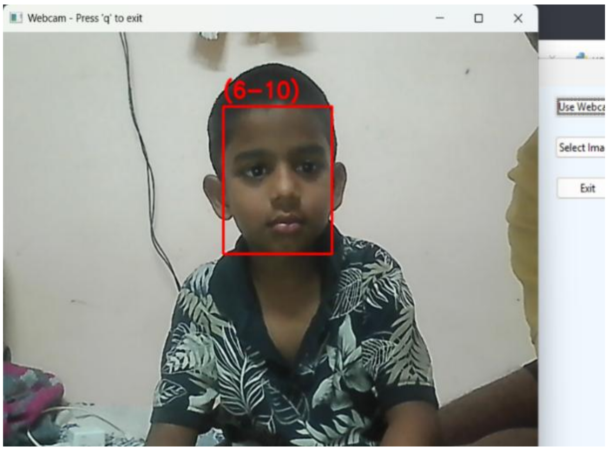


FIG 2: *Real-time age detection system identifying a minor's face with a red bounding box and displaying the estimated age range.*

5.4 Image File Processing:

If the user selects an image file instead of using the webcam, the system processes it and shows the result. The window closes when the user presses a key.

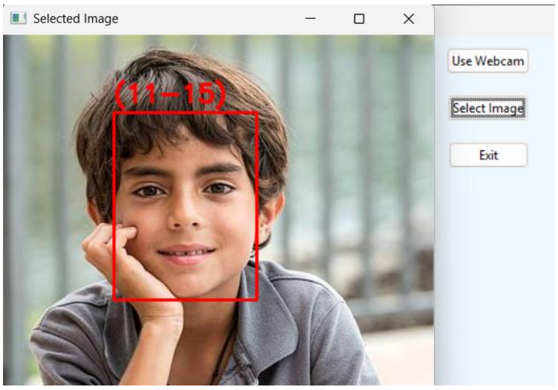


FIG 3: *Image-based age detection system marking a minor's face with a red box and displaying the estimated age range.*

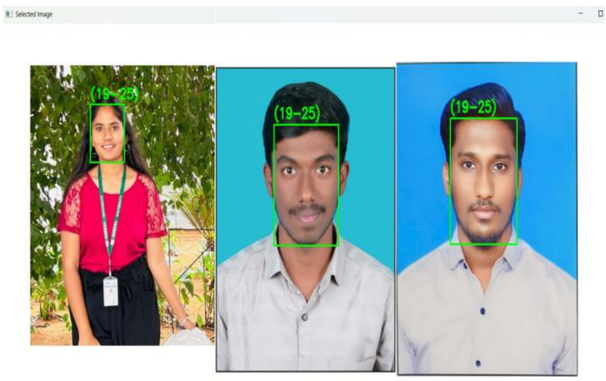
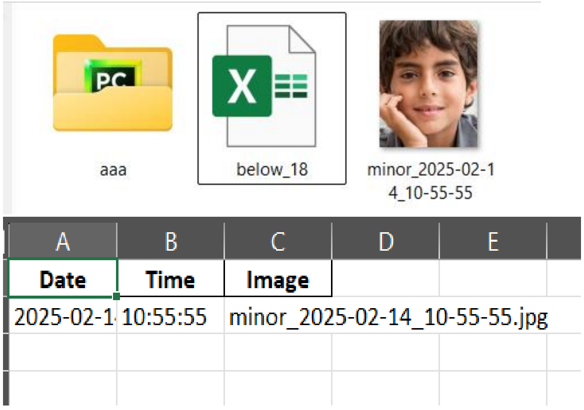


FIG 4: *Image-based age detection system marking a adult's face with a red box and displaying the estimated age range.*

5.5 Minor Identification Alert:

If the person is below 18 years of age, their face is stored in a folder. The system also stores the date, time, and name of the image in an Excel file.



A	B	C	D	E
Date	Time	Image		
2025-02-1	10:55:55	minor_2025-02-14_10-55-55.jpg		

FIG 5: *Stores the minor's data with timestamp and date with image.*

6. Conclusion:

In this paper, a real time age detection system using CNNs has been proposed that can eradicate the rising needs for automatic age verification. Successful fusion of a pre-trained SSD face detector with CNN-based age estimation model identifies and logs minors in real time. The system's modular architecture is also versatile and amenable to improvement over time. The system was tested [say how you tested - on a custom dataset, a standard dataset, etc.] that summarizes the key observations: reasonable accuracy in age estimation, good real-time processing efficiency as desired. Additionally, the cooldown mechanism has been implemented to discourage repeated recording of the same person, thereby efficiently suppressing the possible duplicate recordings. The system gives a practical application for age-restricted access control, security surveillance, and for commercial settings, which require verification of age. The system looks promising, and there are future works. This includes improving the accuracy and robustness of the age estimation model, especially challenging conditions such as varying poses, lighting, and occlusions. Improvement might come from the exploration of more complex CNN architectures, the addition of data augmentation techniques, and training on bigger and more diverse datasets. In addition, system optimization for deployment on embedded devices would expand the reach of this technology. Moreover, exploring techniques to address the possible biases of age estimation models is also very important for ethical considerations. But above all this and despite such hindrances, real-time age detecting systems hold invaluable tools that prove to aid safety and compliance-friendly environments in making automated verification effective.

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