International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

March 2023	Issue 54	Volume 15	Number 1	Pages 232-240

AGE FACE INVARIANT RECOGNITION MODEL BASED ON VGG FACE BASED DNN AND SUPPORT VECTOR CLASSIFIER

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Abstract- One of the most significant and widely utilized biometric techniques nowadays is facial recognition. However, a number of difficulties, such as pose, lighting, occlusion, and aging differences, may make the task of face recognition complex. Face recognition over ages is crucial because wrinkles and other age-related characteristics make it very challenging to extract facial features from human faces as they change over time. Deep learning techniques have gained popularity recently for their effectiveness and ability to extract deep characteristics from the biometric methods. As a result, this paper focuses on a deep learning technique based on the CNN model to facial recognition across the aging. This methodology consists of three primary phases: preprocessing, feature extraction, and classification. One of CNN's variations, VGG face, is utilized in this study. First, using the weights from the pre-trained (VGG face) model and applying them to our work dataset in the (VGG face) model to extract the required face features. Second, features are reduced and the task remains from them only by using a deep neural network (DNN), which is reliant on those weights. Finally, the (SVC) method is then given the DNN's final layer to use in the classification process. The proposed approach had a 97.00% accuracy rate as its maximum. for everyone of all ages in the dataset. We can draw the conclusion that the proposed model can effectively control the age - related changes.

Keyword: Face Recognition, Deep Learning, Biometric, VGG Face-CNN, DNN.

1. INTRODUCTION

In many areas of life, the use of biometric identification systems has recently grown to include individuals recognizing. A biometric identification system uses one or more of the person's biometric traits to uniquely identify or verify the individual. where each individual has a variety of distinct biometric identifiers, including their face, voice, iris, ears, DNA, and fingerprints. One of the most significant biometric methods is face recognition.

Face position, illumination, facial expression, and aging are some of the issues this system may encounters, which negatively affect verification performance [1]. As people grow older, their facial characteristics change, making it challenging to verify a person's identity. Even the ability of a human cannot verify a person in two images when there is a significant age difference (huge time difference) [2]. Numerous studies have succeeded in overcoming some of these difficulties, including those related to illumination, face posture, facial expressions, and even aging. However, research into aging was still in its development, and face recognition with age may be accomplished by employing the most recent technologies to make these biometric identification methods more reliable. Since we concentrated on those who developed methods based on the CNN model, many researchers worked on creating various methodologies for verifying and recognizing faces through aging and solve this issue.

The most often conducted studies in this area include: the researchers in [3] have used (VGG Face) model to determine robust features that are robust to age variations across many datasets. Using ensembles of discriminant classifiers, the extracted features demonstrate strong inter-class and low intra-class variability. As a result, generalization errors on aging datasets are reduced. (FG-NET) and the accuracy obtained was 80.6%. The authors of [4] have introduced model-based CNN, specifically the (VGG Face) model, which was used in the process of extracting significant features from images on the FG-NET dataset. Then, the classification was done using two techniques: the first was the classification by the KNN technique, which obtained an accuracy of 80.4%, and the second was the classification technique SVM, which obtained an accuracy of 81.5%. Another research has been done by the same researchers [5] based on (VGG Face) model of extracting important features from images on the FG-NET dataset but they used Genetic Algorithm (GA) as an optimization algorithm and the KNN technique as a classification method, the obtained accuracy of their model was 86.2%. The researchers in [6] also used the (VGG Face) model to extract important features from images and the SVM classifier to classify images of faces, the accuracy achieved from this study was 70%.

In one of the most recent experiments in [7] the (VGG face) was established along with the FG0NET and Age datasets. According to those datasets, the accuracy obtained was 61.04% for the FG-NET dataset and 60.37% for the Age dataset. Moreover, one of the convolutional neural networks (CNN) models was used to validate faces (VGG face) to deal with a person's aging process in [8]. Age categories from the age dataset were utilized to test the model. An overall accuracy percentage of (88.6%) is produced by this model. Any of the aforementioned techniques could still lead to improved results when there is room for improvement. Thus, in this study, we used weights from the (VGG-Face) pre-trained model and apply them to our datasets to extract the features we need from the images, these features were entered in to deep neural network (DNN) to reduce these features and the task remains only to be entered into (SVC) method to classification. The body of this paper is arranged following: The problem statement in part 2, the theoretical background in part 3, the proposed methodology in part 4, the experimental results in part 5, and concluded in part 6.

2. PROBLEM STATEMENT

As people age, their faces change in appearance. As a result, the face recognition system encounters various challenges that prevent it from verifying faces with adequate performance. The capacity to represent some singularities generated by face wrinkles and bone structural deformation (such as the jaw bones) of the person's face is crucial for face identification across decades. So, the anatomy and significant deformation of human faces' look (facial texture) continue to be mostly caused by the aging process. Since aging presents one of the most compelling challenges for autonomous human identification systems, we can claim that it is one of these problems. Recent advances in the field of deep learning and machine learning have made it possible to successfully solve many of these issues. The great majority of deep learning models, on the other hand, require a massive dataset to train and process the neural network. Extraction of chosen traits from the face, which directly affects the verification process, is one of the key responsibilities in effectively verifying a face.

3. THEORETICAL BACKGROUND

In this section we will explain theoretical background for the utilized approaches in this paper such as general face recognition procedure by the (VGG face-CNN) model and deep neural network (DNN) and support vector classifier (SVC).

3.1. The Standard Face Recognition Structure

There are various phases that should be completed in any typical facial recognition method in order to accomplish the process of identifying and recognizing the individual in the proper manner. As shown in Figure 1, these phases entail gathering or finding an acceptable dataset, followed by a pre-processing step for the images, a feature extraction step to locate the key features, and a matching step to confirm the person and reach a decision.

3.2. Deep Neural Networks (DNNs)

Deep neural networks (DNNs) have recently demonstrated outstanding performance in challenging machine learning tasks, particularly in voice and image classification. An artificial neural network (ANN) with several layers between the input and output layers is referred to as a deep neural network (DNN). However, due to its multi-layered structure, it is opaque and DNNs are typically thought of as "black boxes," meaning that it is challenging to comprehend how it comes to a specific rating or recognition conclusion [9]. Although there are various kinds of neural networks, they all share the same building blocks: neurons, synapses, weights, biases, and functions. These components can be trained like any other machine learning algorithm and collectively perform similarly to the human brain.

3.3. Support Vector Classifier (SVC)

Support vector machine (SVC) algorithm is employed when categorizing data sets with many classes. Instead, we may say that (SVC) technique is one of the subtypes of (SVM) technology, but it has performed better when there are more than one class, whereas (SVM) is more frequently employed when the classifiers are binary. Given that the Linear Support Vector Classifier (SVC) method incorporates additional parameters like penalty normalization and loss function, classification is performed using a linear kernel function. Additionally, there are variations in how SVC is implemented in practically [10].

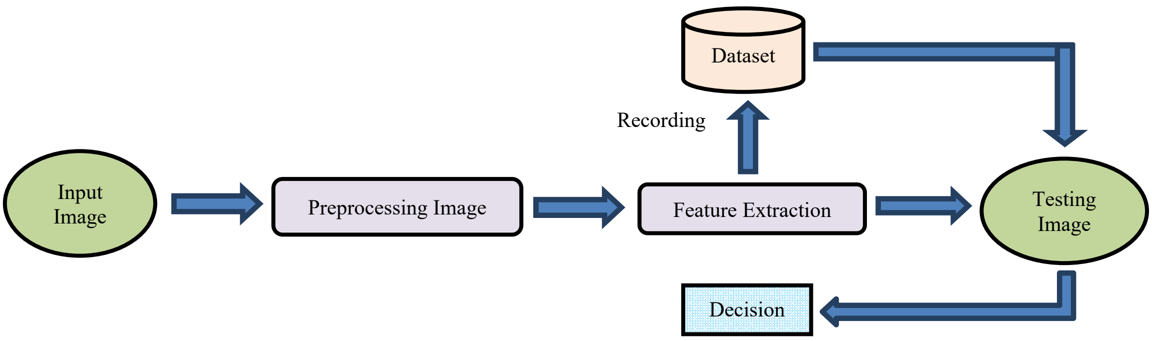

Figure 1. The fundamental structure of a face recognition system

4. THE PROPOSED METHOD

The main advantage of the neural network is the ability to learn the connection between the input and output of a system by finding the values of the weights of the successive layers of the neurons in the training process by showing several examples of past inputs and outputs to the neural network [11]. The proposed Method for age-invariant face recognition approach is based on (VVG Face), a variation of CNN models for feature extraction, and DNN for feature reduction. The goal of this network is to identify individuals who display certain aging differences. It composed of preprocessing, feature extraction, features reduction using DNN and classification using SVC method. The suggested structure is displayed in Figure 2.

4.1. Preprocessing Stage

The datasets primarily contain images that vary in size, position, and illumination. As a result, it could cause some issues with person recognition. Therefore, using a variety of methods, such as defining the area of the image to be worked on, image preprocessing aids in overcoming these difficulties. Here, a face detection and cropping from the provided image were included in our work. The RGB image should then be converted to a grayscale image. Images are afterwards reduced to 224 by 224 pixels to meet the size of the model used. Data Augmentation is additionally utilized for preprocessing to properly train the model. Additionally, the image that was entered into the system had normalization, and restricting its values to the range of (0-1). All of these processes were done with the goal of enhancing the model's performance.

4.2. CNN Architecture for AIFR

Deep learning models have witnessed great development and interest due to their efficiency in various fields, such as pattern recognition, object detection and classification, in addition, their outstanding and high ability to learn direct complex relationships from data made DNN well suited to perform intelligent tasks with high efficiency.

The Convolutional neural Network (CNN), one of the famous and incredible deep learning models which at first introduced for PC vision [12]. After essential pre-processing operations, features must be extracted. Convolutional Neural Network (CNN) model (VGG face) was employed in features extraction because the CNN it has the ability to extract features and classify them with the single structure. However, the classification could occur within the network itself or with the use of additional classification methods from the machine learning community [13]. The input image is convoluted by trained kernels for features extraction. After then, the size of the resulting layers is reduced using a pooling layer, which plays a crucial role in CNN since it is chiefly answerable for the invariance to data variation [12]. Where, the obtained feature maps are presented as inputs for the next layers, this process continues until deep features are extracted and presented finally as inputs for a DNN architecture. In this paper, we focus on the features extraction part. Therefore, the (VVG Face-CNN) model was applied.

4.2.1. VGG Face Model

In this research, we employed the VGG-Face architecture, which consists of 15 layers, 12 convolutional layers, and 3 fully linked layers. The Max-pooling layers execute subsampling with a factor of (2×2) whereas the convolutional layers utilize filters of dimension (3×3). The fully connected VGG Face layers' vector of activities is frequently employed as an effective general descriptor in feature extraction and is transferable to different face datasets. This model was pre-trained using a sizable face dataset that included 982,803 web images of 2622 popular people and superstars. However, this (VGG Face) pre-trained can recognize the subjects in its only training dataset. but, can be utilized as a feature extractor for any given facial image by processing the image and application of special architecture to extract features. As for the classification process, we removed the last layers of the classification because we used (SVC) technology in classification and accuracy test [3]. This is shown in Figure 3.

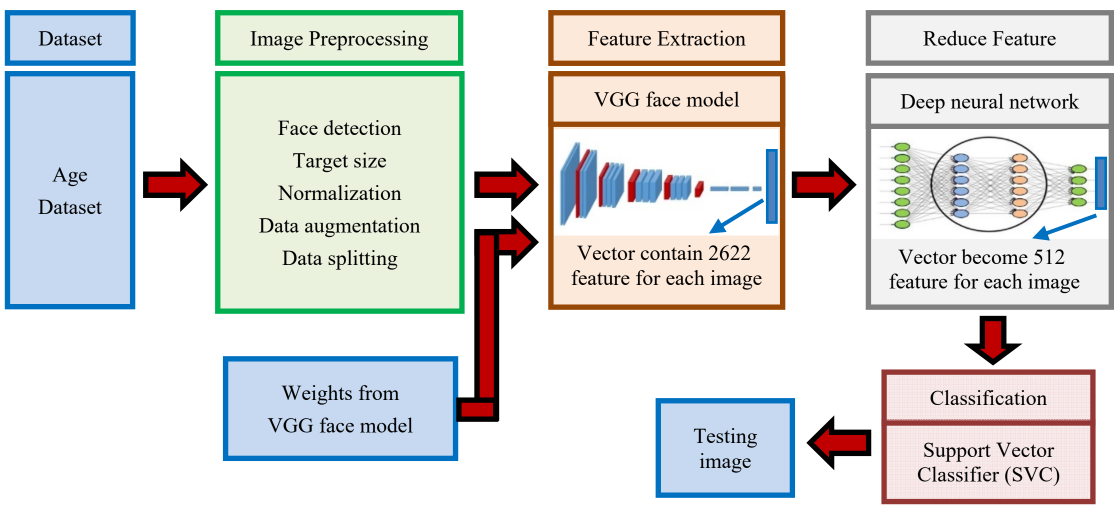

Figure 2. Age Invariant Face Recognition Methodology

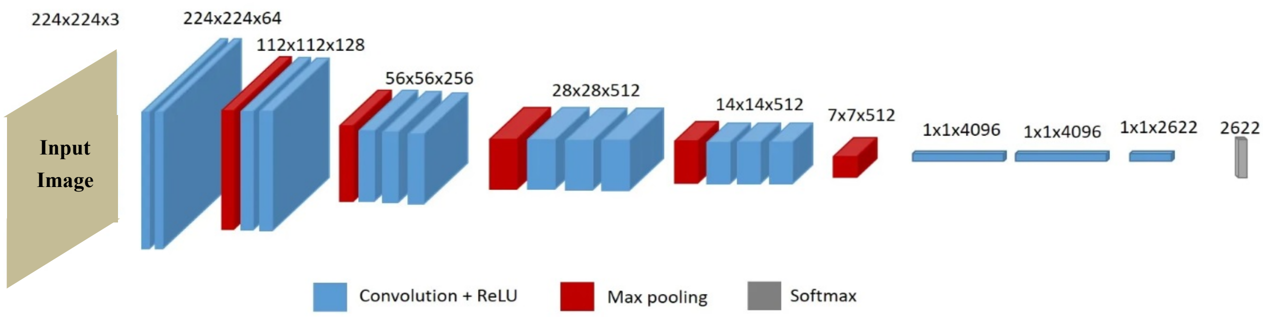

Figure 3. VGG Face construction [14]

Table 1. Summarize the suggested architecture for the VGG Face Model

Layer Kind	Filter size	No. of filter	Input Image	Output Image	Activation Function	No. of Parameter
INPUT	----	----	224×224×3	224×224×3	----	----
Convolution2D + ZeroPadding2D	3×3	64	224×224×3	224×224×64	ReLU	1792
Convolution2D + ZeroPadding2D	3×3	64	224×224×3	224×224×64	ReLU	36928
MaxPooling2D	2×2	----	224×224×64	112×112×64	----	0
Convolution2D + ZeroPadding2D	3×3	128	112×112×64	112×112×128	ReLU	73856
Convolution2D + ZeroPadding2D			112×112×128	112×112×128	ReLU	147584
MaxPooling2D	2×2	----	112×112×128	56×56×128	----	0
Convolution2D + ZeroPadding2D	3×3	256	56×56×128	56×56×256	ReLU	295168
Convolution2D + ZeroPadding2D	3×3	256	56×56×256	56×56×256	ReLU	590080
Convolution2D + ZeroPadding2D	3×3	256	56×56×256	56×56×256	ReLU	590080
MaxPooling2D	2×2	----	56×56×256	28×28×256	----	0
Convolution2D + ZeroPadding2D	3×3	512	28×28×256	28×28×512	ReLU	1180160
Convolution2D + ZeroPadding2D	3×3	512	28×28×512	28×28×512	ReLU	2359808
Convolution2D + ZeroPadding2D	3×3	512	28×28×512	28×28×512	ReLU	2359808
MaxPooling2D	2×2	----	28×28×512	14×14×512	----	0
Convolution2D + ZeroPadding2D	3×3	512	14×14×512	14×14×512	ReLU	2359808
Convolution2D + ZeroPadding2D	3×3	512	14×14×512	14×14×512	ReLU	2359808
Convolution2D + ZeroPadding2D	3×3	512	14×14×512	14×14×512	ReLU	2359808
MaxPooling2D	2×2	----	14×14×512	7×7×512	----	0
Convolution2D	7×7	4096	7×7×512	1×1×4096	ReLU	102764544
Dropout (rate = 0.5)	----	----	----	----	----	0
Convolution2D	1×1	4096	1×1×4096	1×1×4096	ReLU	16781312
Dropout (rate = 0.5)	----	----	----	----	----	0
Convolution2D	1×1	2622	1×1×4096	1×1×2622	ReLU	10742334
Flatten	----	----	----	2622	----	----
Activation	----	----	----	150	SoftMax	----
Total params: Trainable params: Non-trainable params:	145,002,878 145,002,878 0					

a) The Convolution Layers

Each convolution layer is connected to one or more feature maps from the layer above it. This layer is 2-D weight matrix, employs a 2-D filter for the purpose of convolution and feature extraction, each plane's convolution is computed. [12]. A grayscale, 224×224 face image is accepted by the first input layer and sent to the first convolutional layer, which contains 64 filters of 3 3 pixels in size. The output of this layer is then sent to the next layer. These layers are the result of the feature extraction process. The following formula is used to calculate the convolution layer's feature map:

$$Y_k = f(W_k \times x) \quad (1)$$

where, x represents the input image, and W_k relates to a convolutional filter for the feature map [13]. Convolution layer operation is displayed in Figure 4.

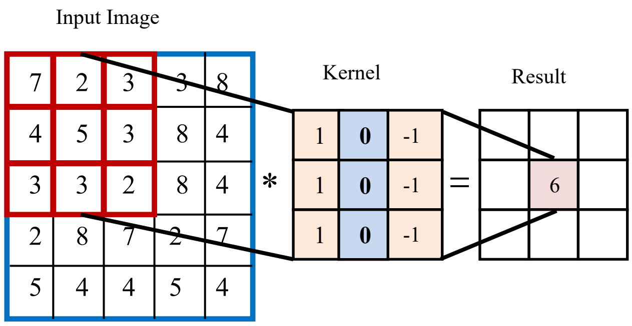

Figure 4. Operation of the convolution layer

b) The Pooling Layers

Each feature map's dimensionality is decreased while still maintaining the most important information. There are three forms of pooling that are possible: The largest element is chosen by max pooling, the average element is chosen by average pooling, and the total element is chosen by sum pooling. In this study [12]. We used the Max pooling stride value of 2×2 to decrease the size of the feature map in half. This phase makes the input representation smaller and more practical by reducing its spatial dimension. One or more of convolution layer are related to this feature map. It increases the convolution layer's output's resistance to local aberrations. Detail map.

The formula for the Pooling layer's feature map is:

$$Y_{kij} = \max\ (p,q) \in ij,\ x_{kpq} \quad (2)$$

where, x_{kpq} is the element at position (p,q) pooling region ij [13]. Pooling layer operation is depicted in Figure 5.

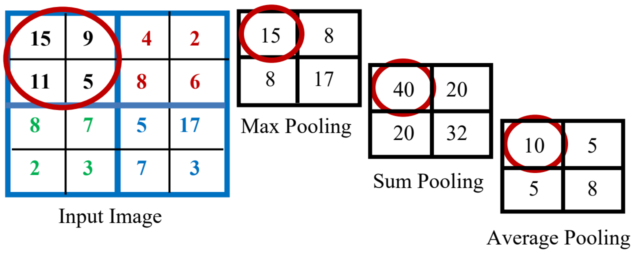

Figure 5. Pooling layer operation

c) Fully Connected Layer

The classification stage now starts after the extraction of the essential features from the face that is prepared for classification. When producing binary classes, this layer often used sigmoid neurons, and when producing more classes, SoftMax neurons. The ultimate outputs to the network are represented by this layer's outputs. By the fully connected layers are captured the correlations between features or (Similar traits that do not vary in the face when a person's age changes) from of various regions face, such as the shape and placement of the eyes and mouth, as shown in Figure 6.

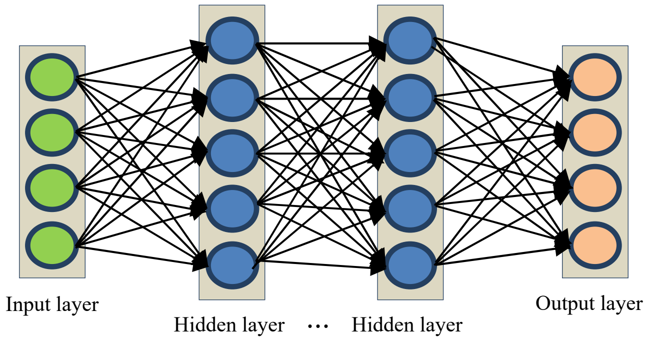

Figure 6. Fully Connected Layer

d) Rectified linear units (ReLU)

This layer's objective is to increase the impact and speed of training. a function (RelU), changing all negative numbers in the output to zeros.

4.2.2 Features reduction using DNN

The process of extracting features from images and selecting them as features of the subject of study is important for network performance and rating. Extracted features may contain some useful features. While, some of the other features may not be of great importance. That is why most often these features are provided by machine learning algorithms, especially deep learning with two steps: First, Extracting general features from data set images by (VGG face) model. Second, Select the important features from the extracted file [15], we used (DNN) network for the purpose of reducing features, decaying weak features, and maintaining strong features, which was considered to be the main part of our work. The output of this vector structure is (512) after it was (2622) resulted and communicate these resulted attributes features to the (SVC) algorithm for classification purposes (e.g. face). The standard deep neural network components are shown in Figure 7.

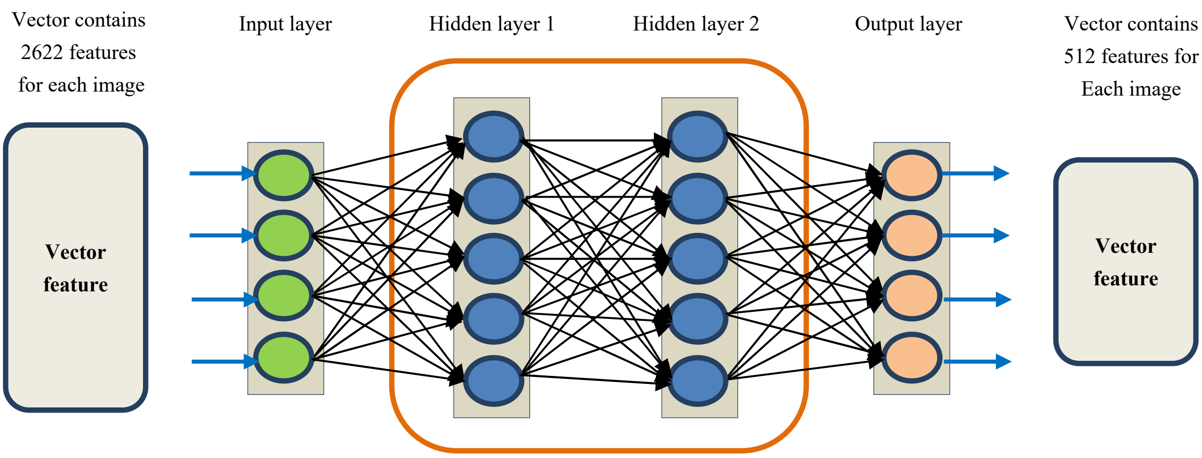

Figure 7. Deep neural networks (DNN)

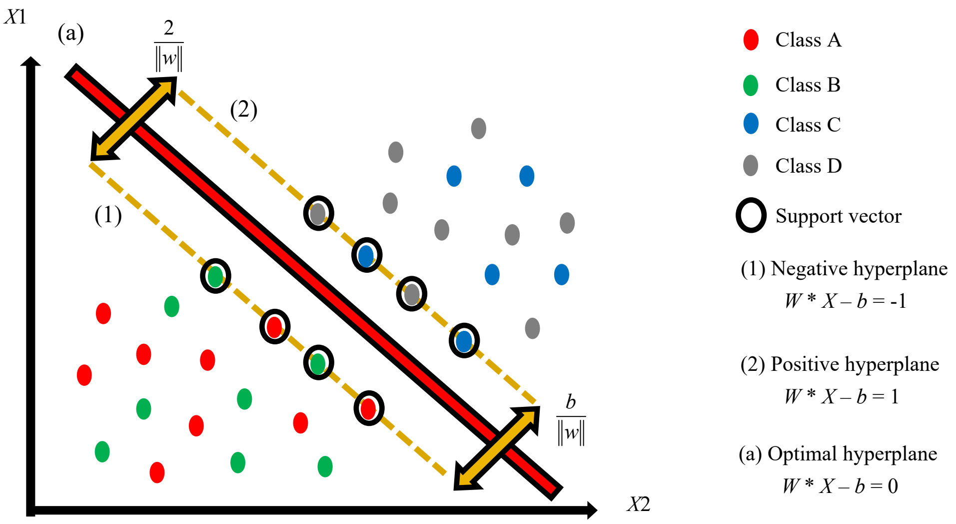

Figure 8. Support Vector Classifier (SVC)

4.2.3. Classification Using SVC Method

In various fields of machine learning, a classifier is any method that organizes data into labelled classes. Here in our work, each image was a vector of length (2622) after the features were extracted from the (VGG face) model, but it was reduced and the strong ones were kept in the (DNN) structure to become (512). It was then combined with the (SVC) approach for classification purposes, which was successful in classifying data into many categories. Figure 8 demonstrates the SVC classifier's operation.

5. EXPERIMENTAL RESULTS

In this paper, Google Colab pro, which offers Python3, served as the environment. The hardware of the machine was an HP model with an Intel Core i5-7200U cpu running at 2.50 GHz and 8 GB of RAM. Age dataset is utilized in the experiments and different evaluation metrics are used to evaluate the proposed model such as an accuracy, recall, precision and f1-score.

5.1. Age Dataset

This dataset includes 16.516 images from 570 different subjects that were taken in real world and it include various positions, expressions, noise, and occlusions. The age range of the data in this dataset is also 1 to 101. The average age range for each person and the average quantity of face images are 29 and 50.3 years, respectively [8]. Information regarding the Age dataset is summarized in Table 2.

5.2. Evaluation Metrics

The most frequent performance measures are used to evaluate the suggested method. These metrics are F1-score, Accuracy, Recall, and Precision.

5.2.1 Accuracy

The ratio of the number of correctly predicted faces to all of the input faces is accuracy. The accuracy can be determined as follows [16]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

5.2.2. Recall

The ratio of appropriately positive faces to all positive faces in the data. The recall may be determined as [16]:

$$recall = \frac{TP}{TP + FN} \quad (4)$$

5.2.3. Precision

The precision is determined by dividing the number of accurately positive faces by the total number of faces that classified as positive [16]:

$$precision = \frac{TP}{TP + FP} \quad (5)$$

5.2.4. F1_Score

The F1 score combines the aforementioned factors, seeks to find a balance between recall and precision, and is used to assess a test's robustness in terms of its ability to classify cases properly. Following are the steps to calculate the $F1\_score$ [16]:

$$F1\_score = \frac{2 \times precision + recall}{precision + recall} \quad (6)$$

Table 2. Information about the age dataset

Name of Dataset	Year of Publication	No. of Images	No. of Subjects	Noise free labels	In the wild
Age Dataset	2017	16516	570	yes	yes

5.3. Visualization of Convolution Layers via Feature Maps Representation

In order to demonstrate the stages of feature extraction and the filters that were utilized in this model, we used feature maps. A collection of filters that were utilized in the model before being applied to the images are shown in Figure 9. In other words, each colored square in this map represents a particular set of filters. This method aids in comprehending how input are passed across layers and how the model picks up new filters. The feature maps closest to the input identify the most precise details, whereas the feature maps closest to the model's output capture more broad information, which is the simplest way to describe the logic behind this work. Figure 10 depicts the steps involved in applying filters to face images. We provide an overview of some samples and how the stages are sequenced for the extraction of key features.

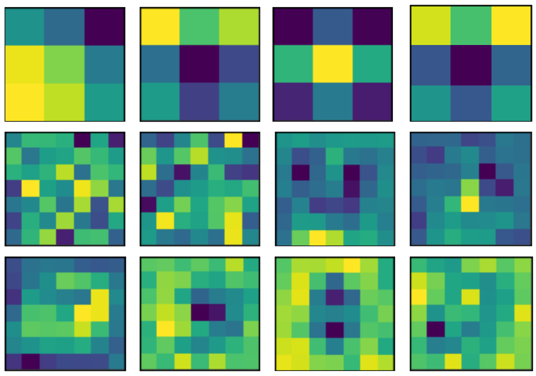

Figure 9. Filters prior to applying to the images

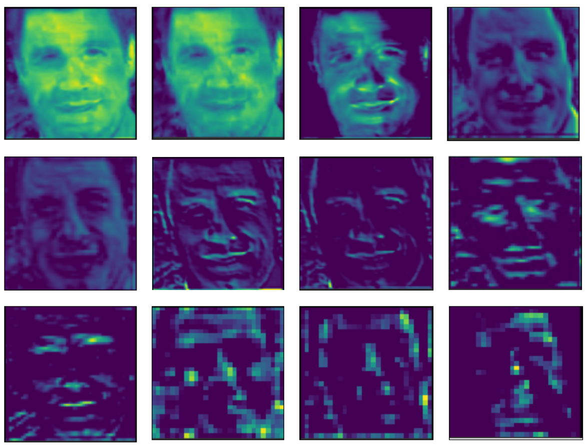

Figure 10. set of images that follow the convolution process

5.3. Experimental on Age Dataset

The (Age) dataset contains 16516 images of 570 subjects, and each subject, in particular, contains different images at various ages. This dataset is used to test and analyse the VGG-face model. The images have been separated into three categories for the assessing the model: the first category is related to the model's training process and extracts the key features from it, the second category of images is for the process of ensuring that the training is following the right steps, and this process is between training and the final test of the model, and the third category of images is for the testing process. Table 3 and Figures 11, 12 and 13 respectively presents the performance outcomes of the proposed model.

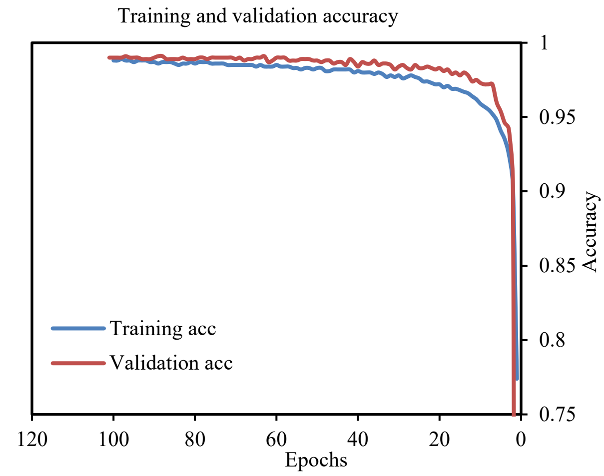

Figure 11. The accuracy from this model

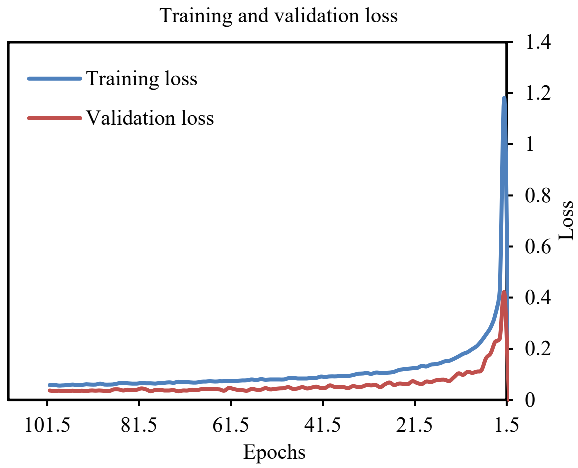

Figure 12. The loss function from this model

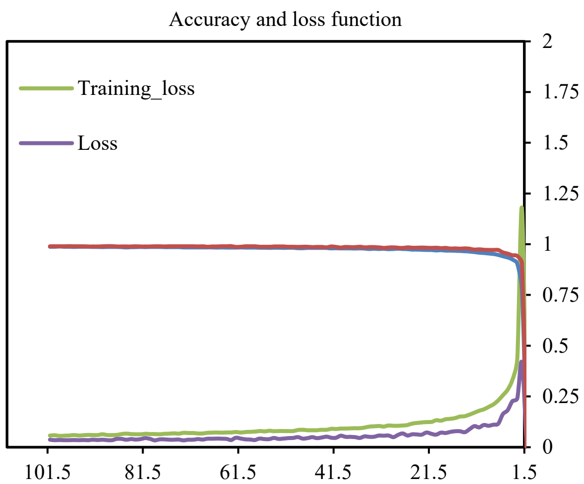

Figure 13. The accuracy and loss function from this model

Table 3. The performance results of the proposed technique

No. of Layers	No. of Total Filters	Activation Function	No. of Epoch	Accuracy	Precision	Recall	F1_Score
6	192	ReLU	50	0.62	0.57	0.60	0.59
5	216	leaky_ReLU	100	0.70	0.72	0.71	0.71
8	480	leaky_ReLU	50	0.65	0.62	0.50	0.55
7	504	leaky_ReLU	100	0.85	0.80	0.82	0.81
9	590	leaky_ReLU	75	0.88	0.86	0.87	0.86
11	666	ReLU	100	0.80	0.79	0.80	0.79
11	710	ReLU	50	0.90	0.85	0.92	0.88
10	1440	leaky_ReLU	50	0.97	0.94	0.96	0.95
15	1264	leaky_ReLU	50	0.92	0.93	0.94	0.93
12	316	ReLU	75	0.75	0.77	0.75	0.76
11	570	ReLU	100	0.86	0.80	0.85	0.82
13	11212	ReLU	75	0.94	0.94	0.95	0.94
15	(Our) 13763	ReLU	100	0.97	0.97	0.97	0.97

6. CONCLUSION

An age face invariant recognition model based on the (VGG face) model with (DNN) network and Support vector classifier (SVC) was presented in this paper. Based on deep learning, the suggested model achieved promising results over Age dataset and offers a substantial solution to the issue of age variations while attempting to verify the subjects using their faces. Because some people experience significant age changes which have a significant impact on facial features, the accuracy and efficiency of person face recognition technology start to decline very clearly when there are age gaps for the entered images, which may be 10 years or more. Therefore, one of the most significant issues at work is locating the right database that contains the correct age gradations for the individual. The focal area in the images used in our research, direction of a person's face, and facial alignment all have a significant impact on how well a person's face can be recognized and verified.

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