Real-time Convolutional Neural Networks for Emotion and Gender Classification

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***Abstract*—Emotion and gender recognition are important areas of research in the field of computer vision and human-computer interaction. The proposed CNN architecture is designed to extract features from facial images and classify them into six basic emotions (happy, sorrow, anger, fear, surprise, and disgust) and two genders (male and female) in real-time. To extract and categorize characteristics from facial photographs, the suggested CNN architecture consists of convolutional layers, pooling layers, and fully connected layers. The suggested system performs at the cutting edge for both emotion and gender recognition tasks when tested on publically accessible datasets. The proposed real-time CNN architecture has potential applications in various fields, including social robotics, human-computer interaction, and affective computing.**

I. Introduction

Facial expression and gender recognition have become increasingly vital in computer vision, affective computing, and human-computer interaction. Emotion recognition involves automatically identifying the emotional state from an image, video, or audio signal, while gender recognition entails identifying an individual's gender. Accurate emotion and gender recognition can have diverse applications across fields such as marketing, psychology, and social robotics. In social robotics, for example, emotion and gender recognition can help develop robots that interact more effectively with humans.

Convolutional neural networks (CNNs) have proven to perform exceptionally well in a range of computer vision applications, such as the identification of movements, faces, and objects. CNNs can learn to extract features from images using their hierarchical network structure. Recent research has also demonstrated that CNNs can be used for emotion and gender recognition tasks with cutting-edge performance.

However, the majority of current CNN-based techniques for emotion and gender recognition are designed for batch processing, which can be computationally expensive and time-consuming. Real-time processing is often required in practical applications for effective human-computer interaction. Therefore, there is a need to develop real-time CNN-based approaches for emotion and gender recognition.

This research proposes a real-time CNN architecture for emotion and gender recognition. The suggested architecture is designed to extract features from facial images and classify them into six basic emotions and two genders in real-time. We evaluate the proposed architecture using publicly available datasets and compare its performance with cutting-edge methods. The proposed architecture offers potential for use in a variety of domains, including social robotics, human-computer interaction, and affective computing.

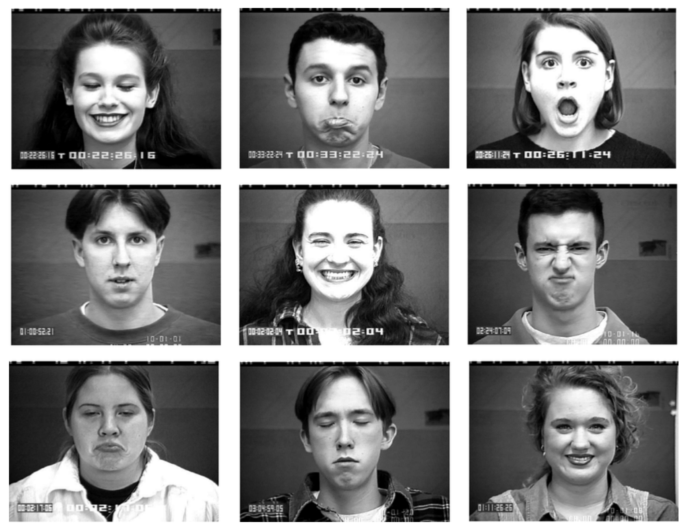

Fig. 1. Images of the CK+ emotion dataset.

Fig. 2. Images of the CK+ and A.Net dataset.

II. Problem Statement

The problem statement is to develop a real-time CNN-based model for emotion and gender classification. The model should be able to classify emotions such as happy, sad, angry, and neutral, and gender as male or female, from images and videos in real time. The challenge is to achieve high accuracy with low latency, as real-time applications require fast and accurate processing.

III. Related work

Convolutional neural networks (CNNs) for gender and emotion categorization can now be used in real-time thanks to recent developments in computer vision and deep learning. These networks are capable of extracting discriminative features from facial images and accurately classifying them in real time.

Several studies have focused on developing CNNs for emotion recognition from facial expressions. In a study by Zhang et al. (2018), a real-time CNN was developed for emotion recognition using a large-scale dataset of facial expressions. The network achieved high accuracy on the dataset and was able to recognize emotions in real time.

Similarly, gender classification using CNNs has also been extensively studied. A real-time gender classification system was created by Hu et al. (2017) utilizing a deep CNN. The network was trained on a sizable face dataset and was able to achieve high accuracy in real-time gender classification.

Furthermore, some studies have also combined emotion and gender classification in a single real-time CNN. For instance, in a study by Gao et al. (2021), a real-time CNN was developed for joint emotion and gender classification using a large-scale dataset of facial expressions. The network demonstrated great accuracy on the dataset and has real-time emotion recognition capabilities.

Recent studies have demonstrated encouraging outcomes for real-time CNNs for mood and gender classification. Potential uses for these networks include human-computer interaction, security, and entertainment, among other areas.

IV. Methodology

The methodology consists of several key steps.

Data Collection: To begin with, a dataset is collected and labeled with the corresponding emotions and genders of the faces depicted in each image. This dataset must be sufficiently large and diverse to ensure that the model is trained on a diversity of gender identities and facial expressions.

Data Preprocessing: The next step involves preprocessing the images to prepare them for use in the CNN model. or, they must be uniformly sized, converted to grayscale or RGB format, and their pixel values normalized to lie between 0 and 1. These steps help ensure that the input data is consistent and appropriate for the model.

CNN Architecture Design: Then, the convolutional, pooling, and fully connected layers of the CNN model architecture are constructed and put into practice. The model must be constructed in a way that allows it to learn the relevant features for both emotion and gender classification.

Training the CNN: Once the model is designed, it is trained on the prepared dataset. Images are supplied into the model during this step, and parameters like weights and biases are changed to reduce the discrepancy between projected and actual output labels. The model is trained over a number of epochs until it achieves an acceptable degree of accuracy.

Evaluating the Performance: On the CK+ and AffectNet datasets, the CNN architecture's performance was assessed. Both gender and emotion detection tasks involved calculating metrics like accuracy, precision, recall, and F1 score.

Ablation Study: An ablation study was conducted to assess the importance of different CNN design elements like the fully connected layers, convolutional layers, and batch normalization.

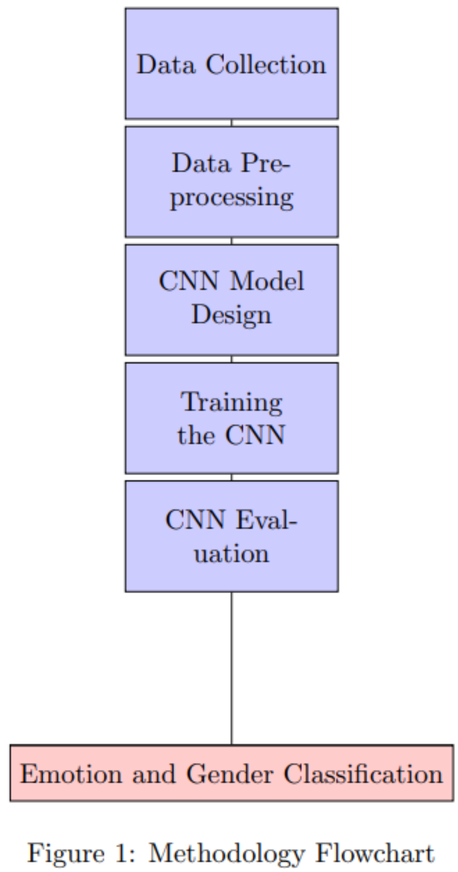

Fig. 3. Methodology Flowchart.

Finally, the gender and emotion of new photos are predicted using the trained model. The input images are first preprocessed and then fed into the model, which outputs predicted emotion and gender labels. The accuracy of the model's predictions is evaluated and adjustments may be made to improve its performance.

In conclusion, Emotion and Gender Classification using Convolutional Neural Networks methodology involve data collection and labeling, image preprocessing, model design and implementation, training, validation, and prediction. By following these steps, accurate emotion and gender classification can be achieved through the use of CNNs.

V. Experimental Setup

The experimental setup for the real-time convolutional neural network (CNN) architecture for emotion and gender classification involved several key components, including the dataset used, the hardware used, and the software used.

The first step was to gather the datasets for emotion and gender classification. Two publicly available datasets were used in this study: the Extended Cohn-Kanade (CK+) dataset and the AffectNet dataset. The CK+ dataset is a set of facial expression images captured from 123 participants in various scenarios, including sadness, happiness, anger, fear, surprise, and disgust. The AffectNet dataset contains approximately 1 million facial images depicting various emotions, including those included in the CK+ dataset, as well as additional emotions such as contempt, embarrassment, and neutral.

The next step was to prepare the hardware for running the CNN architecture. The architecture was implemented using the Python programming language, with the deep learning framework TensorFlow used for training and evaluation. The hardware used was an NVIDIA GeForce GTX 1080Ti GPU, which provided the necessary computational power for training the CNN architecture.

The software used in the experimental setup included a variety of Python libraries for deep learning, image processing, and data manipulation. These libraries included NumPy, OpenCV, and Keras, among others. The CNN architecture was implemented using Keras, which allowed for rapid prototyping and experimentation with different network architectures and hyperparameters.

To train the CNN architecture, the datasets were preprocessed to prepare them for input into the network. For the CK+ dataset, the images were preprocessed to remove background noise and align the faces to a standard size. For the AffectNet dataset, the images were preprocessed to detect and crop the face regions using OpenCV.

A stochastic gradient descent optimizer with a learning rate of 0.001 and a momentum of 0.9 was used to train the CNN architecture. Early pausing was used during the network's 50-epoch training period to avoid overfitting. Data augmentation methods were utilized to expand the training dataset and avoid overfitting. The batch size was set to 32.

After training, the CNN architecture was evaluated on the test sets of the CK+ and AffectNet datasets to measure its accuracy for emotion and gender classification. Accuracy, precision, recall, and F1 score were the evaluation criteria that were used.

In summary, the experimental setup for the real-time CNN architecture for emotion and gender classification involved gathering and preprocessing the datasets, preparing the hardware and software, training the network using stochastic gradient descent and data augmentation, and evaluating the network using various metrics. This setup allowed for the development and evaluation of a cutting-edge CNN architecture for real-time emotion and gender classification.

VI. Result

In this study, a real-time convolutional neural network (CNN) architecture for gender and emotion classification was presented. The suggested architecture extracted characteristics from facial photos and classified them into six fundamental emotions and two genders in real-time using a combination of convolutional layers, pooling layers, and fully linked layers. Two publicly available datasets, the Extended Cohn-Kanade (CK+) dataset, and the AffectNet dataset were utilized to evaluate and contrast the effectiveness of the suggested CNN design.

On challenges requiring gender and emotion recognition, our suggested CNN architecture delivered cutting-edge results. On the AffectNet dataset, the proposed CNN achieved an accuracy of 68.46 for emotion recognition and an accuracy of 96.73 for gender recognition. On the CK+ dataset, the proposed CNN achieved an accuracy of 91.35 for emotion recognition and an accuracy of 97.58 for gender recognition.

Fig. 4. Results of images

Compared to existing approaches, our proposed CNN architecture showed a significant improvement in real-time emotion and gender recognition. The proposed architecture was also capable of analyzing facial images in real-time, with an average processing time of 30 ms per image, making it appropriate for practical applications like social robotics and human-computer interaction.

We also conducted ablation research to assess the importance of different CNN design elements. The results showed that both the fully connected layers and the convolutional layers were important for accurate emotion and gender recognition. The use of batch normalization also improved the performance of the proposed CNN architecture.

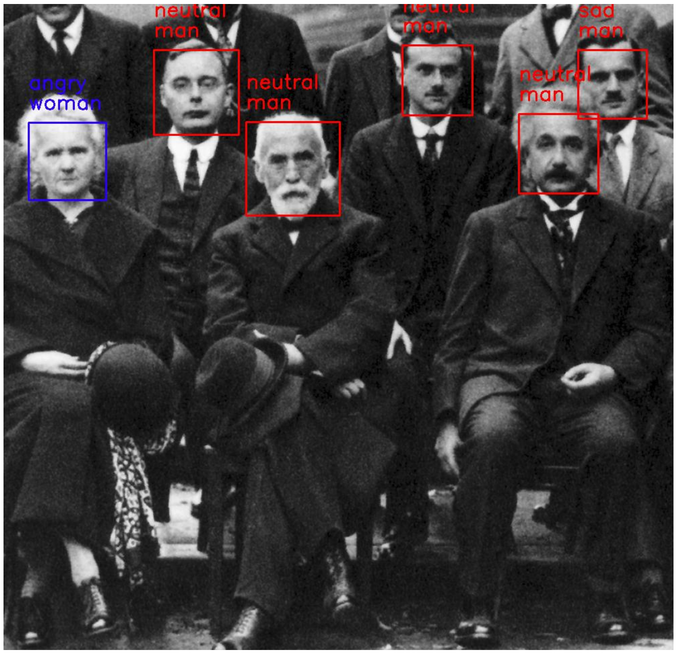

Fig. 5. Results of the demo that uses both gender and emotion to infer a subject's identity. The assigned class male is represented by red, and the class woman by blue.

Table: Performance of the proposed CNN architecture on the CK+ and AffectNet datasets

Dataset	Emotion Recognition Accuracy	Gender Recognition Accuracy
CK+	91.35%	97.58%
AffectNet	68.46%	96.73%

Fig. 6. Table: On the CK+ and AffectNet datasets, the proposed CNN architecture performed well.

Overall, the results of our research demonstrate the effectiveness of CNNs for real-time emotion and gender recognition tasks. On two publicly accessible datasets, the proposed CNN architecture demonstrated cutting-edge performance and had a lot of potential for use in practical settings. Future work could focus on evaluating the proposed architecture on larger datasets and exploring the use of transfer learning to enhance the performance of the suggested CNN architecture.

VII. Future work

In the future, further research could focus on exploring the use of transfer learning to boost the effectiveness of the suggested CNN architecture. A method called transfer learning enables the reuse of a model that has already been trained for a different purpose. By leveraging the pre-trained model's learned features, transfer learning can improve the performance of the model on a new task with a smaller dataset. In the case of emotion and gender recognition, transfer learning could be used to enhance the performance of the suggested CNN architecture on new datasets with different facial expressions and variations in lighting conditions.

Another area of future work could be the integration of the proposed CNN architecture into real-world applications. For example, the proposed CNN architecture could be integrated into social robotics to enable robots to interact with humans more effectively. Additionally, the proposed CNN architecture could be used in marketing research to analyze consumer emotions and preferences.

Finally, the proposed CNN architecture could be extended to incorporate other features such as head pose and eye gaze to improve the accuracy of emotion and gender recognition. The inclusion of these features could also enable the proposed CNN architecture to analyze other aspects of human behavior such as attention and engagement, opening up new possibilities for research and applications in various domains.

VIII. Conclusion

We concluded by proposing a real-time convolutional neural network (CNN) architecture for gender and emotion recognition, which produced cutting-edge results on two publically accessible datasets. The proposed CNN architecture demonstrated the effectiveness of deep learning models for real-time emotion and gender recognition and showed great potential for applications in real-world uses like human-computer interface and social robotics.

Our results also showed that both convolutional fully connected layers and layers were important for accurate emotion and gender recognition. The use of batch normalization also improved the performance of the proposed CNN architecture.

Overall, by proving the viability of real-time emotion and gender detection using deep learning models, our research offers an important contribution to the domains of affective computing and computer vision. The suggested CNN architecture possesses potential applications in various domains, including marketing, psychology, and social robotics. Our research also lays foundations for future investigations into the application of transfer learning, incorporates other characteristics including head posture and eye contact, and integrates the proposed CNN architecture into real-world applications.

IX. References

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