Gender and Age Detection System Using CNNs on Real-Time Video

Prof. Gurudeo Sawarkar[1], Prof. Rahul Bhandekar[2], Miss. Sujata Dake[3] Mr. Prashant B. Tarone[4]

[4] Student, Department of Computer Science Engineering, Wainganga College of Engineering and Management, Nagpur, India, Pin: 441108

[1,2,3] Professor, Department of Computer Science Engineering, Wainganga College of Engineering and Management, Nagpur, India, Pin: 441108

ABSTRACT: *Nowadays automatic gender & age prediction using face pictures has received Much of interest due to its huge variety of applications in many facial investigations. With the use of the aforementioned technologies, we can ascertain an individual's gender & age from a single glance taken by a camera, image, or video. This study will describe Convolutional Neural Networks (CNNs) that use a deep learning approach, also applicable techniques, algorithms, & how everything works together to classify gender & detect age. Also, technology will highlight its significance & potential applications to enhance our daily lives. The goal of the research is to create a gender & age predictor that uses deep learning to approximate the gender & age of a human face in a video image. Also, the map looks at the wide range of applications where this technology could be employed, from marriage sites to CCTV cameras, cops, & intelligence organizations, & illustrates how it might be used for our benefit. Facial photos are frequently used in these applications since they may be used to extract human interaction & include useful information. Image processing, feature extraction, & classification stages are typically employed for gender & age prediction. Depending on the study's goal & the variables to be employed, these procedures could vary. Numerous techniques were used to process the face photos, & computations were made in light of the findings of the studies. There are two basic & customary guidelines that we must adhere to when processing images. The technique of enhancing an image to make it better & more useable for various purposes is known as image enhancement. The other method is the most widely used approach for deriving information from an image. To tackle the problem, the image is segmented into a certain number of objects or sections. This process is known as segmentation. Deep learning techniques are useful for a range of tasks, including gender & age prediction, object recognition, feature extraction, & classification. This is due to the precision of their classification technique. Using this method, we succeeded in identifying the gender & age of each picture in Real-Time videos containing many faces.*

KEYWORDS: Convolutional Neural Networks (CNNs), deep learning, gender classification, age detection.

I. INTRODUCTION

Nowadays, Interest in automatic facial image-based gender & age classification has grown since the emergence of social media. Therefore, gender & age classification is an important step in many applications, including interest group targeting, aging analysis, face verification, & ad targeting. However, in practical implementations, the majority of gender & age classification systems still have some issues. This work uses multiple Convolutional Neural Networks (CNNs) as a method of classifying people based on their gender & age. The four stages of the suggested approach are facing alignment, face detection, backdrop removal, & multiple CNNs(Convolutional Neural Networks). Using three different CNNs (Convolutional Neural Networks) in terms of depth & structure, the multiple Convolutional Neural Networks (CNNs) approach seeks to extract specific characteristics for each of the networks.

In interpersonal interactions within communities, gender & age are important factors. As technology has advanced, so has the use of smart devices, & social media has started to grab everyone's attention. The prevalence of daily studies on gender & age prediction has expanded, this has resulted in a rise in the number of apps using these technologies. Facial photos are frequently used in these applications since they may be used to extract human interaction & include useful information. Image processing, feature extraction, & classification stages are typically employed for gender & age prediction. These procedures could vary depending on the study's goal & the traits that will be used. Numerous techniques were used to process the face photos, & computations were made in light of the findings of the studies. There are two basic & customary guidelines that we must adhere to when processing images. The technique of enhancing an image to make it better & more useable for various purposes is known as image enhancement. The other method is the most widely used approach for deriving information from an image. To tackle the problem, the image is segmented into a certain number of objects or sections. This process is known as segmentation. Deep learning techniques are useful for a range of tasks, including gender & age prediction, object recognition, feature extraction, & classification. This is due to the precision of their classification technique.

Automatic gender and age prediction from face images has lately gained popularity due to its wide range of applications in various facial investigations. With the use of the aforementioned technologies, we can ascertain an individual's gender & age from a single glance captured by a camera, photograph, or video. This study will describe CNNs(Convolutional Neural Networks) that use deep learning, as well as applicable techniques, and algorithms, & how everything works together to classify gender & detect age. Also, technology will highlight its significance & potential applications to enhance our daily lives. The major goal of the research is to construct a gender and age detector that employs deep learning to estimate the gender and age of a human face in a photograph. Also, the map looks at the wide range of applications where this technology could be employed, from marriage sites to CCTV cameras, cops, & intelligence organizations, & illustrates how it might be used for our profit.

In interpersonal interactions within communities, gender & age are important factors. As technology has advanced, so has the use of smart devices, & social media has started to grab everyone's attention. The popularity of daily research on gender and age forecasting has grown, increasing the number of apps that use these approaches. Facial photos are frequently used in these applications since they may be used to extract human interaction & include useful information. Image processing, feature extraction, & classification stages are typically employed for gender & age prediction. Depending on the study's goal & the variables to be employed, these procedures could vary. Population techniques were used to process the face image, & computations were made in light of the findings of the studies. There are two basic & customary guidelines that we must adhere to when processing images. The technique of enhancing an image to make it better & more useable for various purposes is known as image enhancement. The other method is the most widely used approach for deriving information from an image. To solve the task, the image is separated into a predetermined number of objects or components.

The machine learning methods of the previous system were not used to enhance the ability to classify a large quantity of data & images that were accessible online. In this work, the gender & age of an individual is accurately estimated from a single facial capture using Deep Learning algorithms/approach. 'Male' or 'Female' will be the anticipated gender. We could predict someone's age using age categories derived from the trial. The important feature of face photos in a variety of applications, like emotional expression & facial identification, is the eyes. Many clues & indicators provided by Human Facial Image Processing can be used in a range of industries, including security, entertainment, & business. A person's facial expressions can convey a lot about them, level of agreement or disagreement, irony/rage, including their emotional state & more. For this reason, faces have grown in importance as a topic of research in psychology. For instance, gender identification can give hiring teams at companies a plethora of information. Verification of identity documents, including voter ID cards, which are used by millions of voters to cast ballots in elections, & so forth. Using human facial image analysis to identify eligible or fraudulent individuals makes things easier.

II. LITERATURE WORK

[1] M. Rajput et al, In the paper, a system was proposed for gender & age estimation for iris images, employing a CNN trained for age identification & modified Deep Convolutional Neural Networks(D-CNNs) models like AlexNet & GoogLeNet for gender estimation. The proposed system achieved 89.34% accuracy in gender classification using AlexNet & approximated the age of individuals based on iris features, with gender classification outperforming age prediction due to a larger number of subjectsin gender classes**.**

[2] H. Liao et al, The author utilized an aspect assessment approach to identify robust characteristics, a technique that uses deep learning to identify facial attributes, & a divide-and-rule face age estimator. ***[3] X. Liu - [4] S. Chen et al,*** The Convolution Neural Networks(CNNs) methodology for deep learning has gained popularity recently since it performs better than previous techniques***. [5] P.A. Melange et al – [6] A Rybintsev,*** The deep learning technique is superior to the standard SVM and SVR algorithms. Researchers have also shown that LBP-based feature extraction is more effective & popular for estimating gender & age from face images. ***[7] C. Dalvi et al***, one hundred subjects in two age groups were used in the second method fifty among the more youthful group (22-25) & There are fifty is in the elderly group (>35). From every iris image, they were able to extract 630 texture features. The trials were carried out using the random-forest approach (Weka with 300 trees), with a ten-fold cross-validation procedure. The performance of the suggested method was 64.68%. This paper presents an exhaustive examination of AI-based techniques for Face Expression Identification (FEI), encompassing a range of age groups & addressing the growing demand for online platform integration. It closes a vacuum in the literature by offering a thorough summary of earlier studies & directing FER research in new directions. It also covered the phases of FER & contrasted CNN models, offering suggestions for future lines of inquiry & possible uses in the developing discipline.

[8] A. Bansal et al, the iris image was categorized by the authors into one of three classes: 1. Youngsters (60). They used a Bio-Secure Multimodal database for their experiments. This database's images were taken with the LG Iris Access EOU3000 system. There are 200 subjects altogether in the database, ranging in age from 18 to 73. From the iris, they only extracted five geometrical traits. The classification algorithms employed were KNN, SVM, MLP, and multi-classifier (fusion and negotiation-based). By employing the multi-classifier-negotiation method, they were able to attain 75% accuracy. ***[9] V.Thomas et al***, alternative methods for predicting gender involve extracting features from the iris using different techniques, like geometric & texture features, combining geometric & texture features ***[10]M.Fairhurst et al***, texture & statistical features ***[11] S.Lagree et al***, LBP-based features ***[12]J.E.Tapia et al- [13]M. Christeena et al***, Binarized Statistical Image Features (BSIF) ***[14] D. Bobeldyk et al***, & using only statistical features ***[8] A. Bansal et al.*** For gender identification, ***M. Singh & S. Nagpal [15]*** used the ND-GFI iris dataset. They suggested using Deep class encoding in conjunction with two classifiers, RDF & NNet, in their studies. They claimed an accuracy of 73.17%. ***H.Zhu et al [16]*** To estimate age, a deep learning method was developed that used global convolutional neural networks (CNNs), three local convolutional neural networks, and an ordinal distribution regression model. The head, body, & feet are the three distinct GEI components that the three local Convolutional Neural Networks(CNNs) are trained on. The entire GEIs are used to train the global CNNs(Convolutional Neural Networks). Using the OULP Age Dataset, the model was trained & tested. It produced an MEA of 5.24 & a CS (k = 5) of 69.95%. Deep learning algorithms, such as Convolutional Neural Networks (CNNs), have made it unnecessary to actively extract features from the gait description since they can recognize & automatically learn from its unique patterns. Sakata et al. conducted another recent investigation

[17] A. Sakata et al, the author suggested the cutting-edge Convolutional Neural Networks-based technique for estimating gender & age. For the age regression & estimation of gender & age group, they employed sequential Convolutional Neural Networks(CNNs). The GEI would first pass through a CNNs(Convolutional Neural Networks)that predicts its gender, & then it would pass through two more Convolutional Neural Networks(CNNs*)* that predict its age & age group, respectively. The OULP Age dataset was used to train and evaluate the model, and the results suggested hope, with the approach achieving an average age of 5.84 years. The framework predicts less accurately for aged participants. ***Murat Berksan [18],*** the reduced number of participants in the senior age category that are available in the OULP database is what causes this trend. After examining several Convolutional Neural Networks (CNNs) Systems over gait a silhouette mean approximation**,** was able to estimate gender with an accuracy of 79.45% & age with an MEA of 5.74 years. ***[19] A. Dzedzickis – [20] J. A. R. Eliot et al,*** in many different kinds of interactions between humans and computers, including those involving intelligent robotics, control systems, smartphones, behavioral research, affective computing, social media, defense, & other domains, pattern recognition, human facial expression recognition has been widely utilized.

[21] M. Spezialetti through [22] S. Ramis et al, the dispute that Ekman's theory of the six basic emotions, which is meant to be global, is culturally particular & not global has been spurred by current developments in psychology & neuroscience research. This has led to inquiries into whether emotions vary according to gender, age, & culture. Since the world is moving toward online platforms, there is a greater need than ever for emotion classification. Examples include on the basis of violent behaviors of criminals or those mentally disturbed, deepfake robotics, detection, and psychiatric evaluation. Mood swings research on youngsters to help advise them mentally; virtual learning to educate or obtain knowledge digitally internationally to all remote locations; and many other applications that are now being pioneered employing the latest technologies. Due to its applicability in intelligent robotics, criminal psychological analysis, the Internet of Things, driver fatigue monitoring, security surveillance, & other human-computer interface mechanisms, and medical treatment, a large amount of research has also been conducted on facial expression identification using computer vision. ***[24] V. Carletti et al,*** this paper reviews recent advancements in age estimation from faces, particularly focusing on deep learning approaches over the past six years. It analyzes various aspects including network architecture, datasets, preprocessing, & the utilization of additional data such as gender, race, & facial expressions. The conclusion highlights the impact on system performance & identifies ongoing challenges in the field. ***[25] E. Di Nardo to [29] M. Al-Shabi et al,*** the most recent Convolutional Neural Networks (CNNs) models, including InceptionNet VGG, Resnet, SqueezeNet, & many others, have been the subject of extensive recent studies using various combinations of innovative techniques.

[30] A. Khan et al, Several computer vision applications include facial expression recognition, scene classification, and visual detection. After utilizing several techniques for FER, extensive study in the literature on emotion recognition concludes that Convolutional Neural Networks (CNNs) are a useful tool for facial expression recognition. Convolutional Neural Networks (CNNs) outperform RNN and Deep Learning. Autoencoders, Multilayer Perceptron (MLP), & DBN when it comes to position shifts & scale variations. Convolutional, pooling, & fully connected layers comprise a typical CNNs(Convolutional Neural Networks). Convolutional Neural Networks has two features: local connection & weight sharing, which lead to fewer

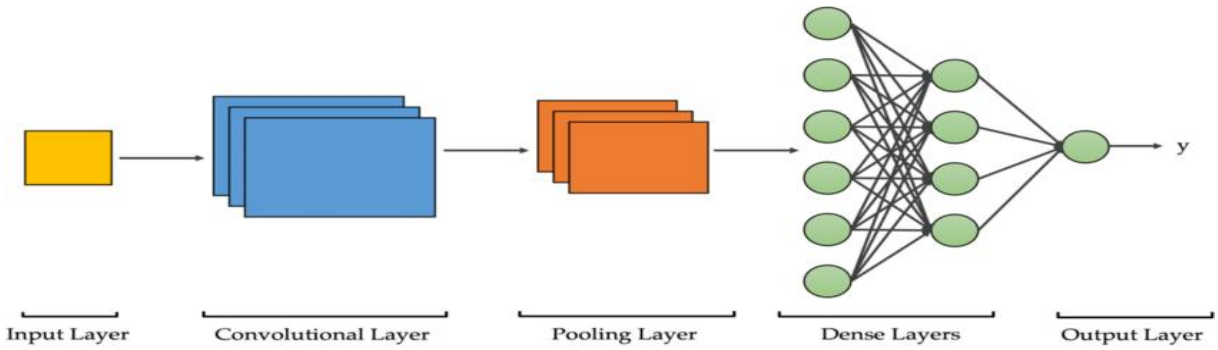

Figure 1. Convolution neural network architecture.

network parameters, faster training, & an impact on regularization. An illustration of a Convolutional Neural Networks (CNNs)-based FER method as shown in Fig1.

[31] Haing Htake The age of facial photos was predicted by Khaung Tin using Principal Component Analysis (PCA). With the use of CNN & OpenCV, Nagesh Singh Chauhan can accurately identify the gender & age of any human face that appears in a video**. *[32]* Haibin Liao et al,** the author estimated the age of facial photos***, &*** employed Convolutional Neural Networks(CNNs) & the divide-and-rule method. The robust characteristics in the photos were extracted by Convolutional Neural Networks (CNNs*)*, followed by a divide-and-rule face age estimator that is suggested, & an age-based & sequential examination of rank-based age estimation learning approaches. The significance of precisely determining the age range & gender of consumers for organizational initiatives was discussed in the paper. It suggested a novel method for estimating age & validating gender from user images using Deep Learning—more especially, Convolutional Neural Networks—& implemented a web application for validation. ***[33] R. Yamashita et al***, Neural Convolution One of the primary deep learning algorithms, CNNs(Convolutional Neural Networks) is capable of learning to do classification tasks directly from images. This algorithm, it handles the prediction of gender and age range as a classification problem, with both classes for gender (male & female) & multiple classes for age ranges, will be quite helpful in our situation. In this research, we try to offer a form validator based on an automatic gender classification & age detection using Convolutional Neural Networks(CNNs) & assess it using a dataset of actual people's images to validate a gender & age range that is reflected by user photos.

[34] Islam T. UI et al, the study demonstrated the advantages of deep learning-based techniques by offering a comprehensive view of the Age estimation from gait challenge. It was determined that more research was required to solve the issue, exp& the Gait databases, & improve accuracy by using deep learning models to directly process video data. ***[35] Wang et al,*** the study looks at the growing usage of biometric techniques' auxiliary data**.** The photos were categorized into age groups using the Furthest Nearest Neighbor (FNN). ***Shang & Ai [36],*** employed a pre-trained GoogleNet to extract the aging-related characteristics. They divided the characteristics into several groups using the clustering algorithm k-means++, & then they retrained the network for each category. ***[37] Rodríguez et al,*** presented an alternative model that includes an unconstrained dataset validation stage. Their attention mechanism & feedforward Convolutional Neural Networks (CNNs) pipeline served as the foundation for their model. The mechanism of attention was used to extract more comprehensive attributes of the face to gain more details about certain areas of the face.

Eidinger et al. [38], T*he purpose of utilizing this approach was to eliminate unnecessary information & simplify the task. In particular, down-sampled photos that belong to high-resolution photographs were used to generate discriminative patches. Refinement of pre-trained models with sparse aging data yields significant gains. The work that recommends using the feature descriptor combination was presented by. ***[39] Z. Hu et al,*** although using h&-crafted ways to represent the face and extracting features offers the benefit of molding less complicated algorithms, it could end in a deletion of crucial data and the requirement for additional manual knowledge. There has been a recent trend toward using more potent feature-learning approaches in place of h&-crafted features. On the other hand &, because so many crucial data are lost throughout the feature extraction & selection process, the conventional approaches might not be age-appropriate. In a perfect world, age image representation would include all relevant age information. These models extracted the aging-related characteristics using conventional methods. Researchers have worked very hard to enhance the accuracy of age estimate systems, whether they are used for calculating an individual's actual age or classifying people into age groups. We found that, when compared to other methodologies, utilizing a hybrid or fusion strategy can boost performance. The primary differences between various feature extraction techniques are presented in Table no. 1. To create a more reliable & accurate system, it is most beneficial to combine different feature techniques into a single model; nevertheless, this may result in a more complex system.

Feature Model	Strength(s)	Weakness(es)
Anthropometric	-Appropriate to the age from child to adult.	-While this approach is considering only the geometric features, it might be inappropriate for adults & old people. -To measure the facial geometric, images should be in frontal view, because of the sensitivity of computing the ratios of distances from 2D facial images. -This model has been experimented only on small private datasets
Texture	-Can effectively handle small transformations including translations, rotations & scale changes.	-Some descriptors are less accurate such as LBP. -Some descriptors are complex & slow such as HOG & Haar-like. -Different illumination conditions may change the surface texture. -The loss of some skin areas & wrinkles information.
AAM	-Can deal with any age & consider both texture & geometric models.	-The intensive computations & the need of large number of images to learn the features that are related to the shape & appearance. -Dealing with image intensities in the gray level, may lead to a vulnerable model.
AGES	-Learning a subspace representation helps to compensate for the missing ages while modeling the related series of aging faces.	-Many images are needed at several ages to represent the same person.
Age Manifold	-Many images are not needed at several ages to represent the same person. -Flexible means of face representation	-Is not suitable to encode the wrinkles for senior people. -Large datasets are needed for manifold subspace learning.
Multi-Feature Fusion	Combines the features from different models, so the features will complement each other, to get a more robust system. -Enhancing the performance of the AE system.	More complex model

TABLE 1. Comparison of different feature models.

[40] Simonyan et al, ConvNet settings (displayed in columns) in the table. 2. As additional layers are added (the new layers are highlighted in dark shaded), the configurations' depth increases from side (A) to side(E). The equation conv (open field size)-(number of inputs) indicates the convolutional layer's characteristics.For simplicity, the ReLU activation feature isn't shown.

ConvNet Configuration					
A	*A-LRN*	*B*	*C*	*D*	*E*
11 weight layers	*11 weight layers*	*13 weight layers*	*16 weight layers*	*16 weight layers*	*19 weight layers*
input (224×224 RGB image)					
conv-3-64	*Conv-3-64 LRN*	*Conv-3-64 Conv-3-64*	*Conv-3-64 conv-3-64*	*Conv-3-64conv-3-64*	*Conv-3-64 conv-3-64*
MaxPool					
Conv-3-128	*Conv-3-128*	*Conv-3-128 Conv-3-128*	*Conv-3-128 Conv-3-128*	*Conv-3-128 conv-3-128*	*Conv-3-128 conv-3-128*
MaxPool					
Conv-3-256 Conv-3-256	*Conv-3-256 Conv-3-256*	*Conv-3-256 Conv-3-256*	*Conv-3-256 Conv-3-256 Conv-1-256*	*Conv-3-256 Conv-3-256 Conv-3-256*	*Conv-3-256 Conv-3-256 Conv-3-256 Conv-3-256*
MaxPool					
Conv-3-512 Conv-3-512	*Conv-3-512 Conv-3-512*	*Conv-3-512 Conv-3-512*	*Conv-3-512 Conv-3-512 Conv-1-512*	*Conv-3-512 Conv-3-512 conv-3-512*	*Conv-3-512 Conv-3-512 Conv-3-512 Conv-3-512*
MaxPool					
Conv-3-512 Conv-3-512	*Conv-3-512 conv-3-512*	*Conv-3-512 conv-3-512*	*Conv-3-512 conv-3-512 conv-1-512*	*Conv-3-512 conv-3-512 conv-3-512*	*Conv-3-512 conv-3-512 conv-3-512 conv-3-512*
MaxPool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table. 2. ConvNet Configuration [11]

[41] E. R. Enbar et al, Feature selection is a technique used in neural network training, particularly with VGGNet, to help the network learn the weights involved in feature extraction. From an unprocessed input image, the Deep Convolutional Neural Networks (D-CNNs) can extract a wide range of attributes from which little to no pre-processing is necessary**.** When it comes to geometric deformation, transformations, & two-dimensional alterations in shapes & fig, Deep Convolutional Neural Networks (D-CNNs) provide midway resistance & boosts**.** Since the other feature extractors on the market are characterized by static behavior, Deep Convolutional Neural Networks (D-CNNs) are specifically designed to overcome this.

[42] Fu, G. Guo et al, the advantage of using Deep Convolutional Neural Networks(D-CNNs) is that it is relatively simple to help the input, hidden, & output network layer(loss through BPNN) learn parameters & weights. They contain fewer parameters than fully connected multi-layer perceptron modeling neural networks, and they employ the same number of hidden layers between the input and output layers. As a result, Deep Convolutional Neural Networks (D-CNNs) have demonstrated outstanding achievement in many different kinds of applications, including face recognition (FR), traffic signal recognition (TSR), Optical Character Recognition (OCR), surveillance systems that deal with objects, articles, & people, tracking people in mobs (also known as Human Tracking Systems or HTS), & many more Deep Convolutional Neural Networks (D-CNNs) is also widely used in computer vision applications.

[43] ***Zakariya Q et al,*** a deep neural network VGG-face model was trained for the LFW database by the authors in. A connected layer was swapped out for four brand-new fully connected layers. The first layer has a size of 4096, while the next three layers have a size of 5000. There are eight age classes in total in their output layer. 80.57% one-off accuracy was attained. Where the outcome class is faulty by one neighboring age symbol on the left-right, it is represented by the symbol I1 off accuracy. By altering completely linked layers, they also trained a pre-trained GoogLeNet network, achieving a 45.07% age estimation accuracy. ***J. Tapia & C. Aravena [44],*** An unsupervised method for pre-training a Deep Belief Network with a large number of unlabeled iris images was proposed. The Deep Multilayered System was then used to classify gender. They achieved 74.66% accuracy with data enhancement and 83.00% using CNN-2 for identifying genders. ***[45] O. Agbo-Ajala et al***, A unique Convolutional Neural Networks(CNNs) model was proposed by Olatunbosun Agbo-Ajala & Serestina Viriri to classify & extract features from unconstrained real-life facial photos according to gender & age. They obtained 74.8% accuracy in age group classification & 79.7% accuracy in gender classification**.** The significance of precisely determining the age range & gender of consumers for organizational initiatives was discussed in the paper.

[46] A.M. AbuNoda gender prediction using University of Palestine student pictures was evaluated, & the results showed that age prediction was difficult**.** A.M. Abu-Noda & associates. It suggested a novel method for estimating age & validating gender from user images using Deep Learning more especially, Convolutional Neural Networks & implemented a web application for validation. Gender prediction using University of Palestine student pictures was evaluated, & the results showed that age prediction was difficult A. M. Abu-Noda & associates. Using a huge & complicated model that has been trained on over 500K person images, the approach advises improving gender & age prediction & optimizing its performance for application forms. To address low accuracy in gender prediction from female photographs, it also suggests training a new Convolutional Neural Networks(CNNs) model using a big dataset that includes a sizable number of female photos wearing hijabs.

[47] E. Alajrami et al, using a huge & complicated model that has been trained on over 500K person images, the approach advises improving gender & age prediction & optimizing its performance for application forms. To address low accuracy in gender prediction from female photographs, it also suggests training a new Convolutional Neural Networks(CNNs) model using a big dataset that includes a sizable number of female photos wearing hijabs**.** ***[48] B. Martinez et al,*** one of these innovative models, GoogleNet, was developed by Google & was employed in the investigation to identify emotions from video samples. However, these facial feature categories are produced by a cluster-based technique in which frames of images captured from videos in similar situations are grouped and allocated to a specific area. This stands beside the comprehensive technique of using geometric features of the face and detecting landmarks of the face, those are the major determining elements of categorized emotions. For GoogleNet training & testing, the closest centroid among all the clusters was thought to be the best framework. When these outputs are combined with substantial output values, audio emotion classification data, & a far greater accuracy level than predicted by existing audiovisualmodels are obtained.

***[49] R.G. Guimaraes et al**,* according to the research, by detecting common writing tendencies among age groups, including user profile information—particularly age group—improves sentiment analysis accuracy. A deep neural network is able to predict age groups & high precision by examining multiple features such as punctuation usage & topic preferences. This resulted in improved sentiment analysis metrics. To identify pertinent criteria for categorizing age groups on Twitter, the study thoroughly examined 7000 words. It stressed the significance of taking user profile information & writing style into account. When user age information is absent, the deep convolutional neural network (DCNN) performs better overall because it can accurately classify age groups better than other machine learning algorithms. This improves sentiment intensity measurements like eSM**.** It emphasizes the merits of deep learning in AE, but also stresses the necessity of large datasets & top-notch systems, as well as the advantages of applying transfer learning to boost robustness & accuracy.

[50] A.S.AL- Shannaq et al, Transfer learning, attention mechanisms, validation on various datasets, & deep learning-based age estimate methods are employed. It addressed issues such the uncontrollably fast aging process & small datasets & suggested ways to improve resilience, such as fusing & augmenting data with other biometrics***. [51] M. Grimmer et al***, the goal of the review is to pinpoint biases on gender, age, color, ethnicity, & culture as well as the variables—like algorithm design, training data, & database diversity—that contribute to these biases. Recent developments in deep generative networks were worked on to increase accuracy & visual fidelity, but the importance of a structured analysis & taxonomy to direct further research in this field was also emphasized**.** It talks about how advances in deep generative networks have led to a rise in interest in FAP, pointing out problems including the lack of information for marginalized age groups. The requirement for customized age progression models. ***[52] Eidinger et al,*** the difficulty of determining facial characteristics like gender & age from photos taken under various settings is discussed in this research. It proposes a strong face alignment strategy, a dropout-SVM approach to prevent overfitting, & a unique dataset gathered from mobile devices, showing better performance than previous approaches. It refers to the identity-labeled Audience dataset, which may improve face recognition in the future**.** This paper reports on a study that used image processing techniques to estimate gender & age from facial photographs. The research offers two approaches that exhibit acceptable runtime & efficiency, attaining 86.6% & 76.3% accuracy in gender & age categorization, respectively.

[53] R.R.Atallah et al, This paper summarizes the reviewed state-of-the-art techniques for age estimation & face recognition. It also identifies the highest accuracy rates achieved by SVM, LBP, & GAP methods, while emphasizing the need for robust systems to account for aging effects, especially in newborns***. [54] S. Kumar,*** They evaluated the algorithm on their own huge, unstructured dataset and used LBP with Four Patch LBP codes (FPLBP) for the extraction of features. For identification, concentrating on traits like gender & age that are retrieved from faces. It examines the state-of-the-art facial recognition methods for estimating gender & age, talking about how well they work & offering ideas for future research.

[55] S.T.Rahman et al, Testing on other databases also yields encouraging results**.** This study provides an extensive analysis of AI-based approaches for Facial Expression Recognition (FER), covering a range of age groups & addressing the growing dem& for online platform integration. ***[56] A.A. Vogan et al,*** the study covered in the paper focuses on the problems that emerging nations face due to an aging population & age-related cognitive impairment. Humanoid & pet robots show promise in improving cognition & emotional health markers, especially when equipped with AI & Deep Learning capabilities, according to a study that looks at the current & potential uses of Artificial Intelligence (AI) & Human-Robot Interaction (HRI) as intervention strategies for cognitive training***. [57] A. Khalil et***

al, this research describes an investigation into bias & discrimination in commercial facial analysis systems through a systematic examination of the literature.

[58]. Dantcheva A. et al, writing as an author sounds fascinating! The use of dynamic data from smiles to estimate gender brings an intriguing new aspect to the area. Including both dynamic elements & look, particularly for varying age groups, sounds like a thorough strategy. It's exciting to see how advancements like this might benefit a variety of applications, such as human-computer interaction and video monitoring.

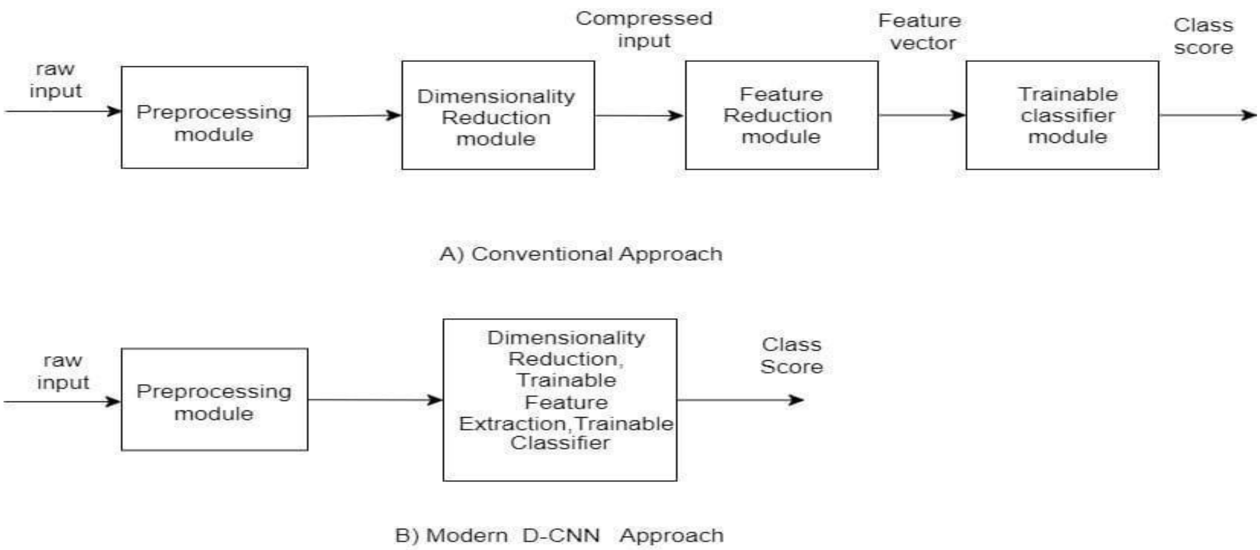

Fig. 3.

Fig.2 Pattern Recognition Approach to CNN

With the LeNet-5 design, Deep Convolutional Neural Networks(D-CNNs) have become widely employed for feature detection & recognition. LeNet-5's network architecture was relatively moderate in comparison to more advanced Deep Convolutional Neural Networks (D-CNNs) like VGGNet. This was due to the limited computational resources, including time, memory, & processing power, as well as the different algorithmic challenges involved in training such large networks. However, Deep Convolutional Neural Networks (D-CNNs) architectures—a neural network with an enormous number of neuron layers—have a lot of potential. Lately, they have gained popularity due to an unanticipated increase in both computational power through the use of Graphical Processing Units (GPU) & the volume of datasets that are readily available online or prepared by researchers for practical use. One of the most common applications of Deep Convolution Neural Networks (D-CNNs) in the real world is image classification & recognition on a variety of facial databases containing millions of raw, unfiltered face images, such as LFW & celebrity faces. Other applications of Deep Convolutional Neural Networks (D-CNNs) in this area include expressed pose estimation, body setup processing, face parsing, recognition of faces, detecting objects, path detection, plant disease estimation using a plant leaf image, age and expression identification using an individual's face, face key-point detection, and recognition of speech.

III. CONCLUSIONS

The concept of automatic detection of gender is crucial to many domains, including age estimation, security systems, biometric systems, credit card verification systems, visual surveillance systems, & human-computer interface systems. Due to high levels of variety in things like lighting, emotion, posture, age, scales, camera quality, & occlusion, it is quite taxing. Capturing images in identical atmospheric conditions isn't always feasible. Variations in lighting circumstances, head posture, facial expressions, partial occlusion by hats or spectacles, & camera quality can all affect how well the gender classification algorithm performs in terms of categorization rate. Therefore, it is ideal to have an algorithm that can withstand & changes in illumination, position, occlusion, & emotion.

The primary purpose of this research is to develop novel techniques for both age & gender classification based on images of people in diverse situations and wearing different kinds of face cosmetics. In our project, we provide a novel method that incorporates into consideration the facial shape & texture aspects to classify gender under different positions. Male & female gender classes are classified using CNNs(Convolutional Neural Networks). After that, a unique approach to gender-invariant makeup classification is suggested. Gender classification is done by the CNNs(Convolutional Neural Networks) Model. finally, a brand-new framework for calculating age in various positions is put down. A support vector regression with a CNNs(Convolutional Neural Networks) model is used to estimate a person's true age. Then a deep-learning-based method is Used to figure out the age of a person wearing facial makeup. Several approaches have been devised for the effective completion of the gender & age identification process in this proposed research project.

- In a marketing organization, the target audience is identified.

1. During the recruitment process, to ensure the applicants' validity.
2. Verification of the identity of those applying for government identification cards.
3. In the medical sector, a forensic department collects information about deceased people.
4. In the banking industry, gender & age detection can be used to extract information about an individual from photos.
5. The Criminal Investigation Department will compile information on the suspects based on their gender & age

- In the future, it might be expanded in the following ways.

1. To handle input faces with glasses & other barriers, the gender & age identification procedures may be expanded.
2. It can be expanded to use facial expressions to determine gender & age.
3. To increase accuracy, three-dimensional photographs can be used with the gender & age prediction methods.
4. The gender & age identification method can be tested using databases gathered from different nations.
5. An individual's gender & age can be identified by glancing at a heavily made-up face.
6. Gender & age identification can be done using the noisy faces in different stances.

As a result, the research project offers a thorough analysis of gender classification with improved accuracy when compared to the body of existing literature. Future studies in this area may involve developing a novel method for classifying gender in addition to identifying the age & ethnicity of faces captured in unrestricted environments.

REFERENCES

[1]. M.R.Rajput, G.S. Sable, "Deep Learning Based Gender & Age Estimation from Human Iris", Proceeding of ICAEEC-2019 vol:06, pp:8-10

[2]. H. Liao, Y. Yan, W. Dai, P. Fan.: Age Estimation of Face Images Based on CNN & Divide-&-Rule Strategy. In: Hindawi Mathematical Problems in Engineering (2018).

[3]. X. Liu, S. Li, M. Kan.: AgeNet Deeply Learned Regressor & Classifier for Robust Apparent Age Estimation. In: ICCV '16 (2016).

[4]. S. Chen, C. Zhang, M. Dong, J. Le, M. Rao.: Using Ranking-CNN for Age Estimation. In: Proceedings of theIEEE Conference on Computer Vision & Pattern Recognition pp. 742–751. (2017).

[5]. P.A. Melange, Dr. G. S. Sable.: Age group estimation & gender recognition using face features. In: International Journal of Engineering & Science, Vol.7, pp-1-7. (2018).

[6]. &rey Rybintsev.: Age estimation from a face image in a selected gender-race group based on ranked local binary patterns. In: Complex Intelligent. System. Vol.3, Issue 2, pp 93–104. (2017)

[7]. C. Dalvi, M. Rathod, S. Patil, S. Gite, K. Kotecha. "A Survey of AI-Based Facial Emotion Recognition: Features ML & DL Techniques, age-wise Dataset & future directions", IEE Access, vol:09, pp: 165838,2021, doi: 10.1109/Access.2021.3131733.

[8]. A. Bansal, R. Agarwal, R.K. Sharma.: SVM based gender classification using iris images. In: Fourth International Conference on Computational Intelligence & Communication Networks pp. 425–429. (CICN) (2012).

[9]. V. Thomas, N. V. Chawla, K. W. Bowyer, & Patrick J.Flynn. : Learning to predict gender from iris images. In: 1st IEEE International Conference on Biometrics: Theory, Applications, & Systems, pp. 1–5. (2007).

[10] M.Fairhurst, M. Erbile, M. DaCosta-Abreu.: Exploring Gender Prediction from Iris Bio-metrics. In: International Conference of the Biometrics Special Interest Group (BIOSIG). (2015).

[11]. S. Lagree, K. W. Bowyer.: Predicting ethnicity & gender from iris texture. In: IEEE International Conference on Technologies for Homel& Security (HST), (2011).

[12]. J. E. Tapia, C. A. Perez, K. W. Bowyer.: Gender Classification from Iris Images using Fusion of Uniform Local Binary Patterns. In: Lecture Notes in Computer Science, pp. 751- 763 (2015).

[13]. M. Christeena, V. KMS, K. Shanmugan.: Gender classification from the iris code used for recognition. In: International Journal of MC Square Scientific Research Vol.9, No.1, pp. 218-229. (2017).

[14]. D. Bobeldyk, A. Ross.: Iris or periocular? Exploring sex prediction from near infrared ocular images, In: Lectures Notes in Informatics (LNI), (2016).

[15]. M. Singh, S. Nagpal.: Gender & Ethnicity Classification of Iris Images using Deep Class-Encoder. In: IEEE

[16]. H. Zhu, Y. Zhang, G. Li, J. Zhang, H. Shan, Ordinal Distribution Regression for Gait-based Age Estimation (2019). arXiv:1905.11005

[17]. A. Sakata, N. Takemura, Y. Yagi, Gait-based age estimation using multi-stage convolutional neural network. IPSJ Trans. Comput. Vis. Appl. 11(1), 4 (2019)

[18]. M. Berksan, Gender recognition & age estimation based on human gait (Master's thesis, Ba¸skent Üniversitesi Fen Bilimleri Enstitüsü) (2019)

[19]. A. Dzedzickis, A. Kaklauskas, & V. Bucinskas, ''Human emotion recognition: Review of sensors & methods,'' Sensors, vol. 20, no. 3, p. 592, Jan. 2020, doi: 10.3390/S20030592.

[20]. J. A. R. Eliot & A. Hirumi, ‘‘Emotion theory in education research practice: An interdisciplinary critical literature review,’’ Educ. Technol. Res. Develop., vol. 67, no. 5, pp. 1065–1084, Feb. 2019, doi: 10.1007/ S11423-018-09642-3.

[21]. M. Spezialetti, G. Placidi, & S. Rossi, ‘‘Emotion recognition for human robot interaction: Recent advances & future perspectives,’’ Frontiers Robot. AI, vol. 7, p. 145, Dec. 2020, doi: 10.3389/FROBT.2020.532279.

[22]. S. Ramis, J. M. Buades, & F. J. Perales, ‘‘Using a social robot to evaluate facial expressions in the wild,’’ Sensors, vol. 20, no. 23, pp. 1–24, 2020, doi: 10.3390/s20236716.

[23]. Y. K. Bhatti, A. Jamil, N. Nida, M. H. Yousaf, S. Viriri, & S. A. Velastin, ‘‘Facial expression recognition of instructor using deep features & extreme learning machine,’’ Comput. Intell. Neurosci., vol. 2021, pp. 1– 17, Apr. 2021, doi: 10.1155/2021/5570870.

[24]. V.Carletti, A.Greco, G.Percannells, M. Vento. “Age from Faces in the Deep Learning Revolution”, IEEE Translations on pattern Analysis & Machine Intelligence-2019

[25]. E. Di Nardo, V. Santopietro, & A. Petrosino, ‘‘Emotion recognition at the edge with AI specific low power architectures,’’ Microprocessors Microsyst., vol. 85, Sep. 2021, Art. no. 104299, doi: 10.1016/J.MICPRO.2021.104299.

[26]. V. Franzoni, G. Biondi, D. Perri, & O. Gervasi, ‘‘Enhancing mouthbased emotion recognition using transfer learning,’’ Sensors, vol. 20, no. 18, pp. 1–15, 2020, doi: 10.3390/s20185222.

[27]. M. S&ler, A. Howard, M. Zhu, A. Zhmoginov, & L.-C. Chen, ‘‘MobileNetV2: Inverted residuals & linear bottlenecks,’’ Jan. 2018, arXiv:1801.04381. Accessed: Aug. 29, 2021.

[28]. B. Li & D. Lima, ‘‘Facial expression recognition via ResNet-50,’’ Int. J. Cognit. Comput. Eng., vol. 2, pp. 57–64, Jun. 2021, doi: 10.1016/J.IJCCE.2021.02.002.

[29]. M. Al-Shabi, W. P. Cheah, & T. Connie, ‘‘Facial expression recognition using a hybrid CNN–SIFT aggregator,’’ in Proc. Int. Workshop MultiDisciplinary Trends Artif. Intell., in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence & Lecture Notes in Bioinformatics, vol. 10607, Aug. 2016, pp. 139–149, doi: 10.1007/978-3-319-69456-6_12.

[30]. A. Khan, A. Sohail, U. Zahoora, & A. S. Qureshi, ‘‘A survey of the recent architectures of deep convolutional neural networks,’’ Artif. Intell. Rev., vol. 53, no. 8, pp. 5455–5516, Apr. 2020, doi: 10.1007/ S10462-020-09825-6.

[31]. N. Chauhan, "Predict Gender & age using Convolutional Neural Network & openCV", Medium, 2020. [Online]. Available: https://towardsdatascience.com/predict-age-&-gender-using convolutional-neural-network-&-opencv-fd90390e3ce6. [Accessed: 05- Jun- 2020].

[32]. Liao, Haibin, et al. "Age estimation of face images based on CNN & divide-&-rule strategy." Mathematical Problems in Engineering, 2018.

[33] R. Yamashita, M. Nishio, R. K. G. Do, & K. Togashi, ―Convolutional neural networks: an overview & application in radiology, Insights into Imaging, vol. 9, no. 4. Springer Verlag, pp. 611–629, Aug. 01, 2018, doi: 10.1007/s13244-018-0639-9.

[34] T.UI Islam, L.K.Awasthi, V. Garg, “ Gender & Age Estimation from gait: A Review”, IEEE International conference on Analysis of Image , Social Network & Texts-2021, pp-6-15

[35] J. Wang, E. Sung, & W. Yau, ‘‘Active learning for solving the incomplete data problem in facial age classification by the furthest nearest-neighbor criterion,’’ IEEE Trans. Image Process., vol. 20, no. 7, pp. 2049–2062, Jul. 2011.

[36] C. Shang & H. Ai, ‘‘Cluster convolutional neural networks for facial age estimation,’’ in Proc. IEEE Int. Conf. Image Process. (ICIP), Sep. 2017, pp. 1817–1821.

[37] P. Rodríguez, G. Cucurull, J. M. Gonfaus, F. X. Roca, & J. González, ‘‘Gender & age recognition in the wild with deep attention,’’ Pattern Recognit., vol. 72, pp. 563–571, Dec. 2017.

[38] E. Eidinger, R. Enbar, & T. Hassner, ‘‘Gender & age estimation of unfiltered faces,’’ IEEE Trans. Inf. Forensics Security, vol. 9, no. 12, pp. 2170–2179, Dec. 2014.

[39] Z. Hu, Y. Wen, J. Wang, & M. Wang, ‘‘Facial age estimation with age difference,’’ IEEE Trans. Image Process., vol. 26, no. 7, pp. 3087–3097, Jul. 2016.

[40] Karen Simonyan, &rew Zisserman(10 April,2015) “Very Deep Convolution Networks ForLarge ScaleImageRecognition”,,Published as a conference ICLR arXiv:1409.1556 [cs.CV].

[41] Eidinger, R. Enbar, & T. Hassner (Dec 2014) “Gender & age estimation of unfiltered faces”IEEE Transactions on Information Forensics & Security,9(12):21702179,.

[42] Fu,G.Guo, & T.S.Huang(Nov 2010)”Age synthesis & estimation via faces:A Survey”, IEEE Transactions on Pattern Analysis & Machine Intelligence,32(11):19551976.

[43] Zakariya Q., Arafat A., M., B. D. Barkana.: Deep Convolutional Neural Network for Age Estimation based on VGG-Face Model. In: CoRR (2017).

[44] Tapia J., Aravena C.: Gender Classification from NIR Iris Images Using Deep Learning. In: Bhanu B., Kumar A. (eds) Deep Learning for Biometrics. Advances in Computer Vision & Pattern Recognition. Springer, Cham. (2017).

[45] O. Agbo-Ajala & S. Viriri, "Face-Based Gender & age Classification Using Deep Learning Model", Image & Video Technology, pp. 125-137, 2020.

[46] A.M. AbuNoda, E. Alajrami, A. A. AI saqqal, S.S. Abu Naser. “Gender & age Prediction & Validation Through Single user Image Using CNN”. IEEE, Vol-4; Issue 8 Aug-2020, Page 21-24

[47] A.M. AbuNoda, E. Alajrami, A. A. AI saqqal, S.S. Abu Naser. “Gender & age Prediction & Validation Through Single user Image Using CNN”. IEEE, Vol-4; Issue 8 Aug-2020, Page 21-24

[48] B. Martinez, M. F. Valstar, B. Jiang, & M. Pantic, ‘‘Automatic analysis of facial actions: A survey,’’ IEEE Trans. Affect. Comput., vol. 10, no. 3, pp. 325–347, Jul. 2019, doi: 10.1109/TAFFC.2017.2731763.

[49]. R.G. Guimaraes, R.L. Rosa, D.D. Gaetana, D.Z. Rodriguez (Senior Member, IEEE), G.Bressan. “Age Group Classification in Social Network using Deep Learning”. IEEE Access, DOI: 10.1109/Access.2021.2706674,2021

[50]. A.S.AL-Shannaq, L.A. Elrefaei(Senior Member,IEEE), “Comprehensive Analysis of the Literature for Age Estimation From Facial Image”. IEEE Access, DOI: 10.1109/Access.2019.2927825, Vol: 7.2019

[51]. M.Grimmer, R. Ramach&ra (Senior Member, IEEE), C. Busch(Senior Member,IEEE), “ Deep Face Age Progression: A Survey”, IEEE Access, DOI: 10.1109/Access.2021.3085835, Vol: 9,2021

[52]. E.Eidinger, R. Enbar, T.Hassner. “Gender & age Estimation of Unfiltered Faces”. IEEE Transaction on Information Forensics & Security, Vol: 9,2020

[53]. R.R. Atallah, A. Kamsin, M.A. Ismail, S. Ali Abdelraman, S. Zerdoumi. “Face Recognition & age Estimation Implications of changes in facial Features: A Critical Review Study”. IEEE Access, DOI:10.1109/Access 2018.2836924. Vol: 6, 2018

[54]. S.Kumar, S.Singh, J.Kumar. “A Study on Face Recognition Techniques with Gender & age Classification”, IEEE conference on Computer vision & Image Underst&ing, DOI: 10.1109/Access 2017.8229960, Vol:6, pp: 4-8

[55]. S.T. Rahman, A. Arefen, S.S.Mridea, A.L.Khan, S.Subrina, “ Human Gender & age Estimation using Facial Image Processing”, IEEE Access, Region 10 Symposium (TENSYMP), DOI: 10.1109/Access 2020.1102986, Vol: 6, pp: 6-28, 2020

[56]. A.A.Vogan, F. Alnojiar, M. Gochoo, S.A. Khalid. “Robots, AI & Cognitive Training in an Era of mass Age- Related Cognitive Decline: A Systematic Review”, IEEE Access, DOI: 10.1109/Access 2020.2966819, Vol: 8,2020, pp:18284-18304

[57]. A.Khalil, S. G. Ahmed, A.M. Khattak(Member,IEEE), N.AL-Girim(Senior Member, IEEE), "Investigating bias in facial Analysis Systems: A Systematic Review", IEEE Access, DOI: 10.1109/Access 2020.3006051, Vol: 8,2020. PP: 130751-130761

[58]. A. Dantcheva, F. Bremond, "Gender Estimation Based on Smile-Dynamics", IEEE Conference on ComputerVision & Pattern Recognition, Vol:4, pp: 146-158, 2018

[59]. Ahonen, T, Matas, J, Pietikainen, M & Zhao, G 2012 , „Rotation-invariant image & video description with local binary pattern features", IEEE Trans. Image Process., vol. 21, no. 4, pp. 1465-1477.

[60]. Ballihi, L, Ben Amar, B, Daoudi, M, Srivastara, A & Aboutajdine, D 2012, „Boosting 3-D geometric features for efficient face recognition & gender classification", IEEE Trans. on Information Forensics & Security, vol. 7, no. 6, pp. 1766-1779.

[61]. Caifeng Shan 2012, „Learning local binary patterns for gender classification on real world face images", Pattern Recognition Letters, Elsevier, vol. 33, no. 4, pp. 431-437.

[62]. Duan-Yu Chen & Kuan-Yi Lin 2010, „Robust gender recognition for uncontrolled environment of real-life images", IEEE Trans. on Consumer Electronics, vol. 56, no. 3, pp. 1586-1592.

[63]. Fang, Y & Wang, Z 2008, „Improving LBP features for gender classification", Int. Conference on Wavelet Analysis & Pattern Recognition (ICWAPR), vol. 1, pp. 373-377.

[64]. Graf, AB & Wichmann, FA 2002, „Gender classification of human faces", International Workshop on Biologically Motivated Computer Vision, Springer, LNCS 2525, pp. 491-500.

[65]. Iga, R, Izumi, K, Hayashi, H, Fukano, G & Ohtani, T 2003, „A gender & age estimation system from face images", SICE Annual Conference in Fukui, Japan, vol. 1, pp. 756-761.

[66]. Irene Kotsia & Ioannis Pitas 2007, „Facial expression recognition in image sequences using geometric deformation features & support vector machines", IEEE Transactions on Image Processing, vol. 16, no. 1, pp. 172-187

[67]. Ker J, Wang, LP, Rao, J & Lim, T 2017, „Deep learning applications in medical image analysis", IEEE Access, vol. 6, pp. 9375-9389.

[68]. Levi, G & Hassner, T 2015, „Gender & age classification using convolutional neural networks", IEEE Conference on Computer Vision & Pattern Recognition Workshops (CVPRW), pp. 34-42.

[69]. Lian, H & Lu, B 2007, „Multi-view gender classification using multi1resolution local binary patterns & support vector machines", International Journal of Neural Systems, vol. 17, no. 6, pp. 479-487.

[70]. Makinen, E & Raisamo, R 2008, „Evaluation of gender classification methods with automatically detected & aligned faces", IEEE Trans. Pattern Analysis & Machine Intelligence, vol. 30, no. 3, pp. 541-547.

[71]. Singh, V, Shokeen, V & Singh, MB 2013, „Comparison of feature extraction algorithms for gender classification from face images", International Journal of Engineering Research & Technology, vol. 2, no. 5, pp. 1313-1318.

[72]. Wang, C, Huang, D, Wang, Y & Zhang, G 2012, „Facial image-based gender classification using local circular patterns", Int. Conference on Pattern Recognition (ICPR), pp. 2432-2435

[73]. Ziyi Xu, Li Lu & Pengfei Shi 2008, „A hybrid approach to gender classification from face images", in Proc. of International Conference on Pattern Recognition, pp. 1-4.

[74]. Azarmehr, R, Laganiere, R, Lee, WS, Xu C & Laroche, D 2015, 'Real1time embedded gender & age classification in unconstrained video', In Proceedings of the IEEE Conference on Computer Vision & Pattern Recognition Workshops, pp. 57-65.

[75]. Baluja, S & Rowley, HA 2007, 'Boosting sex identification performance', International Journal of Computer Vision, vol. 71, no. 1, pp. 111-119.

[76]. Borgi Mohamed Anouar, Maher El'Arbi, Demetrio Labate & Chokri Ben Amar 2014, ‘Face, gender & race classification using multi 1 regularized features learning’, In IEEE International Conference on Image Processing (ICIP), pp. 5277-5281.

[77]. Chen, C, Dantcheva, A & Ross, A 2013, ‘Automatic Facial Makeup Detection with Application in Face Recognition’, In 2013 international conference on biometrics (ICB), IEEE, pp. 1-8.

[78]. Chen, C, Dantcheva, A, Swearingen, T & Ross, A 2017, ‘Spoofing Faces Using Makeup: An Investigative Study’, IEEE International Conference on Identity, Security & Behavior Analysis, ISBA, pp. 1-8.

[79]. Choi, SE, Lee, YJ, Lee, SJ, Park, KR & Kim, J 2011, ‘Age estimation using a hierarchical classifier based on global & local facial features’, Pattern Recogn., vol. 44, no. 6, pp. 1262-1281.

[80]. Dong, Y, Lang, C & Feng, S 2019, ‘General Structured Sparse Learning for Human Facial Age Estimation’, Multimedia Systems, vol. 25, no. 1, pp. 49-57.

[81]. Eidinger, E, Enbar, R & Hassner, T 2014, ‘Gender & age estimation of unfiltered faces’, Transactions on Information Forensics & Security, IEEE, pp. 2170-2179.

[82]. Han, H, Otto, C & Jain, AK 2013, ‘Age estimation from face images: human vs. machine performance. In: International Conference on Biometrics (ICB), pp. 1-8.

[83]. Han, H & Jain, AK 2014, ‘Age, gender & race estimation from uncon- strained face images’, MSU Technical Report, MSU-CSE-14-5, pp. 1-9.

[84]. Fu, Y, Xu, Y & Huang, TS 2007, ‘Estimating human age by manifold analysis of face pictures & regression on aging features’, In IEEE International Conference on Multimedia & Expo, pp. 1383-1386.

[85]. Geng, X, Zhou, ZH & Smith-Miles, K 2007, ‘Automatic age estimation based on facial aging patterns’, IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 29, no. 12. pp. 2234-2240.

[86]. Gupta, S 2015, Gender Detection using Machine Learning Techniques & Delaunay Triangulation’, International Journal of Computer Applications, vol. 124, no. 6.

[87]. Erbilek, M, Fairhurst, M & Da Costa-Abreu, M 2014, ‘Improved age prediction from biometric data using multimodal configurations’, In: 2014 International Conference of the Biometrics Special Interest Group (BIOSIG) pp. 1-7.

[88]. Khan Muhammad Usman, Hafiz Adnan Habib & Nasir Saleem 2012, ‘A Hybrid Approach for Gender Classification of Web Images’, International Journal of Computer Applications, vol. 54, no. 7, pp. 11-16.

[89]. Kim, HC, Kim, D, Ghahramani, Z & Bang, SY 2006, ‘Appearance1based gender classification with Gaussian processes’, Pattern Recognition Letters, vol. 27, no. 6, pp. 618-626.

[90]. Khan Sajid et al. 2015, ‘Optimized Features Selection using Hybrid PSO-GA for Multi-View Gender Classification’, International Arab Journal of Information Technology (IAJIT), vol. 12.2, pp. 183-189.

[91]. Liu Hong, Yuan Gao & Can Wang 2014, ‘Gender identification in unconstrained scenarios using self-similarity of gradients features’, In 2014 IEEE International Conference on Image Processing (ICIP), pp. 5911-5915.

[92]. Mousavi, SMH & Lyashenko, V 2019, ‘Age Estimation in Make-up (Cosmetics) Using Color & Depth Images’, 3rd International Conference on Soft Computing.

[93]. Lian Hui-Cheng & Bao-Liang Lu 2006, ‘Multi-view gender classification using local binary patterns & support vector machines’, In International Symposium on Neural Networks, Springer, Berlin, Heidelberg, pp. 202-209.

[94]. Nazir Muhammad & Anwar M Mirza 2012, ‘Multi-view Gender Classification using hybrid Transformed’, International Journal of Multimedia & Ubiquitous Engineering, vol. 7.2, pp. 661-669.

[95]. Li Zhen, Yun Fu & Thomas S Huang 2010, ‘A robust framework for multiview age estimation’, In 2010

IEEE Computer Society Conference on Computer Vision & Pattern Recognition-Workshops, pp. 9-16.

[96]. Khan Sajid Ali, Muhammad Nazir & Naveed Riaz 2013, 'Gender classification using multi-level wavelets on real world face images', Acta Polytechnica Hungarica, vol. 10.4, pp. 193-208.

[97]. Ojansivu, V & Heikkil, J 2008, 'Blur insensitive texture classification using local phase quantization', In Elmoataz A, Lezoray O, Nouboud F, Mammass D. (eds), Image & Signal Processing, LNCS 5099, Springer, pp. 236-243.

[98]. Prince, SJ & Aghajanian, J 2009, 'Gender classification in uncontrolled settings using additive logistic models', In 2009 16th IEEE International Conference on Image Processing (ICIP), pp. 2557-2560.

[99]. Ren Haoyu & Ze-Nian Li 2014, 'Gender recognition using complexity aware local features', In: 22nd International Conference on Pattern Recognition, pp. 2389-2394.