SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

A Novel Approach for Human Face Extraction and Detection Using SAE-AFB-RFCN Framework

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ARTICLE INFO

Article history:
Received 22 March 2023
Received in revised form 22 August 2023
Accepted 31 August 2023
Available online 25 November 2023

Keywords:
Artificial intelligence; auto encoder; artificial feeding bird; stacked auto encoder; deep learning; region based fully convolutional network; binary cross entropy

ABSTRACT

This research work is carried out with Facial Recognition Technology (FRT), which uses a person's face to identify them, has become a trend topic among scientists. Face recognition relies heavily on feature extraction and classifiers. Occlusion, illuminations, and a complicated background provide the most difficult problems for face recognition systems to overcome. With the advent of Artificial Intelligence and Deep Learning techniques it is become easier to identify different features of an Image and to detect a face. Therefore, a novel approach is developed using Stacked Auto Encoder (SAE), Artificial Feeding Bird (AFB), and Region Based Fully Convolutional Network (RFCN) for human face feature extraction and detection. Initially, the dataset is normalized using rescaling method. Then the Stacked Auto Encoder with Artificial Feeding Birds (SAE-AFB) optimization algorithm is used for facial feature extraction and Region based Fully Convolutional Networks (RFCN) algorithm is used for detection and classification. The WIDER Face dataset is used for training and testing. Experimental results demonstrate that the proposed SAE-AFB-RFCN framework outperforms the existing algorithms in terms of accuracy (96.5%), precision (96.2%), recall (95.4%) and F1-score (94.8%).

1. Introduction

Artificial intelligence with the part of deep learning techniques is used to extract and detect face by the vision of camera in different fields. Human facial features can be used to identify a person using face recognition technology. FRT was created in response to the growing need for data security and is now being used in a variety of fields. Many academics are interested in Facial Recognition Technology since it uses a human face as its recognition target and can reliably identify its user. Face recognition relies heavily on feature extraction and classifiers. In order to achieve a high level of face recognition technology, scientists have used a different way to extract the features of human faces and the relative positions of the nose, eyes, mouth, and chin. A number of popular methods for analyzing facial feature recognition are developed. Face recognition from a computer can be utilized

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https://doi.org/10.37934/araset.34.1.5162

for a variety of additional purposes, including criminal identification, security protection, advertisements [15], and authentication.

A person can be recognized visually, but it is difficult to do with computer vision. Therefore, some pre-processing steps are used for the images in the dataset to acquire accuracy. A gray scale conversion is needed for the images in the database. To detect a face and a non-face region of the image; Viola-Jones algorithms are used to detect a face. Viola-Jones provides a competitive object detection technique in real time application and it is one of the robust algorithms, having high detection rates which can process two frames per second.

Sentiment vibes of a client is predicted through digital image processing techniques using CNN. A large dataset is trained with CNN model to recognize a face. Different facial expressions can be recognized with this model like neutral, angry, fear, happy, sadness, surprise. The CNN model can be developed using OpenCV, Tensorflow, Keras, Pandas, and Numpy using Python library [3]. More complex ML algorithms have replaced more traditional computer vision techniques in recent years for the purpose of face detection occlusion, illuminations, and a complicated background provide the most difficult problems for face recognition systems to overcome. To deal with these problems, a wide range of methods have been presented to improve accuracy. A CNN algorithm for extracting the high-level distinctive features and Multi-Block Local Binary Pattern modules to extract handcrafted features can be fused and passed to a classifier to identify individuals [4].

The objectives are to efficiently detect and to classify the human faces from the given image SAE-AFB and RFCN algorithms are utilized. Stacked Auto Encoder with Artificial Feeding Birds optimization algorithm is used for facial feature extraction and RFCN algorithm is used for detection and classification.

2. Related Works

Face detection and face recognition algorithms are introduced in Ref. [1] are robust and effective, and can be used in real-time video surveillance. Face detection and recognition are all part of a health information management system that includes video image collecting, image preprocessing, and face identification. Occlusion, illuminations, and complicated backgrounds are the biggest problems in face detection. To address these issues, numerous different algorithms have been put forth. The algorithms that are currently available can basically be classified into two categories: feature-based and image-based approaches [10].

Different feature extraction and face recognition techniques have been used in Ref. [2] to construct a CCTV image-based system for recognizing human faces. Face detection, location, extraction, and recognition is all part of the proposed method for acquiring CCTV images. PCA and CNN were used to extract features. More than 40K real-time photos were collected and used for the simulation and performance evaluation of the recognition techniques by applying them to the dataset. Finally, they were able to identify faces with a high degree of accuracy.

As there is complex challenge in the environment to achieve a high rate of facial expression recognition systems [5] has proposed a facial feature extraction and facial recognition system. Data enhancement and is proposed as an important task to locate the range of face target. A hybrid feature extraction is used to extract the features and effective deep learning model is developed to train and test the samples to have a better accuracy.

The authors of Ref. [6] recommend developing a facial recognition system that is fast, scalable, elegant, and affordable. As a starting point, certain feature extraction approaches were used to learn more about the advantages of a face (Image Face). After that, the KNN algorithm is used to determine the degree of similarity between the training image and the test image. When they applied the strategies, they found that the hog algorithm had an 85% success rate compared to other algorithms in their collection of roughly 100 photos of distinct persons.

Emotions are taken as important role for communication in social life [7]. Also, here a method to method was developed called triangulation to extract geometric features to classify six emotional expressions. Eight virtual markers are positioned in subjects face. By the movement of the markers during the facial reactions, the Area of Triangle (AOL), Inscribed Circle Circumference (ICC) and Inscribed Circle Area (ICC) are used to extract features to classify the face expressions. Although it has been demonstrated that face obfuscation (blurring) is successful at protecting privacy, studies on object recognition normally presume access to whole, unobfuscated photos. Therefore, the impact of face occlusion on the well-known ImageNet challenge recognition of faces benchmark was investigated [8].

A metaheuristic called AFB was developed in response to the extremely unimportant behaviour of birds seeking food. AFB is relatively easy yet effective, and it is simple to modify for use with different optimisation issues [9].

In Ref. [11], the mixture of two main component analyses such as Principle Component Analysis (PCA) and Linear Discrimination Analysis (LDA) feature extraction are used. This method uses Euclidean distance classifications for upgrade the efficiency on face-based real-time authentication method. To increase the precision of face recognition, an efficient end-to-end deep model has been carried out [13]. To determine the face target's range, improve the image contrast, and retrieve discriminative features, a combination of four standard feature extraction techniques was applied.

A hybrid approach involving Genetic Algorithms (GA) and Bacterial Foraging (BF) algorithms was proposed for function optimization problems [16]. This method was proposed using four test functions and the performance is analysed based on mutation, crossover, variation of step sizes, chemotactic steps, and the lifetime of the bacteria.

K-mean algorithm [17] was used to analyze the face features. Here the biometric features of the face are extracted at first and then the K-mean method was used to cluster the face features. Finally, the SVM method was used for classification of images.

3. Proposed Methodology
3.1 Overview

In this method, Stacked Auto-encoder with Artificial Feeding Bird Algorithm with Region Based Fully Convolutional Network (SAE-AFB-RFCN) approach is developed for human face feature extraction and detection. Initially, the dataset is normalized using rescaling method. Then the Stacked Auto-Encoder with Artificial Feeding Birds (SAE-AFB) optimization algorithm is used for facial feature extraction and Region based Fully Convolutional Networks (R-FCN) algorithm is used for detection and classification. The WIDER Face dataset is used for training and testing. The block diagram of the proposed SAE-AFB-RFCN framework is shown in Figure 1.

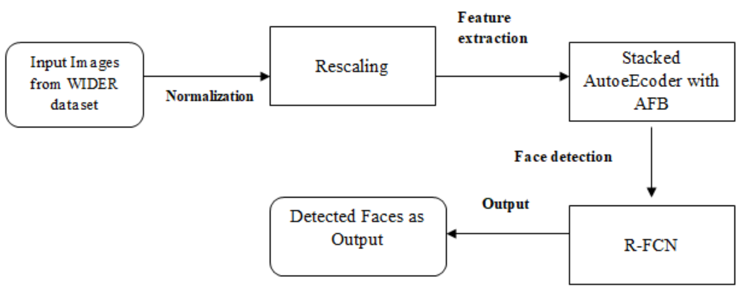

Fig. 1. Block diagram of SAE-AFB-RFCN approach

3.2 Normalization of Datasets

Depending on the data, a few different ways to data normalization exist. Standardization of features such as scaling up or down in units of measure and rescaling. The rescaling method is used to normalize features in this study. Scale each data dimension so that the final vectors fall within the range of [0, 1] or [0 255], depending on the algorithm's requirements. It's helpful for later processing because it allows for an acceptable range of values for many of the default parameters for data. Rescaling a natural image's pixel values from [0 255] to [0 1] is done by multiplying the data by 255.

3.3 Facial Feature Extraction Using Stacked Auto Encoders (SAE)

In this phase, the facial features are extracted using SAE.

3.4 Auto Encoders (AE)

A back propagation algorithm, an Auto encoder is a feature learning algorithm which comes under Artificial Intelligence that employs back propagation to set output values equal to input values. They were developed to aid in the discovery of data structure without the need for labels, hence facilitating unsupervised learning and ensuring that output matched input.

For an input aj, j=1,2...n and bias bi, i=1,2... and weight values Wi,j , the encoding and decoding operations are given by Eq. (1) and Eq. (2), respectively.

$$Encoding: a^{l+1} = f(R_{j-1}^{n} W_{ij}^{l} a_j^l b_i^l) \tag{1}$$

$$Decoding: a^{n+l+1} = f(R_{j-1}^{n} W_{ij}^{(n-1)} a_j^{(n+1)} b_i^{(n-1)}) \tag{2}$$

In Eq. (3), the activation function f(x) is a sigmoid function with output range [0 1].

$$f(x) = \frac{1}{1+e^{x}} \tag{3}$$

Pretraining: Learning useful features begins with AE's Cost function, which has a crucial role to play. There are three parts to it: Average sum-of-squares error, weight decay, and the sparsity penalty are all factors to consider.

Let (x, y) = (x, y) = ($x^{(1)}$, $y^{(1)}$), ($x^{(2)}$, $y^{(2)}$), ($x^{(k)}$, $y^{(k)}$) denote the k training samples for a given weight vector W and bias b, the computed output at layer L is denoted by Eq. (4)

$$S_{w,b}(x) = f(R_{i=1}^{3} W_i x_i + b) \tag{4}$$

Then the cost function is given by T (W, b: x, y).

Average sum-of squares error term: It is a way to quantify the difference between what is actually being seen and what is expected, or what is estimated. Backpropagation is used to modify the weights. According to the formula in Eq. (5), this works out like

$$J(W, b, x, y) = \frac{\#1}{m} R_{j=1}^{m} \frac{1}{2} \, ||hw, b\ (x) - y||^2 \tag{5}$$

Weight decay term: To penalize the error function, it's employed. As a result, the risk of over-fitting is reduced by using this phrase. According to Eq. (6)

$$J(W,b,x,y) = \frac{\#1}{m}\ R_{j=1}^{m} \frac{1}{2}\ ||hw, b\ (x) - y||^2 + \frac{m}{2} R_{j=1}^{n-1} R_{i=1}^{\$} R_{j=1}^{\$+1} (W_{ji}^{l})^2 \quad (6)$$

Sparsity penalty: With this constraint in place, concealed units can only be activated a limited number of times, allowing researchers to identify data's underlying structure. The following is the final tally.

$$J(W,b,x,y) = \frac{\#1}{m}\ R_{j=1}^{m} \frac{1}{2}\ ||hw, b\ (X) - y||^2 + \frac{m}{2} R_{j=1}^{n-1} R_{i=1}^{\$} R_{j=1}^{\$+1} (W_{j,i}^{l})^2 \quad (7)$$

In Eq. (7), K denotes the different classes of training label y.

It's critical to pre-train each layer in order to speed up feature learning and make the model substantially more computationally powerful. In AE, each layer will have its own pre-training stage. Phases include the following:

i. Initializing weights: The primary goal in pre-training is to keep the training costs as low as possible (J (W, b)), and one way this can be accomplished by setting the weight and bias parameters (W, b) as small near-zero values based on their respective values of W and b. now minimize the cost function to optimize the parameters, J (w, b).
ii. Optimization of cost function: In order to minimize the cost function, optimization has to be applied. In this work, the Artificial Feeding Birds (AFB) [12] algorithm has been applied for optimization of cost function, which is explained in the next section.

3.5 Optimization of Cost Function using AFB Algorithm

A bird's metaheuristic eating behavior has inspired Jean-Baptiste Lamy. An artificial bird is used as a multi-agent system. When solving an optimization problem, all the birds' positions represent possible solutions. Additionally, each bird remembers the best place that he or she found, i.e., the solution that minimizes the best costs. “Fed” status is given to birds if their present posture is better than their previously learned position. Cycles are performed by the metaheuristic.

Explorations as well as exploitation are the two fundamental search behaviours used by swarm intelligence in general and metaheuristic techniques in specific. Exploitation refers to the search of the immediate vicinity of a promising zone, whereas exploration relates to the discovery of uncharted area of the viable region.

Each bird in the cycle performs one of the previously outlined four manoeuvres. A bird's next move is determined by whether he flew or walked in the previous cycle. The bird walks if he has eaten during the previous cycle. A random selection is made from among these options, with varying probabilities attached to each one.

Small and large birds were also taken into consideration. Performing move 4 and joining another bird (small or large) is only possible for huge birds. Although this criterion does not exactly match our observations, it effectively prevents all birds from becoming trapped in a local minimum.

3.6 Sparse Auto Encoder (SAE)

Multiple layers of sparse AEs make up SAE, an unsupervised learning algorithm from Artificial Intelligence in which the outputs of one layer feed into the input of the next. SAE is broken down into the following steps:

i. Sparse Auto Encoder (SAE) is a great tool for training the initial layer of a neural network.
ii. Train the second layer using the output of the first layer. Freeze the first layer parameters.
iii. If needed, repeat this process for an infinite number of layers and use the final layer as input to a supervised soft-max regression.
iv. Fine-tune the entire network by releasing all weights.

The SAE is shown in Figure 2. Layer-wise pre-training is widely used in SAE training to extract the best features from the network; fine-tuning will integrate all layers and do forward propagation to slightly tweak the network features and adjust the boundaries between the soft-max regressions in order to increase performance.

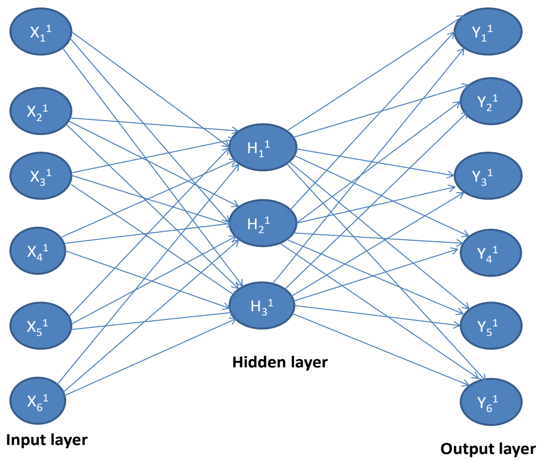

Fig. 2. Process of SAE

3.7 Region Based Fully Convolutional Networks(R-FCN) Based Classification

An artificial intelligence technique, with convolutional neural networks has a high level of classification accuracy, using the region-specific operation method directly on FCN results in poor detection performance. Instead, R-FCN [18] is being considered as a solution to this issue. Reducing the number of regions used to balance the learning of classification and detection is one of the main advantages of RFCNN over R-CNN-based approaches.

3.8 Basic Components of R-FCN

Figure 3 shows the architecture of R-FCN and its basic components are briefly explained below:

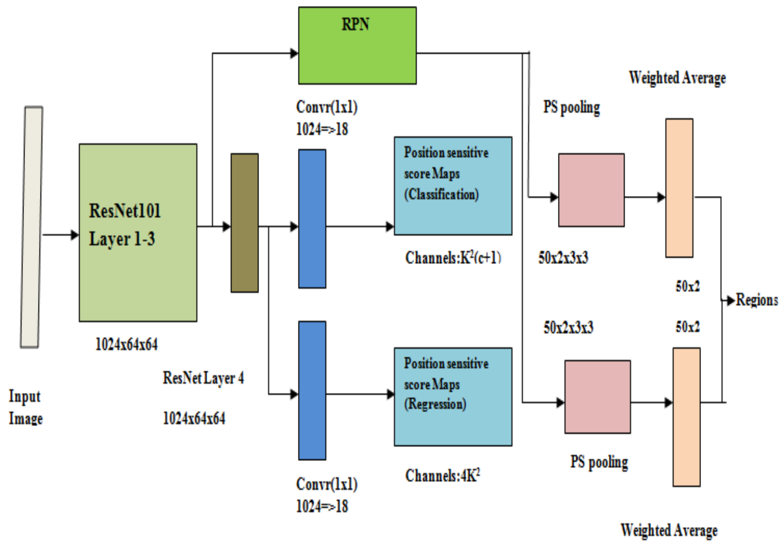

Fig. 3. R-FCN Architecture

3.9 Region Proposal Network (RPN)

The Region Proposal Network is responsible to generate regions which may contain faces as a part of the image foreground. These shall later be evaluated and pruned. The RPN has a proposal layer which generates Regions of Interest (ROIs) and an Anchor Target Layer (ATL) which helps evaluating these regions using loss functions.

3.10 Proposal Layer

The Proposal layer is responsible for generating the proposals for a given input image. The layer generates anchors for all positions in the features of the image and keeps only the top 2000 anchors. These are the initial proposals.

3.11 Anchor Target Layer (ATL)

The ATL is responsible for generating targets for regression loss calculation. This layer generates anchors similar to the Proposal layer. Based on overlap with the ground truth boxes, hard positive and hard negative are passed for regression loss calculations and classifications. All remaining positions are labelled and not considered for losses.

3.12 Proposal Target Layer (PTL)

The PTL is used while training the end-to-end model to help the model learn better ROI examples by adding the Ground Truth boxes along with the generated ROIs of the RPN.

3.13 Position Sensitive Pooling Layer (PSPL)

The PSPL pools the position sensitive score maps which are generated by the R-FCN network. The R-FCN algorithm is illustrated below:

Algorithm 1 R-FCN pipeline

INPUT: Image
RESULT: Regions with faces
1: features $\leftarrow$ extractor(INPUT) .
Features @ RESNET Layer 3
2: ROIs $\leftarrow$ region proposal(features)
3: scores $\leftarrow$ compute scores(features)
4: ps_scores $\leftarrow$ Conv(scores)
5: R $\leftarrow$
6: for all roi ϵ ROIs do
7: for all P ϵ PATCHs do
8: P_i $\leftarrow$ argmax(ps_scores[C * i : C * (i + 1)]) .
C, i: Classes, position
9: Q $\leftarrow$ vote(P)
10: R $\leftarrow$ R U regression[Q] .
Location and Dimensions for Q
11: return R

3.14 Average Pooling Layer (APL)

In most of the RFCN [14] architectures, only global APL has been implemented as they usually predict multiple classes. This operation is awed when faces are involved as different positions of the grid could contribute differently to the overall probability that a face exists in that image.

Usually, the grid locations for the eyes are paid more attention during face recognition tasks. Hence, weights can be applied to each region before getting the average for both the classification and regression position sensitive branches as shown in Eq. (8)

$$y_i = \frac{1}{N^2}\sum_{j=1}^{N^2} w_j x_{i,j} \tag{8}$$

3.15 Classification Loss

It is calculated as the Binary Cross Entropy loss between the labels and the prediction scores obtained from the anchor target layer, as shown in Eq. (9)

$$BCELoss = -(ylog(y) + (1-y)\log(1-y)) \tag{9}$$

In this algorithm, the extracted features are passed as input to the RF-CNN algorithm. Then the corresponding Regions of Interests (ROIs) are determined using the region proposal network (RPN) by generating the regions containing faces as a part of the image foreground. Then the position sensitive scores (ps-scores) for each ROI are obtained. The Pooling layer pools the ps-score maps. An average voting is performed on the output to determine the most probable class (face or no face) for a given region. An additional 3x3 convolution layer is used to act as a learnable weight to increase the performance. Using regression, bounding boxes are drawn for the detected region (face).

4. Experimental Results

The proposed SAE-AFB-RFCN approach is implemented in Python with Anaconda Platform.

4.1 Dataset Descriptions

In this work, the WIDER Face dataset [19] is used, which is the currently the largest face detection dataset. It consists of 32,203 labelled face images with a high degree of variability in scale, pose and occlusion. This dataset is organized based on 60 event classes. For each event class, 40%/10%/50% data are randomly selected as training, validation and testing sets. The images are grouped by their image size into three scales: small (between 10-50 pixels), medium (between 50-300 pixels), large (over 300 pixels). Figure 4 show some of the input images and their corresponding detected faces (annotated in a green box) using the proposed algorithm. The recognizable faces are detected using green bounding boxes which cover the forehead, chin, and cheek.

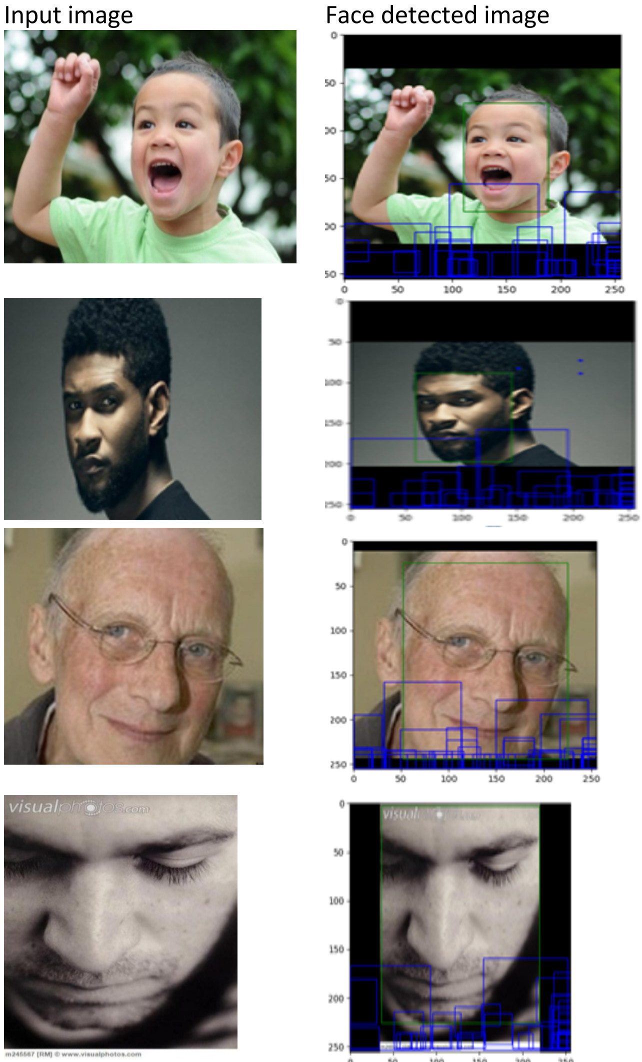

Fig. 4. Detected face images for the input images

Figure 5 shows the loss function against the Epoch values. The training and validation phases are based on the Epoch values and loss function. The iteration with the minimum validation loss will have the optimum weights. The optimum weights will increase the accuracy level to be higher.

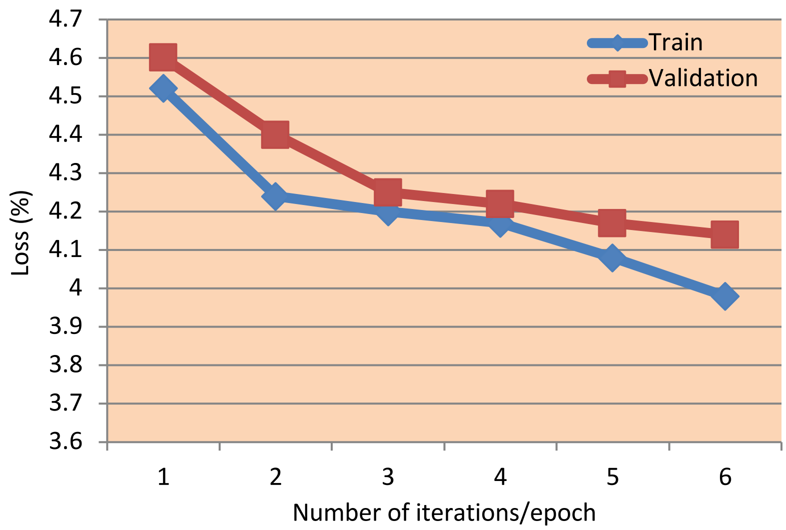

Fig. 5. Loss curves for training and validation

The performance of the proposed SAE-AFB-RFCN framework is compared with AE-Bacterial Foraging Genetic Algorithm (BFGA)-RFCN [20], AE-BFGA and RFCN algorithms. The performance is evaluated in terms of the metrics accuracy, precision, recall and F1-Score. Table 1 show the comparison results of the metrics for these algorithms.

Table 1
Comparison results for various algorithms

Parameters	SAE-AFB-RFCN (%)	AE-BFGA-RFCN (%)	AE-BFGA (%)	RFCN (%)
Accuracy	96.5	95.5	94.6	95.2
Precision	96.2	94.2	93.4	95.1
Recall	95.4	94.7	92.7	94.3
F1-Score	94.8	93.7	92.5	92.6

The accuracy of SAE-AFB-RFCN is 1% higher than AE-BFGA-RFCN and 2% higher than AE-BFGA and 1% higher than RFCN. The Precision of SAE-AFB-RFCN is 2% higher than AE-BFGA-RFCN and 3% higher than AE-BFGA and 1% higher than RFCN. The Recall of SAE-AFB-RFCN is 1% higher than AE-BFGA-RFCN and 3% higher than AE-BFGA and 1% higher than RFCN and the F1-score of SAE-AFB-RFCN is 1% higher than AE-BFGA-RFCN and 2% higher than AE-BFGA and 2% higher than RFCN.

4. Conclusion

In this method, SAE-AFB-RFCN framework is developed for human face feature extraction and detection for the field of Artificial Intelligence. Initially, the dataset is normalized using rescaling method. Then the Stacked Auto-Encoder with Artificial Feeding Birds (SAE-AFB) optimization algorithm is used for facial feature extraction and Region based Fully Convolutional Networks (R-FCN) algorithm is used for detection and classification. The WIDER Face dataset is used for training and testing. The performance of the proposed SAE-AFB-RFCN framework is compared with AE-BFGA-RFCN, AE-BFGA and RFCN algorithms. The performance is evaluated in terms of the metrics accuracy, precision, recall and F1-Score. Experimental results demonstrate that the proposed SAE-AFB-RFCN framework outperforms the existing algorithms with accuracy (96.5%), precision (96.2%), recall (95.4%) and F1-score (94.8%). However, all samples from a single image may be correlated (i.e., have similar features), it may take a long time for the network to attain convergence. Therefore, in future work more accurate and efficiency methods can be developed by hybridizing various CNN methods for classification.

Acknowledgement
This research was not funded by any grant.

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