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GENDER AND AGE DETECTION USING IMAGE CLASSIFICATION AND REGRESSION

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Abstract:

Classification and regression datasets are used, in conjunction with deep learning techniques, to determine the type of individual (e.g., gender and age). Stage-wise or phase-by-phase in terms of time, the activities conducted are given below: data used, training algorithm applied, and the use of accurate 89% and 92% for age and gender classification, respectively. Through the work, it can, however, be inferred that it has primary components that can be helpful for prior research, and, of course, it's suitable for demonstrating that deep learning can be applied to facial recognition tasks. Additionally, a confirmation section will be included to allow those who wish to dig deeper into this topic to verify the source of the information.

Keywords: *Regression, Machine Learning, Gender Detection*

Introduction

The most essential human identities in interaction with others are gender and age[1]. Age and gender detection, which consists of three parts facial recognition, gender calculation, and an estimate of age, are combined into a single detection system stage[2].Gender and age detection algorithms effectively infer demographic information through the examination of facial characteristics by applying machine learning methods[3], specifically deep comprehension models. The potential use of these techniques across a variety of applications, such as analytics for marketing[4], security systems[5], and human-computer interaction[6], has attracted significant attention. Nevertheless, despite tremendous progress[7], difficulties still arise when aiming for excellent precision, particularly in challenging real-world scenarios with fluctuating lighting, varying facial expressions, and obstructions.

Concerns about privacy and morality have drawn significant attention to the problem of automated gender determination[8]. Particularly, gender identification finds use in technical surveillance, consumer demographic data collection, human-computer interaction, statistical analysis for largescale text programs, and targeted database searches.

Poor data quality and non-universality are often linked to the use of single modalities in human-computer interaction and systems research; multimodal approaches may help address these issues. It can be accomplished by merging data from various sources that may provide extra or complementary information and be accessible for particular applications.

This paper thoroughly examines the most recent advancements, strategies, and challenges in gender and age detection research. We study the fundamentals of deep learning architectures used in cutting-edge detection systems, including recurrent neural networks (RNNs), convolutional neural networks (CNNs)[9], and others. We also go over the significance of evaluation metrics, preprocessing methods, and dataset quality when comparing the effectiveness of gender and age detection algorithms.

The familial method of feature extraction can be broadly categorized into two groups according to the features that are employed: appearance-based methods and linear feature-based techniques[10]. The distance between different facial features, like the lips, nose, chin, and eyes, is often referred to as a geometric feature. By returning the location for various characteristics, the Viola Junes method may be used for obtaining facial characteristics from a facial image. After that, the detected features' Euclidean distance and the French Ar's triangulation technique can be determined. Because it is essential to make

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sure that facial features are detected accurately, each image in the database was carefully chosen and mined in accordance with appropriate detection techniques[11]. As a result, a billion variables are utilized for training models on numerous samples.

2) Literature Review:

Many systems are available on the marketplace that use various technologies and methods and seek to determine age and gender. Deep learning methods are an increasingly common set of methods that academics in software engineering use to automate development tasks[12]. These methods have become popular due to their automated feature engineering abilities, which facilitate software artifact modeling. However, it is challenging to extract the achievements, difficulties, and future directions of the current research landscape due to the rapid adoption of deep learning techniques[13]. One area of artificial intelligence with a lot of potential is deep learning.

Currently, a crucial task for human security concerns the creation of structures that utilize age and gender for different mediums like mobile devices, programs that use social networks like Instagram, Facebook, and Snapchats, and different matrimonial and dating websites like shadi.com, happen, tinder, bumble, and others. [7]

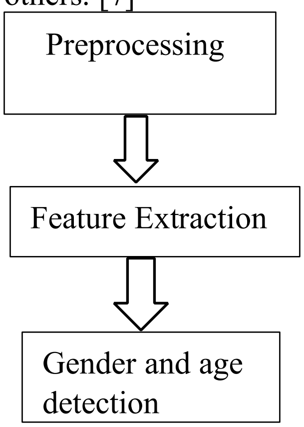
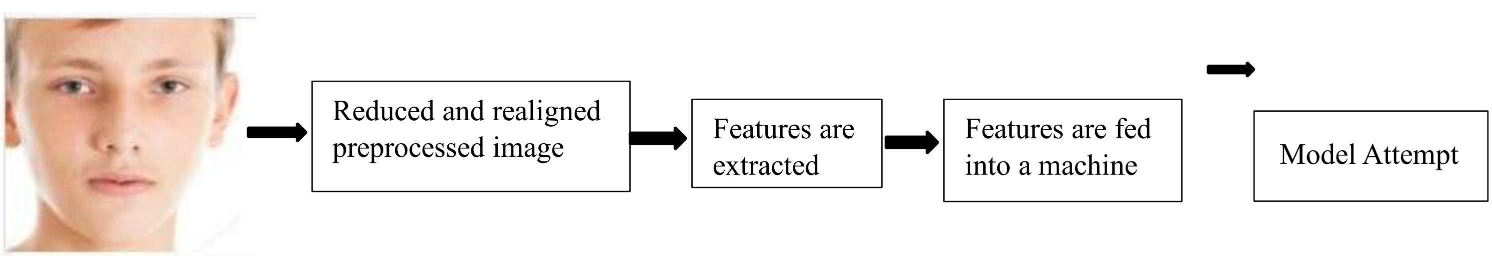


Fig 1: Steps involved in gender classification

learning model.



Overview of the training model process

To achieve consistent results, we trained, tested, and validated both of our using the same set of images. To achieve this, the data sets were divided in 80:20 ratios into train, test, and validation sets.

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3) Methodology

3.1) Dataset:

In this paper, we use the UTKFace dataset [14], consisting of 20,000 face images annotated with age, gender, and ethnicity, to carry out our experiments. The dataset spans a wide age range, from 0 to 116 years old, and is a large-scale face dataset. The dataset comprises more than 20,000 face photos with age, gender, and ethnicity annotations. There are wide variations in the images' resolution, occlusion, lighting, facial expressions, and poses. Many tasks, such as face detection, age estimation, age progressionorregression, and landmark localization, can be performed using this dataset. However, we are primarily concerned with age estimation and face detection in that dataset. Figure 2 displays some sample images from the UTKFace dataset. A three-element tuple containing the following information is labeled on each image: age (in years), gender (Male-0, Female-1).

3.2) Plotting the Age Distribution:

In this paper, I am plotting the age distribution. As shown in Fig. 3, the distribution is roughly normal, though not perfect. It is executed on the right side, but there are outliers at the higher end of the curve. The median we get from the age distribution is 27 years old.

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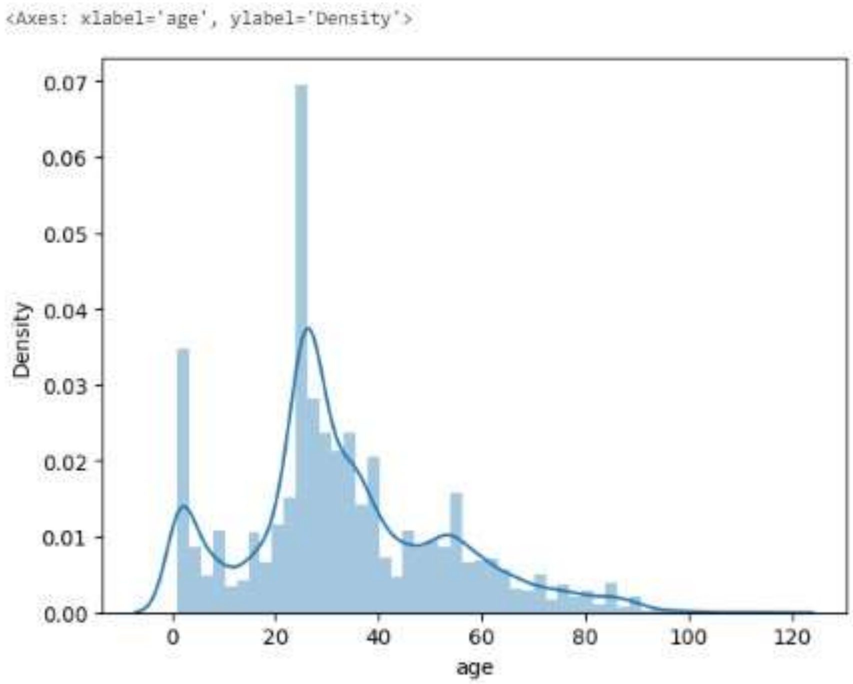

Fig 3: Graph of age distribution

3.3) Method:

In addition to describing the system we have suggested, this section provides instructions for replicating the procedure for further study. Our method includes of two primary elements. An estimator of gendor, which classifies input photos based on the gender of their faces, makes up the first part. The age estimation module, the second part, consists of two VGG16 models. Model A, the first model, has only been trained on images of female subjects. Model B is the second model and has been trained only on male subjects. The labels A and B only refer to the models. Our gender classifier is trained on the Kaggle gender dataset , and our age estimation models are trained and tested on the UTKFace dataset. To reduce biases that could arise if we trained our gender estimation model on the age estimation dataset, we opted to train it on a separate dataset.

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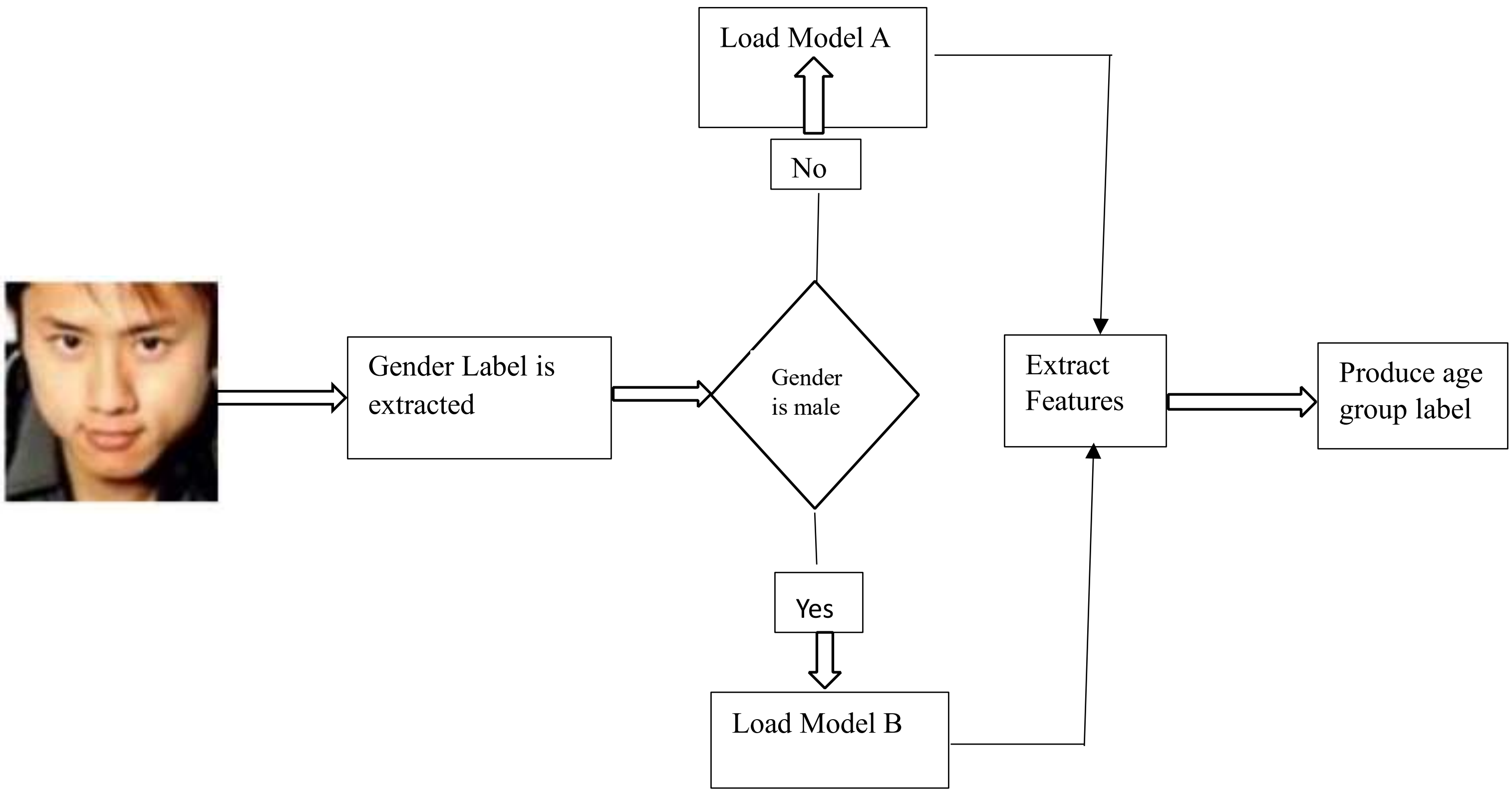


Figure 4: Overview of proposed system

3.4) Face recognition:

The CNN model was selected because it performed better than the other methods (Haar Cascade, Eigenface, and Fisherface) in terms of speed, accuracy, CPU-based real-time operation, and the ability to detect faces of different sizes and alignments. First, the image was taken out of the dataset and converted to grayscale. The pixels were then fed through the opencv pretrained model ("haarcascade frontalface alt2.xml"), which produced the corner points for the rectangle where the face was detected, using the opencv cascade classifier. The face was then placed into a different folder in preparation for further processing. After the images were processed through a size filter function that removed outlier images (those smaller than 5 kb in size), the resulting image was used as the dataset for training the model.

3.5) Gender Forecasting:

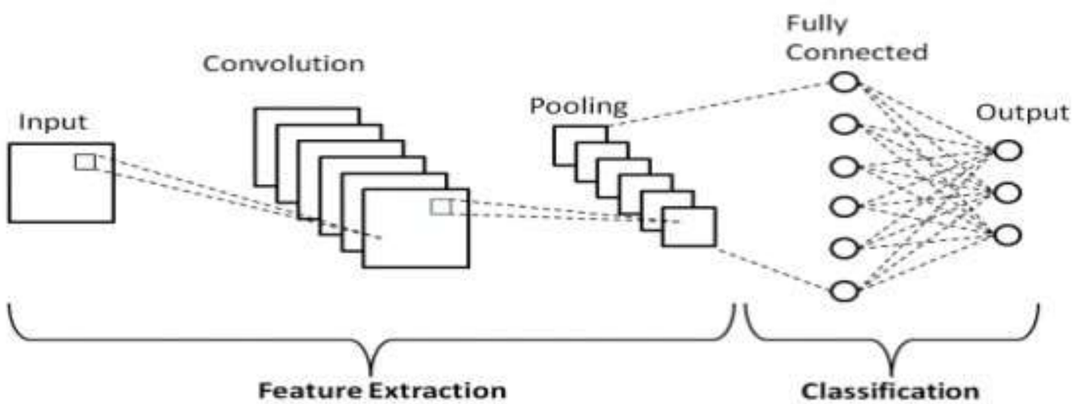
The output layer of the architecture uses a 'Sigmoid' function, with one node representing Male or Female (0: Male, 1: Female). Gender prediction is thought to be a 'classification issue'. The model used is a four-layer convolution architecture with a maxpooling layer and a convolution layer in each layer. The output of these layers is subsequently subjected to a "relu" activation function, succeeded by a dense layer. Thick layers with sigmoid functions are used to create gender-specific nodes. This model was 88.09 percent accurate in terms of precision. The 'Sigmoid' function is used in the output layer of the following model architecture, where two nodes (index 0: Male, index 1: Female) represent the two probabilities for the Male and Female classes, respectively. The model used is a three-layer convolution architecture, consisting of a maxpooling layer, a batchnormalization layer, and a convolution layer. These layers send their output to a flattening layer, which uses the "relu" activation function to send the output to a dense layer. The node with gender probability for both classes is finally generated using a dense layer and a sigmoid function, following the removal of 50% of random nodes.

3.6) Preprocessing the model:

A pre-trained face identification model was used to analyze every picture in the dataset. For this, the OpenCV cascade classifier 'haarcascade frontalface alt2.xml' was employed. After being placed in a new folder, the images were filtered to remove outliers, such as misidentified faces. The final picture folder is where processing was completed. Ultimately, opencv was used to scan the photos. The pixels were then extracted into an array, and "age, gender, and ethnicity" were extracted from the filename and entered into aA pre-trained face identification model was used to analyze every picture in the dataset. For this, the OpenCV cascade classifier 'haarcascade frontalface alt2.xml' was employed. After being placed in a new folder, the images were filtered to remove outliers, such as misidentified faces. The final image folder contains the processed images. Ultimately, images were scanned using OpenCV, and after the pixels were extracted into an array, the filename's "age, gender, and ethnicity" were extracted and added to a dataframe. This procedure was continued in Step 2. Every age was linked to an age class and the age array was mapped to various bins. 24 age classes were formed in all, and the information was forwarded for additional processing.

3.7) Feature Extraction:

A convolution technique called feature extraction helps to isolate and identify each unique feature of the image so that it can be analyzed. The output of the convolution is fed into a fully connected layer, which forecasts the class of the image by utilizing the data collected in previous rounds. "Convolutional, pooling, and fully-connected (FC) layers" are the three layers that make up the



CNN. A CNN is created when these layers are combined. Two matrices representing photos are multiplied to create an output from which features can be extracted

Deep CNNs

4) Network Architecture:

Age estimation and gender and age classification are addressed by the deep CNN method. The core components of all three models are a collection of convolutional units after a sequence of Fully connected layers for regression and classification. The model is given an RGB image which resizes it to 180 x 180 x 3 Convolutional units, or stacks of convolutional layers with a 3x3 filter size, make up each architecture. The next steps are batch normalization, max pooling (2x2), non-linear activation (ReLU), and shift in covariates. To encourage independence between them, the deeper levels in this instance also exhibit spatial

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dropout (drop values of 0.15–0.2), which removes entire feature maps. The output is fed into the FC layers after being flattened after the
convolutional blocks. Batch normalization, dropout (value between 0.2 & 0.4), and ReLU ures of these FC layers. Fig 5 **Fig 5: CNNs Architecture** shows the architecture that was used to activation function are feat
calculate age.The output layer of the architectures for age and gender classifications, respectively, with softmax activation function, and the convolution layer has 3 & 2 blocks with 256 filters.

Model: "model_1"

Layer (type)	Output Shape	Param #	Connected to
input_11 (InputLayer)	[(None, 128, 128, 1)]	0	[]
conv2d_6 (Conv2D)	(None, 126, 126, 32)	320	['input_11[0][0]']
max_pooling2d_6 (MaxPooling2D)	(None, 63, 63, 32)	0	['conv2d_6[0][0]']
conv2d_7 (Conv2D)	(None, 61, 61, 32)	9248	['max_pooling2d_6[0][0]']
max_pooling2d_7 (MaxPooling2D)	(None, 30, 30, 32)	0	['conv2d_7[0][0]']
conv2d_8 (Conv2D)	(None, 28, 28, 32)	9248	['max_pooling2d_7[0][0]']
max_pooling2d_8 (MaxPooling2D)	(None, 14, 14, 32)	0	['conv2d_8[0][0]']
conv2d_9 (Conv2D)	(None, 12, 12, 32)	9248	['max_pooling2d_8[0][0]']
max_pooling2d_9 (MaxPooling2D)	(None, 6, 6, 32)	0	['conv2d_9[0][0]']
flatten_1 (Flatten)	(None, 1152)	0	['max_pooling2d_9[0][0]']
dense_2 (Dense)	(None, 256)	295168	['flatten_1[0][0]']
dense_3 (Dense)	(None, 256)	295168	['flatten_1[0][0]']
dropout_2 (Dropout)	(None, 256)	0	['dense_2[0][0]']
dropout_3 (Dropout)	(None, 256)	0	['dense_3[0][0]']
gender_out (Dense)	(None, 1)	257	['dropout_2[0][0]']
age_out (Dense)	(None, 1)	257	['dropout_3[0][0]']

Total params: 618914 (2.36 MB)
Trainable params: 618914 (2.36 MB)
Non-trainable params: 0 (0.00 Byte)

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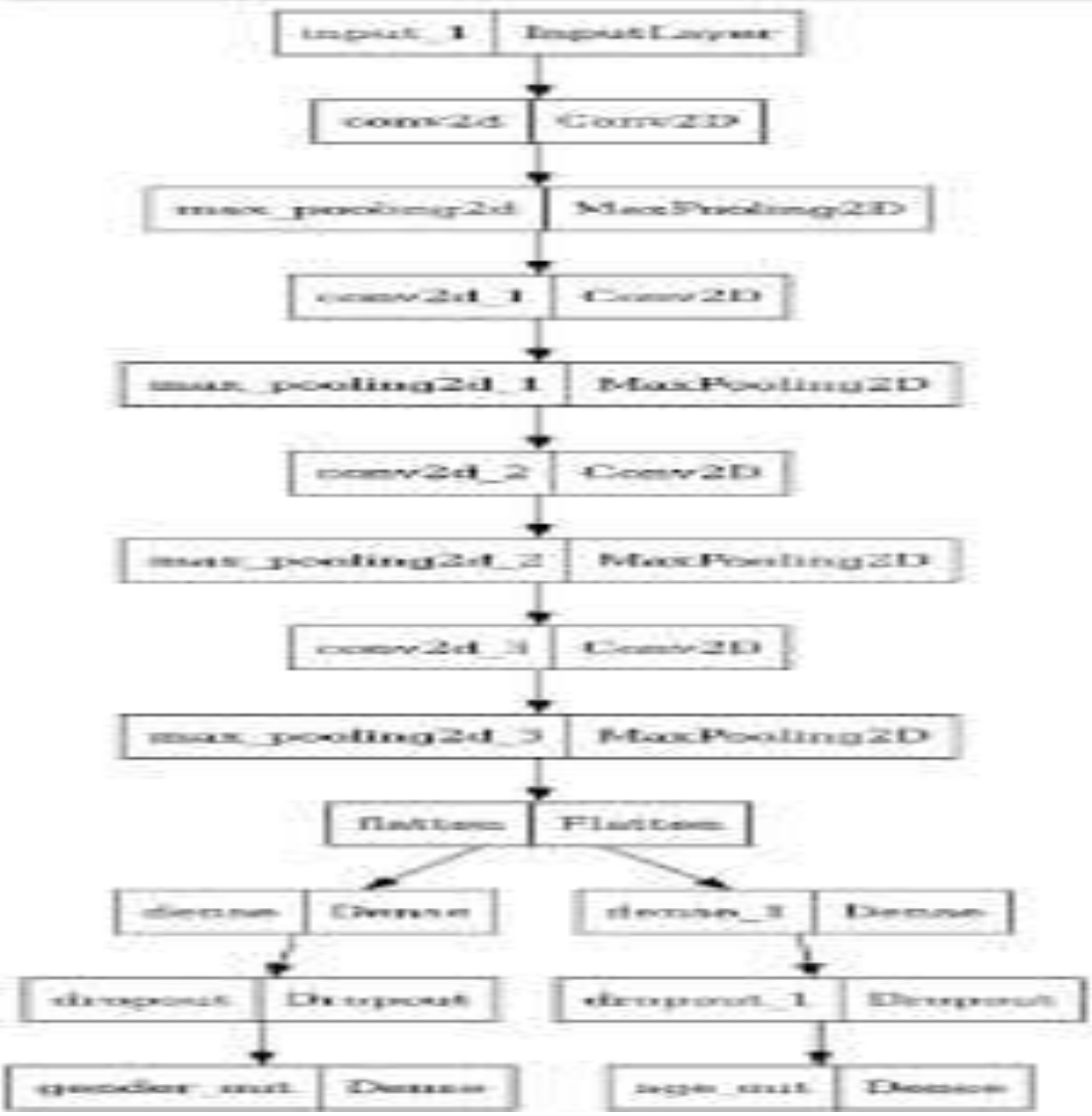

Fig 7: Plotting Model

_out_loss	
nder_Out_Accuracy	**5%**
_age_out_loss	
_gender_out_accuracy	**%**

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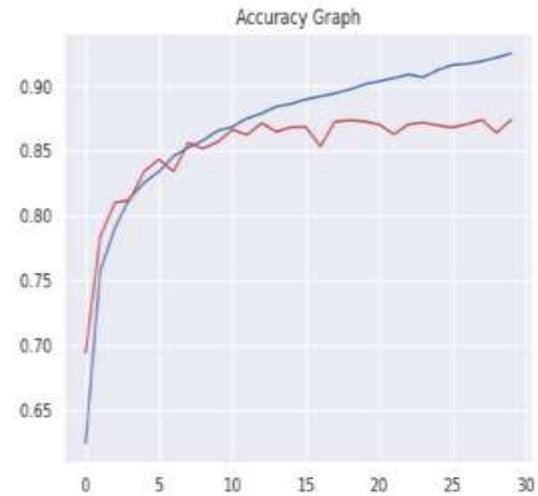
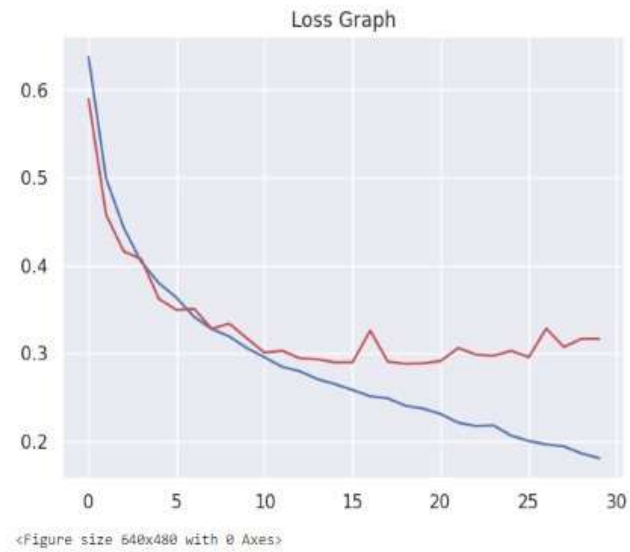
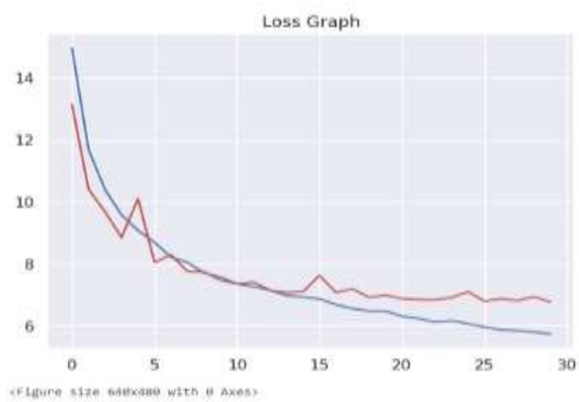
Fig 8: Provides an examination of different methods results.

Result:







Conclusion:

This paper examined various methods for determining gender, accounting for the diverse range of uses that require gender identification, including but not limited to tracking, computer forensics, electronic marketing, statistical analysis, and gathering demographic data.

we train our dataset for 80% and 20% for testing and we get accuracy for 92 % in gender out accuracy and 89% for val age out accuracy and age out loss is 5.7% and val gender age out loss 6.7.

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Reference:

[1]. Shaker, Shaimaa Hameed, and Farah Qais Al-Khalidi. "Human Gender and Age Detection Based on Attributes of Face." *International Journal of Interactive Mobile Technologies* 16, no. 10 (2022).

[2]. Abouelenien, Mohamed, Verónica Pérez-Rosas, Rada Mihalcea, and Mihai Burzo. "Multimodal gender detection." In *Proceedings of the 19th ACM international conference on multimodal interaction*, pp. 302-311. 2017.

[3]. Arif, Aftab, Fadia Shah, Muhammad Ismaeel Khan, Ali Raza A. Khan, Aftab Hussain Tabasam, and Abdul Latif. "Anomaly detection in IoHT using deep learning: Enhancing wearable medical device security." *Migration Letters* 20, no. S12 (2023): 1992-2006.

[4]. Hassaan, Ahmed, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, Zeeshan Akbar, and Sikander Niaz. "ETHICAL ANALYTICS & DIGITAL TRANSFORMATION IN THE AGE OF AI: EMBEDDING PRIVACY, FAIRNESS, AND TRANSPARENCY TO DRIVE INNOVATION AND STAKEHOLDER TRUST." *Contemporary Journal of Social Science Review* 1, no. 04 (2023): 1-18.

[5]. Khan, Muhammad Ismaeel, Hassan Tahir, Aftab Arif, Md Ismail Jobiullah, Ali Raza A. Khan, Sakera Begum, and Ihtasham Hafeez. "Enhancing IoT Security: A Lightweight Cloning Approach for RFID/NFC Access Control Systems." *Cuestiones de Fisioterapia* 52, no. 2 (2023): 231-248.

[6]. Akbar, Zeeshan, Ahmed Hassaan, Muhammad Mudaber Jamshaid, Muhammad Nouman Siddique, and Sikander Niaz. "Leveraging Data and Artificial Intelligence for Sustained Competitive Advantage in Firms and Organizations." *Journal of Innovative Computing and Emerging Technologies* 3, no. 1 (2023).

[7]. Nasim, F., Masood, S., Jaffar, A., Ahmad, U., Rashid, M. (2023). Intelligent Sound-Based Early Fault Detection System for Vehicles. *Computer Systems Science and Engineering*, *46(3)*, 3175–3190. https://doi.org/10.32604/csse.2023.034550

[8]. Gupta, Sarthak. "Gender detection using machine learning techniques and delaunay triangulation." *International Journal of Computer Applications* (2015).

[9]. Arriaga, Octavio, Matias Valdenegro-Toro, and Paul Plöger. "Real-time convolutional neural networks for emotion and gender classification." *arXiv preprint arXiv:1710.07557* (2017).

[10]. Meinedo, Hugo, and Isabel Trancoso. "Age and gender detection in the I-DASH project." *ACM Transactions on Speech and Language Processing (TSLP)* 7, no. 4 (2011): 1-16.

[11]. Saxena, Aryan, Prabhangad Singh, and Shailendra Narayan Singh. "Gender and age detection using deep learning." In *2021 11th international conference on cloud computing, data science & engineering (Confluence)*, pp. 719-724. IEEE, 2021.

[12]. Wang, Xiaofeng, Azliza Mohd Ali, and Plamen Angelov. "Gender and age classification of human faces for automatic detection of anomalous human behaviour." In *2017 3rd IEEE International Conference on Cybernetics (CYBCONF)*, pp. 1-6. IEEE, 2017.

[13]. Raman, Valliappan, Khaled ELKarazle, and Patrick Then. "Gender-specific facial age group classification using deep learning." *Intell. Autom. Soft Comput* 34 (2022): 105-118.

[14]. KAGGLE: https://www.kaggle.com/datasets/jangedoo/utkface-new.2019