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Deep Learning Convolutional Neural Network for Face Recognition: A Review

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Abstract:
Face recognition is increasingly being used for solving various social-problems such as personal protection and authentication. As with other widely used biometric applications, facial recognition is a biometric instrument such as iris recognition, vein pattern recognition, and fingerprint recognition. Facial recognition identifies a person based on certain aspects of his physiology. Deep Learning (DL) is a branch of machine learning (ML) that can be used in image processing and pattern recognition to solve multiple problems, one of the applications is face recognition. With the advancement of deep learning, Convolution Neural Network (CNN) based facial recognition technology has been the dominant approach adopted in the field of face recognition. The purpose of this paper is to provide a review of face recognition approaches. Furthermore, the details of each paper, such as used datasets, algorithms, architecture, and achieved results are summarized and analyzed comprehensively.

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1. Introduction

Face recognition is one of the most significant research topics with great importance nowadays in this new world of science and technology, computer-vision, pattern-recognition, fingerprint-recognition, biometrics, image processing, protection (Gondhi & Kour, 2017; Annagrebah et al., 2019; Zhao et al., 2003). The latest developments in deep learning or, in particular, the development of CNN have benefited from face recognition. Emotions formed in the human face have a significant effect on judgments and arguments on diverse subjects (Cowie et al., 2001). A person's emotional circumstances can be divided in psychological philosophy into six major categories: surprise, terror, disgust, rage, happiness, and sadness (Lu & Zhang, 2019; Jin & Xu, 2019; Zeebaree et al., 2018; Ahmed & Brifcani, 2019). A daunting issue in the area of human-computer interaction has been the recognition of human emotions. The robot must be able to understand, recognize, and respond to human feelings for there to be more normal contact between humans and computers (Salunke & Patil, 2017; Tumen et al., 2017).

ML is a data processing system that automates analytic model construction. It is a subset of artificial intelligence that has supervised, unsupervised, reinforcement learning and is focused on the premise that systems can learn from data, identify patterns and make decisions with minimal human involvement(Bkassiny et al., 2013; Zeebaree et al., 2019; Maulud & Abdulazeez, 2020; Ahmed & Brifcani, 2015).

DL which is part of a larger family of ML strategies is effective against several domains in the computer vision field over the last few years. It gains a lot from working with data sets for large-scale training. Function learning is the nucleus of deep learning. It aims to gain practical knowledge on the hierarchical network to solve the essential problems that require artificial design before (Zhao et al., n.d.; Han et al., 2018; Sharma, 2019; Mahmood & Abdulazeez, 2017) . Deep learning is a system comprising many important algorithms. CNN is one of the most important algorithms for deep learning (Litjens et al., 2017; Baccouche et al., 2011; Zeebaree et al., n.d.; Amiri et al., n.d.).

CNN has recently seen major advancements and is one of the most common and effective applications in multiple image recognition. CNN's key benefit is the ability to retrieve complicated hidden features with intricate structures from high-dimensional data. The CNN model is also commonly used for facial recognition activities (Luo et al., n.d.; Li et al., 2014). DL has now become the predominant solution to two-dimensional (2D) face recognition and has been done an outstanding impact. However, typically it is very difficult to specifically apply deep learning to three-dimensional (3D) face recognition due to the difficulty of the point-cloud in the three-dimension face model (Guo & Fan, 2013; Liu et al., 2020). The CNN based two neural networks (twin network) is used to overcome the problem of three-dimensional face recognition with small scale samples (Xu et al., 2019; Fangmin et al., 2017; An et al., 2018). The current research focused on both face recognition and detection algorithms on Deep CNN, which showed amazing accuracy in extremely difficult databases such as the (ORL) face dataset (Qiao & Ma, 2018) and the Mega-Face Challenge (Nan et al., 2019), As well as older databases such-as Labeled Faces in the Wild (LFW)(Pu et al., 2019). The paper is organized as follows: Section 2 Convolution neural network, Section3 Feature extraction, and feature matching, Section 4 Reviews some research about Face Recognition based on CNN, Section 5 Comparison and Discussion. Finally, in Section 6 the paper is ended with a conclusion.

2. Convolution Neural Network

CNN's have demonstrated high-performance in fields such as image-recognition and are a class of neural network classification. CNN's are a type of neural feed forwarded networks consisting of multiple layers (Sharma et al., 2018; Paoletti et al., 2018; Liang et al., 2018). CNN's consist of neurons or filters that have weights or parameters and bias that can be trained (Lu et al., 2020). The structure of CNN involves Convolutional, pooling, and Fully Connected layers. the CNN consists of two-part: part one is the feature extraction, i.e. the input from each neuron is associated with the local receptive field of the previous layer; the other part is feature mapping CNN integrates extraction and classification in one stage compare to conventional recognition algorithms with complex extraction processes (Chen et al., 2014; Dang et al., 2019; Omar et al., 2020). The overall architecture of CNN is shown in Figure 1.

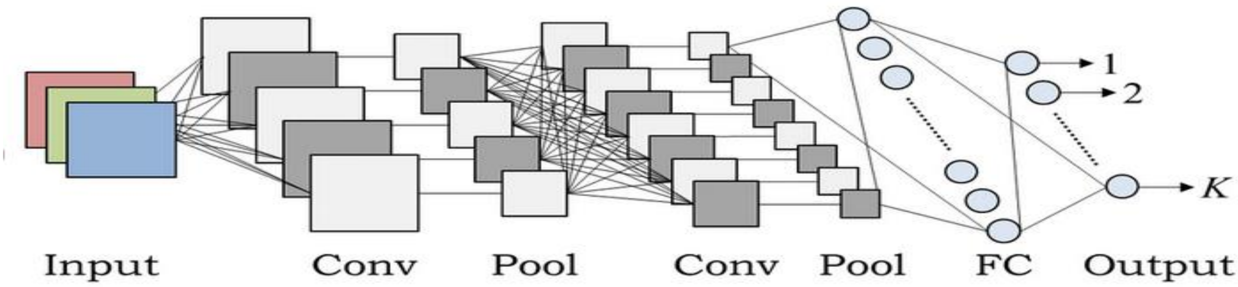

Figure: 1 Architecture of the CNN (Coskun et al., 2017)

A- Convolution Layer

The convolutional layer is the central part of a Convolution network that conducts the heaviest computational elevation. The convolution layer's objective is to extract important features from image input-data (Zhu & Bain, 2017; Soltau et al., 2014). Convolution preserves the spatial relationship between pixels by the use of tiny input squares to learn image properties. A variety of learning neurons can be used to transform the image into the input. This results in an activation map or map on the output image and then the function maps are fed into the next convolution layer as input data(Zhang et al., 2017; O'Shea & Nash, 2015; Wu, n.d.).

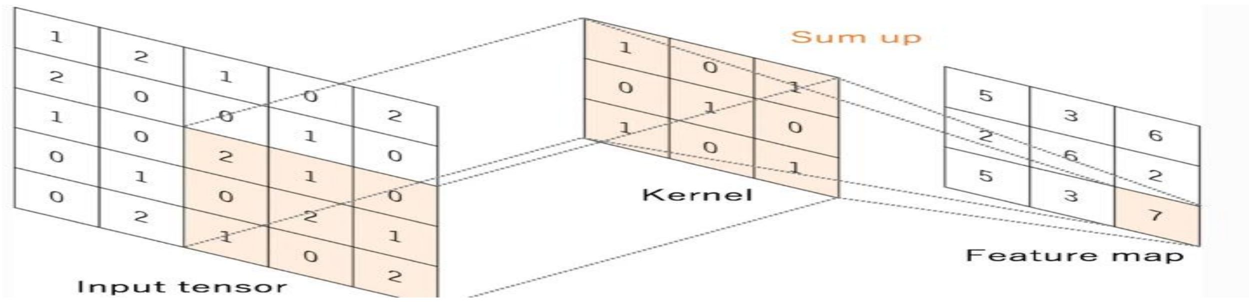

Figure: 2 Convolution-Layer (Yamashita et al., 2018)

B-Pooling Layer

The pooling layer reduces each activation map's dimensionality but has still the most significant details. The photos input are divided into a collection of rectangles that do not overlap(Giusti et al., 2013; Singh et al., 2020). A nonlinear activity, such as limit or average, will sample each area. This layer achieves a more generalization, quicker integration, more resilient to translation and distortion (Albawi et al., 2017; Devi & Borah, 2018; Ahmadi et al., 2018).

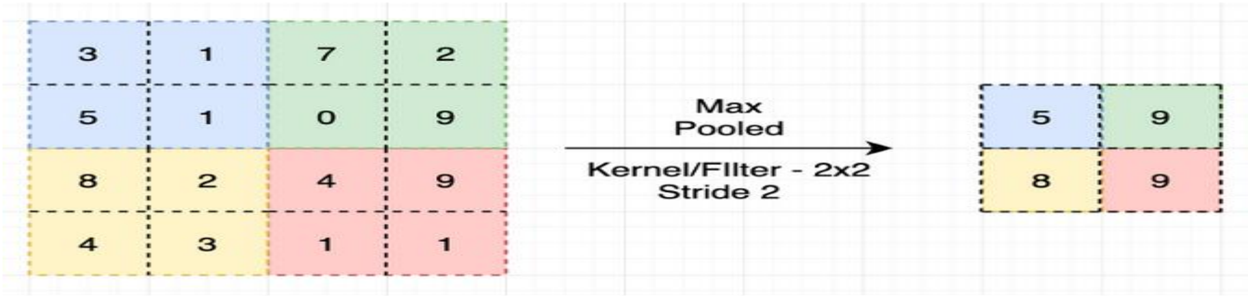

Figure: 3 Pooling-Layer (Albawi et al., 2017)

C-Fully Connected Layer

A fully-connected layer is a feed-forward neural network and makes up the last few years in the network. the entrance to a fully-connected layer is the output of the final-pooling or convolution layer, which is flattened and then entered into a fully connected layer(Li & Zhang, 2020; Nakahara et al., 2017) (Liu et al., 2018) (Ma & Lu, 2017).

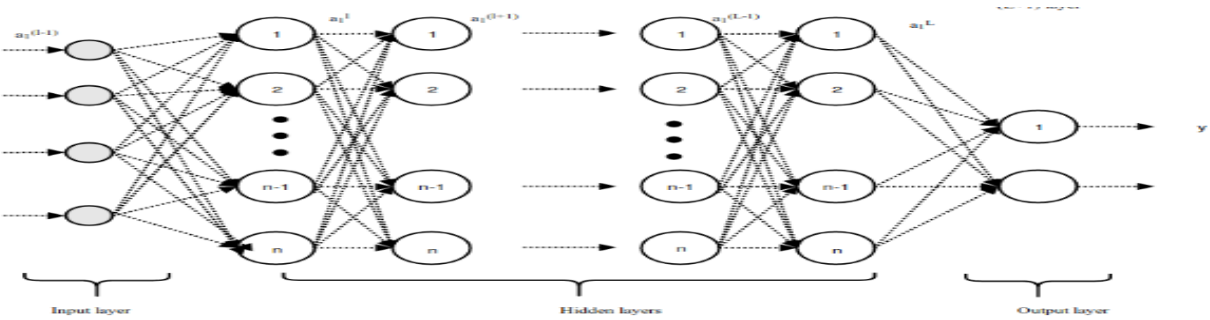

Figure: 4 Fully-Connected Layer (Murugan, 2017)

3. Face recognition (Feature Extraction and Feature Matching)

A facial recognition system is a technology which matches a human face from a digital image or a video picture to a database of faces, usually used to authenticate users by means of ID checks, by labeling and by measuring facial features in a certain image. In Figure 5, the main mechanism of the classic facial recognition technology is shown.

Figure: 5 the process of face recognition (Jadhav & Holambe, 2009)

3.1 Feature Extraction

Facial feature extraction is the method of extracting features of a facial component such as eyes, nose, mouth, etc. from a human face picture. For initializing techniques such as facial detection, face expression recognition or facial recognition, facial feature extraction is very important. Among all facial features, it is important to locate the eye and detect where the other facial features are located. (Zeebaree et al., 2019b; Nevatia & Ramesh Babu, 1980; Pedersen, n.d.; Hong, n.d.; Mahmood & Abdulazeez, 2019).

3.2 Feature matching

Simply put, a face-matching algorithm is a series of rules that a machine uses to identify a face in an image and then equate that face to another face (or faces) to decide whether there is a match (He et al., 2019; Ersi & Zelek, 2006; Liang & Cheng, 2015). A selection of attribute points is extracted for each face image at positions with the greatest deviations from standards The identification is done based on the overall resemblance between the best matching points in the face of the probe and each face of the gallery (Serlin et al., 2020; Yu et al., 2018; Eesa et al., 2015).

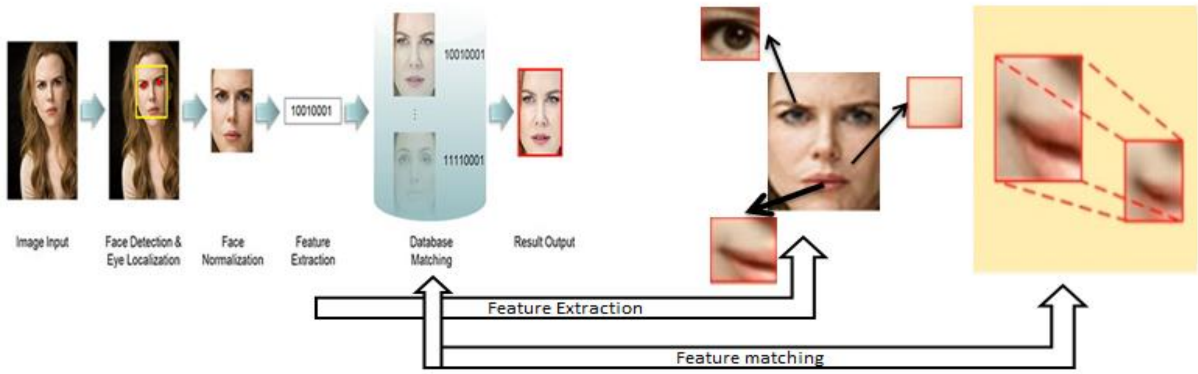

Figure: 1 Face Recognition (Feature Extracting and Matching) (Zou et al., 2019)

4. Related Work

Jafri et al. (2020) identified a deep neural networks-based face recognition approach to test human face detection with livenessNet. It searches for the position and dimensions of all features belonging to a class called a face. The biggest value of this technique is that it is extremely precise and can be carried out in real-time. Open CV is used for the application of this facial recognition technology using deep neural networks. The primary principle of the detection paradigm is frontal face detection. Facial recognition as FPAF (Face Priority Auto Focus) is also represented. The biggest value of this technique is that it is extremely precise and can be carried out in real-time. Gao et al., (2020) suggested Chinese facial ethnicity recognition (CFER) model based on the deep convolution network's transfer learning form. First, 5 Chinese ethnic groups were gathered to create a face dataset containing ethnicity information. They then applied CFER to identify ethnicity characteristics and 10-fold cross-validation methods to approximate the model's accuracy rate primarily. In the meantime, the model's average identification rate is 80.5%, while the model still has strong generalization efficiency. The process of DL is feasible for the identification of facial ethnicity. Ahmed et al. (2020) proposed a comparative analysis using CNN-based models such as VGG16, VGG19, MobileNet, and AlexNet to capture the size of faces from a personalized dataset of (10) identities of various celebrities. With the implementation of transfer learning and Fine Tuning, these pre-trained models previously trained on the ImageNet dataset are used. They used TensorFlow with Keras API back-end written in Python in their experiment. The performance review involves preparation, evaluation, and checking on multiple initial dataset images. VGG19 model validation accuracy is found to be higher than the other three, but better test accuracy was shown by the MobileNet model. Yao (2020) suggested a compact convolutional neural network for face recognition. Their work not only offers a compact basis for DL but also greatly increases the efficiency of face recognition. They use the Caffe toolkit for preparation and rollout in the implementation process. For the conventional face verification pipeline, with 94.8 percent face verification precision on LFW, they accomplished an incredibly successful method. Comparison findings on different face recognition tasks suggest that there is the possible use of the proposed compact CNN structure in face recognition systems. Ruan et al. (2020) suggested a method of scaling the activation values of its training and testing processes, which is conducive to determining the model at one time, and then by adjusting its hold/abandon likelihood will the training and testing process be done on the same model. Experiments demonstrate that this technique can successfully mitigate the issue of overfitting and, to a certain degree, achieve regularization. At the same time, after repeated testing, the accuracy of the test set was increased by 1.5 percent using a specialized face picture database for training. Xu et al. (2020) designed a generalized deep convolutional neural network system that has high robustness for face recognition under limitless conditions. The structure can increase the precision of training speed and face recognition and is ideal for small-scale data sets. Incorporated Siamese Convolutional Neural Networks (IMISCNN) Initiation Module (IMISCNN) is built by implementing the Siamese network layout based on one efficient reduction of external intervention and improved extraction functionality. An acyclical rate of learning approach for improved model integration is also implemented in IMISCNN. PCANet, CNN, and the original SNN, similar to classical facial-recognition algorithms such as PCA, PCA, and SVM. The precision of IMISCNN is 99.36% and 99.21% respectively in the regular face database of CASIA-web face and Expanded Yale B.

Liu et al. (2020) proposes a network FER architecture based on a Sobel-enhanced CNN operator and a combined L2-SVM network. This model applies Sobel edge detection pre-processing steps to the CNN input layer to sharpen the face picture and extract the edge, which essentially improves the edge of the face. It then inputs pre-processed facial expression data to CNN for the extraction of features. Finally, it uses the feature vector performance of the fully connected CNN layer as the input feature of the multi-classifier developed by the L2-SVM, to recognize and distinguish facial expressions that increase the system's recognition efficiency. Kadambari et al. (2019) suggested attendance method using face-recognition. Deep-Learning based identification was favored over the Viola-J face detection algorithm. Face-recognition using DL was applied, and even with the imperfection in the input image given, the best results were achieved. The attendance entries were reported in an excel-sheet to keep track of the attendance of the pupil. It was found from the output of both facial detection methods that, while the results obtained using the Viola-Jones Algorithm are adequate. Perdana & Prahara (2019) suggested a light-CNN to identify faces with a small dataset based on an updated VGG16 model. VGG16 has very deep-layers with many narrow convolution-layers with separate kernels numbers followed by max-pooling optimized for large-scale classification. The planned architecture uses (120 X 120) pixels as the input-image size and has two types of convolutional-layers, followed by max-pooling. Every Convolutionary layer is preceded by the activation feature of the rectified linear unit (ReLU). The proposed light-CNN is small but delivers good efficiency with 94.4% accuracy. Zadeh et al. (2019) suggested a human emotion recognition system. The suggested system uses the Gabor feature extraction filters and then the Classification Convolutional Neural Network (CNN). They used the JAFFE database containing 213 Japanese female model images containing seven face emotional states, of which six modes, face natural states, and regular face are included. The experimental findings indicate that the approach suggested improves both the CNN pace training mechanism and the precision of identification. Wu et al. (2019) suggested a new strategy focused on DL to classify the occluded mask. The face recognition algorithm is trained and learned based on the DL neural convolution network, which has high robustness to the variation in light, change in facial expression, and facial occlusion. The occluded face recognition score will reach up to 98.6 percent through a vast range of laboratory experiments and outcome analysis. The paper thus considers facial detection of occlusion in diverse settings and satisfies the criteria of functional implementations.

In comparing the gray value of the central-pixel and that of the neighbor-hood pixel, which makes partial facial-features missing, the conventional algorithm of LBP does not take into account the role of the central pixel and the interaction between it and the neighborhood pixel. By targeting the above issues, (Hao & Li, 2019) demonstrated the LBP algorithm and introduces a multidirectional function of LBP. The paper finds a new facial textural function by redefining the estimation of the gray-value of central-pixel and the neighbor-hood pixel and designs a seven-layer CNN for the classification of the features to complete detection of facial expression. The test conducts JAFFE verification and obtains an 86.7% identification score, which shows the efficacy and viability of this process. Ziani & Sadiq (2019) suggested an approach to increase the age and gender identification rate based on Shearlet Transform and Deep Convolutional Neural Networks. This is the first time in their experience that shearlets and DCNN are merged in such a system. To ensure a higher recognition performance, the strength of these two strategies is very promising. Khan et al. (2019) proposed A face-recognition system using a Convolutional Neural Network (CNN) which is AlexNet. It is a deeply learned paradigm with many layers. They also conducted this network's transition learning. The network was then educated on their servers. This network was ultimately used for facial recognition. This network needs a broad database for training, but the precision is good. The four different classes in the database were used for instruction. Each class contains 1000 images. Epochs equivalent to 20 and a batch size equal to 10 are the training solutions. 97.95 percent is the precision obtained by training the network using these options. To enforce the framework, they used MATLAB. Liu (2019) suggested Facial Expression Recognition (FER) system by using the fer2013 dataset and an effective deep convolutionary neural network to train an efficient model and then use the Tkinter name tool used by the Graphical User Interface (GUI) to evaluate the image of expression and achieve realistic performance. Also, AlexNet, VGG16, VGG19, and ResNet152 are used. The final research accuracy of the tests was 15.2%, 37.4%, 39.68%, and 48.67% on these networks.

Zhou et al. (2019) suggested a CNN model based on MobileNet's local and global feature fusion to allow good use of feature information of each image layer since the standard CNN would not fuse the information of high and low convolutional layers in the training phase of face photos. After the principal component analysis, the algorithm fuses the local features of the first layer of the network with global features. Therefore, the expression of shallow features is enhanced, the extraction effect of deep features is enhanced, and the data retrieved by the enhanced MobileNet is more accurate. Chen et al. (2019) suggested a Convolutional Neural Networks(CNN)-based approach to achieve a better standard of face recognition on deep images. The IIITD Kinect database experiment shows that the proposed CNN architecture has greater output recognition than certain conventional manual methods of retrieval of features, such as HOG and LBP. The CNN is specifically built for small datasets and can reach an 86% recognition rate. The noise atmosphere is also stable and barely influenced by the Gaussian noise. The proposed CNN is more appropriate in realistic implementation compared to the standard depth face recognition process, both in terms of better recognition rate and robustness. Xie et al. (2019) proposed an idea to block the band for hyperspectral face recognition to maximize the efficiency of band preference. A tiny SI-CNN network is educated in spatial knowledge to obtain discrimination characteristics. Applied to pick multiple optimized bands on separate blocks, the modified AdaBoost. MS algorithm. PolyU-HSFD studies have been conducted. Finally, the methods of hyperspectral face recognition are compared. The findings of the experiment indicate that the suggested hyperspectral facial acknowledgment is preferable to other approaches, the optimum bands of each block differ and may enhance identification. Mocanu et al. (2019) introduced a facial recognition technology based on CNN, the system is intended to enhance the engagement and contact of blind people in social encounters. The VGG16 model and the ImageNet dataset are used. The accuracy of their system is 90% when checked on 30 video sources. Wang et al. (2018) proposed a system based on depth volume and network for detection of facial expression. the paper uses a deep convolutional neural network model to derive facial features and uses the Softmax classifier to identify facial expressions. The algorithm that is used does not need human intervention in supervised learning and offers an automatic method of extraction of features so that the effect found is greater. They conducted and compared tests on the JAFFE and CK+ datasets with other approaches. The experimental findings indicate that this approach is much more successful than other methods of identification of hand-extraction facial features. Deep convolutional neural networks can conduct recognition of facial expressions effectively.

Ke et al. (2018) a facial recognition algorithm based on the combination of LBP and CNN was investigated. The LBP operator was used to get a local coded binary pattern image. Second, the photos were used to practice CNN. The CMU-PIE face database has been used as a benchmark. Experiments have shown that batch size selection could have an effect on the identification rate and that the optimal batch size is 100 for this network. The original network could substantially increase the identification rate of the face. The highest accuracy is 97.65 percent. To improve the identification rate, the network was configured by introducing three layers of batch standardization. Wan et al. (2017) proposed a system focused on (CNN) and subspace learning for facial recognition. As a function extractor, a very-deep CNN architecture called VGG-Face, which was learned from a large-scale database is used to extract the activation-vector of the completely linked-layer in the CNN architecture. Then, to know the sub-space of the activation vectors for face-recognition under multiple samples per subject and single sample for each subject conditions, two types of subspace learning methods are implemented, namely Linear Discriminate Analysis (LDA) and (WPCA). Compact representation (dimensionality-reduction) and performance enhancement are the purposes of applying sub-space learning to the activation vector. Compared with the state of the art approaches, tests on two Face datasets (CMU FERET and PIE) show the usefulness of LDA+ VGG-Face and WPCA+ VGG-Face. Arsenovic et al. (2017) suggested a method of face recognition attendance. The entire process of developing a portion of face recognition by integrating state of the art techniques and DL advances is identified. It is determined that high precision can be obtained with the smaller number of face images along with the proposed augmentation process, 95.02% overall. In an IT organization Five workers volunteered in this study, the system that is proposed was evaluated. The dataset contained their photos. Also, just for training the DNN was this dataset included. When being photographed, the workers took several different roles. To make this method applicable for use in manufacturing. Fu et al. (2017) suggested Guided CNN for solving problems with cross-resolution face-recognition. Their suggested design learns the parallel model on the (LR) ones with special loss functions by advancing the CNN model pre-trained on HR images as a reference. Inside and across image-resolutions, the implemented loss functions enable them to jointly maximize the similarity of photos. They confirmed from their tests that their system outperforms several baseline and recent cross resolution face recognition methods, and robust face recognition extension was also successfully tested. Wan & Chen (2017) proposed a MaskNet module that can be built with current CNN architectures. MaskNet discovers a proper way of adaptively producing various feature map masks for various occluded face images with end-to-end instruction supervised by just the personal identity marks. Intuitively, MaskNet dynamically signals higher weights to the secret units triggered by the facial parts that are not occluded and lower weights to those activated by the facial parts that are occluded. Data set tests consisting of real-life and simulated occluded faces to reveal that MaskNet can effectively enhance the robustness of CNN models in facial recognition against occlusions. Zeng et al. (2017) suggested a new approach to solving the problem of face-recognition(FR) with a Single Sample Per Person (SSPP). Firstly, for SSPP FR, a novel expanding sample approach is proposed. Secondly, it implements a well-trained (DCNN), then the expanding samples are used to fine-tune the (DCNN) model. Finally, the AR face database is used to test SSPP FR's accuracy on the fine-tuned DCNN model. Experimental findings indicate that the approach proposed achieves some higher illumination and expression detection rates than the second in session two and also achieves the highest accuracy on all AR face database images. Li & Zhu

(2016) proposed a framework for smartphone face recognition. First, using images from the YouTube Faces collection, they trained the neural network and then used the model to extract the human face attribute from the picture captured by a smartphone, eventually measuring the resemblance using Cosine Similarity and returning it to the mobile phone. The findings indicate that on the mobile phone, the suggested strategy is quick and easy to accomplish. The faces used for the training model shift in voice, posture, lighting, and other situations in a limited range, but it is not completely unregulated, which inevitably decreases the comfort of cell phone face recognition.

5. Comparison and Discussion

After reviewing some papers the used datasets, methods, architectures of CNN, and achieved results in 15 new papers are summarized in table1:

Table.1 Comparison Table of Related Work

Ref	Datasets	Methods	Architecture	Accuracy
(Gao et al., 2020)	Chinese multi-ethnic face	SGD with momentum combined	VGG16	80.5%
(Yao, 2020)	CASIA-Webface and LWF	PCA,DCT,	VGGnet	94.8%
(Jafri et al., 2020)	Video record	LBP,SVM	LivenessNet	98.5%
(Ruan et al., 2020)	SWUNs	Dropout	Lenet-5	98.4%
(X.-F. Xu et al., 2020)	CASIA-Webface, Etended Yale B	PCA,SVM, PCANet	IMISCNN	99.36% for CASIA-Webface, 99.21% for Extend YaleB
(S. Liu et al., 2020)	CK+, JAFFE	SVM	VGG11	94.81% for JAFFE, 95.96% for CK+
(J. Chen et al., 2019)	IIITD kincet	LBP,HOG, KNN	AlexNet	86%
(Khan et al., 2019)	GreyScale Image	Haar-cascade	AlexNet	97.95%
(Hao Li & Li, 2019)	JAFFE	LBP	AlexNet	86.7%
(Zhou et al., 2019)	LFW,CASIA-Webface	PCA	SqueezeNet, ShuffleNet, MobileNet	CASIA LWF 93.12% 93.57% 94.28 % 95.13% 95.12% 95.78%
(Perdana & Prahara, 2019)	ROSE-Youtu	SGD	VGG16	94.4%
(Hao Li & Li, 2019)	JAFFE	LBP	AlexNet	86.7%
(Xie et al., 2019)	PolyU-HSFD	AdaBoost,SVM	SI_CNN	88%
(Mocanu et al., 2019)	ImageNet, WIDER	ATLAS	VGG16	90%
(Ke et al., 2018)	CMU-PIE	LBP	VGGnet	97.65%

In the above table it has appeared that each paper had used different methods, architecture, and datasets such as (SGD, LBP, SVM, PCA, Haar-cascade, Dropout) and (AlexNet, MobileNet, VGG16, SqueezeNet, ShuffleNet, LeNet, IMISCNN) and (CASIA-web face, ExtendYaleB, LFW, IIITDkincet, etc) respectively. The result was that the most used architecture and methods were AlexNet and SVM, PCA, LBP respectively. PCA which is used for feature extraction and dimensionality reduction and SVM used for classification. in (Yao, 2020) PCA method has been used to implement convolution filter parameters and feature extraction also, CASIA web face and LFW datasets are used and the accuracy reached 94.8%. Also, In (Zhou et al., 2019) PCA is utilized by using different CNN architectures and different result was showed for each architecture. The accuracy of the SqueezNet model for CASIA web face dataset is 93.12% and for LFW is 93.57%, the accuracy of the ShuffleNet model for CASIA web face is 94.28% and for LFW is 95.13%, the accuracy of the MobileNet model for CASIA web face is 95.1% and for LFW is 95.78%. in (X.-F. Xu et al., 2020) both SVM, PCA are used and CASIA web face, ExtendYaleB are used, the accuracy for CASIA web face is 99.36% and for ExtendYaleB is 99.21%. In the end, it was proved that PCA and SVM were the best among others for feature extraction and classification.

6. Conclusion

This paper aimed to review a significant number of papers to cover recent innovations in the field of facial recognition. Current research demonstrates that new algorithms need to be built using hybrid soft computing techniques such as PCA, SVM, LBP, and HOG that produce better results for improved face recognition. In addition, it was obvious that the best algorithms for facial feature extraction and classification are PCA and SVM respectively.

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