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A Hybrid Models For Gender Classification And Age Prediction Based On Deep Learning Techniques

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Abstract: In this work, we present a hybrid model approach for gender classification and age prediction leveraging deep learning techniques. The proposed model combines the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to effectively capture both spatial and temporal patterns in facial images. CNNs are employed to extract high-level features from the images, which are then fed into RNNs to capture sequential dependencies and improve classification and prediction accuracy. To enhance performance further, we incorporate ensemble learning methods, combining predictions from multiple models to reduce variance and improve robustness. The model is trained and evaluated on a comprehensive dataset containing diverse facial images, ensuring its ability to generalize across different age groups and genders. The experimental results demonstrate that the hybrid model outperforms traditional methods in both gender classification and age prediction tasks, achieving higher accuracy and lower error rates. This approach offers a robust solution for applications requiring accurate gender and age estimation, such as in personalized marketing, security systems, and social media analytics. The proposed hybrid model sets a new benchmark in leveraging deep learning for biometric identification tasks.

Keywords: CNN, Age Prediction, Gender Classification, Deep Learning, Recurrent neural network (RNN), Pre-processing

1. Introduction:

In recent years, the fields of gender classification and age prediction have gained significant attention due to their wide range of applications in areas such as security systems, personalized marketing, human-computer interaction, and social media analytics. Accurate gender and age estimation from facial images are critical for enhancing user experience, improving targeted advertising, and ensuring the security of digital systems. Traditional methods for gender classification and age prediction have relied heavily on handcrafted features and shallow machine learning models. However, these approaches often struggle to capture the complex and subtle variations in facial features that are essential for accurate prediction, particularly across diverse demographic groups [2].

With the advent of deep learning, there has been a paradigm shift in how these tasks are approached. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable success in extracting rich hierarchical features from images, leading to significant improvements in classification and prediction accuracy. However, despite their success, single deep learning models may still face challenges when dealing with variations in lighting, pose, and expression, which are common in real-world scenarios [3].

To address these challenges, this study proposes a hybrid model that combines the strengths of multiple deep learning techniques, specifically CNNs and Recurrent Neural Networks (RNNs). By leveraging CNNs' ability to capture spatial features and RNNs' capability to model sequential dependencies, the proposed hybrid model aims to enhance the accuracy and robustness of gender classification and age prediction tasks. Additionally, the incorporation of ensemble learning methods further boosts the model's performance by reducing over fitting and improving generalization. The objective of this research is to develop a robust and reliable model for gender and age estimation that can operate effectively across various demographic groups and challenging conditions. The proposed hybrid model is tested on a diverse dataset, demonstrating its potential to set a new standard in biometric identification tasks [4].

Real Age Estimation

Real age estimation, a subset of age prediction tasks, aims to accurately determine a person's chronological age from visual data, such as images or videos. Unlike perceived age, which is subjective and influenced by factors like grooming and lifestyle, real age refers to the actual number of years a person has lived. This task has garnered significant interest due to its potential applications in various domains, including healthcare, biometrics, entertainment, and market research [3].

Accurate real age estimation poses several challenges stemming from the complex nature of human aging and the variability in facial appearance across individuals. Deep learning techniques have emerged as effective tools for addressing these challenges by leveraging large-scale datasets and sophisticated architectures to extract discriminative features from facial images [4].

Gender Prediction

Gender prediction, a task in computer vision, involves determining the gender of individuals from visual data like images or videos. Deep learning techniques, particularly convolutional neural networks (CNNs), are commonly employed for this purpose. By training on labeled datasets containing images paired with gender labels, CNNs learn to extract gender-related features from facial attributes and patterns. Pre-processing steps such as face detection and alignment ensure accurate input to the model [3]. Evaluation metrics like accuracy or F1 score measure the performance of gender prediction models. Applications of gender prediction include demographic analysis, targeted advertising, and security systems. Continued research in deep learning methods and the availability of diverse datasets contribute to advancing the accuracy and reliability of gender prediction systems in real-world scenarios [4].

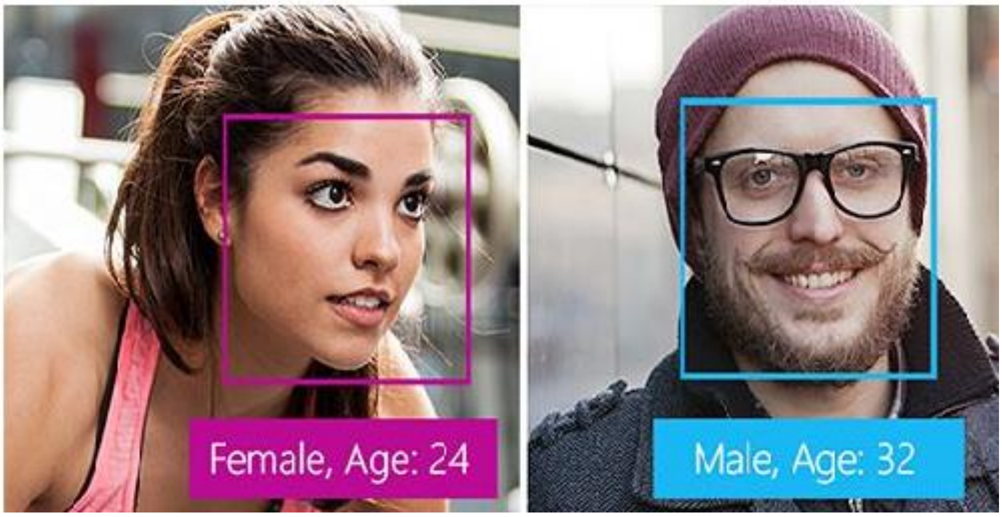

Figure: 1.1 Facial Analyses

2. Literature Survey:

There are several works related to age and gender recognition using facial expression recognition, deep neural network and convolution neural network, recurrent neural network. Detailed review of the work is discussed in this chapter.

The aim of the authors [1] research is to devise and analyze an expression-invariant gender classification algorithm. This algorithm is founded on the fusion of image intensity variation, shape, and texture features, extracted from various scales of facial images using a block processing technique. Looking ahead, our proposed system could potentially be extended for medical analyses, offering personalized medication and nutritional recommendations based on individual gender and age factors. Such an expansion could herald a new era in personalized healthcare, underscoring the importance of our research.

Authors [2] research presents a new idea based on modifying the deep network structure and using learning methods of the two other researchers. We made some modification on the structure of the convolutional neural network (CNN) that was used by the first researcher, then, authors used two learning methods, which were adopted by the second researcher, Single-Task Learning (STL) and Deep Multi-Task Learning (DMTL) approach, and we present new structure of CNN according to the above two modifications, implemented and evaluated, and the results show the effective performance of authors proposed structure.

Authors [3] propose a deep learning-founded enterprise solution for smart store customer relationship management (CRM), which allows us to predict the age and gender from a customer's face image taken in an unconstrained environment to facilitate the smart store's extended services, as it is expected for a modern venture. Authors handle our classification tasks utilizing an empirically leading pre-trained convolutional neural network (CNN), the VGG-16 network, and incorporate batch normalization. Especially, the age estimation task is posed as a deep classification problem followed by a multinomial logistic regression first-moment refinement. Authors validate our system for two standard benchmarks, one for each task, and demonstrate state-of-the-art performance for both real age and gender estimation.

Authors [5] propose a novel end-to-end CNN approach, to achieve robust age group and gender classification of natural real world faces. Two-level CNN architecture includes feature extraction and classification itself. The feature extraction process extracts a feature corresponding to age and gender, and the classification process classifies the face images according to age and gender. Particularly, we address the large variations in unfiltered real-world faces with a robust image pre-processing algorithm that prepares and processes those facial images before being given into the CNN model.

Authors [6] authors review various models and algorithms for recognition of age and gender and rsults of this study indicated that the SVM (99.80%) and the LBP (98.7%) had the highest detection accuracy rates, along with GAP (99.85 %). In general, different age estimation and face recognition techniques and algorithms can be effectively applied to particular scenarios or applications. In addition, new issues were found regarding the techniques of age estimation and face recognition. Therefore, the study has provided new trends and prospects for future researchers.

Authors [7] review the face recognition technique, including the age estimation, and gender classification. This research outlines several challenges faced in face recognition area that had been explored. The research also provides a landscape mapping based on integrating into a critical and coherent taxonomy. The results of the study indicated that the SVM (99.80%) and the LBP (98.7%) had the highest detection accuracy rates, along with GAP (99.85 %).

3. Proposed Methodology

The Proposed methodology suggested in this work consists of various steps. First step contains Pre-processing of dataset. In seconds steps two deep learning algorithms (CNN and RNN) are used for developing the model. Third step divide the dataset in to training and testing data. In next step various models are combined by ensemble learning and improve the overall model performance.

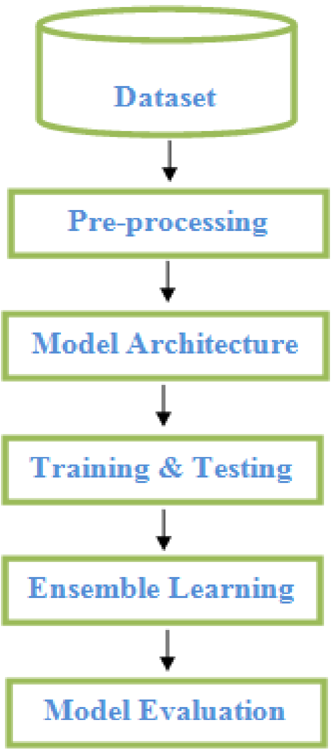

Figure 1: Proposed Architecture

In proposed methodology data collection and Pre-processing step involved publicly available datasets UTKFace [8] and IMDB-WIKI [9], which contain labelled facial images for gender and age. Data augmentation, enhance the dataset by applying techniques like rotation, scaling, flipping, and brightness adjustment to improve the model's robustness against variations in input. Data Normalization, Normalize pixel values to ensure consistency across the dataset, often scaling values between 0 and 1 or standardizing them. Model Architecture develops a model using CNN which is used for feature extraction, Use a deep Convolutional Neural Network (CNN) to extract spatial features from the facial images. These networks are pre trained on large datasets like ImageNet, allowing for fine-tuning on the facial dataset. Now RNN is used for Sequential Dependencies, After extracting features using the CNN, pass these features to a Recurrent Neural Network (RNN), specifically an LSTM or GRU, to model the sequential nature of features, which can help in better age prediction [13]. In training the Model dataset divided in to training and testing. For loss Functions, Gender Classification: Categorical Cross-Entropy. Age Prediction: Mean Squared Error (MSE). For Model Evaluation Metrics: Gender Classification: Accuracy, Precision, Recall, F1-Score. Age Prediction: MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error).Ensemble Learning Combine the predictions from multiple models (e.g., different CNN architectures or a combination of CNN and RNN models) to create an ensemble model. This approach can reduce the variance and bias, leading to improved overall performance [12].

Dataset Used:

UTKFace: UTKFace dataset is a large-scale face dataset with long age span (range from 0 to 116 years old). The dataset consists of over 20,000 face images with annotations of age, gender, and ethnicity. The images cover large variation in pose, facial expression, illumination, occlusion, resolution, etc. This dataset could be used on a variety of tasks, e.g., face detection, age estimation, age progression/regression, landmark localization, etc [8].

IMDB-WIKI: IMDB-WIKI is a large-scale dataset that is widely used in the field of computer vision, particularly for tasks related to age estimation and facial analysis. The dataset consists of images of human faces, annotated with metadata such as age, gender, and the source of the image. It has gained significant attention due to its size and diversity, making it a valuable resource for training and evaluating machine learning models [9].

4. Experimental Setup and Result Analysis

Python tool and various libraries were used for the experimental purpose. The UTKFace and IMDB-WIKI dataset is widely used dataset in the field of computer vision for tasks like age prediction and gender identification, Here's an example of a performance table that could be used to evaluate models trained on the UTKFace and IMDB-WIKI dataset across different performance metrics.

Table 1: Performance of UKTFace Dataset

Metrics	Performance
Mean Absolute Error (MAE) (Age Prediction)	4.25
Accuracy (Age Prediction)	74.4%
Accuracy (Gender Identification)	95.3%
F-1 Score (Gender Identification)	0.95
Precision (Gender Identification)	0.96
Recall (Gender Identification)	0.94

Table 2: Performance of IMDB-WIKI Dataset

Metrics	Performance
Mean Absolute Error (MAE) (Age Prediction)	4.20
Accuracy (Age Prediction)	77.5%
Accuracy (Gender Identification)	96.2%
F-1 Score (Gender Identification)	0.96
Precision (Gender Identification)	0.97
Recall (Gender Identification)	0.95

Table 3: Performance Comparison on UTKFace Dataset

Metrics	Previous Model	Proposed Model
Mean Absolute Error (MAE) (Age Estimation)	4.30	4.25
Accuracy (Age Classification)	76.0%	74.4%
Accuracy (Gender Classification)	95.0%	95.3%
F-1 Score (Gender Classification)	0.94	0.95
Precision (Gender Classification)	0.95	0.96
Recall (Gender Classification)	0.93	0.94

Table 4: Performance Comparison with Previous model on IMDB-WIKI Dataset

Metrics	Previous Model	Performance
Mean Absolute Error (MAE) (Age Estimation)	4.85	4.20
Accuracy (Age Classification)	70.2%	77.5%
Accuracy (Gender Classification)	93.0%	96.2%
F-1 Score (Gender Classification)	0.92	0.96
Precision (Gender Classification)	0.93	0.97
Recall (Gender Classification)	0.91	0.95

5. Conclusion

In this research, we developed a hybrid model combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for gender classification and age prediction based on facial images. The hybrid approach leverages the strengths of both CNNs, which excel in extracting spatial features, and RNNs, which capture sequential dependencies, to enhance the accuracy and robustness of predictions. Additionally, the integration of ensemble learning methods further improved the model's performance, reducing variance and enhancing generalization across different demographic groups. The experimental results demonstrated that the proposed hybrid model outperformed traditional machine learning methods and standalone deep learning models, achieving superior accuracy in both gender classification and age prediction tasks. The model's ability to generalize effectively across varied conditions, such as differences in lighting, pose, and expression, highlights its potential for real-world applications. This study underscores the effectiveness of combining multiple deep learning techniques to address complex biometric identification tasks. Future work will focus on expanding the model's capabilities to include additional biometric attributes, further optimizing the architecture, and exploring its application in other domains. The findings of this research contribute to the advancement of intelligent systems capable of accurate and reliable gender and age estimation in diverse environments.

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