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Gender and Age Estimation from Human Faces Based on Deep Learning Techniques: A Review

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Abstract: Due to the advancement of the methodologies employed in this field and the increased attention being paid to the deep learning (DL) techniques' implementation, focusing on convolutional neural networks (CNNs), gender and age estimates have recently assumed a significant amount of relevance. It is important to precisely predict the gender, including the age of a person, provided that it is used in many applications for smart devices, including those related to security, health, and other areas. Although there have been several studies and research in this area, gender, and age estimation still confront certain problems and difficulties, such as existing of earrings, races, masked faces, makeup, etc. which might interfere with the systems' operations and decrease their accuracy. In this paper, we assess the accuracy of the models employed in three of the most well-known datasets: MORPH2, FG-NET, and OUI-Adience. Our focus is on the best and most recent technology available in this field. Additionally, we have mentioned a list of most of the challenges that may face in the process of estimating age and gender, as well as a list of applications and areas in which it can be used.

Keywords: Age Estimation, Comparison of Datasets, Deep Learning Techniques, Gender Classification, Review.

1. INTRODUCTION

The human face reveals important details of gender, age, ethnicity, identity, and mood. It is an important demographic factor as well as a soft biometric attribute for identifying individuals. Here, age plays a significant role in human interaction. The attraction between people is influenced by facial traits. They can serve as health cue indicators. These elements can thereby increase someone's success and productivity [1]. Age and gender are the two essential face attributes that form the basis of social interactions [2]. It is extremely difficult to determine the physical ages of people from face photographs, both for computers and for humans, because physical ages are sometimes quite different from perceived ages. Because there are only two groups that need to be distinguished as male or female in gender categorization, it appears to be an easier process than estimating age, which can range from 0 to 100 [3]. As we age, the skin thickens, texture and color alter, the facial skeleton wrinkles and lines start to show, and the tissue composition changes to be more subcutaneous. Aging is an extremely difficult process that differs widely depending on the individual. Due to the numerous variances in facial appearance, Automatic Age Estimation (AAE) using facial images is a difficult subject. A combination of internal and external variables is considered in the detection process. Living conditions, health, way of life, and others are regarded as extrinsic variables, whereas intrinsic factors include physiological components like DNA. Face emotions and variations in appearance should be handled by robust AAE systems based on facial images [4]. Previously, age estimates for minorities including Asians, Hispanics, women, children, and the elderly were occasionally dramatically wrong. In addition, gender predictions appeared to be mostly focused on the presence or lack of long hair and were susceptible to head tilt [5]. Many factors can affect human age estimation such as race, face post, gender, lifestyle, etc. The best performance can be achieved when considering more factors [6].

Many computer vision-based applications depend on the estimation of gender and age depending on face images, which the processing research is still exciting and active for human facial images [7]. When compared to previous machine learning approaches, DL-based gender categorization and age estimate performed much better and were more robust to environmental changes [8].

Due to the unique characteristics of each individual, the tasks at hand encounter several challenges. Exposure,

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weather, gender, and way of life are all relevant factors. It can be difficult to discern the aging characteristics of each age group, even while certain tendencies are comparable for faces from the same age group. The human eye is capable of identifying familiar faces, while the human mind is capable of estimating a person's age. Even though being human, it is never totally accurate. When using computers, a person's face may reveal a lot about their age. Moreover, gender, identity, as well as age, may all be determined in everyday interactions by developing an automated system for predicting a person's age from their facial image [9].

Finally, the techniques for determining gender and age obtained out of possession of facial images are encompassed by the most well-known, and they have gained more popularity than the other methods that rely on other factors, such as gait and voice tone because it is simpler to read facial data from a distance than gait and voice tone can be seen due to a large number of people present, and voice tone can also be obscured by background noise in public places. Despite the advancements made in this field, all of these systems employ DL from the acquired data in conjunction with artificial intelligence methods. Since artificial intelligence learns from its failures and the human corrections for them as well as from its successes that raise its understanding of the proper analysis process in each situation, it makes continual progress over time and increases the sample size of the pictures being matched, such as the light that draws attention to one's eye shadows and may make them appear older than they are; the differences between the analysis of female's and male faces; people with dark skin compared to people with light skin; the similarity of Southeast Asian people's faces in terms of features; and the change in the amount of fat in users' faces after gaining or losing weight. These and other elements encourage researchers to create novel algorithms that get around any challenges or issues they may face.

Inclusion and exclusion criteria for gender and age classification in this study include studies that use facial images, report accuracy metrics, use diverse images for evaluation, and compare different algorithms, while the exclusion criteria include studies that use non-facial images, do not report accuracy metrics, use limited image sets, do not use standard evaluation metrics, and do not compare different algorithms.

The remaining sections of this paper discuss related research on gender and age estimation in section two, introduce the applications and challenges of both tasks in sections three and four, and then list the most popular datasets in section five. Section six explains the most often used metrics for testing the model performance. Finally, the performance of several algorithms is compared in section seven.

2. RELATED WORKS

The topic of estimating gender and age is still a hot topic and challenging task and attractive to many researchers. In this section, different studies are considered and analyzed.

A. Age Estimation

(B. Zhang and Y. Bao) proposed a learning technique on the cross-dataset training CNN (CDCNN) in employing a wide framework concerning cross-dataset training in predicting age. This problem was solicited as a classification problem using CNNs with VGG-16 architectures that had been trained on ImageNet. Their approach was applied to the MORPH2 dataset, and the outcome was 2.76. Ultimately, their CDCNN approach may be used for jobs that include estimating additional facial features, for example, expression, ethnicity, gender, or health status. Nonetheless, the baseline network's accuracy may still be raised, in which more facial data may be employed for training purposes [10].

(F. Anda et al.) emphasize the significance of age estimation in digital forensic investigations, including the victim's identification, suspects, and losing kid, as well as the reduction of investigators' exposure to psychologically distressing content. The authors suggest using Vec2UAge, a unique regression-based model. The VisAGe and Selfie-FV datasets were utilized to extract FaceNet embeddings as extracted features, which were then used for training the model. The performance was enhanced and the experiment run times were shortened by using a cyclic-based learning rate finder. Moreover, applying the SWA optimizer produced the best results, and the convergence time was far quicker. Their model's MAE result was 2.36 years. This model cannot suit all situations; it is just for underage single-faced photos and will only be efficient for sorts of images and such age ranges [11].

(H. Zhang et al.) suggested an improved label distribution paradigm; the authors restrict age-label distribution to just covering a respectable number of adjacent ages. To enhance the effectiveness of the suggested learning model, they also investigated other label distributions. To estimate age, they use CNN and enhanced label distribution learning. Because label ambiguity may be learned from neighboring ages, label distribution learning can efficiently address the problems associated with a lack of data. To increase learning effectiveness, proper label distribution is essential. On the FG-NET and the MORPH2 datasets, their findings indicate an MAE of 3.14 and 2.15, respectively. The experimental findings reveal that their approach outperforms the DLDL for face age identification and that the Gauss distribution performs better compared to the triangular distribution for estimating age [12].

(Y. Deng et al.) proposed a portable multi-feature learning and fusion technique for estimating age. The authors employed three subnetworks originally to gather information on age, ethnicity, and gender. Then, they developed new, more accurate features for age estimation using these complementary characteristics. Finally, to transform the fusion features into particular ages, the authors established a regression-ranking age-feature estimator. Their model was smaller than prior methods, requiring just 20 MB of additional memory, and it may be used in embedded or mobile devices for age estimation. Compared to advanced techniques, the findings obtained on the MORPH2 dataset indicate an MAE of 2.47 and 2.59 on the FG-NET. It has very high competition in terms of performance of estimating the age [13].

(A. Akbari et al.) recommended a loss function for LDL-based age prediction based on optimal transport theory. The authors maximize the impact of strongly linked ages by enabling the loss function via the suggested metric function, which efficiently utilizes the similarity among ages. Their result on MORPH2 was 1.79 of MAE and 3.41 on the FG-NET. There were two benefits to using the concept of optimum transport to handle the label distribution problem. First, it has been demonstrated that optimum transport can accurately calculate the distance between two label distributions. Second, the learned age estimation model is improvised by constructing the ground metric function about the optimal transport to closely represent the semantic similarity of surrounding classes. They point out that their original formulation contains a flaw that causes it to be impracticable for comparison purposes concerning the distributions supported on a variety of topological spaces [14].

(M. Duan et al.) introduced a hierarchical method known as EGroupNet. The approach consists of two basic stages: feature improvement by uncovering relationships between age estimation and age-related characteristics employing a variety of age grouping methods. On the MORPH dataset, the result indicates 2.13 of MAE. The experimental findings confirm that categorizing the image into particular age groups before making an age choice may enhance the final prediction performance. The hierarchical structure can be improved and used to process multi-facial features including smiling, hair, chin, etc. [6].

(F. Anda et al.) suggested a technique called (DeepUAge) for a precise estimate of the age of cases that can classify the ownership of explicit content during the investigation as illegal, helping law enforcement determine victims related to the child sexual exploitation material (CSEM) distribution and creation. This paper proposed a deep CNN for estimating the facial age of children that relies on a residual neural network with 50 layers (ResNet50). Other than that, the ImageNet dataset served as pre-training for their algorithm. DeepUAge had a logarithmic loss of 1.799 despite having the optimal outcomes concerning the age estimators assessed. Compared to previous age-predicting services, the DeepUAge has been demonstrated to more accurately catalog ages (9 to 18), and the result was 2.73 (MAE) on both the ImageNet dataset and the VisAGe set of underage photos [15].

(X. Liu et al.) presented a modified ShuffleNetV2 network depending on a lightweight CNN and depending on the (MA-SFV2: Mixed Attention-ShuffleNetV2). This study used a lightweight CNN to integrate classification and regression with age estimation techniques, mixed attention mechanisms, and visual enhancement. The model described in this article is still too heavy to be used on a mobile terminal. The network recommended in this study converges rapidly during the training phase and performs very well when estimating age. Their results show an MAE of 2.68 for the MORPH2 dataset and 3.81 for the FG-NET dataset. Their solution is very competitive, requires little training, is space-efficient, and is easy to implement [16].

(W. Cao et al.) suggested the COnsistent RAnk Logits (CORAL) framework, which has strong theoretical ensures for rank-monotonicity as well as consistent confidence ratings, to address these discrepancies. They introduced an approach and theorem that can be readily applied to a variety of neural network designs without the need for rank or training label-dependent weighting methods, allowing for simple implementations and effective model training. The MORPH2 dataset displays an MAE value of 2.64. Their approach is easily adaptable to other common regression issues and other neural network topologies, such as multi-layer perceptrons and recurrent neural networks [17].

(F. Dornaika et al.) are pioneering the application of robust loss functions into DL regression networks for estimating age. The L1 norm error, as well as the adaptive loss function, which preserves the benefits of both the L1 as well as L2 norms, are two resilient regression functions that were studied. According to experimental results, deep CNN training using an adaptive loss function that is robust to outliers led to better performance as well as generalization than using the traditional MSE loss. The employment of such a loss function speeds up the convergence of the training process. The MORPH2 dataset and the PAL dataset yielded findings of 2.75 in MAE [18].

(X. Zeng et al.) proposed an approach to deal with the difficulties in figuring out the facial age. Their Soft-Ranking method of novel age encoding encodes the ordinal characteristic and the relationship between surrounding ages, two essential elements of face age. Thus, soft ranking offers a richer supervision signal concerning the training of deep models. The identity overlap between the testing sets and training affects how well different age encoding strategies work in comparison, they also extensively investigated the evaluation protocols currently in use for age estimate. They discovered that the MAE for the MORPH2 (RS protocol) dataset is 1.73 [19].

(P. Li et al.) introduced a label refinery network (LRN) having two concurrent processes: slack regression refining and label distribution refinement. Iteratively and progressively learning age-label distributions is the goal of the label refinery network. Without making solid assumptions regarding the fixed distribution formulas, they may adaptively acquire the precise age-label distributions for various facial photos. To further take advantage of the correlations across age labels, they recommended a slack regression refinement to convert the age-label regression model into an age-interval regression model. The experiment's findings on the MORPH2 dataset show how much better the LRN is. It came out to 1.90 in MAE. Even if their system outperforms cutting-edge techniques in label distribution prediction, there is still potential for improvement. When utilizing cross-domain faces, such as poses, emotions, and nations, the accuracy will significantly decline [20].

(N. Liu et al.) presented a CR-MT net, an end-to-end multi-task learning network integrating regression and classification for estimating age. In addition, they proposed two age data grouping algorithms, neighboring age clustering, as well as K-means clustering demonstrating that the latter is superior to creating a homogenous data division and reducing the border impact in classification. The Alexnet, which possesses five convolutional layers, as well as three fully linked layers, refers to the foundational network of their CR-MT net. While Alexnet is less accurate than other deeper networks, for example, Res-Net and VGG have the benefits of more flexibility, a smaller structure, and faster training times. The results of their CR-MT net verification on the MORPH2 dataset were 2.36 of MAE, which demonstrates that the suggested methodology is competitive with state-of-the-art techniques [21].

(K. Zhang et al.) suggested estimation of age depending on the long-short-term memory (AL) network. This technique incorporates the Residual network of Residual network (RoR) or ResNets models having LSTM units to construct AL-RoR or AL-ResNets networks to retrieve local characteristics from age-sensitive areas. This method significantly increases the accuracy of age estimates. Based on the MORPH2 dataset, their technique yields an MAE of 2.36, 2.39 on the FG-NET, and 2.83 on the Adience dataset. The suggested Attention LSTM network automatically extracts regional age-sensitive areas as well as more unique characteristics, greatly enhancing age estimate accuracy [4].

(R. Rothe et al.) suggested a method for determining the age, both actual and apparent, without the help of facial cues. They recommended using CNNs with the VGG-16 architecture, trained on ImageNet, to identify pictures. They built a Deep EXpectation (DEX) formulation, referring to the VGG-16 deep architecture, a classification step, as well as an expected value formulation concerning the problem of estimating age. In addition, they presented IMDB-WIKI, which at that time had the biggest public face photo collection having gender and age annotations. Their method consistently handles small obstructions while validating its suitability for age assessment in the field without relying on landmarks. On the MORPH2 dataset, An MAE of 2.68 years results from further optimization on their IMDB-WIKI dataset and 3.09 on the FG-NET dataset. Their DEX pipeline may be used to predict other facial features, such as a person's gender, ethnicity, attractiveness, or other characteristics [22].

B. Gender Classification

(A. Swaminathan et al.) proposed to carry out gender categorization using the idea of face embeddings. The proposed approach is new since facial embeddings have never been used to predict gender, ethnicity, and age from face photos. In the suggested approach, gender is predicted using a variety of machine learning models employing embedding vectors as features. These embedding vectors are produced by running a pre-trained Facenet model across face picture data. Three steps make up the suggested methodology. First, faces are found and edited out of the photographs that have been provided. Second, each face is run through a neural network to determine its facial embedding. Third, several machine learning models are applied to these embeddings as feature vectors to determine gender. With an accuracy of 97 on the UTK Faces dataset, their model outperforms most existing techniques by employing K Nearest Neighbours (KNN) [23].

(M. Alghaili et al.) suggested a network that combined an NN4 network having a variational feature learning (VFL) loss function. Normal or covered/camouflaged faces are gender-recognized by the network through the center of their faces. This network was trained on the central portion of the faces that comprise both eyes, which has a narrow border from the top-left corner onto the bottom-right corner. Experimental outcomes presented that the recommended network performed state-of-the-art, having an accuracy of 98.23 on the Adience dataset. They then tested the network using a different set of recently acquired data for faces that were covered or disguised, and the results were positive [24].

(M.M. Islam et al.) used Pareto frontier pre-trained CNN networks having the idea of transfer learning to develop a framework for gender categorization. This study uses an unconstrained internet picture dataset to show how Pareto frontier pre-trained DL models may be used to classify images by gender. The study also uses experimental findings to demonstrate Pareto efficiency. The GoogLeNet, SqueezeNet, ResNet50, and Pareto frontier pre-trained CNN networks presented an incredible classification rate of higher than 90 accuracy, providing the ideal network parameter combination despite the wide range of the WIKI pictures. This study is likely the first attempt to classify gender using pre-trained CNN models for the customized Pareto frontier challenge on the unconstrained WIKI dataset [25].

(M. Afifi, and A. Abdelhamed) promoted a novel approach that draws inspiration from how people recognize gender. Instead of dealing with the face picture as a single feature, they depend on a combination of distinct facial traits and a holistic feature that we pertain to as the "foggy face." The resulting gender class is determined utilizing an

AdaBoost-based score fusion after deep CNN was trained using these characteristics. They tested their strategy on four challenging datasets to illustrate its efficiency in accomplishing greater or equivalent accuracy to state-of-the-art approaches. On the Adience dataset, their accuracy was 90.59, while on the FERET dataset, it was 99.49. They also provided a brand-new face dataset (SoF), which we think is an essential tool for gender categorization research because it magnifies the difficulties of obscured faces and lighting variations [26].

(K. Khan et al.) Through segmenting face regions, the authors established a framework for gender categorization. Through the use of Conditional Random Fields, they created a face segmentation model (CRFs). The CRF takes benefit concerning the hierarchy's notion of distinct face components and their interdependence. Three types of features position, color, and shape data are taken from nodes and used to train the CRFs-based model. The model separates a face picture into six groups, including the back, mouth, nose, eyes, hair, and skin. In addition, they formed probability maps for each of the six classes using a probabilistic classification approach (PCS). An RDF classifier is trained to categorize the face photos as either female or male, employing the probability maps that were formed as feature descriptors. On the FERET dataset and the Adience dataset, the model's performance had an accuracy of 100 and 91.4, respectively [27].

(A. Dhomne et al.) discovered that using the Deep CNN technique for learning and classification led to a satisfying improvement in performance on tasks like gender classification. As a result, they decided to suggest the effective convolutional network VGGnet architecture, applied in the unlikely event that there is not enough training data to develop Deep CNN based on the VGGNet architecture. They improved the previously employed approach and obtained significantly more accurate findings by using a new VGGNet architecture, where they reached an accuracy of 95 on the Celebrity Face dataset [28].

(M. Castrillón-Santana et al.) concentrated on gender categorization in the public dataset Groups and noted the psychophysical evidence of the larger significance of the ocular and mouth regions to complete this job. To extract features, they employ holistic and inner facial patches, which are then integrated using a score-level fusion technique. The results obtained corroborate the key details offered by the oral and ocular regions. The Total accuracy increases to over 94 when multiscale-derived features are combined, which is a significant gain in terms of classification error reduction and accuracy [29].

C. Both Gender and Age Estimation

(M.K. Benkaddour) demonstrated how learning representations using deep (CNN) significantly improves gender and age estimation. Instead of focusing on the precise age calculation, he focuses on the problem of age group classification. The research employed feedforward neural networks to improve resilience for highly variable unconstrained recognition tasks to determine the age and gender group. The suggested technique employs face photos in the range of (0–68). On the Adience benchmark and Essex Face dataset, this study's age estimates, and gender prediction were examined and verified. The findings demonstrate that the suggested method produces highly interesting efficiency and cutting-edge performance in age and gender scoring, as well as a significant performance gain. The accuracy was discovered to be 95.6 for gender classification while 91.75 for age estimation concerning the Adience benchmark. On the other hand, gender classification gave 99.10 while age estimation yields 95.41 concerning the Essex dataset [7].

(G. Park and S. Jung) described the issue of creating an inadequate system for keeping track of the data obtained through the mounted camera. Because it must be done manually from a huge number of stored photos, extracting specific object information in an emergency is exceedingly inefficient. They suggested a Comparative CNN-based Multi-task Learning method to get around this problem, which can automatically extract data about a moving object from an image. By using a fine-tuning approach labeled by age to a CNN model trained with a DB labeled with the true age, the authors adopted DEX (Deep EXceptation), which overcomes the restriction of an inadequate DB in predicting the apparent age. Additionally, while estimating the age by regressing it using the classification approach, the expected value was calculated by taking into account the output of each class of the classifier as the likelihood of belonging to that class. Their findings indicate that because there are only two classes for gender categorization, it is less difficult than estimating age. On the MORPH2 dataset, their methodology yields an MAE of 2.79 for the age estimate and an accuracy of 99.4 for gender classification [8].

(M.M. Islam and J.H. Baek) build a system to tackle the classification problems by including batch normalization and the VGG-16 network, an experimentally superior pre-trained CNN, to prevent COVID-19 in modern society, which demands a contactless shopping system to efficiently stop the spread of contagious diseases, In particular, the age estimate challenge is formulated as a multinomial logistic regression first-moment refinement issue after a deep classification problem. Note that 13 of the 16 layers of the VGG-16 network are convolutional layers, including the remaining three levels being dense layers. Moreover, the same configuration for the gender categorization problem achieved noticeably better results than SOA techniques. On the MORPH2 dataset, their method yields an MAE of 2.42 for age estimation and 97.28 on the Adience dataset for gender classification. Their method shows that pre-training on a balanced dataset and having sufficient training data increase the system's performance, eliminate the data sparsity issue with the DEX technique, and identify the target application for model deployment [30].

(A. Micheal and R. Shankar) utilized ELM extensively for both multi- and binary classification processing, due to its advantageous characteristics. The authors combined the benefits of CNNs with ELM, which implies that CNNs extract features from the input pictures while ELM classifies the input feature vectors. The design surpasses prior research, according to experimental findings, showing a considerable gain in accuracy and efficiency, it was 90.2±1.2. The results of the experiment allow for two important deductions. First, despite the substantially smaller size of modern unrestricted picture sets for gender and age classification, CNN+ELM may be employed to generate improved gender and age arrangement outcomes. Secondly, the simplicity of the model increases the potential that more complex frameworks using better-prepared data may improve outcomes [31].

(S. Patil et al.) suggested a solution for the issue of gender detection from the pictures that are taken from a great distance and traits that resemble haar are used. With the use of Haar Cascade, they presented a model that can determine a person's gender for any input image (male, or female). the authors trained the haar cascade classifier on the 1000 images with balanced distribution between the two genders for female face detection. The paper suggested age estimation depending on the Caffe DL network. Caffe has many advantages such as the ability to process 60M images per day, this regards as the fastest network and also provides a meaningful architecture and extensible code. Their algorithms have an accuracy of 89.5 on the Adience dataset [2].

(H.T.Q. Bao and C. Sun-Tae) proposed multi-tasking learning to carry out both tasks (gender classification and age estimation) on a lightweight model at the same time. They employ three branches of convolution layers at the network's commencement, followed by batch normalization as well as the Leaky-Relu activation function to retrieve certain broad characteristics. The network is then built having two more branches: the first branch is intended to recognize gender traits, whereas the second branch is intended to recognize aging features. The second branch comprises extra convolution layers to learn more about age-related information, considering age estimation is a challenging process. On the MORPH dataset, their approach results in an MAE of 2.88 for age estimation and 99.34 percent for gender categorization, and 3.41 on the FG-NET for age estimation [3].

(O. Agbo-Ajala and S. Viriri) suggested deeply learned classifiers. They employed a brand-new six-layer network with four convolutional layers and two fully linked layers employing the CNN architecture. They also created a reliable and strong image preprocessing technique that gets the raw pictures ready for the CNN model. The network was pre-trained on an IMDB-WIKI possessing noisy labels. Correspondingly, we fine-tuned on MORPH2 and ultimately on the training set of the OIU-Adience dataset, in which the accuracy was 83.1 for age prediction and 96.2 for gender classification [32].

(A.A. Adenowo and A.O. Adewole) presented and applied a multi-task CNN-based algorithm with an image preprocessing step based on Histogram Oriented Gradients (HOG) to categorize facial pictures into various age groups, genders, and emotions. With a general accuracy of 97 for gender recognition and 66 for age estimation on their dataset (black faces), the trained model performs poorly. Because the Adience and FER2013 datasets used for training mostly consist of Caucasians, Asians, and a small number of African Americans, and because some traits can only be retrieved from black faces and are not present in white faces (blacks). The two databases do not adequately reflect Black people [33].

(K. Khan et al.) put forth a head position, age, and gender recognition problem-solving end-to-end semantic face segmentation method (MSF-CRFs). Utilizing CRFs between distinct face components, the segmentation model is constructed. Each of the six classes is assigned by the MSF-CRFs model to every pixel in the facial picture (mouth, nose, skin, eyes, background, and hair). For every face class, probability maps are created using a probabilistic classification approach. Each job involves training a distinct probability map on a Random Decision Forest classifier. The best facial features for recognizing head posture, age, and gender have been determined through a variety of trials. On a variety of face datasets, experimental findings are verified for improved outcomes. The results for Adience were 89.7 for gender classification and 66.5 for age recognition [34].

3. APPLICATIONS OF GENDER AND AGE ESTIMATION

A. Age Estimation

1) Age estimates can be employed in vending machines that sell smoked or alcoholic beverages as they run the age prediction program to prevent children from buying the items without permission [9].
2) Identification of minors for justice purposes and age-based application interface adjustments [35].

B. Gender Classification

1) The gender classification system is used in situations where gender is limited, including temples, women-only train cabins, and gender-specific ads [24].
2) Cosmetology and forensic art [32].
3) Gender classification helps in the process of identifying people easily, as it is possible to reduce the number of possible possibilities to obtain a person, separating males from females and thus speeding up the process of identifying a person.

C. Both Gender and Age Estimation

1) Gender and Age can provide health-related indications [1].

2) Control of access and tailored advertising [2].
3) Human-computer interaction [3].
4) Recommendation systems for shopping, parental restrictions for websites, and video services [7].
5) Individual authorization and marketing [8].
6) Electronic customer relationship management, biometrics, and entertainment [32].
7) The system of gender and age estimation can be used in unmanned drones, which can carry cameras with different weights and identify suspects in large gatherings from high distances and different angles.
8) Security control for identifying people [36].
9) Construction of a smart, safe metropolis with tight security and demographic census management [37].
10) Monitoring of public security includes police patrols, borders between nations, and the issuance of identity cards.
11) Investigations using child sexual abuse material (CSAM), including CSEM, may employ gender and age estimation techniques to identify victims and suspects [38].
12) Face retrieval and recognition [39].
13) Simply identifying a person's gender and age can provide information about employing teams, ID verification cards, and voter ID cards, which are frequently used to cast ballots in elections [40].

4. CHALLENGES OF GENDER AND AGE ESTIMATION

A. Age Estimation

1) The experimental findings show that testing on black faces and training on faces of other ethnicities provides the greatest inaccuracy in the testing of faces of other ethnicities due to their more distinctive aging patterns [1].
2) Since it is highly challenging to determine the age of children and babies by the geometric differences in facial features, and because there aren't many facial photographs of persons older than 60, facial images in the age range of 0-68 are often employed [7]. findings demonstrate that gender categorization is easier than age estimation. Estimating age is a highly challenging task since the subject's biological age and the age of the face differ [8].
3) It is difficult to estimate face age accurately in persons who are unsure about their adult status [38].
4) Since aging occurs differently for different people, estimating age automatically is difficult. Getting useful feature sets from a 2D picture for age and gender estimates is another challenge [41].
5) The performance for age estimation is determined by the pre-training task of the utilized CNN in addition to the number of training pictures and subjects in a training database. Given the considerable diversity in real-world images, which are shot in various contexts, the unconstrained face pictures make age estimation more difficult [41].
6) In images of women, the hijab hides different facial features, which often makes it difficult to distinguish between the features of women's faces, and thus makes it difficult to predict their age [42].

B. Gender Classification

1) The gender of children and newborns can be difficult to tell from photos since their facial characteristics can sometimes be similar.
2) Wearing a mask and facial makeup by males to disguise and not reveal their identity.

C. Both Gender and Age Estimation

1) Obtaining a big dataset for the algorithm's training is a complicated process and requires a longer time for gender and age estimation using CNNs [2].
2) Age and gender estimation depend on a variety of factors, including a person's surroundings, health practices, lifestyle, makeup, emotions, and uncontrollable lightning [9].
3) The absence of uniform quality bounds across various demographic groups, which would enable a fair evaluation of the performance of present models, is a concern [35].
4) Human racial taxonomy states that many persons of the same age have quite diverse appearances. The human mind also drives him to use a variety of covert technics to hide his gender and actual age [42].
5) The quality of the pictures diminishes, provided that a low-resolution camera is employed to capture the pictures or if afar, facial pictures of the people are taken. The texture and wrinkles of the face are lost in this situation, so it is impossible to identify characteristics that are essential for determining a person's gender and age [43].
6) Changes in the face, such as the emergence of a specific disease's symptoms, the growth of pimples, exposure to scratches or burns, and other changes that change facial characteristics make it challenging to estimate age and gender.

5. GENERAL FRAMEWORK

A. Gender Classification Framework

Human gender classification from facial images involves several steps as shown in Figure 1, and the exact methodology may vary depending on the specific algorithm or technique used. However, the following are the general steps for human gender classification from facial images [44]:

1) Data preprocessing: Preprocessing is an essential step for enhancing the quality of raw data. This procedure encompasses various tasks, such as normalizing the main signal detection, extracting the relevant information, and rectifying imperfections like filling holes and removing noise.
2) Face detection: refers to the process of locating and identifying faces in an image or a video frame. This is typically achieved by using computer vision

techniques that can detect facial features such as eyes, nose, mouth, and face contour. Once the faces are detected, the next step is to crop the image or video frame to isolate the face region.

3) Feature extraction: is a process that involves capturing the essential characteristics of the preprocessed signal, which serves as input parameters for the classification algorithm. This module aims to reduce the data size by extracting only the relevant features from the preprocessed information that is crucial for classification purposes.
4) The classification algorithm: is the central component of gender identification. There are two main categories of classification approaches: appearance-based and non-appearance-based. The appearance-based approach involves using static images or animated videos to perform gender classification. In contrast, the non-appearance-based approach analyzes a person's physical, biometric, or social network-based information to classify gender.
5) Evaluation: this is the stage where the performance of the gender classification system is assessed using various measures. These measures typically include accuracy, Precision, recall, F1-score, Area under the receiver operating characteristic (ROC) curve, and confusion matrix.

B. Age Estimation Framework

Similar to gender classification, human age estimation from facial images also involves several steps as shown in Figure 2. The general steps for human age estimation from facial images are as follows [45]:

1) Face detection: The first step is to detect and locate the face in the image. This can be achieved using computer vision techniques such as Haar cascades or deep learning-based algorithms.
2) Facial feature extraction: The next step involves extracting facial features from the detected face region. This typically includes features such as the eyes, nose, mouth, and chin.
3) Feature normalization: To reduce the impact of lighting, pose, and other factors on the age estimation, the facial features are often normalized or aligned to a standard reference frame.
4) Age regression model: A machine learning model is trained on a dataset of facial images with known ages to learn the relationship between facial features and age. This model can then be used to predict the age of new facial images.
5) Age estimation: The final step is to use the trained age regression model to estimate the age of the facial image. The predicted age can be a single value or a range of possible ages, depending on the specific algorithm or technique used.
6) Performance evaluation: several metrics can be used to evaluate the performance of an age estimation algorithm. The most common metrics include Mean absolute error (MAE), Mean squared error (MSE), Pearson correlation coefficient (PCC), Cumulative score (CS), and Receiver operating characteristic (ROC) curve.

6. GENERAL METHODS USED FOR GENDER AND AGE ESTIMATION

There are several methods for gender classification, and age estimation, in this section we summarized the most public methods for gender classification as shown in Figure 3, where the prospects and contradictions for these methods are tabulated in Table I. Similarly, the age estimation methods are summarized in Figure 4, and the prospects and contradictions are tabulated in Table II [46].

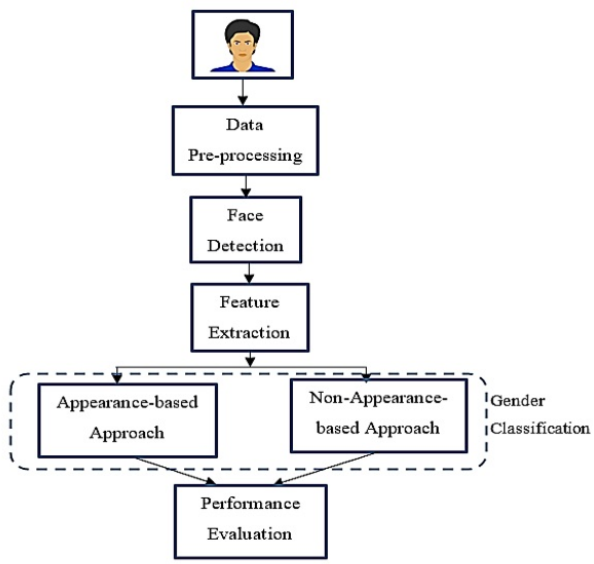

Figure 1. General Gender Classification Pipeline

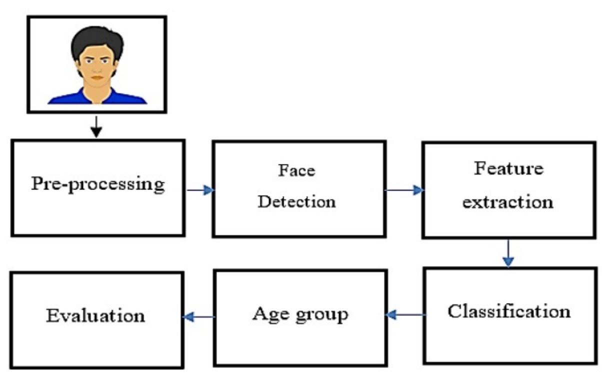

Figure 2. General Age-Group Estimation Pipeline

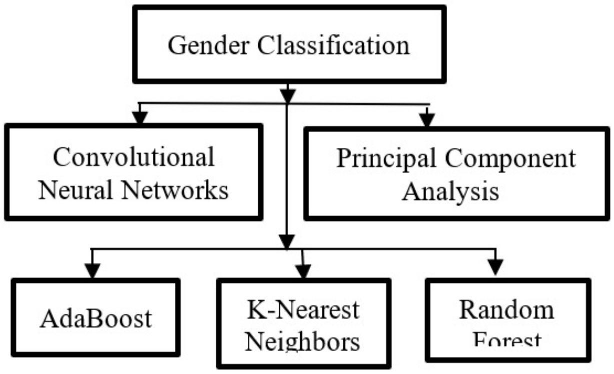

Figure 3. General gender classification methods

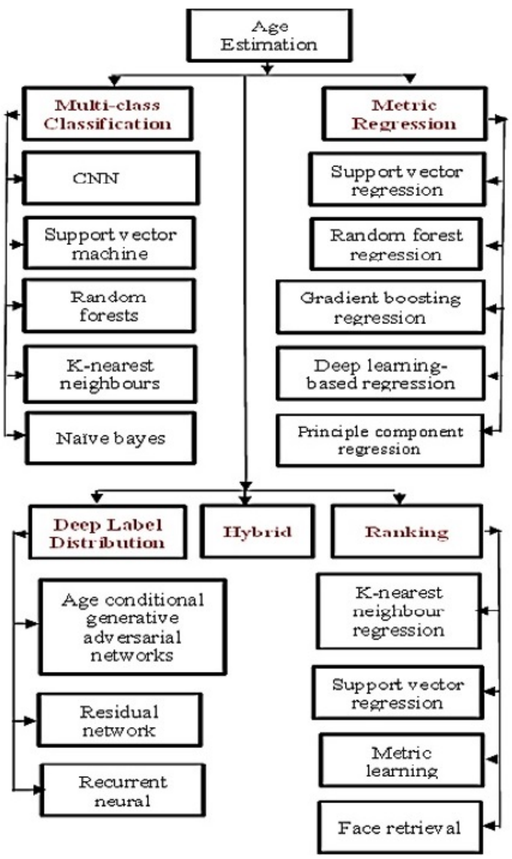

Figure 4. General methods for Age estimation

7. DATASETS FOR GENDER AND AGE ESTIMATION

Several datasets that have been employed for gender and age estimation are displayed in Table III, and we show samples of images from most of the datasets in Figures 5, 6, and 7.

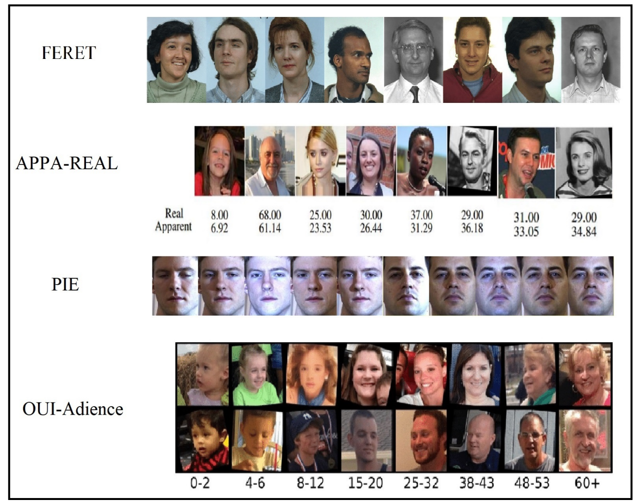

Figure 5. Sample images from FERET, APPA-REAL, PIE, and OUI-Adience datasets

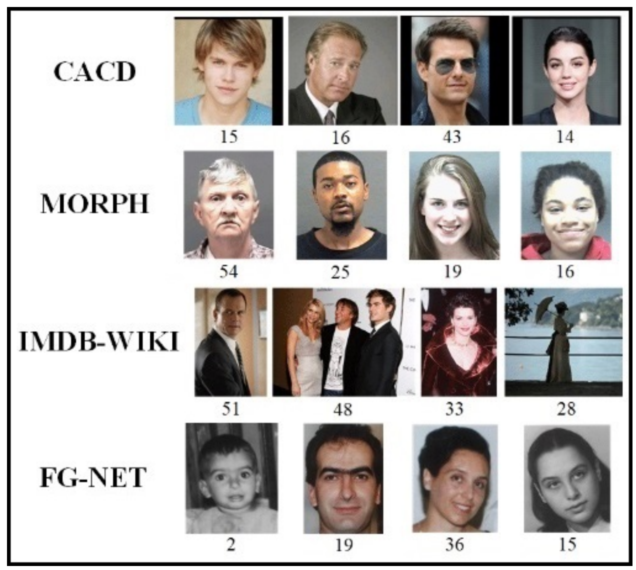

Figure 6. Sample images from CACD, MORPH, IMDB-WIKI, and FG-NET datasets

TABLE I. THE STRENGTH AND WEAKNESSES OF GENDER ALGORITHMS

Algorithms	Pros.	Cons.
K-Nearest Neighbors (KNN)	Simple, works well with small datasets	Computationally expensive, sensitive to outliers
Random Forest	Handles high-dimensional data, provides feature importance	Slow, difficult to interpret, and may overfit
AdaBoost	Handles a large number of features, good with weak classifiers	Sensitive to outliers, prone to overfitting, and slow
Principal Component Analysis	Reduces dimensionality and helps identify correlations	Assumes linear relationships, sensitive to scaling and outliers
Convolutional Neural Networks (CNN)	Learns complex features, and achieves state-of-the-art performance	Computationally expensive, requires large amounts of labeled data, difficult to interpret

TABLE II. THE STRENGTH AND WEAKNESSES OF THE AGE ESTIMATION METHODS

Algorithms	Pros.	Cons.
Multi-class classification (MC)	Maximizes ground-truth and age separately	Overfitting unstable training
Metric Regression (MR)	Minimizes the MAE	Outliers can destabilize training; MR treats age linearly
Deep Label Distribution Learning (DLDL)	Resolves uneven age label distribution; also reduces the need for more training images	DLDL may be suboptimal with training inconsistency
Ranking	Uses the age-axis approach and binary classification for age estimation	Leads to training and evaluation inconsistency; sometimes suboptimal
Hybrid	Combines techniques for better performance and robustness	Combining models can increase storage and computational cost; challenging to deploy on resource-constrained devices

TABLE III. SUMMARIZED THE INFORMATION ABOUT DATASETS UTILIZED FOR AGE AND GENDER ESTIMATION

Dataset	Number of images	Age range	Number of people	Age type	Age Distribution	Environment
MORPH2[47]	55,134	16-77	13,618	Real Age	unbalanced	Controlled
FG-NET[48]	1,002	0-69	82	Real Age	unbalanced	Controlled
IMDB-WIKI[22]	523,051	0-100	20.284	Real Age	unbalanced	Uncontrolled
Age DB[49]	16,516	1-101	570	Real Age	unbalanced	Controlled
OUI-Adience[50]	26,580	0-60+	2,984	Age Group	unbalanced	Uncontrolled
CACD[51]	163,446	14-62	2,000	Real Age	unbalanced	Controlled
FERET[52]	14,126	-	1,199	Real Age	unbalanced	Partly Controlled
LHI[53]	8,000	9-89	8,000	Real Age	balanced	Controlled
PIE[54]	41,638	-	68	Real Age	unbalanced	Controlled
APPA-REAL[55]	7,591	0-95	7,000+	Real and Apparent Age	unbalanced	Uncontrolled
Caucasian Face Database[56]	147	20-62	-	Real Age	unbalanced	Controlled
WIT-BD[57]	26,222	3-85	5,500	Age Group	unbalanced	Uncontrolled
HOIP[58]	306,600	15-64	300	Age group	unbalanced	Controlled
Iranian face[59]	3,600	2-85	616	Real Age	unbalanced	Uncontrolled
YGA[60]	8,000	0-93	1,600	Real Age	unbalanced	Uncontrolled
FRGC[61]	44,278	18-70	568	Real Age	unbalanced	Partly Controlled
PAL[62]	580	19-93	580	Age group	unbalanced	Uncontrolled
GROUPS[63]	28,231	0-66+	28,231	Age group	unbalanced	Uncontrolled

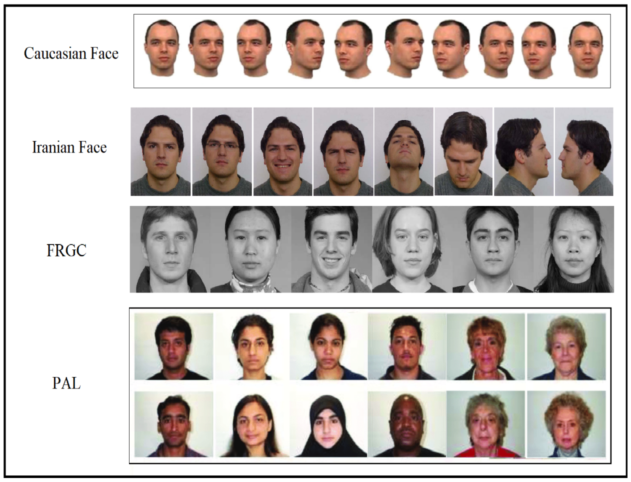

Figure 7. Sample images from Caucasian Face, Iranian Face, FRGC, and PAL datasets

8. PERFORMANCE METRICS

A. Mean Absolute Error (MAE)

Mean absolute error (MAE) represents a measure of errors that occurred between paired observations that describes similar phenomena. Comparisons that were performed about observed and expected values are a few examples of X versus Y. Furthermore, MAE is calculated by utilizing (1) yields the sum of absolute errors divided by the sample size. The better results are those that are smaller, which indicates the difference between the ages over many years.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e|}{n} \qquad (1)$$

Hence, it represents an arithmetic average of the absolute errors ei, in which yi denotes the estimated age of ith image and xi expresses the true age, and n refers to the image's number.

B. Accuracy (ACC)

Accuracy (ACC) is the ratio of the model's overall number of predictions to its number of accurate ones. How many of the image's total number did the model correctly identify as male? The number of the four outcomes of a binary classifier often represented as TP, FP, TN, and FN, is counted to create Figure 8 of the confusion matrix of binary classification, which is a two-by-two table.

ACC is calculated utilizing (2), which represents the sum of all correct predictions divided by the dataset's total number.

$$ACC = \frac{TP + TN}{TP + TN + FN + FP} \qquad (2)$$

		Predicted Class	
		Male	***Female***
Actual Class	***Male***	True Positive (TP)	False Negative (FN)
	Female	False Positive (FP)	True Negative (TN)

Figure 8. The gender classification's confusion matrix models

C. Cumulative Score (CS)

The Cumulative Score (CS) is a critical assessment metric for the age-estimation model. This equation may be employed to determine CS

$$CS(j) = \frac{N_{e \leq j}}{n} X100 \qquad (3)$$

Where Ne≤ j refers to the number of test samples having an age prediction error smaller than j years. CS(j) which represents performance when there is a dense distribution in a big set of data for various ages, may be used to describe the accuracy of classification. The model will perform better if its CS(j) value is larger, and the opposite is true.

9. COMPARATIVE ANALYSIS OF GENDER AND AGE ESTIMATION TECHNIQUES

In contrast to the performance of the methods, we specify the evaluation metrics, MAE to analyze the age prediction task, as mentioned in Table IV of the MORPH2 dataset and Table V on the FG-NET dataset. In contrast, ACC is employed for the gender estimation task as mentioned in Table VI of the OUI-Adience dataset. The performance comparison of handcrafted-based methods for age and gender estimation using different datasets was shown in Table VII.

We conclude that the technology roadmap for predicting gender based on facial images is as follows:
2010-2015: Early stages of development, with an accuracy of around 70-80.
2016-2019: Improvement in accuracy with the advent of deep learning, reaching around 85-90.
2020-2022: Refinement of deep learning algorithms and focus on diversity, resulting in an accuracy of around 90-95.
2023-2025: Further research on multimodal data and robust algorithms, potentially reaching accuracy around 95-98.
2026-2030: Possible approaching of human performance, though 100 accuracy is unlikely due to the complexity of the task.

TABLE IV. PERFORMANCE COMPARISON OF DEEP-LEARNING-BASED METHODS FOR AGE ESTIMATION UTILIZING THE MORPH2 DATASET

Paper	Methods	MAE
(B. Zhang and Y. Bao, 2022) [10]	CDCNN + VGG-16 net	2.76
(H. Zhang et al., 2021) [12]	DLDL + CNN	2.15
(A. Othmani et al., 2020) [1]	Xception + TL	2.01
(M. Duan et al., 2020) [6]	EGroupNet	2.13
(W. Cao et al., 2020) [17]	CORAL (COnsistent RAnk Logits) + CNN	2.64
(F. Dornaika et al., 2020) [18]	DL CNNs + Robust loss	2.75
(H. Liu et al., 2020) [64]	SADAL(Similarity-Aware and Variational Deep Adversarial Learning)	2.59
	VDAL	2.57
(P. Li et al., 2020) [20]	LRN (ResNet-18)	1.90
(M. Xia et al., 2020) [65]	Multi-Stage Feature Constraint Learning (MSFCL)	2.73
(J.C. Xie and C.M. Pun, 2020) [66]	DOEL-2groups-ResNet101 (Deep and Ordinal Ensemble Learning)	2.75
(Y.H. Kim et al., 2020) [67]	Cycle Generative Adversarial Network (CycleGAN)	4.29
(O. Sendik and Y. Keller, 2019) [68]	DeepAge (Dual CNN + SVR)	2.87
(K. Zhang et al., 2019) [4]	AL-RoR-34 (ResNet + RoR + LSTM)	2.36
(S. Taheri and O. Toygar, 2019) [69]	DAG-VGG16 (Directed Acyclic Graph- CNN)	2.81
	DAG-GoogLeNet	2.87
(H. Liu et al., 2019) [70]	ODFL + ODL (Ordinal Deep Feature Learning)	2.92
(C. Zhang et al., 2019) [71]	C3AE (Compact yet efficient Cascade Context-based Age Estimation)	2.78
(B.B. Gao et al., 2018) [72]	DLDL-v2 (Deep Label Distribution Learning)	1.969
(J.S. Kang et al., 2018) [73]	Deep ResNet-152 CNN	5.78
(M. Duan et al., 2018) [74]	Hybrid CNN-ELM	3.44
(K. Li et al., 2018) [75]	Deep Cross-Population (DCP)	3.75
(H. Pan et al., 2018) [76]	CNN + Mean-Variance Loss function	2.16
(B. Yoo et al., 2018) [77]	CMT (Conditional Multitask Learning)	2.91
(K.H. Liu et al., 2018) [78]	Depthwise Separable CNN + SVM	3.08
(J. Wan et al., 2018) [79]	VGG-Net-GPR	2.93
(W. Im et al., 2018) [80]	CNN + Triplet Ranking	2.87
(P. Li et al., 2018) [81]	CEN + ResNet18	1.91
(H. Liu et al., 2017) [70]	ODFL (Ordinal Deep Feature Learning)	3.12
(M. Duan et al., 2017) [82]	CNN2ELM + RAGN	2.61
(H. Liu et al., 2017) [83]	LSDML (Label-Sensitive Deep Metric Learning)	3.08
	M-LSDML (Multi-source LSDML)	2.89
(G. Antipov et al., 2017) [84]	VGG-16 + LDAE + ResNet-50 CNN	2.35
(E. Agustsson et al., 2017) [85]	Anchored Regression Network	3.00
(K. Li et al., 2017) [86]	D2C (Deep cumulatively and comparatively supervised model)	3.06
(S. Chen et al., 2017) [87]	Ranking CNN	2.96
(H. Han et al., 2017) [88]	DMTL	3.00
(Z. Tan et al., 2017) [89]	AGEn (age group-n encoding)	2.93
(R.K. Tiwari, 2016) [90]	SVR + RBF kernel + VGG-Net	3.45
(Z. Niu et al., 2016) [91]	OR-CNN (Ordinal Regression+Multiple output CNN)	3.27
(Y. Liu et al., 2016) [92]	Novel learning scheme + CNN's	2.78
(P. Rodriguez et al., 2016) [93]	Compact CNN (Novel feedforward attention mechanism)	3.23
(M. Uricar et al., 2016) [94]	VGG-16 + Multi-class SO-SVM	2.68
(F. Anda et al., 2015) [95]	LeNet (Caffe model + DEX)	3.88
(L. Boussaad and A. Boucetta, 2015) [96]	Tree kernel adaptive CNN	3.61
(X. Wang and C. Kambhamettu, 2015) [97]	Hierarchical Unsupervised Neural Network	3.81
(D. Yi et al., 2014) [98]	Multi-scale CNN	3.63
(K. Chen et al., 2013) [99]	CA-SVR (Cumulative Attribute-Support Vector Regression)	5.88
(H. Han et al., 2013) [100]	BIF+ SVM (Biologically Inspired Features)	4.20
(K.Y Chang et al., 2011) [101]	Ordinal Hyperplanes Ranker (OHRANK)	6.07
(G. Guo and G. Mu, 2011) [102]	KPLSR (Kernel Partial Least Squares Regression)	4.18

TABLE V. THE PERFORMANCE OF DEEP-LEARNING-BASED METHODS FOR AGE ESTIMATION EMPLOYING THE FG-NET DATASET COMPARISON

Paper	Methods	MAE
(A. Akbari et al., 2021) [14]	Novel Optimal Transport based loss function (-Wasserstein) + LDL	3.41
(H. Zhang et al., 2021) [12]	DLDL + CNN	3.14
(Y. Deng et al., 2021) [13]	Multi-feature learning and fusion + Regression-ranking estimator	2.59
(H.T.Q. Bao and C. Sun-Tae, 2020) [3]	Multi-tasking CNN	3.41
(X. Liu et al., 2020) [16]	MA-SFV2 (Mixed Attention-ShuffleNetV2)	3.81
(M. Ahmed and S. Viriri, 2020) [103]	Bayesian optimization with DL	2.67
(H.Liu et al., 2020) [64]	SADAL (Similarity-Aware and Variational Deep Adversarial Learning)	3.67
	VDAL	2.98
(M. Xia et al., 2020) [65]	Multi-Stage Feature Constraint Learning (MSFCL)	2.71
(J.C Xie and C.M. Pun, 2020) [66]	DOEL-2groups-ResNet101 (Deep and Ordinal Ensemble Learning)	3.44
(K. Zhang et al., 2019) [4]	AL-RoR-34 (ResNet + RoR + LSTM)	2.39
(S.F. Bhat et al., 2019) [104]	SADAL	3.67
(S. Taheri and O. Toygar, 2019) [69]	DAG-VGG16 (Directed Acyclic Graph- CNN)	3.08
	DAG-GoogLeNet	3.05
(H. Liu et al., 2019) [70]	ODFL + ODL (Ordinal Deep Feature Learning)	3.71
(R. Rothe et al., 2018) [22]	DEX + VGG-16	3.09
(H. Pan et al., 2018) [76]	CNN + Mean-Variance Loss function	2.68
(B. Yoo et al., 2018) [77]	CMT (Conditional Multitask Learning)	3.43
(H. Liu et al., 2017) [70]	ODFL (Ordinal Deep Feature Learning)	3.89
(R. Ranjan et al., 2017) [105]	MTL (Multi-task CNN)	2.00
(H. Liu et al., 2017) [83]	LSDML (Label-Sensitive Deep Metric Learning)	3.92
	M-LSDML (Multi-source LSDML)	3.74
(G. Antipov et al., 2017) [84]	VGG-16 + LDAE + ResNet-50 CNN	2.84
(L. Hou et al., 2017) [106]	R-SAAFc2 (Regression-Smooth Adaptive Activation Function)	3.01
(Z. Tan et al., 2017) [89]	AGEn (age group-n encoding)	4.34
(Y. Liu et al., 2016) [92]	Novel learning scheme + CNNs	2.80
(X. Wang and C. Kambhamettu, 2015) [97]	Hierarchical Unsupervised Neural Network	4.11
(K. Chen et al., 2013) [99]	CA-SVR (Cumulative Attribute-Support Vector Regression)	4.67
(K.Y. Chang et al., 2011) [101]	Ordinal Hyperplanes Ranker (OHRANK)	4.48

TABLE VI. COMPARISON OF THE PERFORMANCE OF DEEP-LEARNING-BASED METHODS FOR GENDER CLASSIFICATION UTILIZING THE OUI-ADIENCE DATASET

Paper	Methods	Accuracy
(M.K. Benkaddour, 2021) [7]	Deep CNN (Feedforward neural network)	95.6
(Md. M. Islam and J.H. Baek, 2021) [30]	Multi-task cascaded CNN (MTCNN) + VGG-16 net	97.28
(A.A Micheal and R. Shankar, 2021) [31]	CNN–ELM	90.2
(M. Alghaili et al., 2020) [24]	NN4VFL	98.23
(O. Agbo-Ajala and S. Viriri, 2020) [32]	Deeply learned CNNs	96.2
(M. Afifi, and A. Abdelhamed, 2019) [26]	AFIF4	90.59
(K. Khan et al., 2019) [27]	GC-MSFS-CRFs	91.4
(K. Khan et al., 2019) [34]	HAG-MSF-CRFs algorithm	89.7
(M. Duan et al., 2018) [74]	Hybrid CNN-ELM	77.8
(S. Hosseini et al., 2018) [107]	Wide CNN + Gabor Filter	88
(J.H. Lee et al., 2018) [108]	Lightweight Multi-task CNN (LMTCNN)	85
(Z. Qawaqneh et al., 2017) [109]	Joint fine-tuned DNNs	63.78
(S. Lapuschkin et al., 2017) [110]	Layer-wise Relevance Propagation (LRP) + CNN	85.9
(A. Dehghan et al., 2017) [36]	SAF-BAGE	91.8
(G. Levi and T. Hassner, 2015) [111]	Deep CNN	86.8

TABLE VII. COMPARISON OF THE PERFORMANCE OF HANDCRAFTED-BASED MODELS FOR AGE AND GENDER ESTIMATION

Paper	Methods	Dataset	MAE-Accuracy
	Age Estimation		
(E.N.A. Hammond et al., 2020) [112]	LaGMO	FG-NET	4.42
(E.N.A. Hammond, and K. Kusi, 2020) [113]	Reflexivity+Antisymmetry+Transitivity	Adience	4.07
(A. Günay and V. Nabiyev, 2018) [114]	WLD+LPQ+LBP SVR	MORPH2	4.06
		FG-NET	4.94
		PAL	5.75
(S.E. Bekhouche et al., 2017) [115]	PM-LPQ+PM-BSIF SVM	MORPH2	3.50
		PAL	5.00
(J.K. Pontes et al., 2016) [116]	AAM+LBP+LPQ+GW+Hybrid	MORPH2	5.86
		FG-NET	4.50
(L. Cai et al., 2016) [117]	Dual Histogram LBP+	MORPH2	4.66
	Gaussian Process Regression	FG-NET	4.64
(K.Y. Chang and C.S. Chen, 2015) [118]	CSOHR + Scattering Transform	MORPH2	3.82
		FG-NET	4.70
(O.F. Onifade and D.J. Akinyemi, 2015) [119]	GWAgeER + LBP	FG-NET	2.34
(I. Huerta et al., 2015) [95]	HOG+LBP+SURF+	MORPH2	4.25
	Classification	FRGC	4.17
(K.H. Liu et al., 2015) [120]	LBP+HOG+BIF+Hybrid	MORPH2	2.97
		FG-NET	2.81
(I. Huerta et al., 2014) [121]	LBP + SURF + HOG + CCA	MORPH2	4.25
		FRGC	4.17
(G. Guo and G. Mu, 2014) [122]	BIF+Classification	MORPH2	3.92
(C. Li et al., 2014) [123]	2D age manifold+BIF+	FG-NET	1.3
	Classification	FACES	8.2
(W.L. Chao et al., 2013) [124]	Label-sensitive relevant component analysis	FG-NET	4.4
(K. Chen et al., 2013) [99]	AAM+Regression	MORPH2	5.88
		FG-NET	4.67
(S.E. Choi et al., 2011) [125]	Gabor + LBP + hierarchical	FG-NET	4.65
	classifier based on SVM	BERC	4.68
		PAL	4.32
(G. Guo and G. Mu, 2011) [102]	BIF+Regression	MORPH2	4.2
(M.Y. El Dib and M. El-Saban, 2010) [126]	EBIF+ASM+Hybrid	MORPH2	4.11
		FG-NET	3.17
(P. Yang et al., 2010) [127]	Haar-like+ Regression+ SVR	FG-NET	5.67
(S. Yan et al., 2009) [128]	SSE+Regression	FG-NET	5.21
(G. Guo et al., 2009) [129]	BIF (Bio-inspired features)	FG-NET	4.77
(S. Yan et al., 2008) [130]	Coordinate Patch+Regression	FG-NET	4.95
	Gender Classification		
(I. Neggaz and H. Fizazi, 2021) [131]	AOA-BPNN+ Multi blocks	FEI	99.16
	HOG+LBP+GLCM	GT	99.50
(A.A. Micheal and P. Geetha, 2019) [132]	SVM+ DRLBP+RILPQ+PHOG	FEI	95.30
(A. Geetha et al., 2019) [133]	SVM+8-LDP+LBP	FEI	99
(K. Khan et al., 2019) [27]	MSFS-CRFs+Segmentation based on Super-Pixels	FEI	93.70
(S. Kumar et al., 2019) [134]	SVM+Multi-features (BoW+SIFT)	FEI	98
(B. Ghojogh et al., 2018) [135]	LDA+weighting vote	FEI	94
(A. Goel and V.P. Vishwakarma, 2016) [136]	SVM+DCT	GT	98.96
(A. Goel and V.P. Vishwakarma, 2016) [137]	SVM+ DWT+DCT	GT	99
(A. Goel and V.P. Vishwakarma, 2016) [138]	SVM+KPCA	GT	97.38

10. CONCLUSION

The majority of the methods for estimating age and gender using three datasets MORPH2, FG-NET, and OUI-Adience were compared in this study, along with their MAE and accuracy. We listed the applications and some difficulties that the estimation process faces. No one solution works best for these two objectives because DL techniques used for gender classification, as well as age estimation, are still in the process of being improved. Although there are some effective strategies, ultimately, they still have certain shortcomings and challenges. In the future, we hope to develop technology to its best ability and discover ways of reducing the problems and difficulties that the estimating process for both age and gender now faces.

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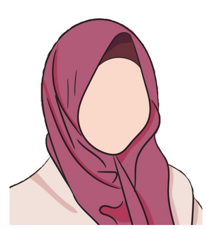

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