Genetic Algorithm in Neural Network for Stress Recognition by Thermal Super-Pixels

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Abstract.

Stress, as a negative reaction caused by environmental conditions or other factors, has become a major issue in nowadays society. Recognizing stress could help researches in many distinct fields such as psychological study, medical treatment, therapy development, metal health, etc.. Stress is traditionally detected and analyzed from the data of self-reports which could be largely biased. Psychological signals measurement for stress detection is also unreliable because people's reflection under stress might be different. There are better methods of using RGB or thermal cameras as non-contact detectors, collecting statistics from participants and predicting their stress level regarding to extracted features. This experiment was conducted to detect stress from features extracted and assessed from RGB and thermal camera detection. Dataset used in this case were collected from 24 participants, each of them was measured in 12 different conditions. Research and experiment are carried by constructing a neural network classification model with distinct feature selection algorithms, and applying backpropagation and genetic algorithm for network training. Moreover, using genetic algorithm is tune the network hyperparameters is also involved in this study. The analyzing results show that the best performance can achieve around 97.22% with filtering feature selection and backpropagation. The best accuracy achieved with genetic algorithm training is 93.05%. The optimal hyperparameters achieved by evolutionary algorithm provides the accuracy as 97.22%. The analyzing results stated that it is possible to classify the stress level using images detected from RGB and thermal camera with acceptable accuracy. And evolutionary algorithm can an alternative of training but generally cannot achieve generalization as backpropagation with limited generations and populations, however, it performs well in tuning hyperparameters.

Keywords: RGB, Thermal Camera, Stress Recognition, Feature Correlation and Selection, Neural Network Classification, Genetic Algorithm, backpropagation, Hyperparameters Tuning.

1 Introduction

Stress has become a major problem in the fast pace society which can be cost by time pressure or other environmental conditions (Ramin Irani, et al.). Traditional method of collecting stress related data was self-reporting and psychological signals detection, however, people's condition and reflection facing stress situations might be distinct hence lead to different psychological signals. The fact indicates that the data collected from those method could be largely biased and inaccurate. Furthermore, these systems are not able to monitor changes in a short period of time, nor to monitor the subjects instantaneously and continuously (Ramin Irani, et al.). RGB and thermal camera can assist in this case to overcome the issues identified above. RGB and thermal camera detection can be combined with face recognition technique, image assessment, feature extracting method to form a mature stress detection system (Ramin Irani, et al.). Thermal images are represented as a group of super-pixels which is a set of pixels with similar characteristics (Figure 1.).

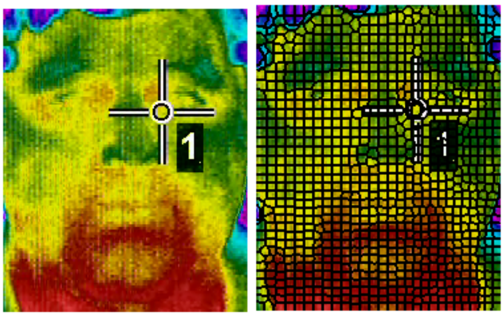


Figure 1. Super-pixel technique applied on facial region(Jessica Sharmin Rahman, et al.).

Similar to the experiment carried by Ramin Irani, et al., I will apply a stress classification on the data collected from RGB and thermal camera. Dataset created and pre-processed by Ramin Irani, et al. was used in this research with further standardization and selection. Neural network classifier was constructed, tuning for the best accuracy. The most significant part is, constructing evolutionary algorithm for training the network and tuning the hyperparameters, comparing with backpropagation. The rest content of this report will be illustrated in this way: database introduction and applied methods introduction in the method section; network construction, genetic algorithm implementation, performance tuning, statistical and visual results in the result and discussion section, and the final conclusion and future work section.

2 Methods

2.1 Data Source and Preprocessing

Dataset used in this research was collected, assessed, extracted, and preprocessed in a previous research '*Thermal Super-Pixels for Bimodal Stress Recognition*' carried by Ramin Irani, et al.. There are in total 24 participants involved in this experiment, each of them provided 12 different data points indicating distinct stressful conditions, as the experiment carried in the music therapy towards mental health care using machine learning (Jessica Sharmin Rahman, et al.). Data was collected by RGB and thermal cameras, different pixel colors on the images assigned indicates different temperature of the specific regions. The faces in the images of RGB were detected by Viola Jones face detector, then an assessment was applied to remove regions that were less correlated. Then Ramin Irani, et al. extracted Local Binary Patterns as feature points. For thermal cameras, they used a face matcher for face detection, then utilizing a Linear Spectral Clustering super-pixel algorithm and calculating their mean values as feature points (Ramin Irani, et al.).

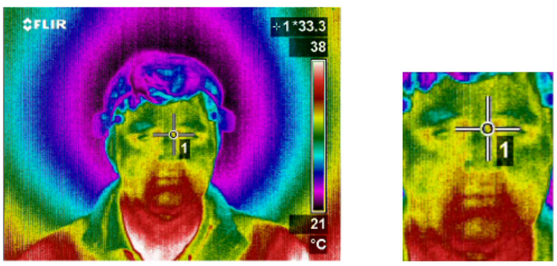


Figure 2. Face matching for face detection in thermal image (Ramin Irani, et al.) LEFT
Figure 3. RGB detected face sub-regions and corresponding LBP features (Ramin Irani, et al.) RIGHT

The dataset contains 212 columns: the ID of participants, 210 statistical columns as the potential features for classification, representing the extracted and preprocessed statistics of each variable (mean_, min_, max_, std_, var_, iqr_, skw_, rms_, sum_, Hjorth_, hurst_, mean_first_diff_, mean_second_diff_, apen_, fuzzy_ of 14 variables). The classification target is the stress condition of each data point, in this case, two classes as stress and non-stress. The dataset was collected, created, extracted and normalized by the research '*Thermal Super-Pixel' for Bimodal Stress Recognition*', detailed thermal detection methodology and super-pixel extracting technique are illustrated in its report (Jessica Sharmin Rahman, et al.). since the dataset was previously cleaned and processed, this is no encoding applied in this experiment. We only use a min-max scaler as data standardization method to eliminate the inference of large variables.

2.2 Feature Selection

There are three kinds of feature selection algorithm, the filtering algorithm, wrapper algorithms and the embedding algorithms. Feature selection is necessary in learning by reducing the complexity of the problem and enhancing training speed. It can also reduce overfitting and enhance accuracy if the right subset of features was selected. Analysis of Variance: It provides a statistical measurement on the level of correlation. This is an effective feature selection method as a filtering method.

All features set -> Subset of features -> training -> result and analysis

Forward selection: this is a wrapper method which is slightly different from the filtering method above. The wrapper method could always achieve the best subset of feature selection rather than filtering method although it would be slower to compute. The forward selection method starts with no feature at all, each time adding one of the most 'useful' feature into the selected subset (the one that improves the model the best) until no improvement can be made by adding more features in.

All features set -> $\boxed{\textit{Subset of features -> training}}$ -> result and analysis

2.3 Genetic Algorithm Trained Network and Hyperparameters Tuning

Neural network is a functional and effective problem-solving method in many applications, however, the way of defining the optimal network structure and hyperparameters is unclear. One possible way of obtaining optimal is trying all possible combinations which, in most cases, is extremely time consuming thus impossible. Researchers are required to have professional experiences of constructing and tuning otherwise. Genetic algorithm is a measure that could help in this case to find the optimal settings automatically. Evolutionary computation was inspired from the nature selection, that those habitats obtaining advantages under certain conditions or challenges are more likely to be selected and survive. As illustration in the evolutionary theory, organisms traits will be different due to random mutations and duplications in offspring. This fact assigns different advantages to organisms. Then the nature apply selection pressure on organisms and makes the organisms with advantages, in other word, more fit, to survive. Survived organisms pass genes to their offspring and enable them more likely to survived (E.Amer, M.). This algorithm can be used in both training the network and tuning the hyperparameters.

Evolutionary algorithm contains several parts as individual representation, mating, mutation, fitness function, selection and evolution. This algorithm can be applied on problem solving when we aim to find a best solution to an application, the procedure of construction as:

- Creating randomly generated individuals as the population
- Creating fitness function calculating the advantage of members
- Selecting the best and producing more from them
- Randomly mutating
- Keeping the best and killing the rest
- Repeat generation to generation until obtaining acceptable population

2.4 Experiment Design

This research was carried and evaluated by neural network models as machine learning technique. The data points are separated into training and testing sets to train the networks and to test their performance, training set contains 75% of original dataset and testing contains 25%. A simple one hidden layered neural network was implemented at first with all 210 columns of feature take in. The network and its hyperparameters, and feature set were then tuned for obtaining better accuracy. The most significant part of this experiment is the genetic algorithm implemented. Evolutionary algorithm was utilised for training the network and tuning the hyperparameters, comparing the highest accuracy achieved. The procedures of this experiment is demonstrated as a flow chart (Figure 4.).

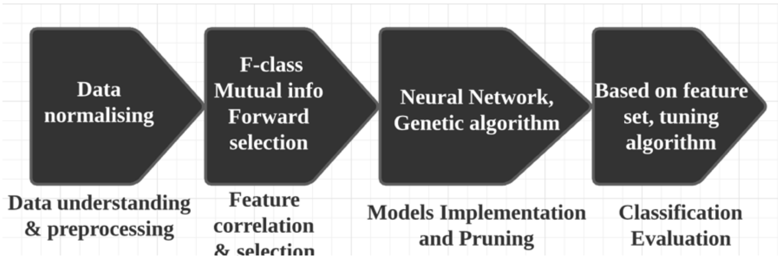


Figure 4. Experiment design flow chart

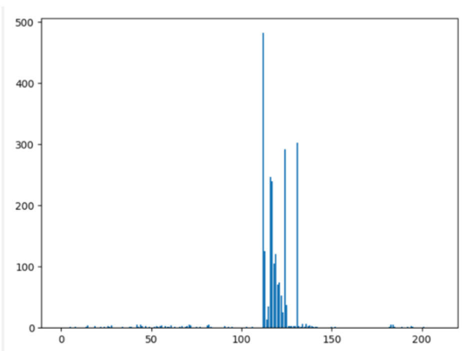
3 Result and analysis

A one hidden layered neural network was constructed at first with all 210 columns take in as features, comparing with different feature selections algorithms applied afterwards. Relu was used as activation function in the hidden layer, whereas the output layer used Sigmoid function. Adam was chosen as the optimizer with the learning rate to be 0.0001, the test accuracy in this case without any feature selection technique is 79.31%. The following table shows the model performance with different feature selection methods, selection 100 features out of 210.

Feature selection	Performance
All features	79.31%
F-class	88.89%
Mutual-info	86.11%
Forward selection	Extremely slow

Table 1. *Model performance regarding feature selection techniques applied with 100 features remain*

The results are obtained by two different training algorithm of neural network. The first one is a two hidden layers neural network with filtering feature selection method. From the figure blow (Figure 4.), we can find that most of columns in the dataset are less relevant to stress recognition, only some features between the index of 100 to 150 are highly correlated. The feature subset was optimal with the size of 15 features. The network takes these 15 features filtered, it has two hidden layers, each obtains 128 and 64 nodes with ReLu activation function. The output layer has one node with sigmoid activation function. The optimizer is Adam with the learning rate as 0.0001, the loss function is binary cross-entropy. The testing accuracy achieved 0.9722, and error on test data is 0.0277.



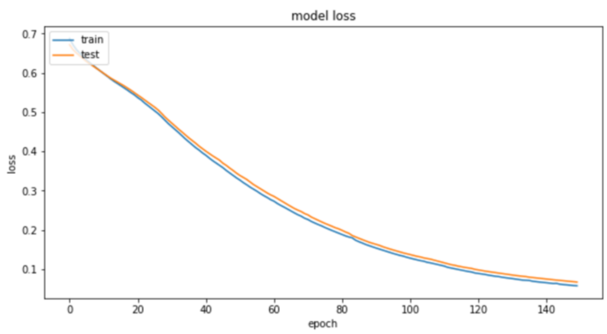


Figure 4. Feature correlation bar chart and best performance achieved
Figure 5. Model loss within 150 epochs

Another algorithm implemented is using genetic algorithm to train the network instead of backpropagation. The evolutional algorithm was implemented by the Python built in lib Pygad. The number of population is 10, the number of generation is 100, the crossover is 5 and the mutating percent is 5. The fitness function indicates whether the solution classified correctly. The optimal solution trained is a one hidden-layer network with 128 hidden nodes, Relu activation function in hidden layer and sigmoid in output layer. The optimal accuracy achieved after 100 generations is 93.05%. Genetic algorithm is also implemented to tune the hyperparameters, the optimal hyperparameters achieved after 10 generations are: 'nadam' as the optimizer, first hidden layer with 32 nodes, second hidden layer with 64 nodes, first hidden layer with the activation function 'relu', second hidden layer with the activation function 'sigmoid', batch size as 10, and 20 epochs.

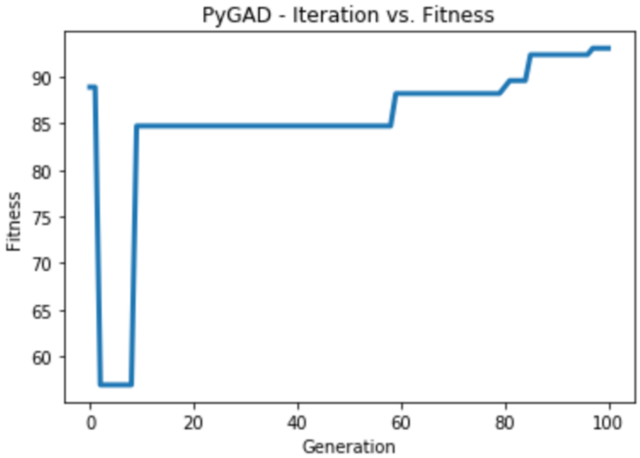


Figure 6. Fitness in each generation.

Database is balanced in the label with 72 instance as 0, and 72 instances as 1. The network trained with backpropagation performs better than genetic algorithm. The backpropagation performs better than genetic algorithm as expected. The backpropagation utilizes gradient descent to adjust weights always to the right directly gradually, whereas genetic algorithm cannot. It might takes genetic algorithm many more generations to get as accurate result as backpropagation. Genetic algorithm is very helpful if there are quite a lot local minima, however in this case, backpropagation is more suitable than genetic algorithm as the training method. On the other hand, genetic algorithm is quite helpful in tuning the hyperparameters, achieving 97.22% accuracy without trying different hyperparameters combinations manually.

4 Conclusion and future work

Models had satisfied classifying performance on stress recognition in this case with the highest testing accuracy as 97.22%, and 93.05%. Feature selection is necessary as its use for enhancing models performance and reducing complexity, however in this case the wrapper method was too time consuming. The neural network training with backpropagation performed slightly better with higher accuracy and faster computation. Machine learning in recognizing human stress regarding statistics collected and extracted from RGB and thermal cameras, this could be further researched and extended to many other areas. The genetic algorithm training network can help to get out of local minima in training and tuning hyperparameters, however in most cases, it is less accuracy or efficient than backpropagation for training.

There are some limitations in this study which can be further evaluated in future work. The dataset used here has few data points with only 24*12 entries from 24 participants which is insufficient and biased. We could utilize larger and more representative dataset in future work to achieve more accurate analysis. More importantly, when tuning hyperparameters, the number and variety of the population generated was too low to achieve better generalization. In the future research, I will enhance its diversity and quantity, and spend more time proceeding the code for better hyperparameters.

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