Detection of Human Age and Gender by Processing Photos: Machine Learning Approach

Presented By-

MD. Rufsan Jani Shanto(221-35-1064)

Supervised by:

Ms. Ishrat Sultana

Lecturer, Department of Software Engineering

Daffodil International University

Outlines

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Research Gaps & Problem Statement

Research Gaps

- **Bias in datasets**: Most datasets lack diversity, leading to reduced model fairness across ethnicities and genders.

- **Lower accuracy in real-world scenarios**: Models struggle with occlusions, extreme angles, poor lighting, and non-frontal faces.

- **Age estimation in children and the elderly**: Facial features in these groups vary widely, making accurate prediction challenging.

Problem Statement

In real-world applications such as targeted marketing, access control, human-computer interaction, and demographic analytics, determining a person's age group and gender from facial images plays a significant role. Existing models struggle with occlusions, extreme angles, poor lighting, and non-frontal faces.
This research addresses the problem by developing a machine learning-based approach to accurately classify age and gender from photos despite these complexities.

Objectives

- **RO1**: To provide insights into ethnicity factors (example: facial structure, skin tone) that influence age and gender detection from photos.
- **RO2**: To assess the impact of lighting and angles on age and gender detection from photos.
- **RO3:** To compare the performance of various machine learning and deep learning models (e.g., CNNs) with real-world scenarios.

Research Scope

✓The study focuses on both early-aged and aged people.
✓It includes both Bangladeshi and foreign people
✓The research examines factors influencing age and gender prediction.
✓The study is limited to the context of human male and female gender prediction. It does not cover other genders.

Literature Review

NO	Title	Authors	Year	Applied Method	Key finding
01	Age Estimation from Facial Images using Transfer Learning and K-fold Cross-Validation.	S. M. Shihab Uddin et al.	2021	Used pre-trained CNNs (VGG16, ResNet50, and SENet50 with VGGFace weights), fine-tuned with custom layers for 8 age groups. Applied transfer learning, 5-fold cross-validation, data augmentation, and layer freezing, trained on Google Colab GPUs (~5 hrs/model). **Dataset:** UTKFace dataset—comprising over 20,000 images with ages from 0 to 116 years, labeled for age, gender, and race	**Result:** ResNet50 performed best with 88.03% validation accuracy, surpassing FaceNet (56.9%), VGG16 (64%), and distillation-based models. **Limitation:** Limited data, design, and real-world variability reduce model generalization.
02	Age and Gender Detection using Facial Images	Esmat Mohamed et al.	2023	The system uses Haar classifiers or YOLOv8 for face detection and CNNs for classification, with preprocessing like alignment and augmentation to enhance robustness, optimized for real-time inference. **Dataset:** IMDB-Wiki, FairFace, UTKFace, Age BD	**Result:** YOLOv8 achieved 94.2% gender and 62.5% age accuracy, with 4,700+ correct predictions, showing strong performance. **Limitation:**Age imbalance and limited evaluation metrics may bias and weaken the model's reliability.

NO	Title	Authors	Year	Applied Method	Key finding
03	Age and Gender Prediction using Deep CNNs and Transfer Learning	Vikas Sheoran et al.	2023	They trained deep models from scratch and with pre-trained networks (VGGFace, ResNet50, SENet50), using transfer learning and linear regression for predictions. **Dataset:** They used the UTKFace dataset with 20,000+ labeled face images under varied conditions.	**Result:** Custom CNN achieved 5.67 MAE (age) and 94.5% (gender). Transfer learning with SENet50 gave best age MAE (4.58) and 94.94% gender accuracy **Limitation:** Faces with occlusion, extreme angles, and low lighting pose challenges.
04	Age and Gender Prediction Using Machine Learning	Bhavana B. Helwate et al.	2024	Uses OpenCV, CNNs, and TensorFlow with attention and multi-task learning for real-time age and gender prediction. **Dataset:** Not explicitly specified, but the approach aims for performance even with limited data.	**Result:** The proposed method outperforms existing techniques with higher accuracy in age and gender prediction. **Limitation:** Limited details suggest issues with diverse faces, accessories, or distorted images.

NO	Title	Authors	Year	Applied Method	Key finding
05	1 Human Age and Gender Prediction from Facial Images Using Deep LearningMethods	Puja Dey et al.	2024	The method uses a CNN with preprocessing, data augmentation, and regularization, trained on an 80/20 split and benchmarked against pre-trained models. **Dataset: 1.**Adience: Unfiltered facial images with age groups and gender labels. **2.**UTKFace: Diverse facial images labeled by age and gender, widely used for prediction tasks.	**Result:** The CNN outperformed existing methods with age accuracies of 86.42% and 81.96% and gender accuracies of 97.65% and 96.32%. **Limitation:** Image variability, demographic gaps, and high compute needs limit model performance.
06	2 Face-based Age and Gender Classification Using Deep Learning Model	Rajiv Kumar et al.	2024	A deep CNN pre-trained on IMDb-WIKI and fine-tuned on OIU-Adience uses dropout, augmentation, and hyperparameter tuning to classify age and gender with accuracy and MAE. **Dataset: 1.**IMDb-WIKI: Used to pre-train CNN on facial features. **2.**OIU-Adience: Benchmark with real-world face images labeled by age and gender.	**Result:**Achieved 84.8% age group accuracy and 2.26 MAE, outperforming CNN2ELM and generalizing well on unconstrained images. **Limitation:** Extreme poses, dataset noise, and limited gender accuracy analysis may affect performance.

NO	Title	Authors	Year	Applied Method	Key finding
07	Face-based Gender Classification Using Deep Learning	Buraq Abed Ruda Hassan et al.	2024	The approach uses Viola-Jones for face detection, preprocessing steps, and transfer learning with AlexNet for classification. **Dataset: 1.**LFW (1,200 images) **2.**Faces94 (400 images) **3.**Family dataset (400 images)	**Result:**Achieved 98.77% accuracy on LFW and 100% on Faces94 and family datasets; CLAHE contrast enhancement boosted performance. **Limitation:** Limited facial variation and real-world factors like lighting or angles may impact performance.
08	Real-Time age, gender, and emotion detection using YOLOv8.	V. Sowmya Devi et al.	2025	Two YOLOv8 models detect faces and classify age, gender, and emotions in a pipeline using bounding box matching, evaluated by accuracy, precision, recall, and F1-score under diverse conditions. **Dataset: 1.**Roboflow dataset with labeled emotions. **2.**UTKFace with 20,000+ images for age & gender. Both are preprocessed for YOLOv8.	**Result:** The algorithm outperforms models with 69.6% intersection and 73.6% concurrency, reducing errors and beating PreactResNet. **Limitation:** Occlusions, extreme angles, low lighting, and streaming issues can hinder performance.

NO	Title	Authors	Year	Applied Method	Key finding
09	Research on Deep Learning-based Image Processing and Classification Techniques for Complex Networks	Jiangli Liu et al.	2025	The proposed method designs an encoder using DCNN, ECANet, and DSA_ASPP modules to effectively capture multi-scale features. It integrates SIFT features as network nodes, with correlation coefficients as edge weights, to construct an image feature network for detailed local information extraction. **Dataset:** CUB-200-2011 and Stanford Dogs for classification, and CamVid and Cityscapes for segmentation evaluation.	**Result:** The proposed algorithm outperforms existing models in detection accuracy, achieving 69.6% intersection and 73.6% concurrency ratios. **Limitations:** data demand, high complexity, poor generalization, and need for encoder optimization.
10	Gender Classification from Human Face Images Using Deep Learning Based on MobileNetV2 Architecture	Nisreen Ryadh Hamza	2025	The study used a fine-tuned pre-trained MobileNetV2 for male/female classification, with data augmentation and transfer learning. Training employed the Adam optimizer, and performance was evaluated using the F1-score. **Dataset:**Biggest Gender/Face Recognition Dataset (Kaggle, 2021): 27,167 images (17,678 male, 9,489 female).	**Result:** The proposed system achieved a 96% F1 score, showing high accuracy and strong precision-recall balance for practical use. **Limitation:** Limited facial variation and real-world conditions may reduce performance.

Methodology

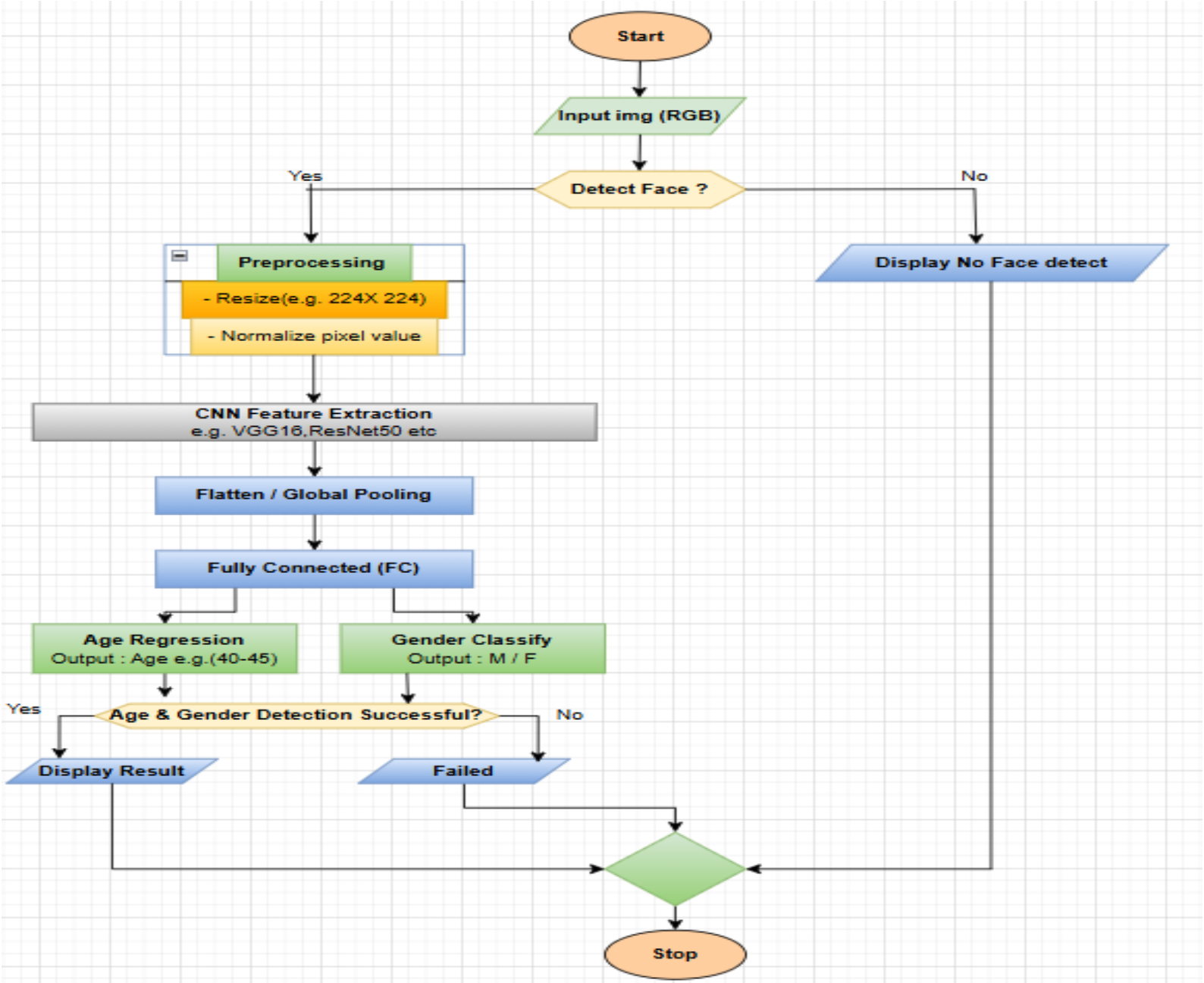

fig : Work flow Diagram

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THANK YOU

Question ???