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PROJECT PROPOSAL

Human Face Aging and Gender Prediction

Under the Supervision of

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BS(CS)-VIII (A)

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1. Introduction:

The ability to predict a person’s age, identify their gender, and visualize how they might look as they age, all from a single facial image, has become a captivating area of research in computer vision and artificial intelligence. While advancements in technology have made gender classification relatively straightforward due to distinct visual differences, age prediction remains a complex task. People age at different rates based on a combination of factors like genetics, lifestyle, and environment, which makes it challenging for machines to accurately estimate age solely based on facial features. As the saying goes, "looks can be deceiving," and it’s true that some people appear much older or younger than they are.

This project explores modern techniques for tackling the tasks of age and gender classification alongside aging progression. Specifically, we use **Generative Adversarial Networks (GANs)** to simulate what a person’s face might look like at various ages, and **Convolutional Neural Networks (CNNs)** to classify people by age and gender based on unique facial features. Our goal is to create a system that can accurately predict age and gender and also generate realistic age-progressed images, illustrating how individuals may look at different stages of life. This approach is both innovative and practical, merging classification with visual progression, which opens up exciting possibilities in various fields like law enforcement, customer engagement, and aging research.

2. Problem Statement

Accurately predicting age and gender, along with modeling how people might look as they age, can have substantial real-world applications. For instance, law enforcement agencies could use age progression to locate missing persons by generating an updated image of how they might look years after their disappearance. Businesses could use age prediction to personalize their services for customers as they grow older, while aging research and healthcare can benefit from non-intrusive techniques for studying facial changes over time.

However, the task is not straightforward due to the diverse and complex nature of human aging. People age differently based on various factors that are not always visible on their faces, such as lifestyle choices, genetics, and environmental influences. Traditional age-prediction models rely on specific facial features that often fail to generalize well, especially in "in-the-wild" images where lighting, pose, and expressions vary. Additionally, gender classification alone can sometimes be challenging when analyzing younger faces, which often show fewer distinct male or female characteristics. Our project aims to address these challenges by using GANs and CNNs in tandem, creating a model that predicts age and gender while also visualizing how a person's appearance might evolve as they grow older.

3. Proposed Methodology

Our Approach:

To address these objectives, we use two powerful types of deep learning models:

- **Generative Adversarial Networks (GANs)**: GANs are advanced neural networks that generate realistic images by having two components—the **generator** and the **discriminator**—compete with each other. In this project, the GAN is trained to create age-progressed images, simulating what a person's face might look like at different ages. The generator attempts to create realistic aged faces, while the discriminator evaluates these images and tries to distinguish between real and fake images. Over time, this process helps the generator improve, eventually producing lifelike images that simulate aging progression accurately.
- **Convolutional Neural Networks (CNNs)**: CNNs are a type of neural network particularly suited for image recognition tasks. Here, we use a CNN for two purposes: (1) to classify the person's age into predefined age categories and (2) to predict the gender of the individual. CNNs work by analyzing images through multiple layers of filters, which identify features such as edges, textures, and facial landmarks. These extracted features are then used by the CNN to predict age and gender with high accuracy.

Training Steps:

We begin by training the CNN model on a dataset of facial images labeled with both age and gender. This will help the CNN learn patterns associated with different age groups and recognize male and female facial characteristics. The GAN will then be trained to create images that represent various stages of aging. Once the models are trained, we will evaluate their performance in two areas: (1) the CNN's accuracy in predicting age and gender and (2) the GAN's ability to produce convincing, realistic images of age progression. This dual approach allows us to both classify and visualize aging in a unified system.

Preprocessing:

For the models to perform optimally, it's essential to preprocess the images before feeding them into the neural networks. This involves several steps, including aligning faces in the images, color conversion, and resizing. By aligning faces, we ensure that all facial images are centered and consistent, which helps the model focus on key facial features rather than being distracted by irrelevant areas. Additionally, we convert images from BGR (Blue, Green, Red) to RGB (Red, Green, Blue) format for better processing, as this matches the color channel order most models expect. Finally, we apply **data augmentation** techniques—such as rotation, scaling, and flipping—to increase the diversity of the training images, which helps prevent overfitting and makes the model more robust to variations in real-world images.

4. Dataset Discussion

For this project, we have selected the **UTKFace dataset** from Kaggle. This dataset contains a broad spectrum of facial images labeled with age and gender, making it ideal for training a model to recognize and categorize different age groups and gender types. The UTKFace dataset includes people of various ages, from young children to elderly adults, and contains images of diverse ethnic backgrounds, allowing the model to generalize well across different demographics.

However, like many real-world datasets, UTKFace is slightly imbalanced, meaning some age categories have significantly more images than others. This could lead to the model favoring certain age groups over others, potentially affecting its accuracy. To address this issue, we will consider applying weighted loss functions or enhancing underrepresented age groups through data augmentation. These techniques help ensure that the model learns equally from all age groups, resulting in more balanced performance across categories.

5. Major Outcomes

Expected Results:
With the methodology we have outlined, we anticipate achieving the following outcomes:

- **Accurate Age and Gender Classification**: The CNN model should accurately classify a given face into an age category and predict the gender with high confidence.
- **Realistic Age-Progressed Images**: The GAN model should generate images that convincingly simulate natural aging progression, enabling the visualization of a person's future appearance.

Applications:
Our project has numerous practical applications across different fields:

- **Security and Law Enforcement**: The model could assist in locating missing persons by producing updated images that show how they might look after several years. Law enforcement agencies could also use it to update criminal profiles over time.
- **Customer Service and Marketing**: Businesses could use age and gender prediction to provide personalized services for their customers based on their current and predicted age group. For example, age predictions could help brands recommend suitable products to customers as they age.
- **Healthcare and Aging Research**: Researchers could use the model to study aging patterns based on gender and other factors, which could contribute to understanding age-related health issues. The tool offers a non-invasive way to observe aging changes over time.

6. Project Timeline

Phase	Duration	Activities
Week 1	Project Planning & Dataset Preparation	Define project objectives, finalize datasets, conduct literature review, preprocess and clean the UTKFace dataset.
Week 2	CNN Model Development for Age and Gender Classification	Develop and train the CNN model for age and gender prediction using preprocessed data, fine-tune parameters for optimal results
Week 3	GAN Model Development for Age Progression	Develop the GAN model for simulating age progression, experiment with different architectures, and train on age-labeled data
Week 4	Model Refinement & Evaluation	Refine CNN and GAN models based on initial evaluation, address imbalanced classes, and improve model accuracy.
Week 5	Integration & Testing	Integrate CNN and GAN models, conduct extensive testing for age, gender, and age-progression predictions, and troubleshoot issues.
Week 6	Final Refinement, Documentation, and Preparation for Deployment	Fine-tune models, prepare documentation, create presentation materials, and finalize for deployment and demo presentation

Table 1.1 Project Timeline

7. Conclusion

This project presents an innovative approach to age and gender prediction by combining GANs and CNNs. This dual-model strategy enables the system not only to predict age and gender with high accuracy but also to visualize aging progression in a realistic way. The potential applications of this technology span across security, customer engagement, and healthcare, making it a versatile tool with numerous benefits. As we continue to improve the model, we anticipate this work will contribute to further advancements in age-related research and open up new avenues for practical, real-world applications.

8. References

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