Gravitational Deep Convoluted Stacked Kernel Extreme Learning Based Classification for Face Recognition

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Abstract – *In recent times, researchers have designed several deep learning (DL) algorithms and specifically face recognition (FR) made an extensive crossover. Deep Face Recognition systems took advantage of the hierarchical framework of the DL algorithms to learn discriminative face characterization. However, when handling severe occlusions in a face, the execution of present-day methods reduces appreciably. Several prevailing works regard that, when face recognition is taken into consideration, affinity materializes to be a pivotal recognition feature. However, the rate of affinity changes when the face image for recognition is found to be illuminated, and occluded, with changes in the age of the subject. Motivated by these issues, in this work a novel method called Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition is proposed for human face recognition problems in frontal views with varying age, illumination, and occlusion. First, with the face images provided as input, Gravitational Center Loss-based Face Alignment model is proposed to minimize the intra-class difference, which can overcome the influence of occlusion in face images. Second, Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction is applied to the occlusion-removed face images. Here, by employing the Convoluted Tikhonov Regularization function, salient features are said to be extracted with an age-invariant representation. Finally, Stacked Kernel Extreme Learning-based Classification is designed. The extracted features are given to the Stacked Kernel Extreme Learning-based Classification and to identify testing samples Stacked Kernel is utilized. The performance of GDC-SKEL is evaluated on Cross-Age Celebrity Dataset. Experimental results are compared with other state-of-the-art classifiers in terms of face recognition accuracy, face recognition time, PSNR, and False Positive Rate which shows the effectiveness of the proposed GDC-SKEL classifier.*

Keywords: *Face Recognition, Gravitational Convoluted, Gravitational Center Loss, Face Alignment, Tikhonov Regularization*

1. INTRODUCTION

Over the past few years, different types of biometric methods have been employed for authentication purposes in security priority systems wherein facial image recognition is one of the most utilized of them. Siamese Neural Network based on Local Binary Pattern (also called LBP) and Frequency Feature Perception (SN-LF) was proposed and applied the Uniform LBP algorithm and Frequency Feature perception to recognize faces under non-restricted conditions. With the application of the LBP algorithm, the influence of lighting on the image was discarded, and that in turn provided vector-level input to the network model. Next, the frequency feature was split into low-frequency features and high-frequency features. The human factor is considered to be probably the weakest element in the security chain because the internal threat is among the top information security issues [1]. Here, the low-frequency features were compressed for improving recognition significance while exchanging information to preserve feature data while discarding noisy data. As a result, the recognition rate was said to be maintained and therefore resulted in the improvement of network computational speed. Though improvement was said to be found in recognition accuracy and robustness, the running time or the recognition time involved in face recognition was not focused.

An age-invariant face recognition system was designed in [2] that was split into four distinct steps, namely, preprocessing, feature extraction, feature fusion, and classification. First, employing Viola-Jones algorithm preprocessing was performed for aligning the frontal face. Second, feature extraction was done using CNN architecture to extract compact face features. The resultant extracted features were then fused utilizing feature-level multi-discriminant correlation analysis to minimize the feature dimensions and therefore obtain the most relevant features.

Current facial recognition methods are designed based on deep neural networks that are found to be efficient but expensive in training. In [3], a lightweight neural network was designed that consisted of fewer factors than the conventional deep neural networks. Moreover, an inhibitory layer was also introduced in the last layer that by reducing the number of trainable parameters also improved the overall performance.

With the prevailing COVID-19 pandemic, wearing masks has become mandatory in our day-to-day life. However, the usage of masks resulted in several issues concerning facial recognition accuracy owing to the reason that most of the facial features were hidden by the mask. To address this issue, a new method for masked face recognition integrating cropping-based models with an enhanced VGG-16 architecture was designed [4].

Yet another method integrating deep learning with Local Binary Pattern (LBP) features was proposed in [5] to identify the masked face. Moreover, multi-task learning integrating joint extra-supervised and self-supervised face detectors was also employed for concentrating on numerous scales of faces. The convolutional neural network was applied in [6] for face detection in the presence or absence of a face mask. Deep learning and parallelism were utilized in [7] for distinct facial expression recognition.

The main contributions of the proposed Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition are:

- The design of a face alignment model minimizes the intra-class difference that can control the impact of occlusion. A novel Gravitational Center Loss-based Face Alignment model is presented in this study and the proposed Gravitational Center Loss is utilized for face alignment. To calculate numerical results of the proposed Gravitational Center Loss-based Face Alignment, 100 face images are chosen and three widely used face recognition methods are utilized for comparisons.
- A model called Deep Convoluted Tikhonov Regularization-based Facial Region Feature extractor has been implemented. The main aim of the proposed Reference Convoluted Tikhonov Regularization-based Facial Region Feature extractor is to extract significant facial region features for further processing across years from facial images.
- The design of a Stacked Kernel Extreme Learning-based Classification to make training easier and improve the recognition accuracy.
- We conduct a series of experiments on the Cross-Age Celebrity Dataset and a comparison analysis is also made. The results show that the proposed method achieves state-of-the-art performance and outperforms the conventional learning methods in terms of face recognition accuracy, face recognition time, PSNR, and false positive rate.

The rest of the paper is organized as follows. Section 2 briefly introduces the related works in face recognition using machine and deep learning algorithms. The proposed WKSRC algorithm is released in Section 3 in detail, and Section 4 gives the experimental results of SRC, KSRC, and WKSRC with the public databases to confirm the better performance of our proposal. And Section 5 concludes this paper and gives some future directions.

2. RELATED WORKS

The face is the most pivotal feature utilized by humans for the recognition process. Hence, Face recognition (FR) is said to be the classical issue and is still very active in image processing. This is owing to the reason that face recognition has become a major necessity in authentication systems for ensuring both safety and security factors. The novice facial format and non-intrusive characteristics have gained a large amount of attention from research communities upon comparison with biometric features like fingerprint, iris, palm, and so on.

Deep learning, in specific the deep convolutional neural networks, has gained immense attention in face recognition, and so enormous deep learning methods have been designed. A summarization of about 330 distinct contributions was provided in [8]. Major deep learning concepts for the analysis of face and recognition were provided and also a precise overview of face recognition issues concerning age, illumination, and expression were provided. In [9], related research on face recognition from numerous angles was investigated. Also, face recognition development stages and related algorithms were provided. Recent advancements in efficient and significant deep learning-based solutions for face recognition were presented in [10].

Video retrieval based on the face images refers to the task of video retrieval consisting of a similar face.

In [11], a comparison of video retrieval based on face images was done using deep learning.

In [12], a wide exploration of face recognition techniques, their advantages, and menaces was surveyed in detail. This survey paper proposes a novel taxonomy to represent potential face identity threats. In [13], a detailed survey of current deep learning-based two dimensions and three dimension representations of face images were analyzed for face recognition.

Face recognition enhancement makes these tasks simpler and quicker. A holistic review of the issue of Facial Kinship Verification to determine the individuals automatically from their facial images provided as input was surveyed in [14]. Numerous facets of three dimension face reconstruction algorithms were explored in [15].

With the evolution of sophisticated environments, the necessity for identifying faces has become significant. Also, face detection and identification have been increasing globally. It necessitates the requirement of security like authorization, authentication, and other crucial inferences. Several algorithms have been designed in the recent past for facial detection. In [16], two face recognition mechanisms using Haar Cascade and Local Binary Pattern were utilized for classification. Many researchers considered a recognition system to detect and recognize individual face images with minimum recognition time [17]. Here, the face recognition process is developed when there are variations in attributes and behaviors both surrounded by different persons. Though, the systems are mostly used to overcome the challenging issues of recognizing the face image [18]. It protects individual human information with efficient recognition. Previously designed algorithms are unable to enhance recognition with minimum time and high accuracy. The above-described methods have minimum accuracy in the recognition of human faces with minimum time and complexity. On considering the above limitations, the following proposed work is developed to provide a better solution to solve these issues.

3. METHODOLOGY

The human face is a critical facet as far as social communication and interaction are concerned. Humans are required to identify others' faces for these purposes. Over the past few years, it is also extensively utilized in providing access control, security concerns, surveillance, and so on. Face recognition enhancement makes those tasks effortless and quicker. Moreover, different robust face recognition methods have been presented to address issues making an appearance for face recognition due to face illumination, occlusion, and age in distinct scenarios [19]. In this section, a method called, Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition is designed. Fig.1. shows the block diagram of the GDC-SKEL method for face recognition.

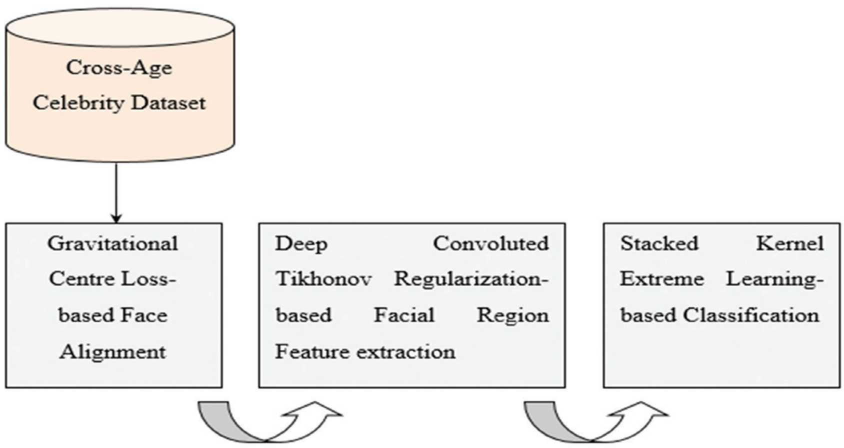

Fig. 1. Block diagram of Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition

As shown in Fig.1. Above the GDC-SKEL method is split into three sections. They are face alignment, feature extraction, and classification. First, with the distinct face images obtained as input from the Cross-Age Celebrity Dataset (CACD) dataset, the alignment of the face is made employing Gravitational Center Loss-based Face Alignment model. Second with the aligned faces, salient features are extracted by utilizing Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction. Finally, with the extracted features, Stacked Kernel Extreme Learning-based Classification is performed for face recognition. A detailed description of the GDC-SKEL is provided in the following sections.

3.1 GRAVITATIONAL CENTER LOSS-BASED FACE ALIGNMENT MODEL

With the evolution of deep learning, several deep models are presented for face alignment and achieve a great deal of performance by referring to various techniques [20]. In this work, a new loss function, namely

Gravitational Center Loss, significantly improves the discriminative potentiality of deeply learned features in neural networks. To be more specific, a center for deep features of each class is learned according to the Gravitational Force. Here, the training process is utilized for updating features to recognize face images. During training, each image feature is determined through estimation, motivation, plan, release, and evaluation. With the result of the training process, center portions are updated and therefore minimize the distances between deep features and their equivalent class centers.

The Gravitational Center Loss in turn significantly obtains the deep features of the same class to their centers. With the integrated management process, not only the interclass features contrasts are augmented but also the intra-class features contrasts are minimized. In this manner, the discriminative potentiality of deeply learned features is said to be improved to a greater extent, therefore enhancing the recognition accuracy with minimum time also. Fig 2 shows the block diagram of the Gravitational Center Loss-based Face Alignment model.

In Fig. 2. the Face alignment model is explained. First, the Cross-Age Celebrity Dataset (CACD) dataset is provided as input with several images. After that, the face image center pixel is obtained and then with the test elements, gravitation force is first applied. According to Gravitation Law, every body mass M_i attracts every other body mass M_j based on the force directing in a straight line l between mass centers, and hence this Gravitation Force is said to be correlative to body masses and inversely proportional to the square of their disjunction. The Gravitational Force is mathematically stated as given below.

$$GF = G * \frac{(M_i * M_j)}{l} \tag{1}$$

From the above equation (1), Gravitational Force GF is presented. Here, G refers to the gravitational constant (i.e., 6.67269 * 10^{-11}), M_i specifies every body mass, and M_j indicates attracted every body mass.

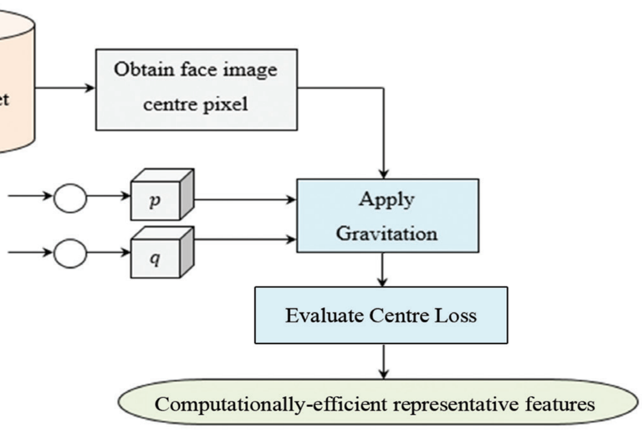

Fig. 2. Block diagram of Gravitational Center Loss-based Face Alignment model

Let us consider a face image FI, face image center pixel as $FI(C)$ of face, (i.e., $FI(C)$) is encircled by eight adjacent pixels, FI_i. Then, the gravitational force applied on $FI(C)$ by the 'th adjacent pixel is denoted by $GFI(C)$, and the p and q elements of $GFI_{ip}(C)$ and $GFI_{iq}(C)$ is mathematically stated as given below.

$$GFI_{ip}(C) = GFI_i(C) * sin\ sin\ \varphi \tag{2}$$

$$GFI_{iq}(C) = GFI_i(C) * cos\ cos\ \varphi \tag{3}$$

Then, based on the application of gravitation force to the face image center pixel concerning the p and q elements is mathematically stated as given below.

$$GFI_{ip}(C) = \sum_{i=1}^{N} \quad G\left[\frac{FI(C)*FI_i}{l_i^2(C)} * sin\ sin\ \varphi\right] \tag{4}$$

$$GFI_{iq}(C) = \sum_{i=1}^{N} \quad G\left[\frac{FI(C)*FI_i}{l_i^2(C)} * cos\ cos\ \varphi\right] \tag{5}$$

From the above equations (4) and (5), N denotes the total number of adjacent pixels, and 'l_i^2' represents the square distance between the ith pixel and center pixel C of face image FI respectively. The face image center pixel is denoted as $FI(C)$, the face image with i^{th} pixel is indicated as FI_i, and G specifies the Gravitational function. Next, for the face alignment process, the main issue is to eliminate the influence of the intra-class similarity and therefore enhance the discriminative potentiality of deeply learned features. Hence, in this work, a Gravitational Center Loss function is proposed to minimize the intra-class variations and retain sufficient useful information. With this, the influence of occlusion can be minimized to a greater extent. The Gravitational Center Loss function is then mathematically stated as given below.

$$CLoss = \frac{1}{2}\sum_{i=1}^{N} \quad (FI_i - C_{CLi})^2 \tag{6}$$

From the above equation (6), the Gravitational Center Loss function $CLoss$ is evaluated based on the 'i-th' deep feature of face image FI, the $CLi\text{-}th$ class center of deep features, and the N number of adjacent pixels respectively. With this model, the face image is reconstructed to minimize the intra-class difference to discard the impact of occlusion, therefore improving recognition accuracy. The pseudo-code representation of Gravitational Center Loss-based Face Alignment is given below.

Input: Dataset DS, Face Image $FI=FI_1, FI_2,\dots, FI_n$

Output: Computationally-efficient face aligned images

Initialize n, angle φ
Begin
For each Dataset DS with Face Image FI
Formulate Gravitation Force as given in equation (1)
Evaluate p and q elements for an angle of φ as given in equations (2) and (3)
Evaluate gravitation force concerning the p and q elements as given in equations (4) and (5)
Evaluate Gravitational Center Loss function as given in equation (6)
Return occlusion-removed face images OFI
End for
End

Algorithm 1 Gravitational Center Loss-based Face Alignment

As given in Algorithm 1 above with the Cross-Age Celebrity Dataset (CACD) dataset provided as input, the objective here remains in improving the face recognition accuracy even in case of the presence of occlusion. With this objective, Gravitation Force is applied to the raw face images to obtain the edge of the image. Next, the resultant image is subjected to distinct elements concerning angle φ to eliminate the disparities arising due to intra-class variations. Finally, Gravitational Center Loss function is applied wherein the most discriminative or representative features are obtained for further processing, therefore addressing the aspects involved during occlusion.

3.2. DEEP CONVOLUTED TIKHONOV REGULARIZATION-BASED FACIAL REGION FEATURE EXTRACTION

Despite obtaining the pivotal points feature information in the feature extraction module, it is nevertheless a great dispute to recognize facial features with illuminative, occlusion, and age-differing faces. Salient features have to be extracted from occlusion-removed face images for representation. In the proposed method, Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction is used. The Deep here represents the utilization of Max Pooling Aggregation (MPA) for aggregating representations across different years or ages and on the other hand, the Tikhonov regularization is applied to the occlusion-removed face images to extract salient features. Fig 3 shows the block diagram of Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction. As shown in Fig.3. above with the occlusion-removed face images provided as input, batch normalization is performed using reference convolute operation. Followed by which pooling is done using the Tikhonov Regularization function, Finally, the Max Pooling Aggregation function is applied to extract salient features.

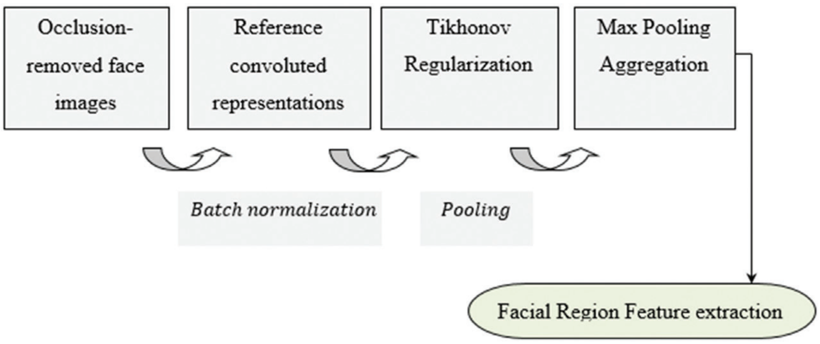

Fig. 3. Block diagram of Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction

In the proposed Tikhonov regularization model, a novel local structure is provided which is referred to as Max Pooling Aggregation (MPA). Utilizing the occlusion-removed face images, the Deep Convoluted Representations are mathematically stated as given below.

$$DC_i^j = \frac{1}{N_{ij}}\sum \quad OFI_i, \forall\, i = 1,2,\dots,n; j = 1,2,\dots,m \quad (7)$$

From the above equation (7), the Deep Convoluted representations DC_i^j are attained for each occlusion-removed face image OFI based on the number of images N and number of years m respectively. Given a set of $RR_i^j=\{RR_1^j, RR_2^j,\dots, RR_n^j\}$ Reference occlusion-removed face images representation Reference Convoluted representations (i.e., for batch normalization) to encode the new feature is mathematically stated as given below.

$$DC_i^j = \left(OFI_i - RR_i^j\alpha^j\right)^2 + \gamma(\alpha^j)^2 \quad (8)$$

The application of Deep Convoluted temporal relationships between representations across different years is not considered. To address this issue, a temporal constraint employing the Tikhonov Regularization function is employed so that the reconstruction error or the false positive rate can be reduced to a greater extent. To model this function, first, a diagonal matrix DM is formulated as given below.

$$DM=|0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0| \quad (9)$$

Then, with the above diagonal matrix DM (9), the Deep Convoluted temporal relationship employing the Tikhonov Regularization function (i.e., pooling) between representations across different years is mathematically formulated as given below.

$$\left[\left(OFI_i - RR_i^j \alpha^j\right)^2 + \gamma_1 (\alpha^j)^2\right]_{\alpha^j} + \gamma_2 (DMOF_i)^2 \quad (10)$$

From the above equation (10), the result of the Deep Convoluted representations DC_i^j is used to reduce the false positive rate (FPR) whereas the second part of the equation is designed with the purpose of face recognition across adjacent years of age to become similar for a subject and vice versa. Finally, Max Pooling Aggregation (MPA) is employed to aggregate representations across different years or ages as given below.

$$a_i = \left(\alpha_i^{(1)} \alpha_i^{(2)}, \dots, \alpha_i^{(m)}\right) \quad (11)$$

From the above equation (11), aggregate representations are provided as $\alpha i^{(1)}$ $\alpha i^{(2)}$,…,$\alpha i^{(m)}$'. By employing MPA, with the presence of two face images of the same person at different ages, face images at a smaller age have a higher response than the older image and vice versa. As a result, face recognition with occlusion-removed face images as input can even result in age-invariant face recognition with a minimum false positive rate. The pseudo-code representation of Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction is given below.

Input: Dataset DS, Face Image FI=FI_1, FI_2,…, FI_n

Output: Error minimized face extracted TF

Initialize n, m, occlusion-removed face images OFI

Begin

For each Dataset DS with occlusion-removed face images OFI

Evaluate Reference Convoluted representations as given in equation (7)

//Batch normalization

Obtain Reference Convoluted representations to encode the new feature as given in equation (8)

Formulate a diagonal matrix as given in equation (9)

//Pooling

Evaluate the Tikhonov Regularization function between representations as given in equation (10)

Evaluate Max Pooling Aggregation (MPA) is employed to aggregate representations across different years as given in equation (11)

Return occlusion-removed age-invariant face extracted TF

End for

End

Algorithm 2 Deep Convoluted Tikhonov Regularization-based Facial Region Feature Extraction

As given in the above algorithm, salient features are extracted from occlusion-removed face images using the Deep Convoluted Tikhonov Regularization function. First, Reference Convoluted Representations are evaluated from the occlusion-removed face images provided as input. Second, Tikhonov Regularization functions between representations to generate image results across years. Finally, with the aid of Max Pooling Aggregation aggregate representations across different years are evolved to reduce the false positive rate.

3.3. STACKED KERNEL EXTREME LEARNING-BASED CLASSIFICATION

Numerous robust face recognition methods have been presented in the literature to address the issues arising from face recognition due to face occlusion and illumination in different scenarios. Finally, in this section, the Stacked Kernel Extreme Learning-based (SKEL) classifier is presented. In SKEL, the input weights and biases are selected arbitrarily and output layer weights are ascertained based on the inverse function on the hidden layer output nodes. This in turn generates the learning process very fast and better recognition results upon comparison with the traditional learning algorithms. In SKEL, Stacked Kernel is utilized at the hidden layer to obtain the output.

The SKEL classifier comprises of 'n' input layer's unit, 'M' hidden layer neurons, and the 'K' output layer's unit. In SKEL, the hidden layer output weights post-training are mathematically stated as given below.

$$Res\beta = O \quad (12)$$

From the above equation (12), β denotes the hidden layer output weights post-training, Res denotes the hidden layer output matrix, and O represents the expected classifier output respectively. Also, SKEL classifier output weights are mathematically obtained as given below.

$$\beta = Res^T (ResRes^T)^{-1} O \quad (13)$$

From equation (13), the result of hidden layer output β is estimated. Based on the estimated result, the output of the SKEL classifier for test face TF is obtained using the mathematical formulation as given below.

$$y = h(TF)\beta = h(TF)[Res^T (ResRes^T)^{-1} O] = \varphi^{EL_{ij}} \quad (14)$$

From the above output of SKEL classifier results (14), the kernel matrix is formulated as given below.

$$\varphi^{EL_{ij}} = Kernel\left(TF_i, TF_j\right) \quad (15)$$

Finally, the proposed SKEL classifier utilizes the Stacked Kernel function φ to measure the output function of the classifier. The expression for Stacked Kernel functions is given below.

$$Kernel\left(TF_i, TF_j\right) = \sum \left(log\, log\, [TF(p,q)] - log\, log\, [TF(p,q) * \alpha_i]\right) \quad (16)$$

$$Kernel(TF_i) = \sum \left(log\, log\, (TF_i) - log\, log\, (TF_i * \alpha_i)\right) \quad (17)$$

$$Kernel(TF_j) = \sum \left(log\, log\, (TF_j) - log\, log\, (TF_j) * \alpha_i \right) \quad (18)$$

From the above equations (16), (17), and (18), TF represent the original test face image, and α_i represents the aggregate representations across different years respectively. The pseudo-code representation of Stacked Kernel Extreme Learning-based Classification is given below.

Input: Dataset DS, Face Image $FI=FI_1, FI_2,\ldots, FI_n$

Output: Accuracy improved face recognition

1: **Initialize** n, m, occlusion-removed age-invariant face extracted TF
2: **Begin**
3: **For** each Dataset DS with occlusion-removed age-invariant face extracted TF
4: Formulate hidden layer output weights post-training as given in equation (12)
5: Formulate SKEL classifier output weights as given in equation (13)
6: Evaluate the output of the SKEL classifier for test face TF as given in equation (14)
7: Evaluate kernel matrix as given in equation (15)
8: Formulate output function via Stacked Kernel as given in equations (16), (17), and (18)
9: **Return** face-recognized results
10: **End for**
11: **End**

Algorithm 3 Stacked Kernel Extreme Learning-based Classification

As given in Algorithm 3 above, to enhance the face recognition accuracy, Stacked Kernel is introduced that utilizes insightful information for identifying and testing sample images. First, with the n input layer's unit, M hidden layer neurons, and K output layer's unit, extreme learning is performed to obtain hidden layer output weights and classifier output weights separately. Second, the output of the SKEL classifier for the test face is obtained by employing the kernel matrix. Finally, a Stacked Kernel is utilized to measure the output function of the classifier that considers occlusion in kernel feature space and provides results with a higher recognition rate.

4. EXPERIMENTS, RESULTS, AND DISCUSSION

The experimental evaluation of the proposed Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition is conducted by comparing with two existing methods. The methods are namely Siamese Neural Network based on Local Binary Pattern (also called LBP) and Frequency Feature Perception (SN-LF) [1] and Age-invariant face recognition system [2] is implemented using MATLAB simulator. To conduct a fair analysis, the comparison is made with the GDC-SKEL and existing methods [1], [2] using Cross-Age Celebrity Dataset (CACD) dataset [*https://bcsiriuschen.github.io/CARC/*].

The experimental evaluation of GDC-SKEL classification for face recognition is carried out using factors such as face recognition accuracy, face recognition time, PSNR, and False Positive Rate concerning different numbers of face images and sizes. First qualitative analysis is presented followed by which a depth discussion with state-of-the-art methods, using graphs and tabulation is provided in detail.

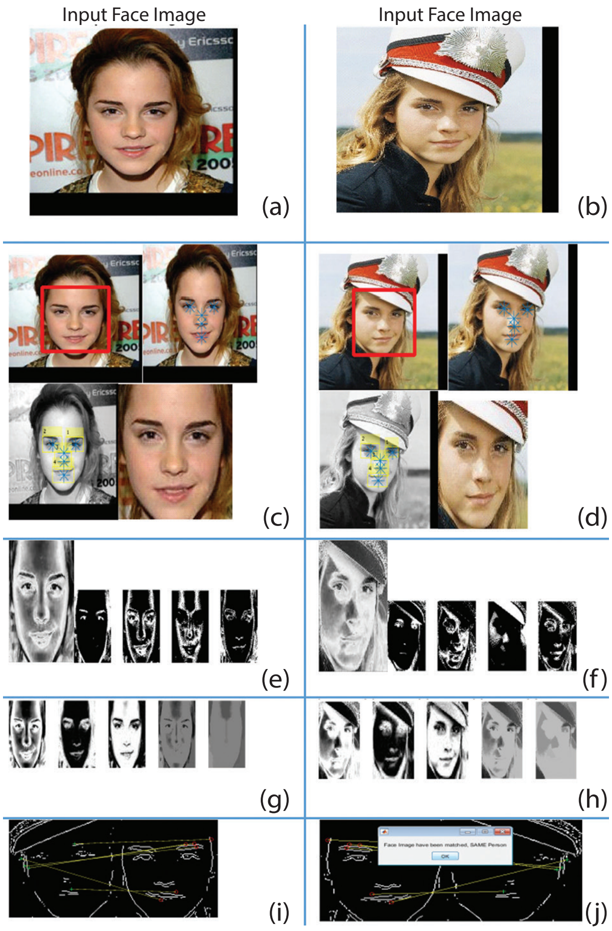

Fig. 4. Illustration of GDC-SKEL classifications for face recognition

In this section, qualitative analysis of Gravitational Deep Convoluted Stacked Kernel Extreme Learning-based (GDC-SKEL) classification for face recognition is done. Fig. 4 given below shows the illustrative details of GDC-SKEL classification for face recognition. As illustrated in the above Fig.4, first, input face images (a) (i.e., original face image) and (b) (i.e., occluded face image) obtained as input fromCross-Age Celebrity Dataset (CACD) dataset are utilized. Next, to the input face image face alignment is performed by applying Gravitational Center Loss-based Face Alignment model (i.e., as in (c) and (d)). Here, by applying this model, the intra-class difference is minimized that in turn eliminates the impact of occlusion in the face image during the recognition process. In the recognition process, 80% occlusion is attained with higher face recognition rates. Second, to the computationally-efficient face-aligned images as input, salient features are extracted by utilizing the Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction algorithm.

Utilizing this algorithm, error-minimized facial images are obtained as output (i.e., as in (e) and (f)). Finally, the actual classification process for face recognition is done using the Stacked Kernel Extreme Learning-based (SKEL) classifier. With this type of classifier, accurate face recognition is made (i.e., as in (g) and (h)). The detected output is provided in (i) and (j).

The quantitative analysis of four distinct performance metrics, face recognition accuracy, face recognition time, PSNR, and False Positive Rate are analyzed in detail.

4.1. FACE RECOGNITION ACCURACY

In this section, the comparative result analysis of face recognition accuracy is provided. Higher the accuracy, the more efficient the method is said to be. The face recognition accuracy is mathematically formulated as given below.

$$FRA = \left[\frac{NICR}{n}\right] * 100 \tag{19}$$

From the above equation (19), face recognition accuracy FRA is measured based on the number of face images correctly recognized $NICR$ to the face images involved in the simulation process n. It is measured in terms of percentage (%). The table reports the simulation of different results of face recognition accuracy of GDC-SKEL, SN-LF [1], and Age invariant face recognition systems [2] for different numbers of face images.

Table 1. Comparative analysis of face recognition accuracy using GDC-SKEL, SN-LF [1], and Age invariant face recognition system [2]

Face Images	Face recognition accuracy (%)		
	GDC-SKEL	SN-LF	Age-invariant face recognition system
100	95	91	89
200	93.25	88.35	86.35
300	91	85.25	82
400	89.15	83	80
500	86	81.55	78.25
600	83.25	78	76
700	81	75.25	73
800	78.45	72	71.05
900	73.15	70	67
1000	70	68	64.35

Fig. 5 given below shows the face recognition accuracy concerning the face images varying between 100 and 1000 of different sizes. A decrease in accuracy rate is observed using all three methods. However, the number of face images correctly recognized using the GDC-SKEL method was found to be comparatively better therefore also improved the face recognition accuracy than [1] and [2]. The improvement in face recognition accuracy can be attributed to the application of the Stacked Kernel Extreme Learning-based Classification algorithm. By applying this algorithm, the first extreme learning was applied to obtain hidden layer output weights and classifier output weights separately. Next, the kernel matrix was employed separately to obtain the output for each test face. With the resultant output only, Stacked Kernel was utilized for classifying that in turn considered occlusion in kernel feature space, therefore improving the face recognition accuracy using the GDC-SKEL method by 6% compared to [1] and 10% compared to [2] respectively.

Fig. 5. Graphical representation of face recognition accuracy

4.2. FACE RECOGNITION TIME

A small proportion of time is said to be consumed in recognizing the face images. To be more specific, face recognition time refers to the time consumed in recognizing the face images even in the presence of occlusion, highly illuminated across years. This is mathematically formulated as given below.

$$FRT = n * Time\left[\varphi^{EL_{ij}}\right] \tag{20}$$

Table 2 Comparative analysis of face recognition time using GDC-SKEL, SN-LF [1], and Age invariant face recognition system [2]

Face images	Face recognition time (ms)		
	GDC-SKEL	SN-LF	Age-invariant face recognition system
100	25	33	41
200	28.15	35.15	43.15
300	31	38	45
400	34.25	39.55	48.25
500	38	42.55	50.15
600	45.25	55.25	57.35
700	53.51	59.15	63.25
800	60.55	70	75.25
900	71.35	74.55	78
1000	78	85.15	87.15

From the above equation (20), the face recognition time *FRT* is measured based on the number of face images involved in the simulation process 'n' and the time consumed in recognizing the face based on classification via extreme learning *Time* [$\varphi^{(EL_{ij})}$]. It is measured in terms of milliseconds (ms). The table reports the simulation of different results of face recognition time of three different methods concerning different numbers of face images.

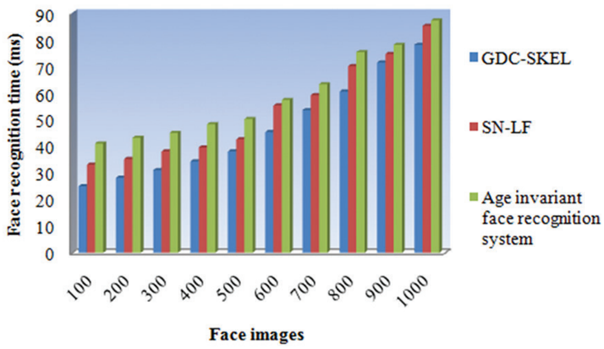

Fig. 6. Graphical representation of face recognition time

Fig. 6 given above shows the face recognition time. But when performed with simulations using 100 face images, the time consumed in recognizing face images using the three methods for the single face was 0.25 ms, 0.33 ms [1], and 0.41 ms [2] respectively. From this simulation results the overall face recognition time was observed to be 25 ms using GDC-SKEL, 33 ms using [1], and 41 ms using [2]. From this, the face recognition time was observed to be comparatively better in GDC-SKELthan [1] and [2]. The reason behind the improvement was due to the application of the Gravitational Center Loss-based Face Alignment algorithm. By applying this algorithm, the influence of intra-class similarity was said to be eliminated, which in turn improved the discriminative potentiality of deeply learned features. This in turn reduced the face recognition time using the GDC-SKEL method by 14% compared to [1] and 23% compared to [2] respectively.

4.3. PSNR

The peak signal-to-noise ratio (PSNR) is evaluated based on the mean square error that denotes the difference between the original face image and the processed face image. The formula for computing the PSNR is formulated below,

$$PSNR = 10\left[\frac{M^2}{S_{ME}}\right] \tag{21}$$

$$S_{ME} = \left[size_{preprocessed} - size_{original}\right]^2 \tag{22}$$

From the above equation (21) and (22), the peak signal-to-noise ratio '*PSNR*', is measured based on the processed size $size_{preprocessed}$ and the original size $size_{original}$ respectively. It is measured in terms of decibels (dB). The table given below shows the performance results of the PSNR concerning varying face image sizes obtained from the CACD dataset. The results obtained confirm that the PSNR of the GDC-SKEL method is improved upon comparison with the other existing methods [1], [2].

Table 3 Comparative analysis of PSNR using GDC-SKEL, SN-LF [1], and Age invariant face recognition system [2]

Sizes of face images (KB)	PSNR (dB)		
	GDC-SKEL	SN-LF	Age-invariant face recognition system
16.3	52.23	46.20	48.70
14.1	54.72	44.27	48.70
19.4	48.70	42.68	46.20
20.2	49.60	44.27	46.65
22.9	48.70	43.14	44.27
21.6	49.30	42.68	46.20
24.9	46.20	43.14	41.35
26.8	48.70	44.27	46.20
25.5	52.64	46.20	48.70
27.2	48.70	42.68	44.27

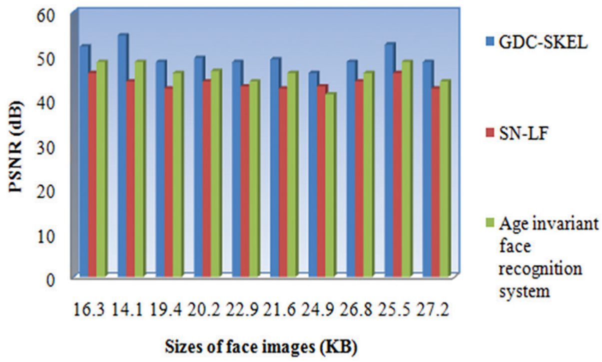

Fig. 7. Graphical representation of PSNR

Fig. 7 given above illustrates the PSNR concerning 10 distinct numbers of face images of varying sizes. However, simulations performed with a 16.3 KB size image saw a PSRN rate of 52.23 dB using the proposed GDC-SKEL, 46.20 dB using [1] and 48.70 dB using [2] respectively. From this result, it is inferred that the PSNR rate is found to be better when applied with the GDC-SKEL method upon comparison with [1] and [2]. The reason behind the improvement was due to the application of the Gravitational Center Loss-based Face Alignment algorithm. By applying this algorithm, the Gravitational Center Loss function was utilized that in turn not only reduced the intra-class variations but also retained useful information. As a result, the occlusion was minimized and in turn, aided in face recognition. Owing to this the peak-signal-to-noise-ratio (PSNR) was found to be improved significantly using the GDC-SKEL method by 14% compared to [1] and 8% compared to [2] respectively.

4.4. FALSE POSITIVE RATE

False Positive Rate (TPR) or specificity denotes the percentage ratio of several face images that were incorrectly recognized during the face recognition process. The false positive rate is measured as given below

$$Rate_{fp} = \left[\frac{NIICR}{n}\right] * 100$$

From the above equation (23), the false positive rate $Rate_{fp}$ is evaluated based on many face images that were incorrectly recognized $NIICR$ concerning the sample face images provided as input for simulation n. It is measured in terms of percentage (%). The table given below provides the performance results of the false positive rate versus the number of face images collected from the database. For conducting the simulation, 1000 numbers of distinct face images in the range of 100 to 1000 were utilized.

Table 4 Comparative analysis of false positive rate using GDC-SKEL, SN-LF [1], and Age invariant face recognition system [2]

Face images	False positive rate (%)		
	GDC-SKEL	SN-LF	Age-invariant face recognition system
100	4	7	9
200	6	9	10
300	7	11	12
400	9	10	11
500	5	8	9
600	3	6	7
700	4	7	8
800	7	8	10
900	5	6	8
1000	4	5	7

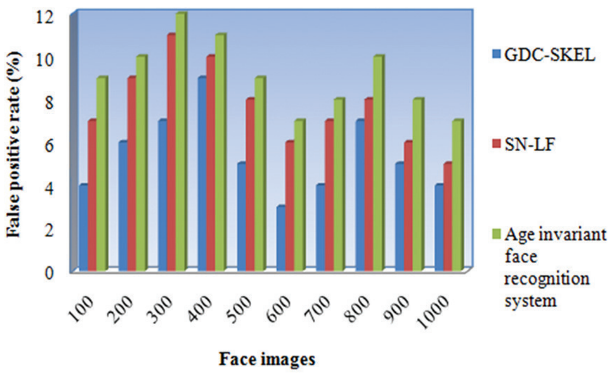

Fig. 8. Graphical representation of false positive rate

Fig 8 given above shows the graphical presentation of the false positive rate concerning ten numbers of face images with varying sizes provided as input. This in turn would result in a significant proportion of falsification of face recognition. But comparative analysis performed with 100 face images found 4 face images incorrectly recognized using GDC-SKEL, 7 face images incorrectly recognized using [1], and 9 face images incorrectly recognized using [2] respectively. From this analysis, the false positive rate using GDC-SKEL, [1] and [2] were found to be 4%, 7%, and 9% respectively. As a result, improvement was found in terms of false positive rates using the GDC-SKEL method. The reason behind the improvement was the application of the Deep Convoluted Tikhonov Regularization-based Facial Region Feature extraction algorithm. By applying this algorithm, Max Pooling Aggregation (MPA) was applied to aggregate representations across different years or ages. By applying this function face image at a smaller age had a high response upon comparison with the older image and vice versa. With this, the false positive rate using the GDC-SKEL method was found to be reduced by 30% compared to [1] and 42% compared to [2] respectively.

5. CONCLUSION

An efficient face recognition method from face images called, GDC-SKEL is designed by exploring and inspecting the affinity points selected from the given dataset. To minimize the face recognition time and improve the face recognition accuracy, therefore, paving the means for face recognition, Gravitational Center Loss-based Face Alignment is first applied to the selected face input image, focusing on occluded images. Second with the occlusion-removed face images provided as input salient features for further processing are extracted using the Convoluted Tikhonov Regularization function. Finally, with the extracted facial regions, Stacked Kernel Extreme Learning-based Classification is performed to obtain the final face image recognition output. For the experimentation, the Cross-Age Celebrity Dataset (CACD) dataset is used. The performance of the GDC-SKEL method is evaluated with different metrics such as face recognition accuracy, face recognition time, PSNR, and False Positive Rate. From the result, it is clearly understood that the proposed GDC-SKEL method outperforms well in the face recognition process with a higher detection rate and minimum time when compared to the state-of-the-art methods. In general, face recognition is only suitable for offline applications. To recognize human faces in online applications, a higher computing system is required. Thus, future work is developed for recognizing the human face in online applications

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