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Deep Learning-Based Gender Recognition from Facial Images using Benchmark Datasets

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Abstract- Gender identification from facial images is an important problem in computer vision and has attracted growing interest due to its applications in surveillance, security, and human-centered systems. Although humans can infer gender naturally, developing automated systems that perform reliably across real-world conditions remains challenging. This work presents a gender classification framework that leverages face recognition feature vectors for prediction. First, face images are detected, aligned, and preprocessed to obtain a standardized facial representation. Next, a face recognition network extracts compact feature embeddings that encode discriminative facial characteristics. Finally, machine learning and deep learning classifiers are applied to these embeddings to determine gender. The proposed system integrates advanced components including VGG-Face, Deep Belief Networks, and shifted filter responses to improve robustness. Multiple deep learning architectures were investigated—CNN, VGG16, ResNet50, InceptionV3, and EfficientNet—with ResNet152 showing the strongest overall performance. Experimental findings indicate that ResNet152 achieves approximately 9% improvement over leading alternatives and demonstrates enhanced resilience to anomalies and variations compared with earlier approaches.

Keywords – Gender Classification, Face Recognition Embeddings, Convolutional Neural Networks (CNN), VGG-Face, Deep Belief Networks, LFW, FERET, VGG16, ResNet, InceptionV3, EfficientNet.

I. INTRODUCTION

Over the past decade, image recognition has advanced rapidly, largely due to the success of deep learning. Among many vision tasks, gender recognition from face images has emerged as a widely studied topic because of its practical relevance in areas such as personalized services, targeted advertising, access control, and visual surveillance [1]. Gender recognition aims to classify an individual's gender using visual information derived from facial structure and appearance.

Earlier gender classification methods relied heavily on handcrafted features, where human-designed descriptors—such as measurements of the eyes, nose, mouth, or facial proportions—were extracted and fed into traditional classifiers [2]. While these approaches established a foundation for face-based gender prediction, their performance was often limited by poor generalization under changing lighting conditions, pose variations, facial expressions, and image quality.

Deep learning, a subfield of machine learning inspired by neural processing, has reshaped computer vision by enabling models to learn discriminative representations directly from raw data. In particular, Convolutional Neural Networks (CNNs) learn hierarchical feature patterns that are highly effective for image understanding tasks. For gender recognition, deep models offer major advantages: they can capture subtle facial cues, learn robust feature representations automatically, and maintain performance across varied datasets and imaging environments.

This work reviews and analyzes the approaches, model architectures, and recent developments that have positioned deep learning at the core of modern gender recognition systems. It provides an overview of state-of-the-art model designs, benchmark dataset challenges, and practical application considerations. To reduce errors in real-world deployment, it is essential to improve both data quality and model robustness.

This includes using large, diverse datasets to reduce demographic bias, applying regularization techniques such as dropout to prevent overfitting, and performing careful hyperparameter tuning to maximize accuracy. In addition, ensemble learning can enhance reliability, while ongoing model updates, cross-validation, and detailed error analysis help ensure adaptability to new data. Finally, ethical considerations must remain central—particularly the identification and mitigation of bias—to support fairness and trustworthy performance in gender recognition systems.

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II. LITERATURE WORK

Recent growth in gender-identification research across multiple domains has led to a wide range of methods and findings. For example, Ref. [1] presents an automated deep learning framework for human identification and gender recognition, highlighting broader machine learning applications in biometric analysis. From a different perspective, Ref. [2] investigates gender-related variation in human papillomavirus (HPV), emphasizing methodological considerations for retrospective cross-sectional studies.

In computer vision, several studies focus on extracting discriminative visual cues. Refs. [3] and [4] apply advanced neural architectures—such as Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs)—to infer gender using eye-region features and enhanced/modified facial imagery, respectively. Complementing these deep learning approaches, Refs. [5] and [6] demonstrate the effectiveness of traditional machine learning by employing multi-class Support Vector Machines (SVMs) for gender classification from facial images, illustrating the flexibility of feature-based models.

Beyond facial analysis, gender recognition has also been explored through alternative biometric signals. Ref. [7] proposes a gait-based gender classification system using a Kinect sensor, underscoring the importance of real-time recognition. In contrast, Ref. [8] introduces handwriting-based gender prediction, reflecting an interesting fusion of behavioral biometrics and computational analysis.

Deep learning remains a dominant direction in this field. Refs. [9], [10], and [12] highlight the role of gender estimation from unconstrained face images, using strategies such as modified CNN architectures and robust feature extraction under real-world conditions. The versatility of deep learning is further demonstrated in Ref. [11], where transfer learning is applied to gender prediction using social media profile images.

Other studies expand gender classification to additional biometic sources. Refs. [13] and [14] explore fingerprint-based gender identification, demonstrating the breadth of modalities available for this task. Ethical and societal considerations are also emerging: Ref. [15] examines bias in image-generative AI systems, particularly in how women are represented (e.g., smiling patterns), drawing attention to fairness concerns in AI outputs. Beyond vision-based approaches, Ref. [16] investigates gender recognition using acoustic features and machine learning, while Ref. [17] presents an ensemble-based framework for gender prediction in surveillance video, reinforcing the growing emphasis on robust, real-time deployment.

III PROPOSED APPROACH

Working of Proposed framework

Figure 1: Methodology using features from VGG16 model

Algorithm

Notation

- Image dataset: D={(I_i,y_i)}_(i=1)^N, where I_i= input face image, y_i∈{0,1}(0 = Female, 1 = Male)
- Preprocessing operator: P(·)
- Face detector: F(·)returns bounding box b_i
- Cropping operator: C(I_i,b_i)
- Feature extractor (CNN/VGG/ResNet): ϕ(·)
- Feature vector: x_i∈R^d
- Classifier parameters: θ

Stepwise Algorithm
Step 1: Data Input

$$\mathcal{D} = \{(I_i, y_i)\}_{i=1}^{N}$$

Step 2: Face Detection and Preprocessing
Detect face:

$$b_i = \mathcal{F}(I_i)$$

Crop face region:

$$I_i^{face} = \mathcal{C}(I_i, b_i)$$

1. Preprocess (resize + normalize):
Resize to fixed size (H, W):

$$I_i^r = \text{Resize}(I_i^{face}, H, W)$$

Normalize pixel range (e.g., $[0, 1]$

$$I_i^p = \frac{I_i^r}{255}$$

Feature dataset:

$$\mathcal{X} = \{(x_i, y_i)\}_{i=1}^{N}$$

Step 4: Classification (Binary Gender Prediction)
Use a binary classifier on features. Common choice: **logistic regression head.**
Logit score:

$$z_i = w^\top x_i + b$$

Sigmoid probability:

$$\hat{p}_i = \sigma(z_i) = \frac{1}{1 + e^{-z_i}}$$

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Predicted label:

$$\hat{y}_i = \begin{cases} 1, & \hat{p}_i \geq 0.5 \\ 0, & \hat{p}_i < 0.5 \end{cases}$$

Training Objective (Loss Function)
Binary cross-entropy loss over the dataset:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{p}_i) + (1 - y_i)\log(1 - \hat{p}_i)]$$

where $\theta = \{w, b, \phi\}$(if end-to-end training)
or $\theta = \{w, b\}$if $\phi$is frozen and only classifier is trained).
Optimization (e.g., Adam/SGD):

$$\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L}(\theta)$$

Final Output
For a new input image I:

$$\hat{y} = \arg\max_{c \in \{0,1\}} P(y = c \mid I)$$

and the system outputs: Tumor/Non-tumor in your earlier task or here Male/Female.

IV. IMPLEMENTATION AND RESULT

Table 1. Hardware and Software Requirements

Component	Specification / Description
Operating System	Windows 10 Home (64-bit), ensuring broad software compatibility
Audio System	High-definition audio support
Graphics	Intel Iris Plus Graphics for advanced visual rendering
Camera	HP HD TrueVision Camera for clear video communication
Programming Language	Python
Deep Learning & Data Science Libraries	NumPy, TensorFlow, Keras
Primary Usage	Data processing, machine learning, and deep learning development

DataSet
The CelebA dataset [18] is a large-scale collection of facial images containing more than 200,000 photos of celebrity faces. Because the images were captured across different sessions and conditions, the dataset includes substantial variation in facial expression, pose, lighting, and background [19]. In addition, the Labeled Faces in the Wild (LFW) dataset contains approximately 13,000 labeled face images collected from unconstrained real-world environments, meaning the faces are captured without strict control over alignment or head pose [20]. Another commonly used facial database includes over 20,000 face images categorized by demographic attributes such as age, gender, and ethnicity [21]. For experimentation, the data were divided into training and testing sets using an 80:30 ratio.

Implementation

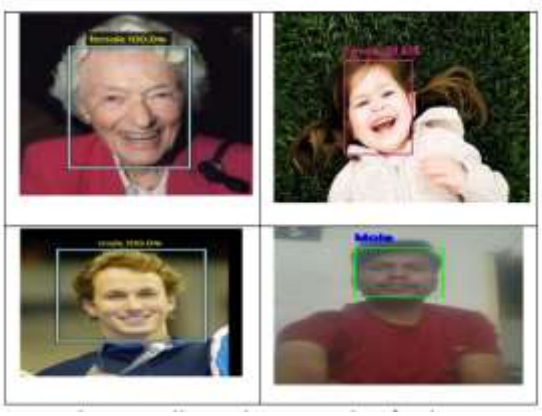

Figure 2: Illustrative example of 4 datasets

Result

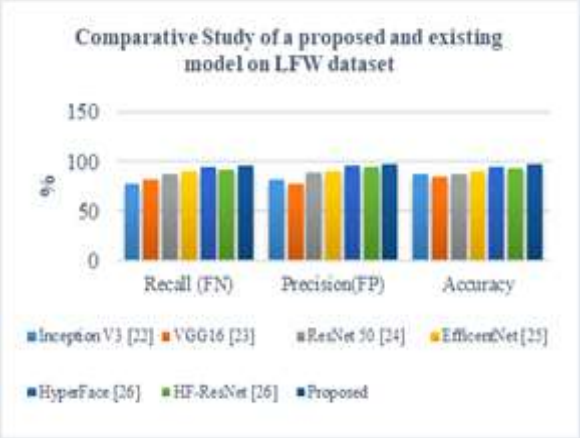

Figure 2: Result of LFW dataset

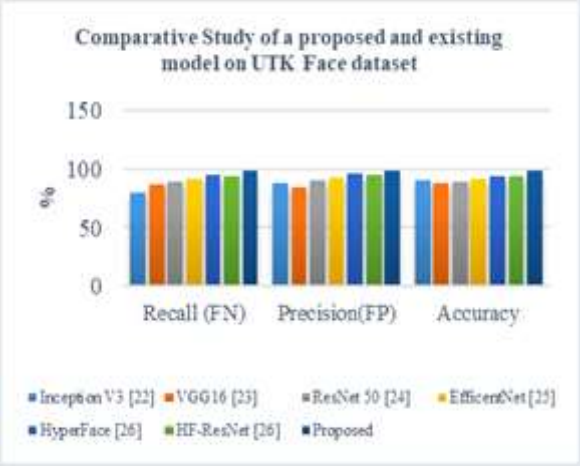

Figure 3: Result of UTK dataset

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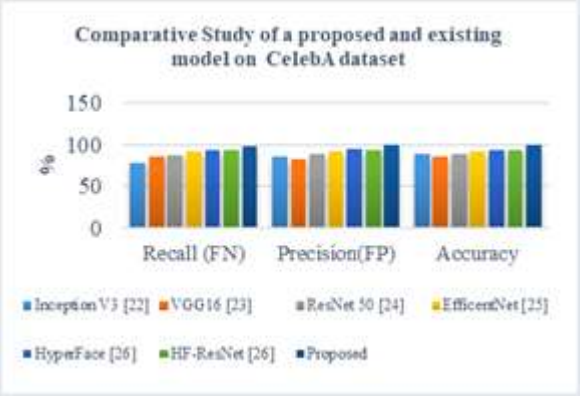

Figure 4: Result of CELEBA dataset

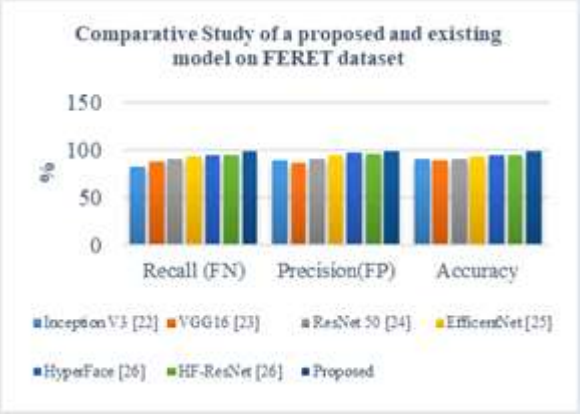

Figure 5: Result of FERET dataset

V. CONCLUSION

Research on gender classification has the potential to strengthen a wide range of real-world technologies, including computer vision applications, biometric identification systems, credit card and identity authentication, surveillance and monitoring platforms, and data security solutions. Progress in this area has also contributed to broader developments in machine learning, image processing, and human–computer interaction, where gender recognition often serves as a supporting component in face-analysis pipelines. In this study, experiments were conducted using well-established benchmark datasets to evaluate several deep learning architectures, including CNN, VGG16, ResNet50, InceptionV3, and EfficientNet. Among all tested models, ResNet152 consistently achieved the best results. Notably, ResNet152 delivered an improvement of approximately 9 percentage points over other state-of-the-art alternatives. In addition, the proposed models showed stronger robustness to outliers and challenging samples compared with earlier approaches, indicating improved generalization in practical scenarios.

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