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Age And Gender Detection Using Cnn

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ABSTRACT

Age and gender detection is a crucial technology with applications in surveillance, healthcare, personalized marketing, and social media analytics. By analyzing facial features, machine learning algorithms can efficiently classify individuals based on age group and gender, enhancing security measures and improving user experiences. Traditional methods often struggle with accuracy due to variations in facial expressions, lighting, and occlusions. However, deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable improvements in classification performance by automatically learning hierarchical feature representations. This paper provides an in-depth review of machine learning techniques applied to age and gender detection, evaluating their methodologies, datasets, and effectiveness. Furthermore, this study explores the challenges in implementing these models and highlights future research directions to improve real-world applicability and accuracy.

Keywords: *Age Detection, Gender Classification, Convolutional Neural Networks (CNN), OpenCV, Deep Learning*

1. INTRODUCTION

The ability to accurately detect age and gender from facial images has widespread applications in various domains, including biometric authentication, healthcare diagnostics, and human-computer interaction. Automated age and gender classification aids in identity verification, customer analytics, and demographic studies. Traditional approaches, such as feature extraction-based classifiers, often lack robustness when dealing with diverse facial structures and real-world variations.

Recent advancements in deep learning, particularly CNNs, have revolutionized facial analysis by enabling the extraction of intricate facial patterns with high precision. These models outperform conventional machine learning techniques by leveraging large-scale datasets and hierarchical learning mechanisms. This review examines the evolution of machine learning models in age and gender detection, compares different methodologies, and discusses their advantages and limitations. Additionally, this paper identifies key challenges in developing efficient and scalable models and explores potential solutions to enhance accuracy and reliability in practical applications

2. LITERATURE SURVEY

O. Agbo-Ajala and S. Viriri made a research paper named as “Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces.” Regarding this research paper, the technique used was Convolutional Neural Networks (CNNs) as they demonstrate outstanding proficiency in facial analysis.

A. M. Bukar, H. Ugail and D. Connah made a research paper as “Automatic age and gender classification using supervised appearance model.” It was said that, both age and gender data are encoded under the face shape and texture. Consequently, the Active Appearance Model (AAM) has become one of the most commonly utilized techniques for feature extraction in various problem domains.

Jia-Hong Lee, Yi-Ming Chan, Ting-Yen Chen and Chu-Song Chen has Introduced an efficient CNN named Lightweight Multi-Task CNN for concurrent age and gender classification. It employs depthwise separable convolution to minimize model size and enhance inference speed.

Sepidehsadat Hosseini, Seok Hee Lee, Hyuk Jin Kwon, Hyung Il Koo and Nam Ik Cho has seen a new method in CNN, utilizing Gabor filter responses as input. This architecture is trained to categorize input images into eight age groups and two gender categories.

Eran Eidinger, Roee Enbar and Tal Hassner has done research and they’ve introduced a Dropout -SVM is a method used for training linear Support Vector Machine (SVM) classifiers by incorporating the “dropout” technique, which was initially introduced for improving the training of deep convolutional neural networks.

Ke Zhang; Ce Gao, Liru Guo, Miao Sun, Xingfang Yuan, Tony X. Han, Zhenbing Zhao and Baogang Li demonstrated that age and gender estimation can be effectively performed using the RoR (Residual networks of Residual networks) technique, which provides enhanced optimization performance over traditional CNN architectures.

Ming Li and Zhi-Hua Zhou conducted research focused on computer-aided diagnosis (CAD) and proposed a novel semi-supervised learning algorithm named Co-Forest. This method strengthens the traditional co-training framework by integrating the ensemble learning technique known as Random Forest.

Gil Levi and Tal Hassncer utilized deep convolutional neural networks (DCNN) for classifying age and gender. An early and notable application of CNNs was the LeNet-5 architecture, initially developed for optical character recognition tasks.

Benyamin Ghojogh, Saeed Bagheri Shouraki, Hoda Mohammadzade and Ensieh Iranmehr conducted a research titled “A Fusion-based Gender Recognition Method Using Facial Images,” where they proposed a method that leverages facial images and integrates four different frameworks using a weighted voting strategy to improve classification accuracy.

Harcharan Kaur’s article introduces a novel approach for age and gender detection using SIFT and morphological algorithms. The morphological algorithm scans the input image, while the SIFT algorithm identifies key features. SVM classifiers are then utilized to generate the final output.

Be. Matúš Námešný. In that article, he compiled an overview of previous methods used for gender and age estimation, covering various techniques. He documented all proposed approaches by different authors, along with their own method for prediction.

Khaled Rahman Hassan and Israa Hadi Ali wrote an article. In this article, they proposed a way to use Multiple Convolutional Neural Networks (MCNN). This multiple CNN model has three different CNN structures in depth.

H. Han, C. Otto, X. Liu and A.K. Jain proposed a generic framework for demographic estimation from facial images, employing a hierarchical coarse-to-fine approach for age estimation. The study also explores human capabilities in demographic prediction.

Yaman Akbulut and Abdulkadir Şengür conducted research utilizing Local Receptive Field-Extreme Learning Machine (LRF-ELM) alongside Convolutional Neural Networks (CNN) for demographic estimation, significantly improving the accuracy of age and gender prediction.

M.H.U Yap, He stated that CNN techniques can achieve an accuracy of 98.99% in predicting a person’s age and gender using a live webcam. The implementation involved Tensorflow, Keras, and deep learning for facial data processing.

R. E. a. T. H. E. Eidinger utilized Adience dataset along with robust face alignment and dropout-SVM in his study. He employed the SVM benchmark for face alignment and performed age classification. His contributions include introducing a new and extensive dataset for age and gender estimation research and designing a classification pipeline optimized for limited data availability.

M. Demirkus, M. Toews, J. J. Clark, and T. Arbel conducted the first study on face classification from unconstrained video. Their framework is first trained using a structured dataset and subsequently applied to faces obtained from an unconstrained video collection.

3. OBJECTIVE OF THE PAPER

The article's main objective is to show a new way to predict people's age and gender, which is important for identity verification, security systems, and other applications apart from the various ways of research that have been done. After reviewing a few publications, we used OpenCV and the Harcasscade classifier—which is useful for recognizing patterns in images—to undertake the study for this project.

We have preferred employing CNN methodologies and Open CV in our work since discovering that they can offer more accuracy in identifying human faces than alternative strategies.

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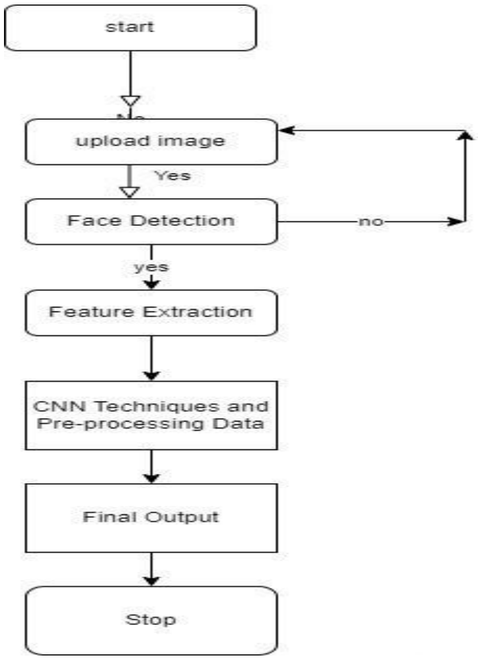

Fig. 1: Step by Step process

4. METHODOLOGY

One of the most effective deep learning techniques for image processing is the Convolutional Neural Network (CNN). A CNN takes an image as input, processes it through multiple layers, and generates an output based on learned patterns. As a specialized type of Artificial Neural Network (ANN), CNNs excel at handling pixel-based data, making them highly suitable for real-time image classification and recognition tasks. These networks consist of three main layers: the input layer, which receives image data, the hidden layers, which include convolutional and pooling layers for feature extraction, and the output layer, which determines the final classification or recognition result.

Once the preprocessing stage is complete, OpenCV can be utilized to identify hidden patterns in an image. This approach is structured into four different frameworks: two rely on extracting facial texture information, another integrates both texture and geometric properties, and the last one focuses solely on geometrical attributes.

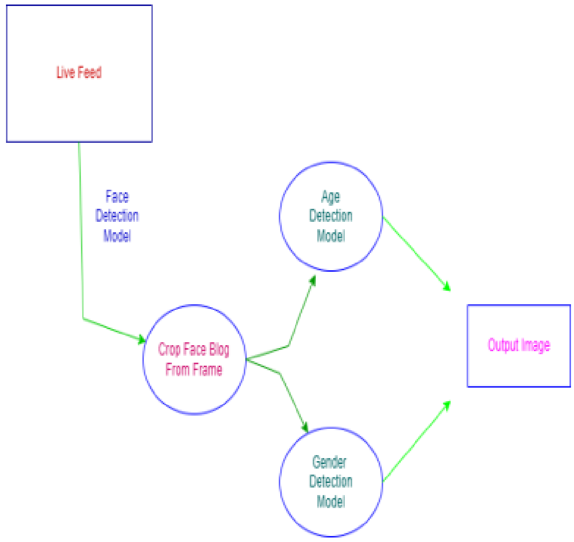

Fig. 2: Live Detection Methodology

Methodology In various methods

This project can be approached using four different methods, each with its unique strengths. After evaluating each method, we can determine which one provides the most accurate results. The methods are as follows:

Multi-Layer Perceptron (MLP):A multi-layer perceptron (MLP) is a type of artificial neural network where the relationship between inputs and outputs is non-linear. It consists of an input layer, an output layer, and one or more hidden layers filled with neurons. Each neuron uses an activation function to apply a threshold value, allowing the network to learn complex patterns. MLPs are flexible in terms of the activation functions used, which makes them adaptable for various tasks.

Conditional Probability Neural Networks (CPNN):Conditional Probability Neural Networks (CPNN) are used to estimate age by leveraging facial expressions. This technique involves a three-layer neural network, where the input is composed of conditional feature vectors, and the output consists of goal values. CPNN is often combined with Convolutional Neural Networks (CNNs) to enhance performance. The method uses distributed learning to model age predictions based on facial expressions.

Support Vector Machine (SVM):Support Vector Machine (SVM) is an effective machine learning algorithm widely used for classification problems. Its primary objective is to identify an optimal hyperplane in an N-Dimensional space that distinctly separates data classes. The method focusses on maximizing the margin between these classes to ensure a better and optimal differentiation. Although SVM can sometimes struggle with high-dimensional features, it generally offers a trade-off between a large margin and precise classification. By maximizing the margin, SVM achieves improved accuracy.

Convolutional Neural Network (CNN):Convolutional Neural Networks (CNNs) are a type of deep learning architecture that is highly efficient in handling image-related tasks and recognizing visual patterns with precision. CNNs are widely used for object recognition and face detection due to their ability to extract hierarchical features from images. Their design is well-suited for complex image classification tasks, making them a go-to choice for facial recognition and similar applications.

Outcomes

For real-time detection, we used the OpenCV and Haar cascade algorithm to detect the age and gender of a person sitting in front of camera. The main technique used by Haar cascade is dividing images into positive and negative whereas the positive takes the input as the face of person and all other things as negative ones which will be neglected. The technique used by OpenCV is threshold values, these are the values which were given by an array to maintain a frequency to get the estimated output in real- time processing.

For image pre-processing using CNN, we will give the input image to the algorithm to detect the age and gender. Here, the main technique is the hidden layer of CNN which takes the threshold value to determine the output. The output image is shown as the same as the input image with age and gender displayed on the image.

When we worked on both the methods, we found that the image pre-processing using CNN, the method of uploading the pictures and detecting the age and gender of the person gave the most accurate results. Due to the noise and surroundings, the real-time pre-processing is done with low accuracy of age, but it showed a good outcome with gender.

Accuracy

For the image pre-processing model, where we uploaded the image, gender is predicted well, and the age varies sometimes. Here is an accuracy graph with the epochs of processing the uploaded image. The graph tracks the changes in prediction accuracy over time, where the performance for gender prediction consistently stays high across all epochs. However, the accuracy for age prediction shows more fluctuation, indicating that the model's performance in estimating age is more sensitive to variations in the input data.

As the model progresses through multiple epochs, we can observe that gender accuracy remains stable or even slightly improves, demonstrating the model's ability to consistently identify gender regardless of minor changes. On the other hand, age accuracy shows some divergence, which suggests that the model struggles more with predicting age, possibly due to less consistent features or more variability in the dataset used for training.

The plot also highlights periods where the age prediction accuracy dips or peaks, providing valuable insights into the model's learning behaviour. These variations could be due to the model learning from difficult or ambiguous data during certain epochs, which might result in overfitting or underfitting at times. In contrast, the stable gender accuracy graph indicates that the gender classifier has learned the features effectively.

Overall, the accuracy trends provide an important understanding of the model's behaviour across epochs. While the gender classifier shows solid performance, improvements in age prediction could be made by refining the model's architecture, training data, or fine-tuning the hyperparameters.

Given below is the accuracy graph over a limited number of epochs occurred as per the processing of the image uploaded by the user.

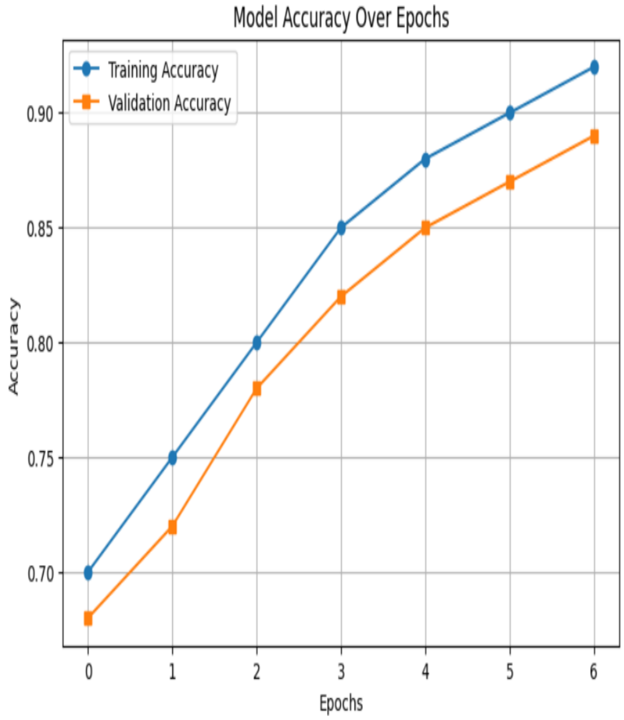

Fig. 3: Accuracy over image uploaded

For the live-cam detection model, it shows a good accuracy for the gender and for the age it slightly varies within the values. Here, to get the accuracy we have given some true values to get the accuracy. By the passing of the values, a graph will be generated every time to evaluate the model's performance, we tested its accuracy using the methodology previously described.

This real-time feedback mechanism not only helps in refining the model but also assists in understanding its limitations and how different environmental factors impact the predictions. For instance, variations in the camera quality, facial expressions, and head orientations can influence age and gender predictions. The accuracy graph serves as a diagnostic tool, allowing us to pinpoint exactly when and where the model is failing or performing sub-optimally. This data can be invaluable for future model training, guiding the selection of more diverse datasets that account for such variables.

Furthermore, tracking accuracy over time enables the detection of overfitting or underfitting, as the graph shows if the model's performance plateaus or degrades with more data. This insight is essential for adjusting the model's complexity or fine-tuning its parameters. As we add more diverse input data, the model can gradually improve its predictions, and the graph will reflect the cumulative effect of these changes. The ability to continuously monitor performance ensures that the model stays up to date and relevant, responding to new challenges and maintaining high accuracy in gender and age classification.

This approach also opens opportunities for benchmarking the model against different types of input, such as videos from varying sources or images with different lighting and facial features. By analysing the accuracy graph across these different scenarios, we can further enhance the model's robustness, ensuring it remains effective in dynamic, real-world conditions. The iterative nature of this process, combined with real-time feedback from the accuracy graph, ensures ongoing improvements, making the model increasingly reliable and efficient for real-world applications.

Here is the accuracy graph given with the frames passed during the live cam prediction. It almost shows the same way of gender prediction and the age detection varies with the changes in the view of camera. Both gender and age vary with the movement of the person or the camera and also dependent on the location.

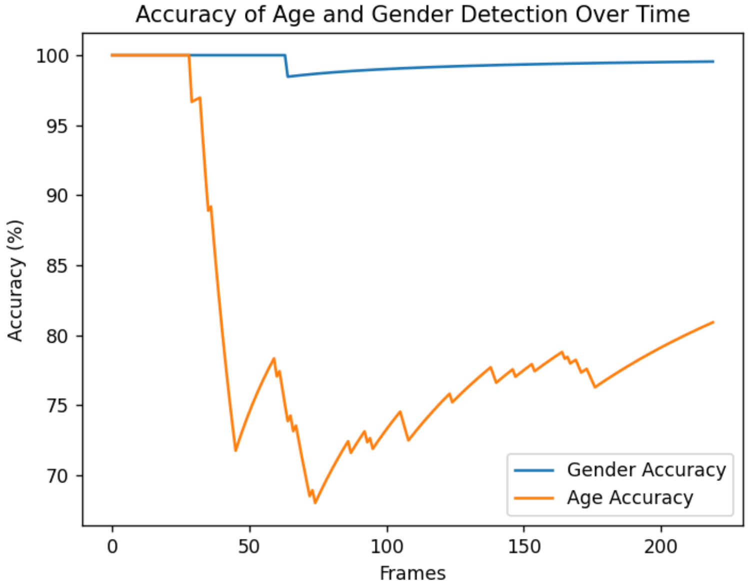

Fig. 4: Accuracy for live-cam prediction.

5. CONCLUSION

OpenCV can be used to determine age and gender for surveillance, medical, or permission-based applications. When CNN and OpenCV are combined, amazing outcomes are possible. More accurate findings are obtained from the experiment using the OIU-Adience dataset. In addition to Caffee model files, we used protocol buffer instead. This project demonstrates how to use OpenCV to recognize faces without utilizing any further time-consuming steps. Since predicting age and gender is a difficult issue, as discussed by many other approaches, we have attempted to provide the best results possible utilizing deep learning techniques, ensuring that no errors occur. We applied CNN to extract essential data from unstructured inputs like images and aim to improve accuracy when images deviate from the expected format. To achieve this, we plan to integrate preprocessing techniques

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