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An Exploratory Model for Face Recognition Problem in Autism: An Artificial Neural Network Approach

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Abstract

Studies have shown that individuals with Autism Spectrum Disorder (ASD) tend to gaze aversion during social interaction. It also has been observed that autistic people have significant problems in performing social tasks, including face recognition. Researches emphasize the role of face gaze, especially visual communication in social interaction and learning. In this paper, we propose an Artificial Neural Network (ANN) to model the ASD's deficiency in face recognition. We used Olivetti Research Laboratory (ORL) face database and chose pictures which fitted our desires. The ANN was trained and tested in three trial experiments; in the experiment 1 (*exp. 1),* we used pictures with up-masked faces (the upper half of the faces had been blurred) in order to model ASD's face recognition problem, in the experiment 2 (*exp. 2),* pictures with normal pictures was used for simulation normal individuals' face recognition; and in the experiment 3 (*exp. 3)*, we used pictures with down-masked faces as a test group. Testing results show 20.00% error in the *exp. 1*, 4.44% error in the *exp. 2*, and 10.00% error in the *exp. 3*. Based on these results, the proposed network emphasizes the face recognition problem in ASD as a result of eye contact aversion.

Keywords: Autism; Face Recognition; Eye Contact; Artificial Neural Network.

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1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition which causes various impairments in social life. Autism has several basic symptoms: Deficit in social-emotional contexts, nonverbal communication impairment, problem in developing a relationship and repetitive behavior. These symptoms together cause severe problems in everyday life of an autistic person (Lohr & Tanguay, 2013). One of the foremost problems in nonverbal communication impairment is the ASD individuals' tendency to eye gaze aversion (Hutt & Ounsted, 1966; Joseph & Tager-Flusberg, 1997; Kasari, Sigman, & Yirmiya, 1993; Klin, Jones, Schultz, Volkmar, & Cohen, 2002; Neumann, Spezio, Piven, & Adolphs, 2006; Pelphrey et al., 2002; Phillips, Baron-Cohen, & Rutter, 1992; Volkmar & Mayes, 1990).

There are lots of studies for eye contact abnormality in autistic people using the eye tracking technology (Boraston & Blakemore, 2007). It has been observed that normal adults have particular gaze pattern mainly on eyes while individuals with autism show a smaller percentage of time examining core features of the face, especially eyes and nose (Pelphrey et al., 2002). Reduced salience in eyes while there is increase mouth saliency was the fixation pattern which has been observed in ASD adults (Klin et al., 2002; Neumann et al., 2006; Osterling, Dawson, & Munson, 2002; Pelphrey et al., 2002).

There is plenty of evidence suggests that the eye contact abnormality has significant effects on initiating and developing a social interaction (Mirenda, Donnellan, & Yoder, 1983; Mundy, Sigman, Ungerer, & Sherman, 1986; Swettenham et al., 1998).

Moreover, studies have indicated that the Face Recognition(FR) in ASD individuals is impaired (Weigelt, Koldewyn, & Kanwisher, 2012). However, the exact reason for this deficiency is not quite clear. Some studies claim that the FR problem in Autistic people is the result of poor eye contact since eye region is an informational part for the face and emotion analysis (Goldstein & Mackenberg, 1966; McKelvie, 1976; Sergent, 1984; Tanaka & Farah, 1993). Joseph and Tanaka (2003) showed that autistic individuals only have intact FR when the task is dependent on mouth area and not related to the eyes (Joseph & Tanaka, 2003). In another study, "Bubble" method was used in order to identify the regions of the face that autistic people use to recognize facial expression (Gosselin & Schyns, 2001). The results suggested that adult with autism use subject's mouth area for the FR rather than eye region (Langdell, 1978; Neumann et al., 2006). These studies together claim that FR impairment in ASD individuals derives from eye contact aversion.

FR is an important ability in initiating and responding to joint attention and is a key factor in most social interactions. Since there is controversy exists over the main reason of FR deficiency in Autism, we decided to choose this task to analyze a deficiency in the autistic social life. Modeling is a powerful tool that helps researcher to find the proper reason for a specific case that is happening. Lack of computational model representing FR impairment related to eye gaze aversion in autistic individuals, led us to design a model using Artificial Neural Network (ANN) to better understand their social interaction deficits.

Artificial Neural Network (ANN) is a computational model, which is inspired by the human brain. Because of the adaptive nature of these networks, they have a successful background in the pattern recognition tasks. For example, FR as a pattern recognition task can be implemented using Artificial Neural Network. Al-Allaf et.al presented a face recognizer using four feed forward ANN models (Al-allaf, Tamimi, & Alia, 2013). The aim of FR task is to find a match for an unknown face image in a trained

image database of faces (Revathy & Guhan, 2012).
Regarding autism researches using ANN, Cohen presented an ANN which is analogous to the learning system in autism. This model generates testable hypothesis about learning system and treatment for ASD (Cohen, 1994). Another ANN application in autism is modeling attention shifting between the sources presented by Gustafsson et.al (Gustafsson & Papliński, 2004).
In this paper, we used an ANN in order to model the FR of ASD and compare it with two test groups. The main idea of this study is investigating the eye contact deficiency effect on face perception capability of autistic individuals. For this purpose, we designed an ANN to model the FR task. In the first experiment (exp. 1), we tested and trained the network with a group of up-masked pictures to model ASD's FR. In the second experiment (exp. 2), we used pictures of not-masked faces as normal FR modeling. Since it would come to mind that certainly, half of the face has less information than the whole face and it is obvious that training the whole face would lead to much better performance, we designed another experiment as a test group which uses down-masked faces to examine this suggestion (exp. 3).

2. Methods

Artificial Neural Network is a popular method for modeling different kinds of brain functions. Artificial Neural Networks (ANNs) are powerful tools that provide this possibility to model different kinds of procedures. They are vastly used in simulation of human learning. An Artifical Neural Network is a set of nodes which are connected to each other with weighted edges. It has been inspired by neurons in the human brain and the learning procedure of human being.
An ANN has input layer, several hidden layers and an output layer; each layer contains several nodes. The input layer get the input data that supposed to be learned by the network. By "learning", we mainly mean finding a pattern and gaining the ability of generalizing that pattern to new data. The learning procedure happens in the hidden layers. These layers contain weighted connections between input and output nodes. During training phase, based on the given input and desired output, the ANN adjust hidden layer weights in a way that a specific input would produce a specific output. This adjustment is called learning. At the end, network's performance and capability will be shown as a response to new data called testing data.
We chose Artificial Neural Network approach for modeling and used Olivetti Research Laboratory (ORL) face database for the training and testing phases. One of the most helpful toolboxes of MATLAB, which was suitable for our purpose, is the Neural Pattern Recognition toolbox (NPRtool). NPRtool designs an Artificial Neural Network based on the given number of hidden layer neurons, the transfer function and other parameters which are the requisites of designing a network. It enables us to train and test the designed network with any desirable data.
Based on the case of learning and its purpose, ANNs have different kinds of structure which are demonstrated in their hidden layers. In this project, we used Scaled Conjugate Backpropagation algorithm as a learning method in face recognition task. The basic idea of backpropagation is to adjust the weights in the negative of the gradient direction. It means that forward simulation is used to adjust the weight of front unit and the signal goes from front to back. However, it turned out that this is not the fastest convergence. In the conjugate gradient, faster convergence is present after a search along

the conjugate direction. Scaled Conjugate Gradient is one of the fastest conjugates method and will result in the convergence and learning in less time.

2.1. Dataset

One of the most reliable face image sources for a FR task is “ORL Database of Faces” which contains a set of face images taken at the Olivetti Research Laboratory (ORL) in Cambridge, U.K. (Olivetti Research Laboratory in Cambridge) The ORL database contains 400 pictures including 10 images from each of 40 subjects in different positions, wearing glasses or not.

In this study, we used 30 subjects (30 different faces) of the ORL database. Some of the subjects in the database have glasses that would be defined as an up-masked images and could interfere with our method; therefore, such faces were removed from the proposed network’s training and testing database. Three pictures of each face were allocated to the training phase and one image was reserved for the testing phase. Samples of training and testing pictures are shown in Fig 1.

(a)

(b)

Fig 1 An example of a subject’s face which is trained and tested (a) Samples of the training phase (b) Sample of the testing phase. We trained three sample images of each subject to the network and tested ANN with another sample image of that subject.

2.2. Model

In order to apply ANN as a pattern recognition network, first it must be trained with some data; this procedure is called *training phase*. During the training phase, neuron weights are set based on an acceptable error. To adjust the FR network’s weights, we require several pictures of each face as the network’s input. The ANN also requires a target vector to specify which picture belongs to what category in order to be trained by adjusting its weights. We assigned a number between [1, 30] to each subject (category) to construct the target vector; we call these numbers as *subject numbers*. After

training, the network is tested with a picture of each face, which has not been used in the training phase (these data are called *test data*). At the end, the network performance is analyzed based on the network's error in response to the test data (the error is called *test error*).
NPRtool divides training input into three subsets called *training*, *validation* and *testing* to increase the neural weight adjustment precision. Over-fitting in machine learning happens when a model's complexity is more than the complexity which is needed and as a result, we would observe a poor performance in simulation we expected. If the model have too many parameters, it might memorize the training data instead of learning its trend and as a result, the model would be incapable of predicting new testing data. . In this situation, the model suffers from the lack of generalization.
One of the solution to this problem is to provide large data set. Another way to avoid over-fitting is to divide the data set into training, validation and testing categories. Training subset would be used to updating network weights and train it. Validation subset is used basically to prevent over-fitting. The error on validation set would be monitored constantly. Normally, this error is decrease during the training phase. Therefore, if this error starts to increase and this increasing continues for several iterations, it is a sign that over-fitting is happening. Thus, we would restore the minimum validation error parameters and weights as the best parameters for trained network.
In the proposed model, 80% of the data are used for the training phase, which includes computing the error gradient and updating network weights. Validation set includes 10% of the original data which prevent the network from over fitting. The remaining 10% are used to test the network generalization. This division is random, so that the network would not be biased ("Classify Patterns with a Neural Network,"). In this paper, we used MATLAB version R2011b (x32). We evaluated the ANN efficiency by using Best Validation Performance which demonstrates the lowest MSE in the corresponding epoch.
The network architecture of this study is a two-layer feed-forward network with a sigmoid transfer function in the hidden layer. Scaled Conjugate Gradient is one of the most popular back propagation methods, which is the transfer function method in our network. The number of input neurons is 10240, equal to the size of each input. The number of hidden neurons is 120, which is obtained by trial and error. The number of output neurons is set to 30, that is the same number as categories. (See Fig 2)

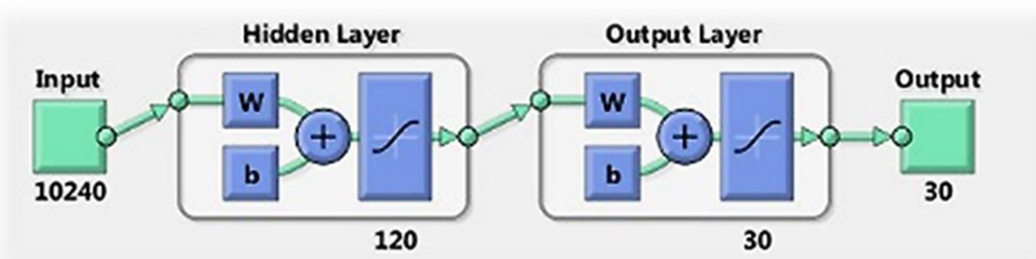

Fig 2 Network Architecture: Input layer includes 10240 neurons that is equal to the size of each input. Hidden layer has 120 neurons, which has been obtained by trial and error. Output has 30 neurons, equal to the number of subjects (categories).

We wanted to find a way to model the ASD individual's eye gaze problem. The idea was to mask the faces' upper half with Gaussian blurring function. Fig 3 shows an example of an up-masked picture. We could remove the upper half of the face or blacken the area; however, blurring has the advantage of not losing the whole information in the upper half which seems to be a more realistic model of the FR.

It is common in the FR research to use a Gabor filter on images before training and testing phases in order to have a biologically plausible model. The reason for using Gabor filter is that J. G. Daugman discovered that the simple cells in visual cortex of mammalian brains can be modeled using this function (Marcelja, 1980). In this study, we used *PhD tool* for constructing and filtering the images (Štruc & Pavešić, 2009, 2010).

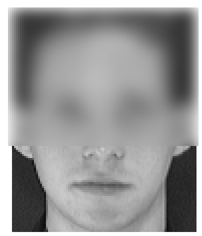

Fig 3 A sample of up-masked face. Upper half of each subjects' face was blurred by Gaussian blur as a model of ASD's FR.

2.3. Training and Testing the Network model

We trained and tested the network in three experiments with different sets of images. In the first experiment (exp. 1) as a model of ASD's FR, three up-masked pictures of each subject's face were trained by the network. Afterward, the network was tested by another up-masked picture of each face. In the second experiment (exp. 2), as a normal FR model, the same training and testing procedure was done using not-masked images. In the third experiment (exp. 3), we trained and tested the network with down-masked images of each. Exp. 3 was designed in order to have a test group for a better interpretation of results.

We did each experiment 10 times and calculate their mean and variances in order to have a more reliable results to evaluate each experiment.

3. Results

To assess each experiment's performance, final gradient/epoch, best validation error, test error percentage and MSE are represented. Note that network's training procedure stops if one of these conditions comes up in the training phase: 1) the gradient becomes smooth 2) the validation error starts to increase 3) the epoch number reaches 1000.

Experiment 1:

In the training procedure of exp. 1, as a model for ASD's FR, the network's training stopped when the mean of best validation error was 0.0194. Best validation error of one trial of exp. 1 is shown in Fig 4. The corresponding gradient error in the same trial is shown in Fig 5.

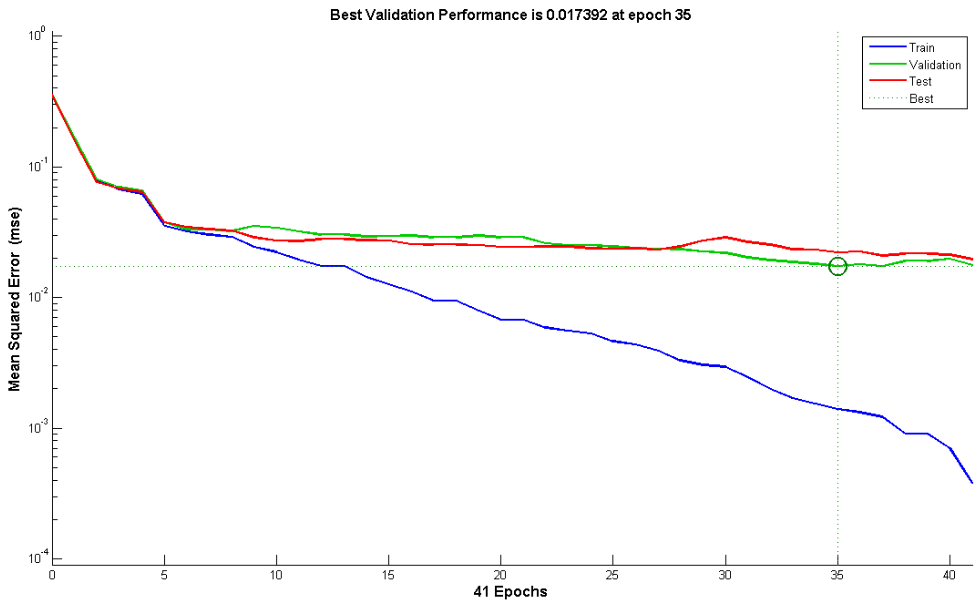

Fig 4 A sample of validation performance in the exp. 1. The best validation performance in this trial was 0.017392 at epoch 35.

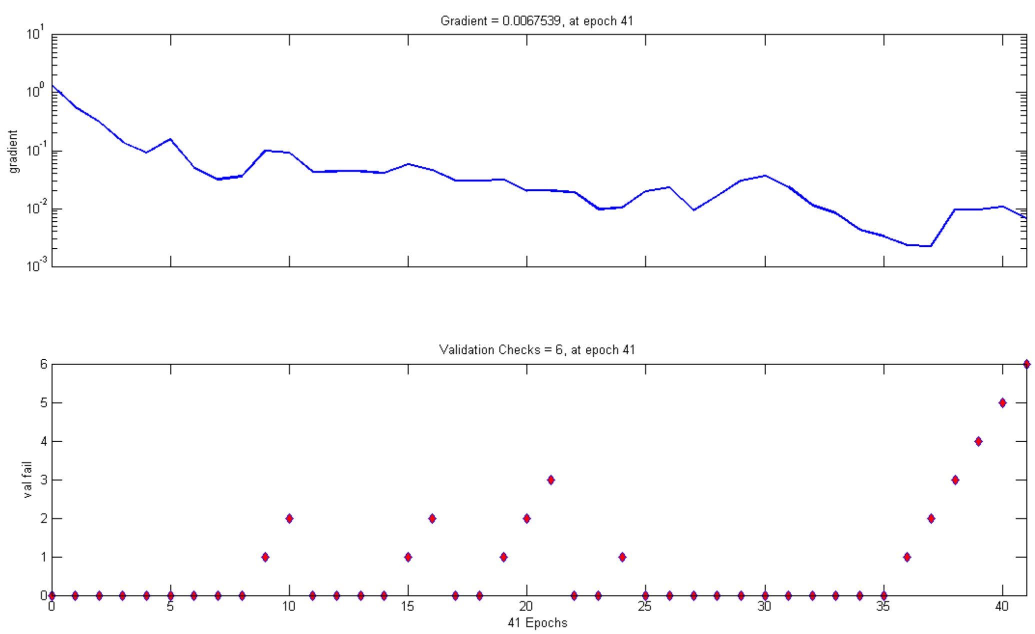

Fig 5 Training state of the same trial of the Fig 4. As we can see in the bottom image, the validation error starts to rise after epoch 35 (the same epoch which was mentioned as the best validation performance in Fig 4). In this trial, the validation error rising was the factor that stopped the training phase; thus, the gradient is not smooth.

In this experiment, we observed a mean of 20.00% test error and 0.0278 MSE.

Experiment 2:
The normal FR model showed a best validation performance equal to 0.015948 at epoch 59. The Best Performance and gradient of exp. 2 are shown in Fig 6 and Fig 7, respectively.

In the exp. 2 the model demonstrated a mean of 4.44% test error in the FR and a 0.0068 MSE.

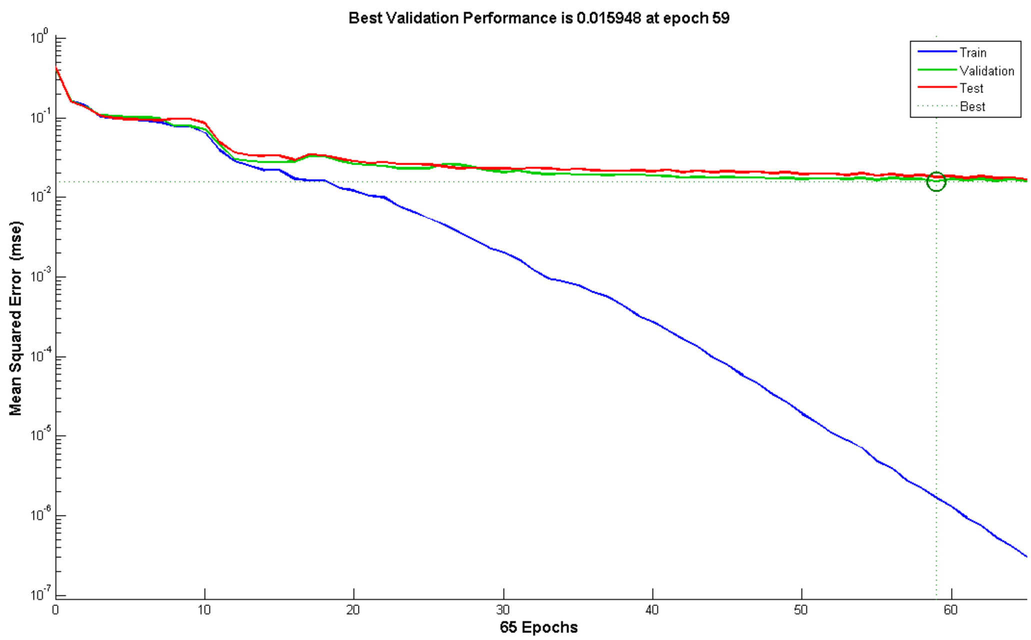

Fig 6 A sample of Validation Performance at exp. 2. The best validation performance in this trial was 0.015948 at epoch 59.

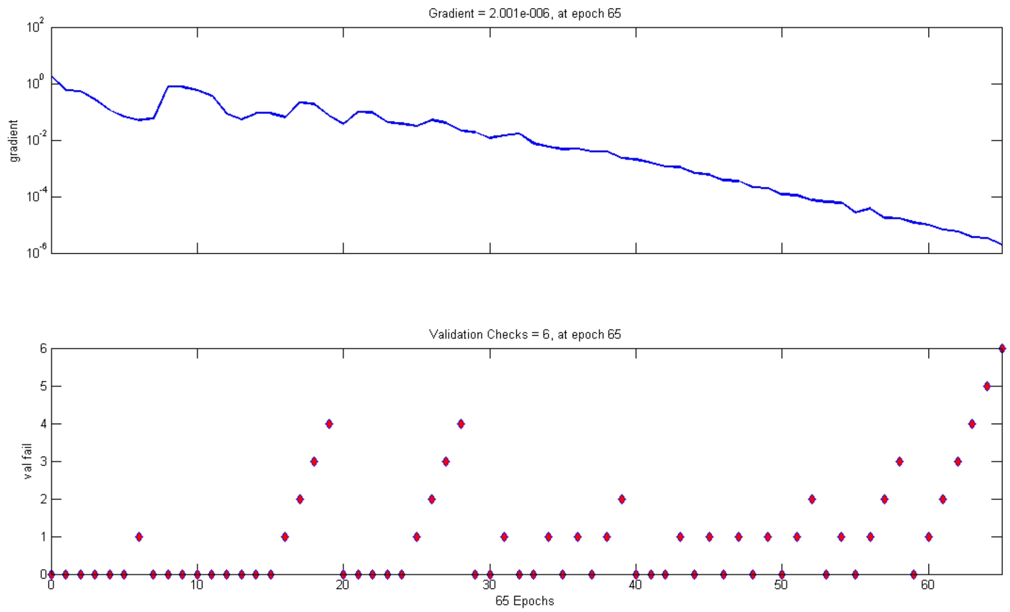

Fig 7 Training state of the same trial of the Fig 6. The bottom image shows that the validation error starts to raise after epoch 59 dramatically (the same epoch which was mentioned as the best validation performance in Fig 6).

Experiment 3:

Exp. 3, which was supposed to be a test experiment, showed MSE equal to 0.015721. The best validation performance is shown in Fig 8. The corresponding gradient is available in Fig 9.

The model in this trial showed a mean of 10.00% test error and 0.0104 MSE in the task.

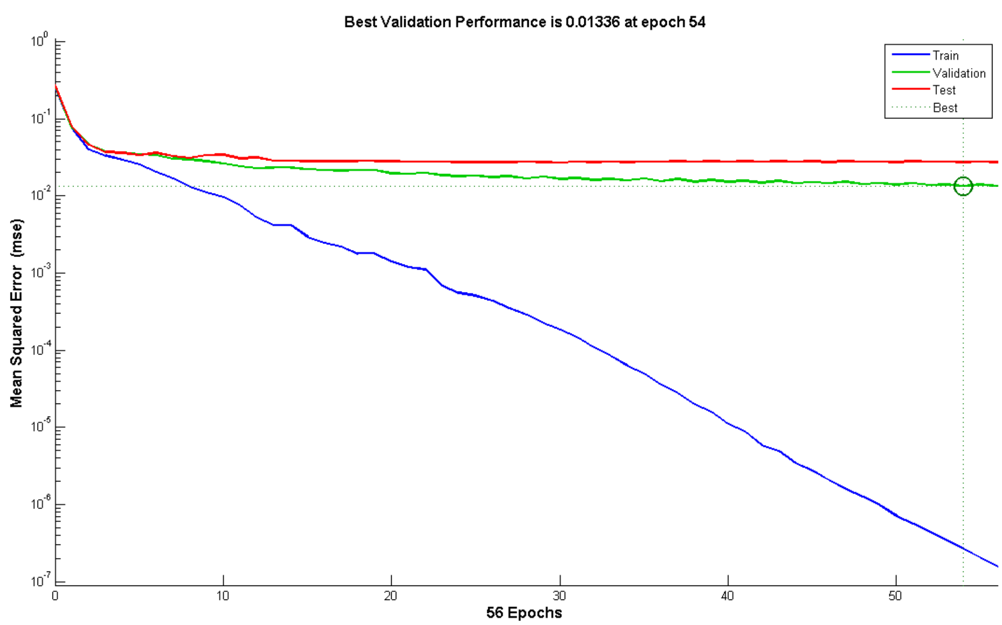

Fig 8 A sample of Validation Performance of exp. 3. The best validation performance in this trial was 0.01336 at epoch 54.

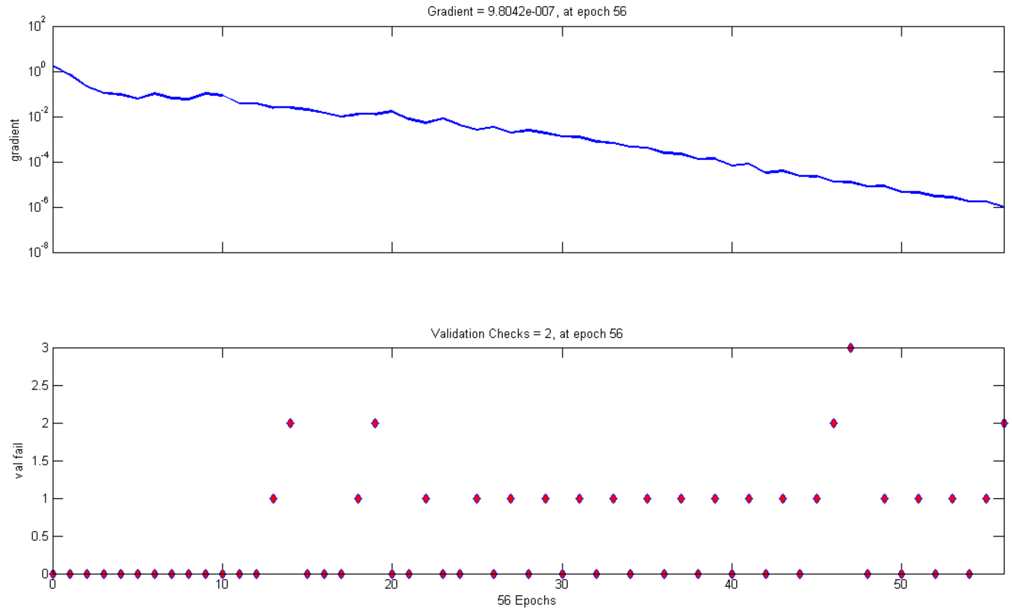

Fig 9 Training state of the same trial in the Fig 8. The bottom image shows that the validation error starts to raise after epoch 54 persistently (the same epoch which was mentioned as the best validation performance in Fig 8).

4. Discussion

Autism is a disorder with several major impairments which make autistic individual's life difficult. One of their foremost deficiencies is their social interaction problem which causes deficits in communication with other people (Lohr & Tanguay, 2013). An important factor in social tasks is FR, which plays a central role in daily interaction. It has been observed that autistic individuals experience difficulty in FR (Weigelt et al., 2012). Since knowing about this deficit's roots would lead us to find some treatment and educational methods for autism, many researchers are focused on probing the main cause of face perception uphill in ASD. The reason for the FR problem in autistic individuals is not quite clear; however, several theories tried to explain the possible causes of face perception deficiency. Several researches have shown that another basic impairment of ASD is eye gaze aversion (Hutt & Ounsted, 1966; Joseph & Tager-Flusberg, 1997; Kasari et al., 1993; Klin et al., 2002; Neumann et al., 2006; Pelphrey et al., 2002; Phillips et al., 1992; Volkmar & Mayes, 1990). It has been observed that during eye contact tasks, the amygdala activity pattern in ASD differs from that of normal people (Kliemann, Dziobek, Hatri, Baudewig, & Heekeren, 2012; Tottenham et al., 2014). The amygdala is mostly related to regulation of fear and anger which helps people to perform different emotions and have a sound social interaction (Adolphs, 2002; Whalen et al., 2001). Since the eye contact plays a significant role in social interaction (Hoffman & Haxby, 2000), some researchers theorize that eye gaze flaw leads to the FR deficit in ASD and as a result, poor social communication are observed in this group of people (Mirenda et al., 1983; Mundy et al., 1986; Swettenham et al., 1998). In another theory, it is suggested that face memory impairment in autistic individuals causes problems in FR task (Halliday, MacDonald, Sherf, & Tanaka, 2014; Weigelt, Koldewyn, & Kanwisher, 2013). A third hypothesis claims that autistic people have a detail-focused processing style named "weak central coherence"; whereby, they are unable to extract global features out of a situation or task such as FR (Boraston & Blakemore, 2007; Happé & Frith, 2006; Watson, 2013). There are several studies on holistic face perception in normal people and its computational models(O'Toole, 2011; Schwaninger, Wallraven, & Bülthoff, 2004). However, more researches should be conducted regarding the computational modeling of local FR in autistic comparing to the global FR in normal individuals.

Controversy exists over the actual reason of FR difficulty in ASD and it needs to be investigated using different approaches to find a comprehensive explanation for it. Computational modeling is a very powerful and beneficial approach which would help researchers to advance the studies in different areas including autism related researches. The scarcity of modeling approach in the FR deficit in ASD motivated us to choose this path and develop a model for this deficit.

Since eye tracking during the FR task showed eye gaze aversion in autistic individuals (Dalton et al., 2005), we became interested to test the hypothesis of FR flaw in the autism disorder and the role of eye contact aversion in this regard. By testing the aforementioned theory utilizing an ANN, the results may help us to support the idea of the connectivity between eye gaze aversion and FR deficiency in autistic individuals.

In order to model the eye contact aversion, exp. 1 was designed. In this experiment, we blurred the eye region with a Gaussian filter, then trained and tested network with these masked images. Two other experiments were defined for better interpretation of the results. Exp. 2, in which we trained and tested the network with full-face images is a model for a normal FR. It might come to the mind that obviously having the half of the face's data causes higher error compared to the full-face data. To refute the validity of the hypothesis that these data reduction is the main cause for the higher mean error in exp. 1, we designed exp. 3, in which the network is trained and tested with down-masked images. The idea of blurring some parts of the face was based on the so-called "blur phenomenon" which states that by focusing her vision on a certain location, an individual experiences a blurred area on other locations which are distant from the focused point (Bittermann, Sariyildiz, & Ciftcioglu, 2007).

The results showed that blurring upper half of the face causes approximately 20% error in the FR task (see Fig 10 or Table 1). On the other hand, exp. 2 and exp. 3 showed 4.44% and 10% test error, respectively. By comparing the results of exp. 1 and exp. 3, it could be concluded that the upper half of the face contains more essential information for an accurate FR. The dramatic difference between exp. 1 and exp. 2 can also support the theory that eye region has a key role in the FR task.

As an overview, based on our model and previous researches such as (Cohen, 1994; Gustafsson & Papliński, 2004) ANN approach seems to be a suitable way to model and test hypotheses about ASD. Moreover, the relation between eye gaze aversion and FR difficulty in autistic people is in correlation with the suggested model's outputs.

Eye contact is of significant importance in the development of social, cognitive and language skills. Several studies have aimed to teach various social skills such as eye contact to the autistic individuals. Carbone et.al designed an experiment and taught eye contact to the children with autism. This study showed that after proper treatment method for training eye gaze to the autistic children, their eye contact response was significantly higher than the baseline (Carbone, O'Brien, Sweeney-Kerwin, & Albert, 2013).

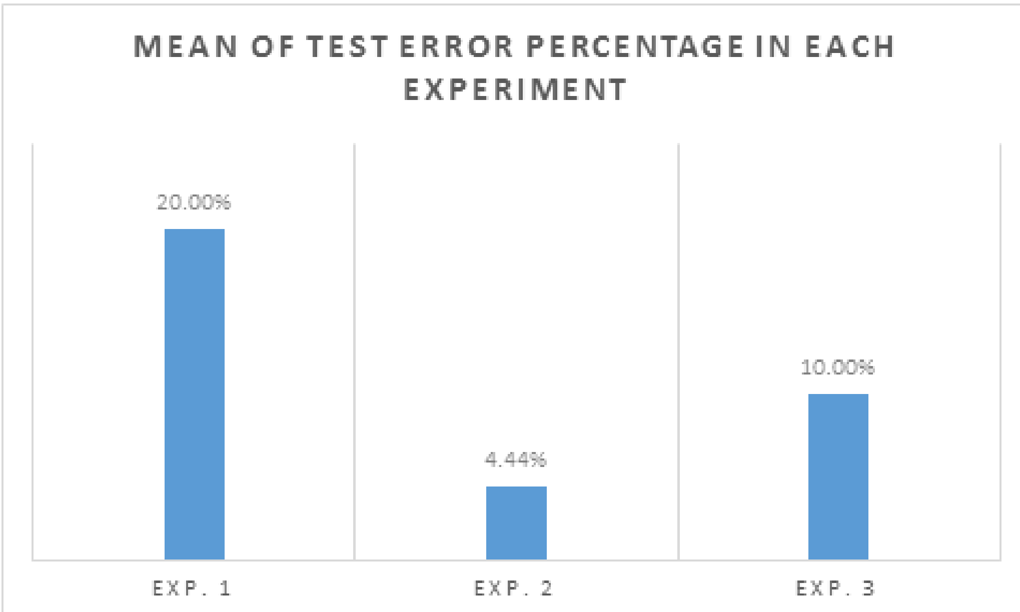

Fig 10 Mean of test error percentage for each experiment: 1) exp. 1 as a model for ASD’s FR shows 20.00% error in the task. 2) exp. 2 as a normal FR has a mean of test error percentage equal to 4.44%. 3) exp. 3 as a control group shows a 10.00% test error in the task.

Table 1 Summary of Three experiments results (mean and variance of Error Percentage(%E), Mean Square Error(MSE), Gradient and Best Validation Error).

Experiment	**%E**	**MSE**	**Gradient**	**Best validation value**
Exp. 1	19.9967 (var=11.1222)	0.0278 (var=0.6221)	0.0069 (var=0.0001e-04)	0.0194 (var=0.0654e-4)
Exp. 2	4.4400 (var=3.6963)	0.0068 (var=0.0062)	0.0007 (var=0.0157e-04)	0.0110 (var=0.1869e-4)
Exp. 3	9.9967 (var=11.1222)	0.0104 (var=0.0007)	0.0061 (var=0.3613e-04)	0.0161 (var=0.0887e-4)

Some researchers claim that holistic processing in FR is necessary, but not enough for the best performance in FR tasks (Watson, 2013). It may be true to say that another important factor in FR, which might complete the holistic approach in a complete FR, is a proper eye contact. In the future prospect, testing the hypothesis of local and global process of FR would be helpful to understand the main reason for ASD's social problems, especially the face perception uphill. Furthermore, the role of face memory in the FR task can be probed using an ANN approach.

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