An Evolutionary-based Neural Network for Distinguishing between Genuine and Posed Anger from Observers' Pupillary Responses

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Abstract: Future human-computing research could be enhanced by recognizing attitude/emotion (for example, anger) from observers' reactions (for example, pupillary responses). This paper analyzes observers' pupillary responses by developing neural network (NN) models to distinguish between genuine and posed anger. Any model's relatively high classification accuracy means the pupillary responses and observed anger (genuine or posed) are deeply connected. In this connection, we implemented strategies for tuning parameters of the model, methods to optimize and compress the model structure, analyze the similarity of hidden units, and decide which of them should be removed. We achieved the goal of removing the network's redundant neurons without significant performance decline and improved the training speed. Finally, our evolutionary-based NN model showed the highest accuracy of 86% with a 3-layers structure and outperformed the backpropagation-based NN. The high accuracy highlights the potential of our model to use in the future for distinguishing observers' reactions to emotion/attitude recognition.

1 INTRODUCTION

With the increase of technology utilization like smartphones and the Internet, computing appears not only as traditional desktop computers but also in myriad applications for the betterment of humans, such as smart classrooms, smart sensing wearables for healthcare, wellness, and sports. Research in human computing is emerging with a particular interest in recognizing, processing, and responding to users' nonverbal cues like emotions (Lim et al., 2020). Users' emotions could be estimated from various reactions such as pupillary response, facial expressions (Hossain and Gedeon, 2017), and speech (Han et al., 2014).

Anger is one of the strongest emotions, and this characteristic makes anger easily felt by others (Kannis-Dymand et al., 2019). However, anger seems to be easily acted out. People are generally poor at distinguishing genuine and acted anger, and their accuracy is only around 65% (Qin et al., 2018). Authors in (Qin et al., 2018) classified genuine and acted anger using pupillary dilation signals in a combination of NNs and crowd prediction techniques, through which they introduced their Misaka networks (collection of multiple NNs, and later their aggregation for the final outcome). (Jin et al., 2020) compared anger veracity classification performance between a fully-connected NN and a long-short term memory network utilizing observers' pupillary responses. They further applied an outlier detection technique to improve performance. Their NN model employed two hidden layers consisting of 20 and 10 hidden units, respectively. Further, they used a dropout layer and a batch normalization technique to prevent overfitting. With a genetic-based feature selection method to select observer's pupillary response features, (Huang et al., 2020) showed a performance improvement of a two-stream NN model having 60 hidden neurons in each sub-stream, followed by another layer for final prediction. Few works (Qin et al., 2018; Jin et al., 2020; Huang et al., 2020) focused on improving performance by incorporating more computational burdens, such as more hidden units, layers, etc. Our contribution is to find out the simplest model possi-

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ble along with preserving a reasonable performance score. We have two specific novel contributions compared to the previous researches above—we further prune our developed simple NN model by removing redundant neurons, and we utilize evolutionary algorithm (EA) training.

Other than anger, there are several works on other emotion / facial expression recognition as well. For example, (Hossain and Gedeon, 2017) classified posed and genuine smiles from observers' peripheral physiology (blood volume pulse, galvanic skin response, and pupillary response), and (Irani et al., 2016) recognized human stress using their facial images. Furthermore, authors in (Han et al., 2014) employed NN to estimate emotional state from speech signals.

In this current paper's scenario, instead of using volunteers' subjective judgment, we use their pupillary responses as an objective discriminating result. We utilize a set of data from (Chen et al., 2017) containing information about perceivers' pupillary response when they were watching genuine or posed anger videos. Consistently, we build up a NN model to train on the collected data. If the model has a good performance, we can say that perceivers can discriminate between the two kinds of anger physiologically and unconsciously. Also, we implement some network optimization and reduction methods according to (Wang, 2018) for improving our NN as good as possible. This good result helps prove people's ability to discriminate posed and acted anger physiologically.

Besides using a usual backpropagation method to train the NN, we also implement an EA to optimize the network. The basic idea of using EA is that the traditional method gives us a model that does not reach very high accuracy. We want to find whether the performance problem can be attributed to the learning being constrained to a local minimum or the best performance of the NN model on this dataset has been reached. Since (Korolev, 2010) showed that EA, as a general method, can have a good effect on multiple-minimum problems, we decided to implement EA. Figure 1 depicts the steps involved in this work.

An EA cannot be used on a classification problem directly. For a NN with a fully-known structure, we can generally regard the collection of all weights and biases in the network as an individual, which means every individual in the population corresponds to one NN with that same structure. After that, we can apply an EA to optimize the individual (NN).

After we train the model, we also want to optimize its structure. The best structure of a NN usually cannot be decided at first (Kowalski and Kusy, 2018). We can initialize a NN with more extra neurons and then reduce its redundancy (Tung and Mori, 2020). Reducing the redundancies is beneficial, but this is difficult to decide which neuron should be removed. One implemented strategy in (Wang, 2018) is to analyze the output from the target hidden layer of the NN and use the analysis result to decide which neurons to be deleted.

2 METHOD

The outline of the technique implemented on the dataset in this paper is divided into three parts. They are explained as follows.

i. Developing a NN prediction model considering observers' pupillary responses: The network is implemented with three layers of neurons with basic techniques, including backpropagation and *cross-entropy* loss function.

ii. Incorporating EA as a substitutional method to optimize the NN model: We apply EA optimization instead of backpropagation training and compare the performance between EA and backpropagation.

iii. Applying an appropriate pruning technique in the NN model for data compression and reduction (Gedeon and Harris, 1992; Wang, 2018): We systematically reduce the number of hidden units from our developed NN model to develop a simple yet effective model.

2.1 Classification of Genuine or Posed Anger

The Anger dataset is collected from the literature (Chen et al., 2017). Before describing specific methods to accomplish the classification task, a detailed inspection of the dataset is given in the following subsection.

2.1.1 Data Inspection

The dataset is utilized to figure out the relationship between humans' unconscious physiological characteristics and the observed anger videos. The experiment where the data comes from asks 20 volunteers to watch 20 videos. Among the 20 videos, there are 10 videos with genuine anger and 10 videos with posed anger. All the videos came from YouTube, and the experiment designer made the videos of genuine anger from documentaries and news, while the posed anger videos were made from movies. All other factors that may potentially influence the volunteers' judgment

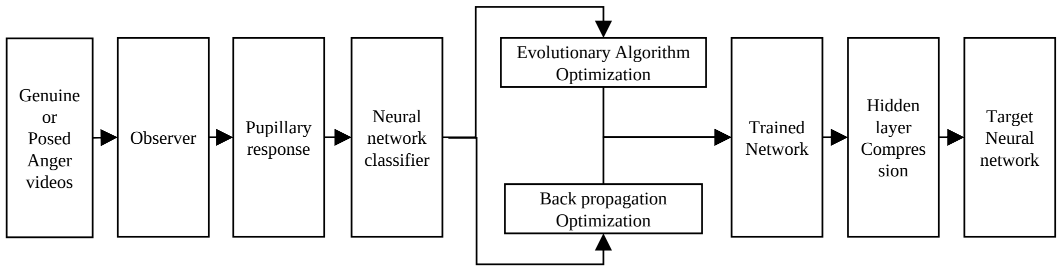


Figure 1: Flowchart to obtain the target neural network architecture either via backpropagation optimizing or evolutionary algorithm optimizing.

are removed as much as possible. For example, the resolution of the videos was kept the same, and the actors in the posed anger movies were not famous. Therefore, the possibility of volunteers knowing the actor and perceiving the acted anger in the movie was reduced. Now, the dataset may seem small. However, a similar work on genuine smile detection from observers' physiological states also collected data from 20 observers watching 19 video samples (Hossain and Gedeon, 2019). Furthermore, they reported accuracy with increasing the number of observers and the number of training videos. Their research reveals that the accuracy did not improve much at around 16–19 observers, and there was no increase in accuracy at all after 14 videos. Therefore, around 16 observers and 14 videos appeared as the minimum number of observers and video samples required for satisfactory performance. Thus, our dataset size having 20 observers and 20 videos is reasonable.

Six features/dimensions were extracted from the dataset. The Mean and the Std refer to the mean and standard deviation of observers' pupillary response. Diff1 and Diff2 refer to the change of observer's left and right pupil size, respectively. Furthermore, PCAd1 and PCAd2 denote the orthogonal linear transformation with the first and second principal components, respectively.

Figure 2 illustrates the density plots of all six dimensions from where we can find some clues, such as different dimensions of data have different distributions when they belong to genuine or posed labels. Five dimensions out of six (except PCAd1) seem to have similar density plots of the genuine and the posed labels, which means they may contribute less to the classification. Only input dimension PCAd1 shows noticeable differences between the two kinds of data. To solve this kind of classification problem, there are some common choices, including k-nearest neighbor (KNN), support vector machine (SVM), and NN according to (Hossain and Gedeon, 2017). However, for this dataset, the difference showed in PCAd1 may not support the KNN and SVM to perform well in classifying the data. Compared with SVM and KNN, authors of (Hossain and Gedeon, 2017) also mentioned that the final accuracy result with the NN was the best on their smile dataset. Thus, we decided to build a NN for this anger classification problem. Accordingly, our developed NN model represents the genuine and posed labels as 0 and 1, respectively.

2.1.2 Data Preprocessing

Table 1 reports the average and standard deviation of the six dimension input patterns, which needs preprocessing. Otherwise, the learning process will be significantly degraded since the Mean dimension can have big weights when the training is in an early phase.

Table 1: The average and standard deviation of six dimensions of input data.

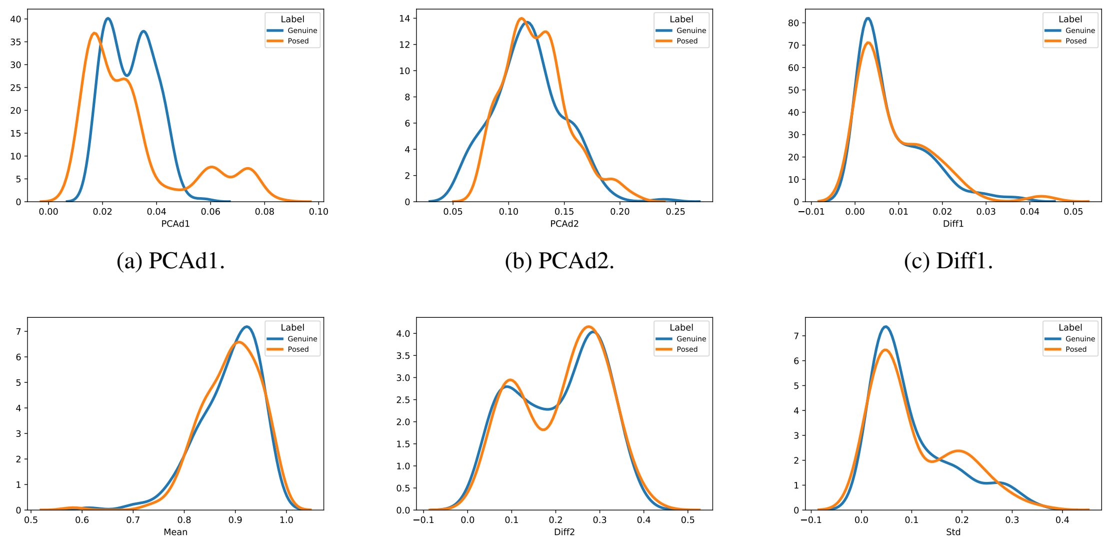
Dimension	Average	Standard Deviation
Mean	0.88909015	0.04603393
Std	0.10246244	0.06934124
Diff1	0.00842139	0.0065422
Diff2	0.20957463	0.08669128
PCAd1	0.03070341	0.01101771
PCAd2	0.12138183	0.0235699

Suitable data preprocessing can improve the performance of data-driven models (Tang et al., 2020). We conduct data preprocessing according to Equation (1).

$$x' = \frac{x - x_{\text{mean}}}{\sigma_x} \quad (1)$$

where, x is the raw data before preprocessing, x_{mean} and σ_x are the mean and standard deviation of x, respectively. The standardized data x' was considered as input in the NN model.

One of the benefits of data preprocessing is speeding up the training process. The Anger dataset takes around 20000 epochs to converge without data preprocessing with the same NN model, optimizer, and loss function. On the other hand, it only takes 5000



(a) PCAd1. (b) PCAd2. (c) Diff1.

(d) Mean. (e) Diff2. (f) Std.

Figure 2: Density plots for different input dimensions of genuine and posed labels.

epochs to converge after the above preprocessing. One interesting thing is that although the learning rate is the same for both cases, the reduction of the training loss for the model without data preprocessing is very little in the first 5000 epochs. After 5000 epochs of training, the reduction comes to a relatively normal speed. This phenomenon implies that the model may consume much time in adapting to the unbalanced data.

2.1.3 Basic Neural Network Model

Except for input neurons, the built network has three layers of neurons with 6, 6, and 1 neuron, respectively. At first, the number of hidden neurons was set to 10; however, it was reduced through systematic performance tests.

The first and second hidden layers use activation function *ReLU*, and the last layer has activation function *Sigmoid* for classification purposes. The loss function is *binary cross-entropy* which fits binary classification problems along with *Sigmoid* function. The optimization method is *stochastic gradient descent (SGD)*.

2.2 Evolutionary Algorithm on Optimizing Neural Network

2.2.1 Coding of Individuals

The target NN, as mentioned above, has four layers with an input of six units, two hidden layers of six units each, and an output layer of one unit. Therefore, to fully store weights and biases of the network, each individual in the population needs to have a length according to Equation (2).

$$\begin{aligned} L = & Units_{input} \times Units_{hidden1} + Units_{hidden1} \\ & + Units_{hidden1} \times Units_{hidden2} + Units_{hidden2} \\ & + Units_{hidden2} \times Units_{output} + Units_{output} \end{aligned} \quad (2)$$

Since the network is fully connected, there are (6×6) weights between the input layer and second layer (i.e., first hidden layer), (6×6) weights between the second and third layers, and (6×1) weights between the third and last layer ((i.e., output layer). Additionally, we have $(6+6+1)$ biases to store. Therefore, the length of the individual code should be 91, consisting of all weights and biases. Individuals should have a form according to Equation (3).

$$X_i^t = [x_{i1}^t, \ldots, x_{ik}^t, \ldots, x_{in}^t] \qquad i = 1, 2, \ldots, N \quad (3)$$

where, x_{ik}^t = real numbers of weights or bias, t = generation of the individual, i = number of individuals, n = number of genes (91), and N = number of populations.

2.2.2 Evaluation Function (Decoding of Individuals)

To evaluate an individual in the population, we extract real numbers from it and assign the real numbers' value to NN parameters.

After assigning the values, we have the new network with weights and biases optimized by the EA. Then we apply the *evaluate_accuracy* method, which is used in the backpropagation optimization to get the accuracy on the whole dataset. Then we take it as the fitness of this particular individual. Accordingly, we need to maximize the fitness function during the process of EA.

2.2.3 Population Initialization

Every individual is initialized by a random number generator that generates 91 real numbers with standard normal distribution. As such, we generate 100 individuals as the initial population.

2.2.4 Selection

We use tournament selection to select the best individuals from the total population, where the *tournsize* parameter is set to three. Therefore, every time, we randomly pick up three individuals from the population and choose the individual with the best fitness to the pool of offspring. The procedure will repeat until the required number of individuals has been selected.

2.2.5 Crossover

We have used *blend crossover* to realize gene transfer in the population.

2.2.6 Mutation

For every gene (real number) in the mutated individual, there will be an independent probability that this gene will change to a random number selected according to the Gaussian distribution with the mean value unchanged. The variance of the Gaussian distribution is set to 0.1, and the independent probability is 0.4.

2.2.7 General Settings

For the EA, we initialize the population as 100 individuals. The crossover probability is 0.8, the mutation probability is 0.4, and we set the algorithm will run for 800 generations.

2.3 Compression on Hidden Layer

After implementing a NN classifying genuine and posed anger and using an EA to optimize it, we want to address the problem that if the 6, 6, 1 layer structure of the network has some redundancies. So, we conduct the following analysis and techniques to reduce the hidden layer units of the trained NN.

2.3.1 Distinctiveness Analysis

This analysis is towards the activation matrix, which is the output matrix of a particular layer of neurons when all training input enters the model. Every column of the matrix is a vector that corresponds to a neuron. Thus, we can analyze the distinctiveness between units according to these vectors. The steps implementing this analysis are shown below:

i. We calculate the activation matrix for the hidden units in the layer to be analyzed, which is the second hidden layer.

ii. We know that every column in the activation matrix corresponds to one hidden unit's output. Thus, by analyzing the similarities between these columns, we can get the distinctiveness of hidden units. We use *cosine similarity* (Equation (4)) to measure distinctiveness.

$$cos\_similarity = \frac{V_i \cdot V_j}{\|V_i\| \cdot \|V_j\|} \tag{4}$$

where, V_i and V_j are the i^{th} and j^{th} column vectors of the activation matrix.

iii. For every two hidden units in the second hidden layer, we analyze their similarities. Then we record the most similar two units' index i and j.

2.3.2 Pruning Network

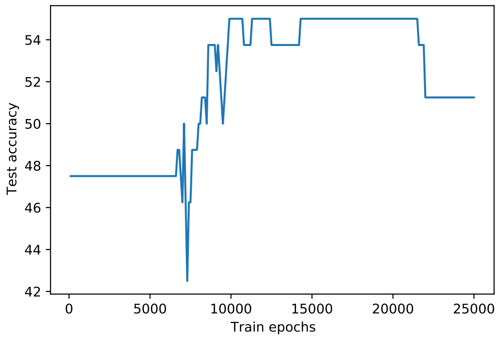
After finding two similar hidden units, we deleted the first unit and added its weights and bias to the second unit. We delete one of the most similar two hidden units in the second hidden layer whenever we prune the network. Then we fine-tune the network with 1000 epochs using backpropagation training.

3 RESULT AND DISCUSSION

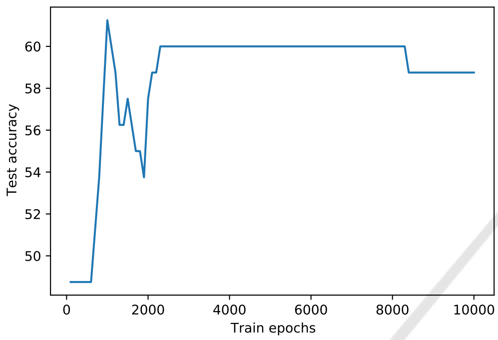
3.1 Neural Network and Its Basic Optimization

At first, the model is trained with not-preprocessed data. After training several times with different learning rates, and finally at 0.05 with a momentum of 0.8, the best test accuracy is not higher than 55% as shown in Figure 3a. First useful optimization is to change the activation function from *ReLU* to *tanh*. After using *tanh* as the first two layers' activation function, test accuracy can reach around 58% as Figure 3b depicts.

Then the data is preprocessed, and thus the speed of learning is found much higher. After using different activation functions, *ReLU* retrieves the best function position. With preprocessed data, *ReLU* function,

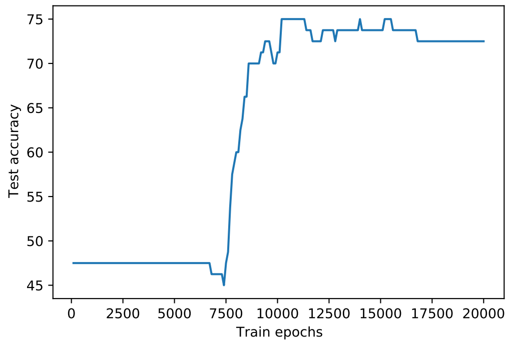


(a) *ReLU*.

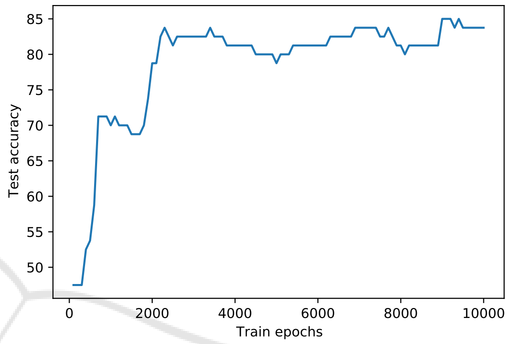


(b) *tanh*.

Figure 3: Test accuracy with not-preprocessed data at two different activation functions.



(a) Learning rate = 0.001.



(b) Learning rate = 0.017.

Figure 4: Test accuracy with preprocessed data and *ReLU* activation function at two different learning rates.

and learning rate of 0.001, the model can achieve the best test accuracy of around 75% (Figure 4a). However, *tanh* does not have a good performance in this case. After preprocessing the data, one of the most important factors of the model which we can tune is the learning rate, and the final progress is made by raising this learning rate. When the learning rate is higher than 0.01 (0.017 in Figure 4b) with a momentum of 0.9, the best test accuracy can reach 85% shown in Figure 4b.

3.2 Evolutionary Algorithm for Optimization

The design of EA for optimizing the NN is presented previously in Section 2.2. The accuracy with that EA optimization is shown in Figure 5.

Since we randomly initialize all weights and biases of the network, the mean accuracy of individuals at initial generation is 50%. Then with the progress of evolution, the best accuracy raises to around 86%. For this optimization method, we can use the best individual in the last generation of the population as the final weights and biases for our NN. Therefore, we can conclude that the EA has trained the model to an accuracy of 86%.

3.3 Neural Network Pruning

While implementing the hidden-layer pruning process, we investigate the influence of pruning hidden units on the model's performance. To demonstrate the pruning process, Figure 6a to 6d shows the accuracy results of the network after pruning one, two, three, and four hidden units, respectively. Without pruning, the network is first trained 10000 epochs of backpropagation. Then every time, we prune one hidden layer unit from the network and train another 1000 epochs.

According to the pruning result, although the network with six hidden units can learn well, there is still space to optimize the model since some hidden units are redundant. When we reduce the number of hidden units to three, the model's performance remains around 90% of its peak. However, when we deleted the fourth unit, the performance declined significantly. Therefore, we can conclude that this model may need at least three hidden units in the hidden layers to learn from data. This analysis supports the conclusion in (Gedeon and Harris, 1992) that when we want to compress an image with a large scaler, the quality will decline because the remaining units in the hidden layer are not enough to store the majority of information of the image.

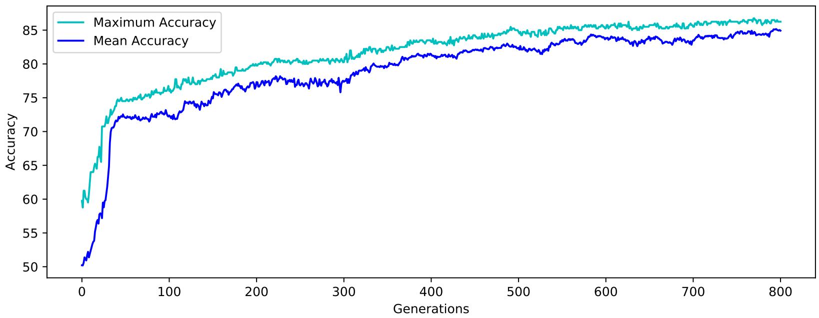
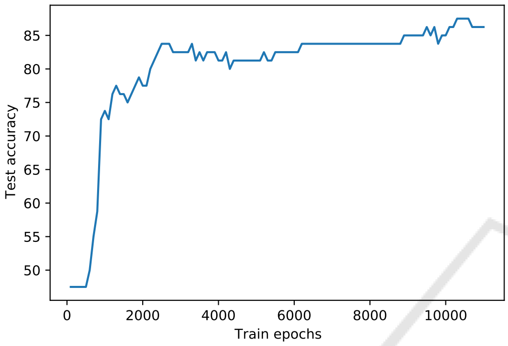
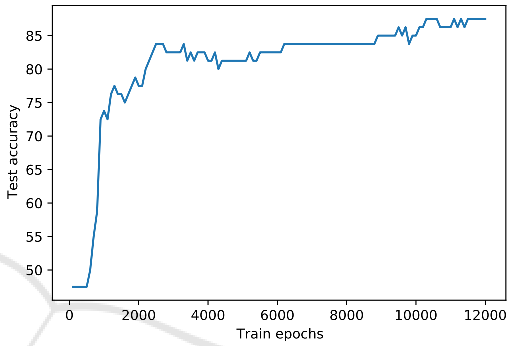


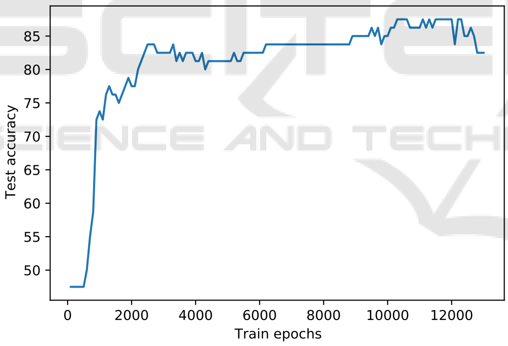
Figure 5: Accuracy of the neural network model optimized by evolutionary algorithm.



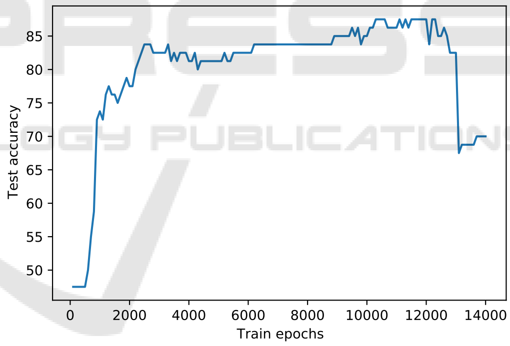
(a) One unit pruned.



(b) Two units pruned.



(c) Three units pruned.



(d) Four units pruned.

Figure 6: Accuracies with the pruning process on the hidden layer. Each time, one hidden unit is removed, and the model is trained for another 1000 epochs of backpropagation.

4 COMPARISON AND LIMITATIONS

Firstly, we can compare the backpropagation training method and EA results on the NN. After tuning several hyperparameters of the backpropagation method, the model after 10000 epochs of training can reach an accuracy of 85%. On the contrary, the EA achieves an accuracy of 86% with 800 generations of evolution. These two similar accuracies can address the problem we mentioned in the Introduction section: can the backpropagation method obtain 85% accuracy due to being constrained by some local minimum? We cannot conclude with complete certainty, but the answer can be 'no' because EA usually has a good performance on finding the global best solution, and its best accuracy is still around 85%.

Table 2 reports a performance comparison among NN-based anger veracity recognition using the same Anger dataset we utilized in this study.

The table reveals that (Huang et al., 2020) reported around 93.6% accuracy. They achieved this

Table 2: Performance comparison among similar NN-based works that utilized the same Anger dataset.

Reference	Accuracy
(Huang et al., 2020)	93.6%
Proposed	**86.0%**
(Qin et al., 2018)	83.3%
(Jin et al., 2020)	79.7%

score using a two-stream NN-based model, where each sub-stream has 60 hidden neurons followed by a single fully-connected final prediction layer. It is worth noticing that we used a simpler feedforward single stream architecture with only twelve hidden units, which is at least ten times less than what they used. We aimed to achieve reasonable accuracy using minimum computational burden (hidden units). We fulfill our aim by accomplishing a reasonably good performance (86%) with a simple structure after tuning the hyperparameter and hidden layer compression.

5 CONCLUSION AND FUTURE WORK

Anger is one of the many powerful emotions of humans, and finding its authenticity is essential in emotion recognition and human-centered computing areas. We have developed a simple NN to classify real and posed anger based on observers' pupillary responses. Our research indicates that the anger classification is achievable by employing this simple structured NN. We have optimized the NN in two ways, namely backpropagation and EA. With some reasonable adjustment during testing the network, we have developed a model that provided as high as 86% accuracy. This high accuracy proved that perceivers' pupillary response patterns could reflect the anger they saw as genuine or posed even though the perceivers are unconscious. Furthermore, our study shows that three neurons can be removed without significant performance degradation through NN pruning.

To ensure the superiority of our proposed approach, future works will include alternative models to benchmark and various statistical tests, for example Augmented Dickey-Fuller test, Kolmogorov-Smirnova test, and Shapiro-Wilk test (Fan et al., 2021) to validate. To build a relationship between emotion and speech, authors in (Han et al., 2014) have developed an efficient single-hidden-layer NN (called extreme learning machine) for emotion recognition based on utterance level speech features. Therefore, for future work, we shall design and optimize a network that uses people's speech emotion to predict whether their facial emotion is genuine or not, which could be interesting. Moreover, we can also implement advanced network pruning techniques, such as using thresholds and structured filter level pruning (Luo et al., 2017).

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