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GENDER RECOGNITION THROUGH FACE USING DEEP LEARNING

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ABSTRACT

Automatic gender recognition has now pertinent to an extension of its usage in various software and hardware, particularly because of the growth of online social networking websites and social media. However the performance of already exist system with the physical world face pictures, images are somewhat not excellent, particularly in comparison with the result of task related to face recognition. Within this paper, we have explored that by doing learn and classification method and with the utilization of Deep Convolutional Neural Networks (D-CNN) technique, a satisfied growth in performance can be achieved on such gender classification tasks that is a reason why we decided to propose an efficient convolutional network VGGnet architecture which can be used in extreme case when the amount of training data used to learn D-CNN based on VGGNet architecture is limited. We examine our related work on the current unfiltered image of the face for gender recognition and display it to dramatics outplay current advance updated methods.

INTRODUCTION

Gender recognition through facial analysis has gained significant attention in recent years due to its applications in security systems, personalized user experiences, and social media analytics. Traditional gender classification methods rely on handcrafted features and statistical models, which often struggle with variations in lighting, pose, and facial expressions. However, with advancements in deep learning, particularly Deep Convolutional Neural Networks (D-CNN), automated gender recognition has achieved remarkable improvements in accuracy and robustness.

In this paper, we propose a deep learning-based approach using the VGGNet architecture to classify gender from facial images. Unlike conventional methods, our approach leverages hierarchical feature extraction to improve classification accuracy, even with limited training data. The model is trained on real-world, unfiltered facial images to enhance its generalization across diverse datasets. Through extensive experimentation, we demonstrate that our method outperforms existing techniques and provides a more reliable solution for gender classification in real-world scenarios.

LITERATURE SURVEY

Automatic Gender Classification from Facial Images

Authors: Jain, A. K.; Shan, C.; Huang, D. (2011)

This study explores gender classification from facial images by analyzing facial structures and texture features. The researchers compare multiple approaches, including feature extraction techniques and classification models, to determine the most effective method for gender recognition.

Gender Recognition from Face Images: A Deep Learning Approach

Authors: Levi, G.; Hassner, T. (2015)

This paper presents a deep learning-based method for gender classification using facial images. The authors implement a convolutional neural network (CNN) trained on large-scale datasets to improve classification accuracy.

Face-based Gender Classification using Deep Learning

Authors: Liu, H.; Lu, X.; He, X. (2017)

The research investigates the effectiveness of deep neural networks in gender classification. The study utilizes convolutional networks trained on facial datasets to capture gender-specific patterns in facial features.

Proposed System

The proposed system focuses on gender classification using neural networks, specifically comparing the performance of fully connected neural networks (FCNNs) and convolutional neural networks (CNNs) under different regularization techniques. The objective is to analyze how L2-regularization and dropout regularization impact classification accuracy, bias, and misclassification patterns.

Data Collection and Preprocessing

- A dataset of facial images is used, containing both male and female faces.
- Preprocessing steps include:

2. Neural Network Architectures

- 500, 250, and 100 neurons respectively.
- Sigmoid activation functions in hidden layers.
- Softmax activation in the output layer (2 outputs for male and female).
- L2-regularization ($\lambda = \{0, 0.2, 0.5, 2.0, 4.0\}$)
- Dropout (0%, 20%, 40%, 60%, 80%)

3. Model Training and Evaluation

- Training Algorithm: Negative log-likelihood loss function with an appropriate optimizer (e.g., Adam or SGD).
- Evaluation Metrics:
- Accuracy

- Female Sensitivity & Precision
- Male Sensitivity & Precision
- Misclassification Analysis

4. Performance Comparison & Analysis

- FCNN vs. CNN performance under different regularization conditions.
- Impact of high dropout (≥40%) on classification bias.
- Effect of L2-regularization on male-female misclassification trends.
- Confusion matrices to visualize prediction errors.

STIMULATION RESULTS

We evaluated our proposed ODFL and ODL on five widely used face aging datasets: MORPH, FG-NET, FACES, LIFESPAN, and the apparent facial gender estimation dataset. MORPH contains 55,608 images from 13,000 subjects aged 16 to 77, while FG-NET has 1,002 images of 82 persons aged 0 to 69. FACES includes 2,052 images from 171 individuals aged 19 to 80 with six expressions, and LIFESPAN consists of 844 images from 590 subjects aged 18 to 94. The apparent gender estimation dataset comprises 4,112 training and 1,500 validation images with an age range of 0 to 100. Face detection and alignment were performed using DLIB and affine transformation, resizing images to 256×256×3. Data augmentation involved horizontal flipping and random cropping. We utilized pretrained VGG-16 Face Net parameters, introducing new fully connected layers (4096-50 for ODFL and 4096-A for ODL). The network was trained with a weight decay of 0.0001 and momentum of 0.9, converging after 2,000 iterations. Random oversampling enhanced feature discriminativeness, ensuring robust training.

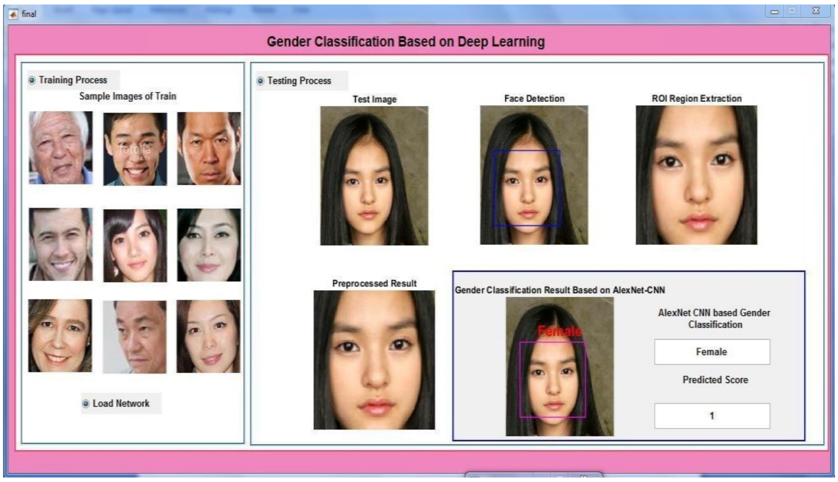

Figure.1 Gender Classification

ADVANTAGES

- High Accuracy & Robustness
- Automated Feature Extraction
- Scalability & Generalization

- Real-time Processing
- Robustness to Variations
- Transfer Learning Capabilities

APPLICATIONS

- Access control systems use gender-based authentication for secure entry in workplaces, banks, and government facilities.
- Crime investigation benefits from gender classification using CCTV footage to help law enforcement.
- Smart surveillance enhances AI-powered monitoring by identifying individuals' gender for security purposes.
- Personalized advertising displays gender-specific ads in e-commerce and retail.
- Audience demographics analysis helps businesses analyze customer behavior in malls, airports, and public spaces.
- Targeted promotions optimize marketing strategies based on gender-related trends.
- AI chatbots and virtual assistants adapt responses based on user gender for better interactions.
- The gaming industry uses gender recognition to enhance user experience in VR and AR applications.

CONCLUSION

In this paper we have presented our findings from our experiments on gender classification and gender classification from facial images using neural networks. We performed nine gender classification experiments on fully-connected neural networks using different L-2 regularization parameters and different dropout regularizations. We also performed nine gender classification experiments on convolutional neural networks varying the L2 and dropout regularizations. The fully-connected neural networks performed only slightly better than that of mere chance. The best performance among the convolutional neural network was a balanced accuracy of about 88.68%, informedness of about 0.7735, and markedness of about 0.7777.

FUTURE SCOPE

Though we have attained significant experimental findings in this research, some areasremain incomplete or at least deserve further investigation. We will extend this research and investigate these areas in our further research.

We will access reliable standard deviations (for each image) to be used with the Gaussian loss function. We will further investigate the comparative performance of convolutional gender classifiers with different cost functions, including the negative loglikelihood cost function and the Gaussian loss function.

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