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Use of learning methods for gender and age classification based on front shot face images

Hussein Razak Hayawi*, Alyaa Al-Barrak

Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq

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Abstract

Facial system estimation is a mature and in-depth research technique in age and gender. Estimation accuracy is an important indicator for evaluating algorithms. By using deep learning-based learning (DL) and machine learning, this work provides a robust approach to estimating the type and age of different external environment changes based on two different algorithms, comparing the results, and analyzing the performance of the two algorithms. The algorithm was evaluated using a data set that is considered the basis in this area of the face estimation system, namely (IMDB-WIKI) an image. The basis of the work depends on the external appearance and the front section. The results obtained: DL(Effacint-B3) AGE Accuracy=0.99 Gender Accuracy=0.97 ML(SVM) AGE Accuracy=0.87 Gender Accuracy=0.97.

Keywords: Face System, Estimation, Age, Gender, Deep Learning, Efficient-B3, IMDB-WIKI
2020 MSC: 68T07, 68U10

1 Introduction

Over the years, face analysis tasks have been a popular study area. Age and gender recognition are two activities that convey some essential but crucial information about a face [2]. Such data can be helpful in various applications, including autonomous surveillance [13]. Biometrics analyzes a person's physical or behavioural traits to verify their identity. It offers advantages over passwords and cards, which aren't transferable, unique to each user, and cannot be lost or stolen [15]. User acceptance, security, cost, and implementation time affect biometric solutions. Face recognition is one of the most exciting tasks in pattern recognition because the human face is a rich source of information [5]. Gender and age are facial features that can be very useful for many applications, such as profiling customers interested in a product or for target advertising. Age and gender categorization are decades-old topics before method details. Face system is computer technology for recognizing and identifying the age and gender of human faces in digital images. It is utilized for numerous purposes [21]. Become a very active and significant area of research in image processing. Most existing face detection algorithms concentrate on identifying frontal human faces, and face recognition is a well-studied topic in computer vision. And Numerous application situations indicate that face recognition in real-world applications remains a challenging task [14]. This paper introduces the age and gender estimation system, its obstacles, the problems the research seeks to solve.

*Corresponding author
Email addresses: husseinyas25@gmail.com (Hussein Razak Hayawi), alyaa.al-barrak@sc.uobaghdad.edu.iq (Alyaa Al-Barrak)

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2 Challenge of Face System

There are many challenges that researchers have faced on the subject of face systems and can be classified in the following point [7]:

- Pose variations.
- Structured elements/occlusions (presence/absence).
- Facial expression changes.
- Ageing of the face.
- Varying illumination conditions.
- Modality and image resolution.

These critical factors can be summarized as the head motions, such as egocentric rotation angles or camera point of view changes, resulting in significant changes in facial look (and) form and intra-subject face differences. The intra-subject variability in facial pictures may be caused by a lack of anatomical traits or occlusions such as beards, moustache caps, or sunglasses [20].

Changes in facial expressions caused by changing emotional states may result in even more variation in facial expressions. Another reason for changes in the human face's appearance could be age. In contrast, significant changes in light can have a detrimental effect on the performance of systems. Face identification and recognition become more complex when the background or foreground illumination weakens. Finally, the clarity and resolution of the face image and the setup and mode of the digital hardware used to record the face are other often utilized performance parameters [8].

3 Soft Biometrics

Images and videos are used for extraction and applications. Soft biometric qualities are physical and behavioural characteristics that are not unique to a given subject but are valuable for identifying, verifying, and describing human beings. Examples include gender, height, and weight [3]. And Soft biometrics is gaining traction as a viable alternative to traditional biometrics for various reasons, including its non-intrusive authenticating nature. For unrestricted situations, standalone soft biometrics experimental systems have been built [9]. And may be traced back to the 18th century, when the Bertillon technique was utilized for criminal identification based on the physical description of the culprit. Anthropometric measurements refer to the features used to quantify the physical description, which include head length, head breadth, middle finger length, left foot length, and cubit length. Body and facial geometry were used to classify these characteristics [19].

The base example of soft biometrics is age and gender, where Gender information is a beneficial indication that expert and intelligent systems in the healthcare, bright spaces and biometric-based access control domains can use. To deliver an enhanced user experience, the operations of intelligent technologies in a bright space can be tailored based on gender information [12]. Similarly, a biometric system can improve performance by using gender as a soft biometric feature. Gender classification is a binary classification problem in which the input character is classified into Two Categories [18]:

- Male
- Female.

Depending on the input features used in the classifier, the gender recognition systems can be classified into appearance and non-appearance-based techniques [10].

And age is. The face characteristic point can be specified as the standard reference point on an individual's face used by scientists to recognize an individual's climate. Morphology alone is considered a format study. Variations in the face texture are specified as the face variations associated with muscle and skin flexibility [6]. Thus, studying the skull and face shapes is defined as craniofacial morphology. The ageing operation affects individuals' appearance and structure in various ways. The occurred changes are associated with facing texture and craniofacial morphology. Specific craniofacial morphology features are seen in individuals of a specific age and change over the operation of ageing. The changes in the texture of the skin typically happen during puberty.

4 Related Work

Many publications in the field of human gender and age classification estimation have been published in recent years, and this thesis highlights a few of them:

- [11]: CNN proposed a facial-image-based age and gender predictor. CNN, regression/classification, and AlexNet, VGG, ResNet, WideResNet were studied. and the WideResNet offers the best age and gender prediction performance, with age predicted by regression and gender by categorization. DMTL improves CNN's accuracy and computation speed and may be evaluated using the IMDB-WIKI dataset.
- [4]: They proposed a system with two CNN (VGG16 type) models and a prediction layer change for edge computing devices. Both networks classify facial gender and age. First (VGG16/10) interprets gender and age as interconnected elements; final neurons retain both simultaneously. In the second prediction layer (VGG16/8+1), one neuron predicts gender and eight predicts age. Such networks were created to provide information on the gender and age of a subject spotted in an image without needing two separate systems. The technique was evaluated using IMDB-WIKI data.
- [17]: Proposed method leverages the IMDB-WIKI dataset image to predict gender and age. Freeze all trained ImageNet layers. The models are trained in four stages with predefined learning rates, and the layers' blocks are unlocked in order. Apply a multi-output neural network to predict age and gender, with the final loss function based on age and gender losses.
- [1]: Biometric facial traits are used to age and gender-specifically identify users. Local Binary Pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM) image features were used to identify facial images based on age and gender. These extracted features are categorized using CNN, RCNN, and Fast RCNN utilizing IMDB wikicrop facial dataset.
- [16]: They Proposed a system that uses CNN to produce a gender prediction and age estimation system for a face image or real-time video. Three CNN network models with varied architecture (number of filters and convolution layers) were built and verified on the IMDB and WIKI datasets.

5 Suggested Method

The proposed system is based on the facial image of a human being needed by the system to estimate age and recognition gender based on using IMDB- WIKI dataset and work on ML and DL gather and compare the result between them and the import stage in the prosed system in the fairest stage (Image preprocessing). Figure 1 shows the structure of the proposed system.

The suggested system's input data is an image of the available data set. The facing system consists of one model with the following steps: image quantization, preprocessing, and the last stage classification using the Efficient -B3 Model and SVM algorithm.

5.1 The dataset in the Proposed System

IMDB-WIKI Dataset is a large dataset of face images with gender and age labels for training, and the total number of images is 62,328 from Wikipedia. In a proposed system using these datasets because of Deep learning, the more it is categorized into a large group, the better results. A correct system because its foundation is depth, so the proposed system uses nearly 209,990 images of the face. Tables 1 and 2 show the proposed system's number.

Table 1: Dataset number before trimming.

IMDB-WIKI	
Image number	62328
Size of Dataset	7GB
Age Range Either	0-100 OR 1-101
Gender	0= Female / 1= Male

Image Dataset Description of Ages and Genders After trimming the data set from the useless images, will review what the data set contains from age groups and genders in terms of men and women according to the following schemes Figure 2.

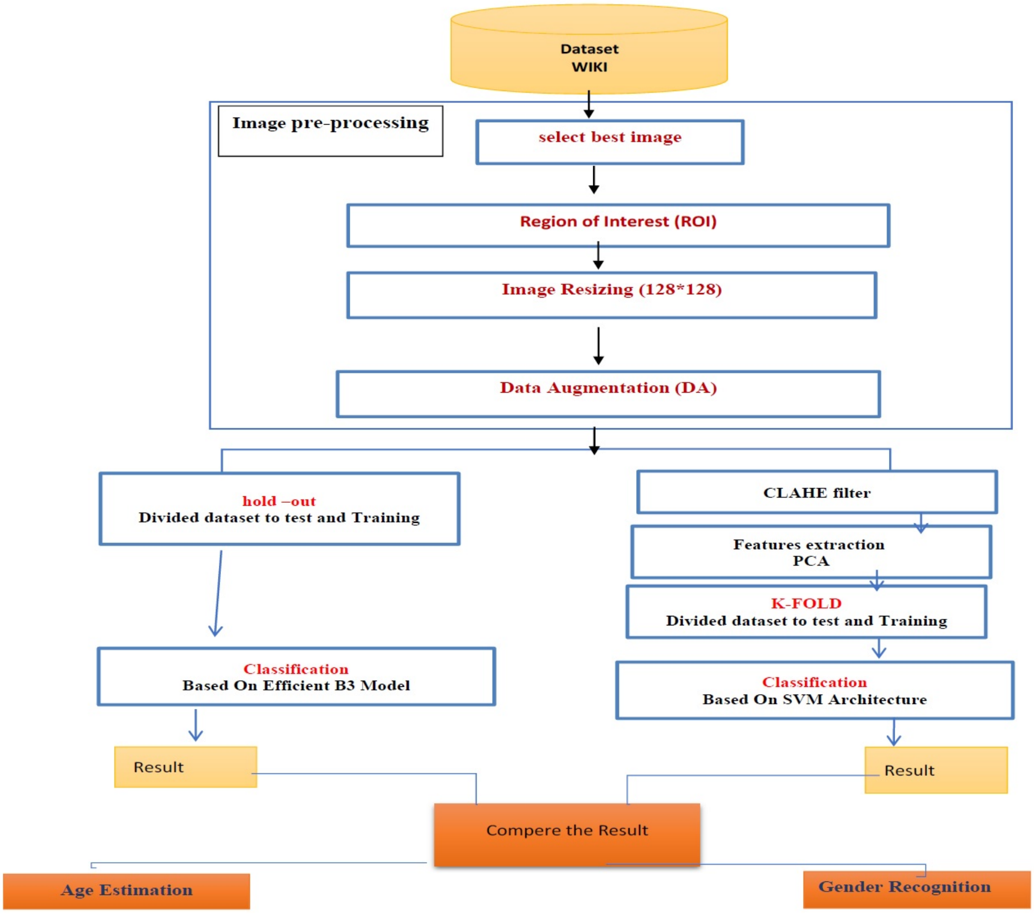

Figure 1: Proposed System Block Diagram.

Table 2: Dataset number after trimming and using the proposed system.

Dataset name	The total number after selecting the image	Train	Test
WIKI	22138	80% 17710 (20 valdation-80 train) (3542-14168)	20% 4428

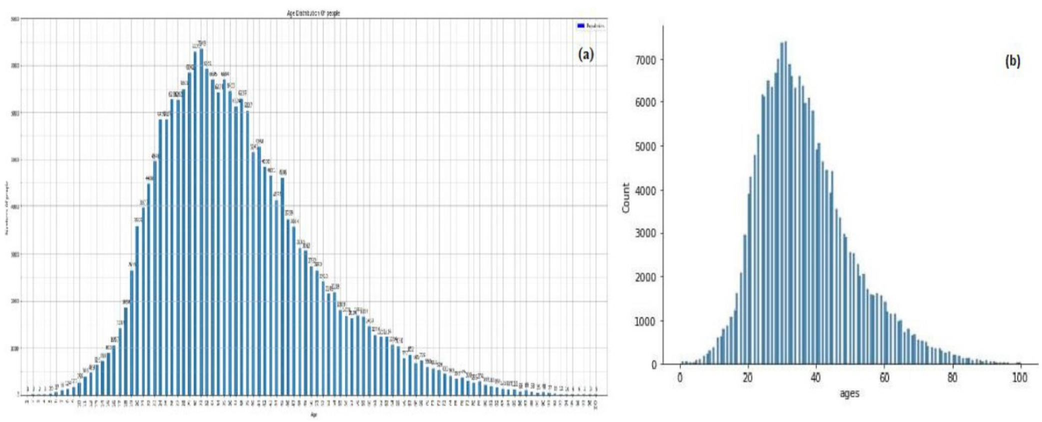

Figure 2: Histogram age description in proposed system dataset.

Note that there are two Figures (a and b)2 that contradict the form, where the first one (a)2 works to describe the ages from one year to 100 years in detail, as each year is described and what is the number of pictures it contains, which is considered an accurate description, but in terms of presentation is weak, so a description was worked out in a second, more straightforward way, which is the second Figure (b)2 describes every twenty years together to review it more beautifully. Figure 3 describes the human race and how many females and males are in two data sets and notices that the total number of females is less than the number of males by 1565 females and 6573 males.

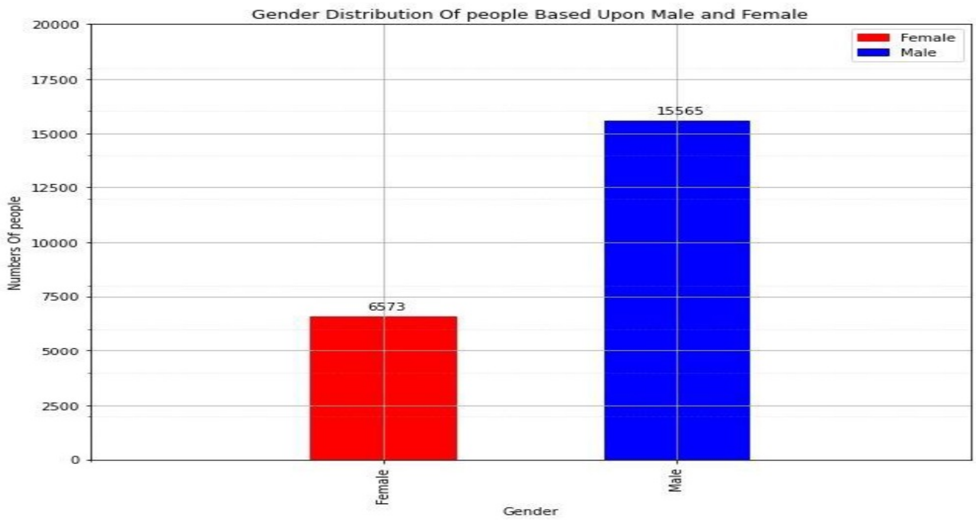

Figure 3: Chart gender description in proposed system dataset.

Table 3: gender description

Male	15565
Female	6573

5.2 Pre-Processing Proposed System

The following section shows the result of the preprocessing steps of the proposed face system. Preprocessing is used for each image to enhance the image and the following points explain how the image is uploaded and what processing of the image:

First: Read the image quantization.

Second: Apply image enhancements.

- Region of interest (ROI).
- Resizing image (128×128).

5.2.1 Region of Interest (ROI)

A region of interest (ROI) is a portion of an image you want to filter or perform another operation on. You define an ROI by creating a binary mask, a binary image the same size as the image you want to process with pixels that define the ROI set to 1 and all other pixels set to 0. ROI is sampled within a data set identified for a particular purpose. In the 2D dataset, the boundaries of an object on an image and description are described in detail in chapter three. In the proposed system, the role of the ROI was to determine the face area based on the Landmark mechanism that identifies 68 points in the face and on which the remaining processors are deducted. Figure 4 shows how it works and the ROI results in the face image.

Note that the original image (a)4 that was recalled from the data set is of a size of 500×500 with its dimensions in the image (b)4 68 points were identified, and it depends on the dimensions of the face, and it is essential in the subject of face recognition and is called a Lendmark based on which cropping and determination of ROI are done in an image and (C)4 the result is an image of the face only (d)4 that sized is 262×260 that contains inside it the essential features that help the system to identify and estimate (that mean ROI size id 262×260).

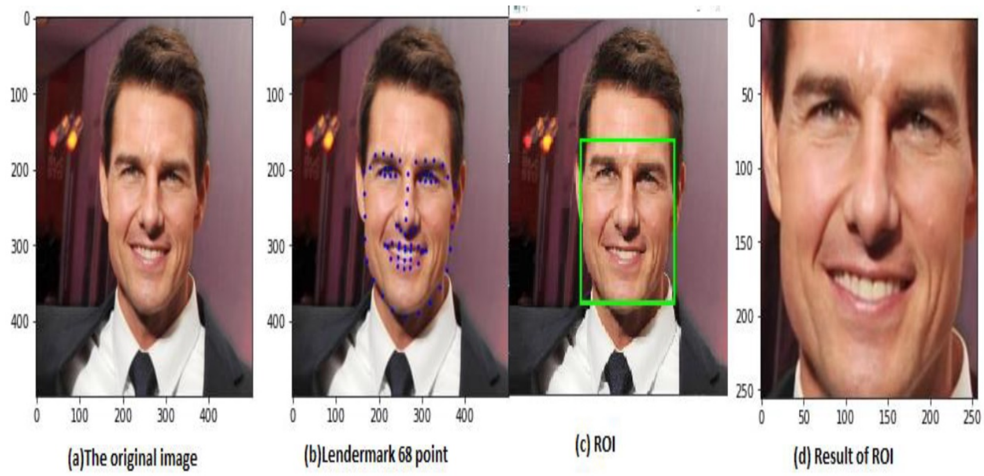

Figure 4: Steps of ROI.

5.2.2 Resizing image (128 × 128)

In this step, the image size is standardized to 128 × 128 due to the considerable variation in image sizes ranging from 70 × 71. The smallest size and the most significant size are 500 × 500. The primary purpose of this step is to standardize the image sizes and reduce the overfitting that occurs due to the contrast of the large data size. The selection of the size 128 × 128 was based on experience and, as explained in detail in the third chapter, Figure 5 shows the difference between the (a)5 original 500 × 500 and the (b)5 Size of the ROI step and (c)5: a result of resizing the image.

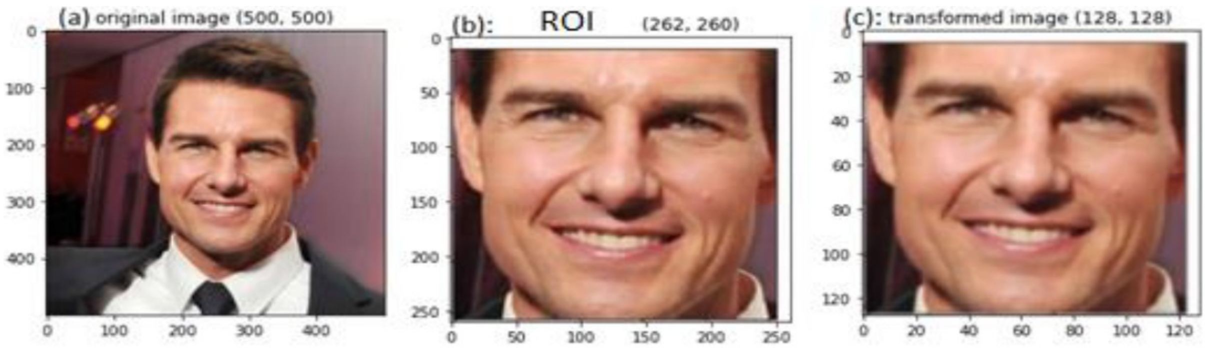

Figure 5: Steps of ROI.

5.2.3 Data Augmentation (DA)

Augmentation is an essential processing process because it trains the model on cases that do not exist in the data set, and thus training on external cases that the system can encounter, as shown in Figure 6, which shows its mechanism of work where (a) is an image from step resizing 128 × 128, (b) is The lighting (brightness) factor and how to change the degree of illumination, (c) Contrast factor and how to notice that the contrast of the image has changed significantly, (d) is a flip of the image horizontally right to left and (e) is transformed (rotate) the image in angle 20. An important note is that the rotation operations are done as shown in Figures 6 and 7.

6 Evaluation The result

For evaluation, use a matrix of confusion. This summarizes the number of the classification model correctly. This base is then evaluated on the experimental data set, and the resulting performance values are compared with previously known classifications. The result of The Train System in Efficient-B3 Model and SVM algorithm is the following section:

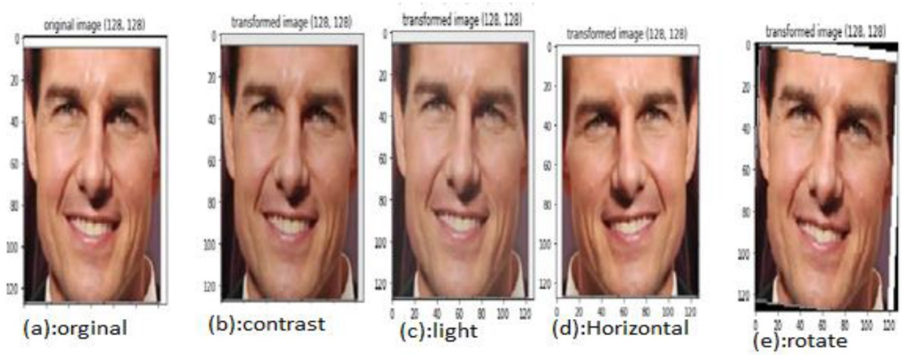

Figure 6: Steps of data augmentation.

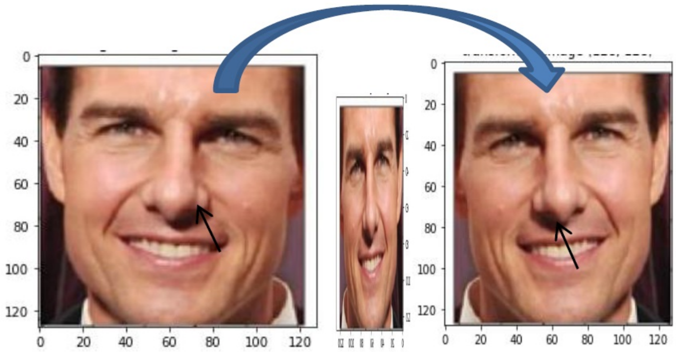

Figure 7: Horizontal step.

6.1 Efficient B3 Model

The first stage will review the training results only, i.e., the results of training the model with an algorithm (Efficient B3) to show the efficiency of the chosen algorithm in terms of training. Figure 8 shows the accuracy of the trained best model.

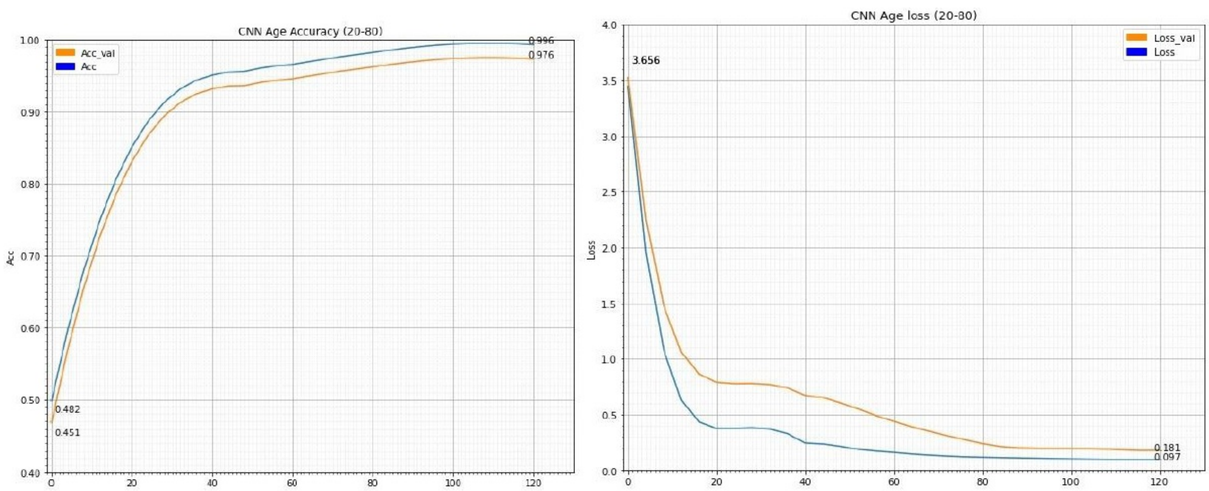

Figure 8: Accuracy and loss of train model in age.

The method used to evaluate the proposed system is the Holdout method is the simplest method to evaluate a classifier. In this method, the data set (a collection of data items or examples) is separated into the Training set and the Test set. A classifier is a performance that assigns data objects in a collection to a target category or class. The best result based on the experiment is a random selection of the data set with varying percentages for training (80%)

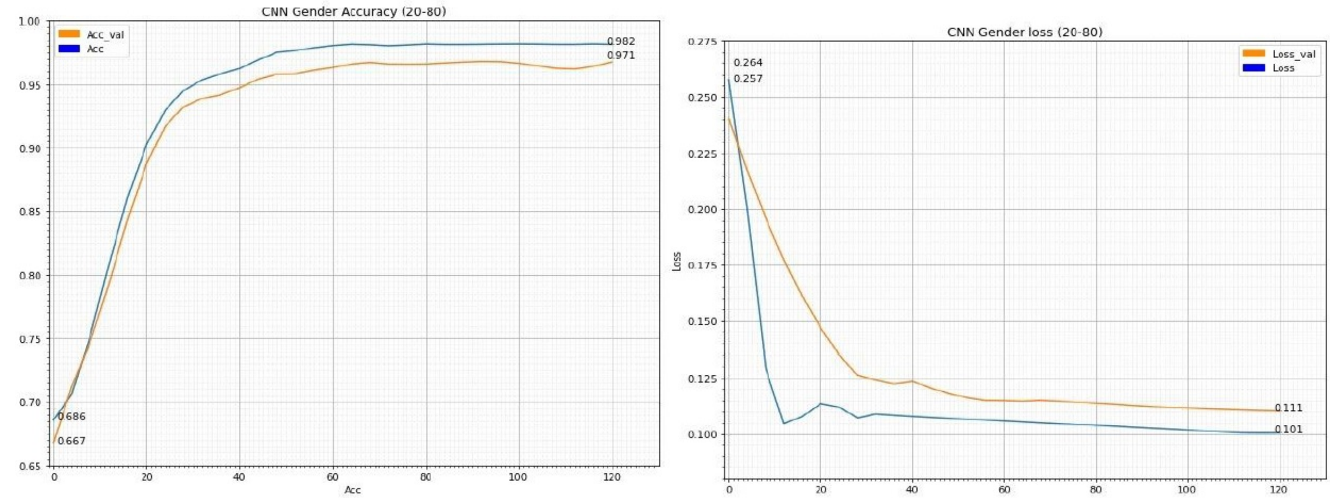

Figure 9: Accuracy and loss of train model in gender.

and testing (20%). Table 4 shows the results of the most important (3 models) of the proposed system to prove that the ratio (80% training –and 20% testing) is the best.

Table 4: Result of the three best models in the proposed system.

NO	Training and testing ratio	Age Accuracy	Gender Accuracy
1	Training (70%) and testing (%30)	0.958%	0.980%
2	Training (80%) and testing (%20)	0.984%	0.982%
3	Training (90%) and testing (%10)	0.978%	0.981%

The following Figures are the two best diagrams of the results obtained from implementing the method Holdout. Based on the above section, note through the implementation that the best results were in the training ratio of 80% and the test 20% through the results obtained for accuracy. The results of the two experiments were presented only because they were the best in terms of experience.

6.2 SVM

The machine learning algorithm used to divide training and testing was K-FOLD, divided into five divisions or trials. Here are the results of the five trials with average results.

Table 5: Result of 5-fold (age) in the proposed system in ML

Fold name	Accuracy
0 Fold	0.9536144578313253
1 Fold	0.943574297188755
2 Fold	0.9635341365461847
3 Fold	0.9236144578313253
4 Fold	0.9536144578313253
Avarge	0.94759036144578312

6.3 Confusion matrix in the proposed system

A confusion matrix is a summary of classification problem prediction outcomes. The number of rights and unsuccessful predictions is total led and broken down by class using count values. The recommended approach for evaluation will be used, which is the key to the confusion matrix. A classification model's correctly or incorrectly predicted number of occurrences is summarized in a confusion matrix.

Table 6: Result of 5-fold (gender) in the proposed system in ML

Fold name	Accuracy
0 Fold	0.893574297188755
1 Fold	0.9036144578313253
2 Fold	0.9036144578313253
3 Fold	0.8835341365461847
4 Fold	0.9036144578313253
Avarge	0.89759036144578312

6.3.1 Confusion Matrix for age and gender in DL

In the proposed system, a confusion matrix was used to evaluate the results, and the following points are the results of estimating age and gender based on the Test part

Gender

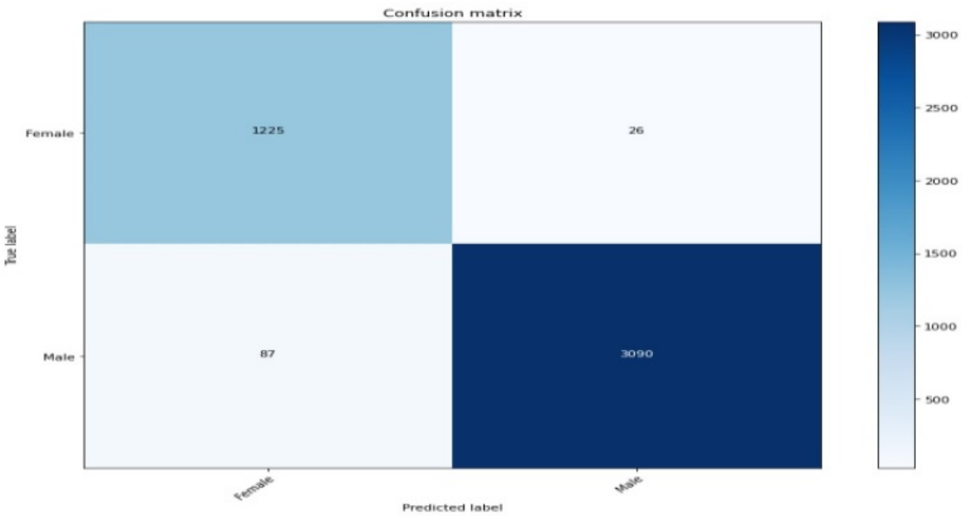

Figure 10: confusion matrixes of gender in DL.

The following Table shows the values of the confusion matrix

Table 7: Value of confusion matrixes in gender.

TP	1225
FP	26
FN	87
TN	3090

The following Table shows the final results of deep learning

Table 8: Final results of deep learning in gender.

Type	Precision	Recall	F1-Score
0=female	0.93	0.98	0.96
1=male	0.99	0.97	0.98
Total accuracy		0.97	

Age

The following Table shows the values of the confusion matrix

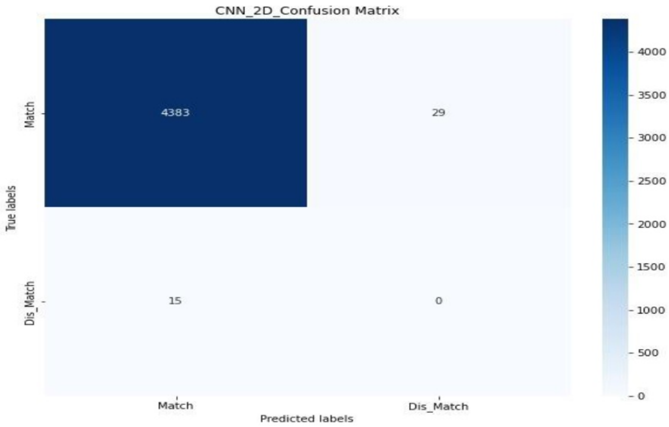

Figure 11: confusion matrices of DL in age.

Table 9: Value of confusion matrices in age.

TP	4383
FP	29
FN	15
TN	0

Table 10: Final results of deep learning in age.

Class name	**Precision**	**Recall**	**F1-Score**
Adult	0.99	0.99	0.99
Child	0.83	1.00	0.91
Senior	0.98	0.97	0.98
Teenage	0.97	0.98	0.97
Young	0.99	0.99	0.99
Total accuracy		0.99	

The following Table shows the final results of deep learning

The following Figure 12 shows the confusion matrixes of age in five classes.

Figure 12: confusion matrixes of age in five classes.

In Figure 12, the reading is done by the intersection of the column with a thousand for class, where the child with the child, the correct capture result is 5. The result of the intersection of a teenage with a teenage is 114, but it has two incorrect intersections. They are in chilled the value of 1 and in young also one, and these intersections are incorrect, and the percentage is negative cases, and in this way, the reading is done.

The following is a Table 11 showing the values of the classes before and after the predicate to know the fundamental values of the classes.

Table 11: values of the classes

Before	
Adult	5
Child	116
Senior	1801
Teenage	2060
Young	454
After	
Adult	5
Child	114
Senior	1790
Teenage	2044
Young	430

6.3.2 Confusion Matrix for age and gender in ML

In the proposed system, a confusion matrix was used to evaluate the results, and the following points are the results of estimating age and gender based on the Test part

Gender

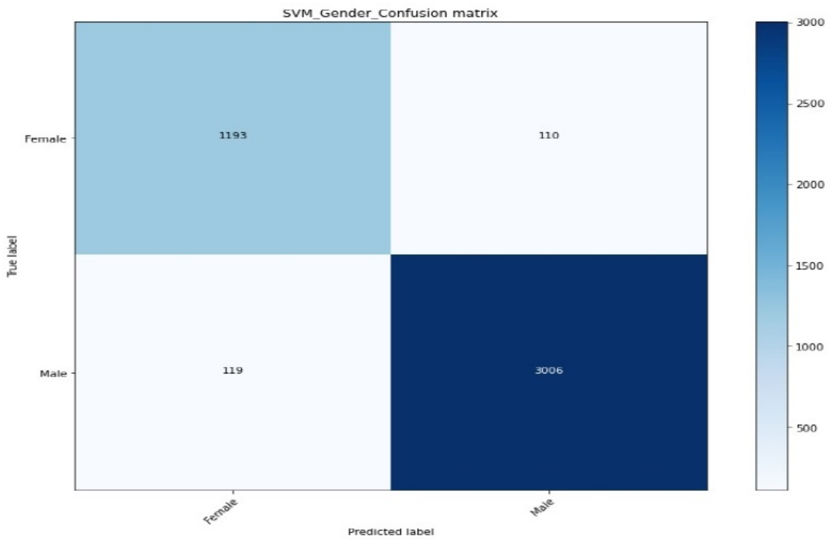

Figure 13: confutation matrices of gender in ML.

The following Table 12 shows the values of the confusion matrix

Table 12: the value of confutation matrices in gender.

TP	1193
FP	110
FN	119
TN	3006

The following Table 13 shows the final results of deep learning

Age

Table 13: Final results of deep learning in gender.

Type	Precision	Recall	F1-Score
0=female	0.91	0.92	0.91
1=male	0.96	0.96	0.96
Total accuracy		0.95	

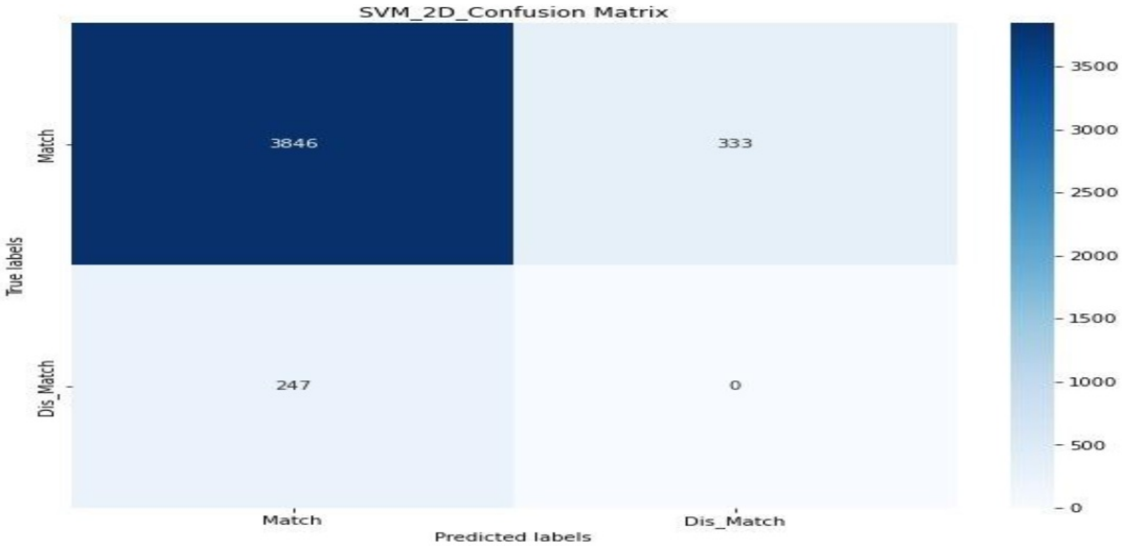

Figure 14: confusion matrixes of ML in age.

The following Table 14 shows the values of the confusion matrix

Table 14: the value of confusion matrixes in age.

TP	3846
FP	333
FN	247
TN	0

The following Table 15 shows the final results of deep learning

Table 15: Final results of deep learning in age.

Class name	Precision	Recall	F1-Score
Adult	0.92	0.87	0.90
Child	0.75	0.75	0.75
Senior	0.88	0.89	0.89
Teenage	0.58	0.44	0.50
Young	0.82	0.90	0.86
Total accuracy		0.87	

The following Figure 15 shows the confusion matrixes of age in five classes.

In Figure 15, the reading is done by the intersection of the column with a thousand for class, where the child with the child, the correct capture result is 3. The total must be four, and the result of the intersection of a teenage with a teenage is 67, but it has two incorrect intersections. They are in chilled the value of 1 and young 83, and these intersections are incorrect, and the percentage is negative cases, and in this way, the reading is done.

The following is a table 16 showing the values of the classes before and after the predicate to know the fundamental values of the classes.

The following Figure 16 is Example of the recognition result

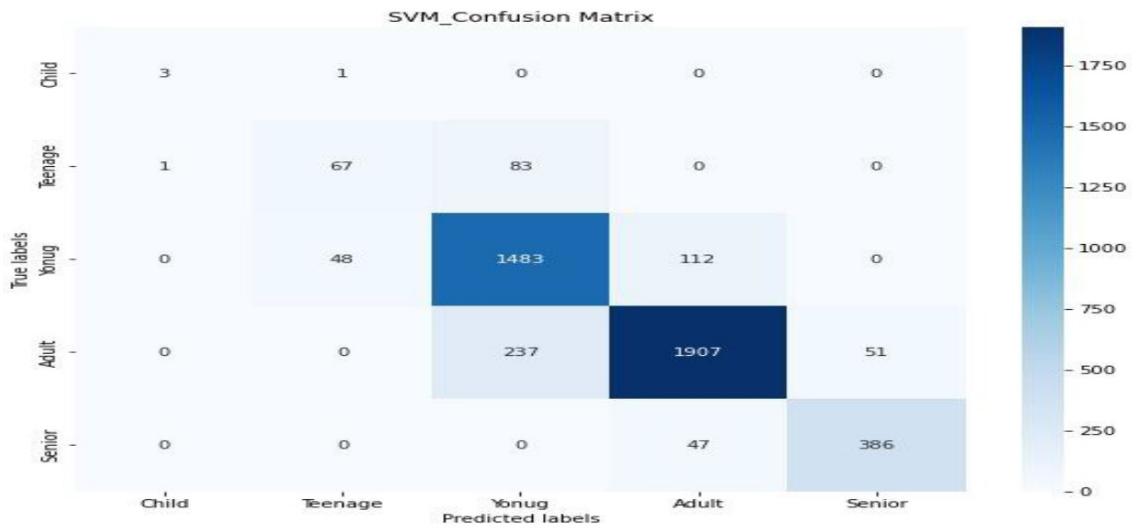

Figure 15: confusion matrixes of age in five classes.

Table 16: values of the classes

Before	
Adult	5
Child	116
Senior	1801
Teenage	2060
Young	454
After	
Adult	4
Child	151
Senior	1643
Teenage	2195
Young	433

Figure 16: Example one of the final results.

7 Previous studies comparing

Numerous types of research on face systems estimation and their conclusions have been published in recent years. The proposed approach's conclusions are compared to those of many other methodologies reported in the literature in this section. The suggested method's detection measurement in the confusion matrix is compared to past research in Table 17. According to the mentioned findings, our recommended technique looks superior to others.

8 Conclusion

With the advancement of information technology, there has been an exponential increase in the number of age and gender estimate systems. This system is regarded as fertile ground for study and development. In the scientific paper,

Table 17: summary of related work

RF.	Dataset	Methods	Result
[11]	IMDB-WIKI	• AlexNet • VGG-16 • ResNet-152 • WideResNet (WRN)16-8	**AlexNet** Gender: Accuracy 91.53% Age: MAE 9.44 - Time 0.038 **VGG-16** Gender: Accuracy 93.36% Age: MAE 8.15 - Time 0.107 **ResNet-152** Gender: Accuracy 92.11% Age: MAE 9.25 - Time 0.527 **WRN** Gender: Accuracy 93.57% Age: MAE 8.59 - Time 0.544
[4]	IMDB-WIKI	VGG16/10 VGG16/8+1	**VGG16/10** Age and Gender Accuracy=39.4% **VGG16/8+1** Age Accuracy =57.0% Gender Accuracy =88.4%
[17]	• IMDB-WIKI • IMDB	• VGG-19 • DenseNet-169	**VGG-19** Gender accuracy 91.09% Age's MAE 15.23 **DenseNet-169** Gender accuracy 70.48% Age's MAE 13.05
[1]	IMDB	CNN RCNN Fast RCNN	**CNN** *(female)* Precision 84.67 - Recall 92.42 - F-measure 88.37 In (18 to 35 age group) *(male)* Precision 97.93 - Recall 94.35 - F-measure 96.10 In (51 to 65+ age group) **RCNN** *(female)* Precision 84.67 - Recall 92.42 - F-measure 88.37 In (the 18 to 35) age group *(male)* Precision 98.95 - Recall 89.35 - F-measure 93.90 In (51 to 65+) age group **Fast RCNN** *(female)* Precision 86.70 - Recall 90.32 - F-measure 88.47 In (51 to 65+) age group *(male)* Precision 98.95 - Recall 91.35 - F-measure 95.00 In (51 to 65+) age group

[16]	• IMDB-WIKI • IMDB	CNN	**IMDB** Accuracy 86.20% **IMDB-WIKI** Accuracy 83.97%
Proposed system	IMDB-WIKI	Efficient-B3 SVM	**DL(Effacint-B3)** AGE Accuracy=0.99 Gender Accuracy=0.97 **ML(SVM)** AGE Accuracy=0.87 Gender Accuracy=0.97

we introduced the age estimation and gender determination system by using a multitasking CNN algorithm based on the architecture (Efficient CNN Network) that provided a significant advantage, which is the work of a system with different outputs without the need to build a hybrid system and worked on the machine learning algorithm SVM whose internal structure is based on support vector machines. Two algorithms produce dual outcomes. In the suggested system, work was based on exterior appearance and the ability to differentiate and identify people of all races and skin tones. This was accomplished by training the system on a massive data set, IMDB WIKI, and the findings have demonstrated that deep learning can produce excellent outcomes. The system introduced a qualitative shift compared to externally based systems. As a future effort, it is feasible to test a different algorithm, which is currently in the development phase. To improve recognition and differentiation, it is also feasible to include a data set tailored to the age range of children.

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