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Graphology Analysis and Identification of Personality Profile using Task fMRI

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ABSTRACT

Graphology or handwriting analysis work on principle that while writing, our hand is controlled by our subconscious mind. The graphic action reflects the state of the subconscious itself. It will be unique for each individual. Instead of graphologist who interprets individual character which is prolonged and susceptible to errors, the work automatically determine the personality trait using Deep learning and Task fMRI to accelerate the process and reduce error .The dataset consists of 129 different person's handwriting on a phone note or tablet pc. The emotional state of participants is assessed by the DASS depression–anxiety–stress scale. DASS-Depression centers around things identified with low inspiration and confidence, DASS-uneasiness to fear and panic and DASS-worry to strain and fractiousness. The characteristics comprise of sorrow, nervousness, stress and the mind state is named Normal, Mild, Moderate, Severe, Extremely Severe. Emotional state is related to handwriting. X position,Y position, Time, pen on, azhimuth, altitude angle, applied pressure. The features also include stroke order, direction and speed. The independent components obtained in analysis of task fMRI and the features obtained by the recognition are fused to classify the emotional state using Deep learning multilayer perceptron as positive nature, negative nature , idealism, broadminded, meanminded, reserved, selfcentered, roll model, average ,attentive. The obtained emotional state proves to be a basic model for Brain computer interaction.

Key words : Graphology, Deep Learning, Task fMRI.

1. INTRODUCTION

The current research work is to utilize fMRI strategies using the tablet innovation, an automated fMRI good tablet framework, comprising of a contact sensitive surface that is possible to work utilizing a pointer, to describe the mind movement related with a NP test grew explicitly to evaluate handwriting execution and features of motion in an object. The stated test was made for utilization with a graphics tablet to survey handwriting hindrances, because of several plan of motor dysfunction or an incompetence to span in Alzheimer's infection, AD patients. Activations incorporated the left lateralized cricial somatosensory and motor cortex, analogously as the reciprocal SMA and motor, essential visual areas. Cerebellum is a major neural surface of handwriting that is to be regarded for in various composing functions, and most has been recommended that it bolsters the motor enforcement in handwriting [2] the network amidst Exner's region and the cerebellum speak to the neural net assisting the correspondence between motor intending to execution. This examination just enrolled a gathering of grown-up members with a tight scope old enough, and along these lines it is muddled regardless if the neural contrast in handwriting equipped by the current investigation could possibly apply to individuals of various ages [1]. Figure 1 shows the sample database of the handwriting, written in note.

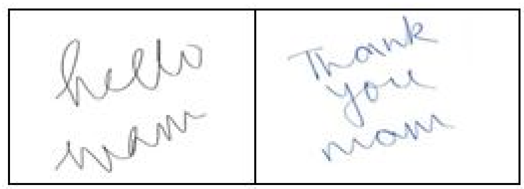

Figure 1: Sample Database of the Handwriting, Written in Note

2. DATA ACQUISITION

Subjects are to write in a cursive hand in their standard composing style, in lowercase content, as fast as could reasonably be expected while looking after exactness. The most extreme length for each piece of work was 10 s. This one was foreseen that right erratic finish times for every assignment task and that from time to time, the fulfillment time would be not exactly the intense as possible [3]. Subjects were along these lines trained to elevate the pointer off the tablet surface once on certain occasion wrapped up all components of a specified task, with the end goal that the pointer contact power information possibly be utilized to document job completion. Each assignment was isolated from the following by a standard state of visual obsession, comprising of a transparent shade with a focal dark obsession pass of 10 sec span [4]. Each separate assignment was replicated multiple times with various conversations and numbers arbitrarily. The time series data of fMRI information were gathered in one gallop of 9 minutes length, containing a handwriting tasks and pattern conditions [5]. Each (x, y) organizes and power boundaries were selected and recorded to a PC at a pace of around 40 Hz. Contacting the pointer to the tablet and squeezing descending to spare as jpeg file

format. Digitized panel chronicles were handled for each task and for one and all subject to remove three measurements comparative.
Movement correction, heart and respiratory physiological noise adjustment , planning timing correction, spatial smoothing utilizing a 6 mm FWHM Gaussian , transient detrending accompanied by zero to third request Legendre polynomials, movement covariate regression utilizing PCA ,movement boundary appraises and relapsing principal components that accounted movement difference, task paradigm covariate relapse to ensure opposing over relapse of task related BOLD signals, subsequent to convolving the function and sign relapse by eliminating the principal segment of PCA , spatial smoothing are performed. Brain masks were generated. The resulting brain maps were earlier transformed into Z-scored measurable parametric guides as in prior to group level analysis. Pearson's correlation coefficients, are determined amongst brain initiation and post imaging pen and paper calligraphy execution. To do this examination, contrast evaluation as linear solution of β estimates are removed from utilitarian ROIs.

3. EXPERIMENTAL ANALYSIS

The preprocessed dataset is organised and ICA features are extracted. Convolutional Neural Network (CNN) calculation is utilized to locate the passionate condition of a person from the handwriting sample. The examined picture is preprocessed by utilizing standardization and picture resizing. The convolutional neural organization calculation is trained on the preparation dataset and approved on the validation dataset. At that point it is tried on the testing dataset. When this is done another input picture is given to CNN model, the model predicts the passionate condition of the image dependent on highlights. Figure 2 shows the prediction of personality trait.

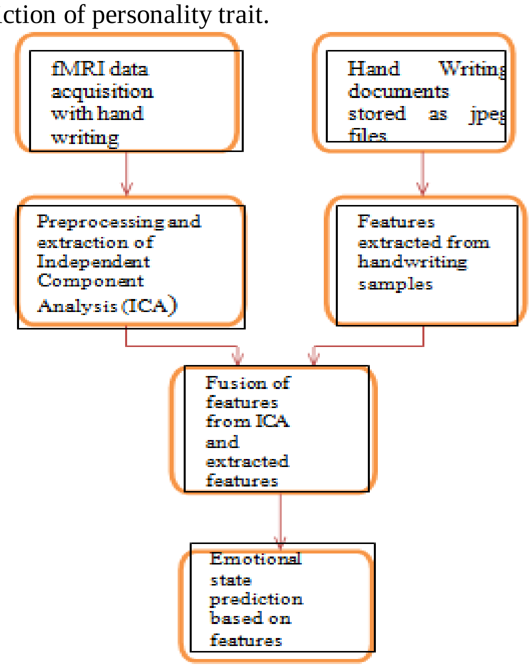

Figure 2: Prediction of Personality Trait

The degree of feeling is distinguished utilizing baseline or incline of the handwriting. The features of handwriting are gauge, incline, size, edge, pressure, dispersing between characters, words and lines, zone. Images in various classes have various blends of highlights. The features saw in the class misery are wide dispersing between words/lines, climbing gauge, lopsided left and right edge, less top edge. For class conservative anxiety, highlights are more weight, left and top wide edge, blended inclination, wide dispersing between lines, more bends of letters. For class extreme tension, the features are correct inclination, wide separating between lines/characters, blended benchmark. For class depression tension, the highlights uneven baseline standard, lopsided edge, long bends for letters like f, y, g enormous size of letters, wide left edge, wide dividing between words. For class tension pressure, the highlights are wide top/left edge, blended/left inclination, plummeting standard, lopsided dividing amidst letters. For class misery nervousness stress, the highlights are more weight, right inclination, blended pattern, little size, rising standard, lopsided edge, enormous bends for letters like s, g, y f and so on for class ordinary, the highlights are even edge, straight gauge, straight/right/left inclination, little medium size.

4. EXPERIMENTAL RESULTS

The three emotional states depression, anxiety and stress are plotted against the number of persons to know the dataset distribution in figure 3.

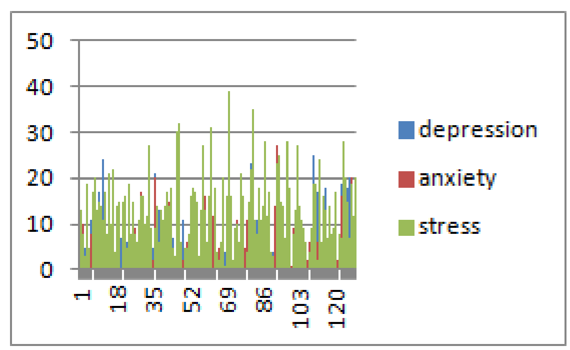

Figure 3: Distribution of 129 person handwriting states and Number of persons

A Deeplearning multilayer perceptron is a feedforward artificial neural association model that has one layer or a more noticeable proportion of concealed layers and nonlinear commencements. Intermediate layers ordinarily have as activation function tanh or the sigmoid capacity as a hiddenLayer class, while the top layer is a softmax layer as Logistic regression class.
The 70 independent components as features and 20 extracted features are collected .These 90 features are given as input to the neurons of the MLP network input layer.16 hidden neurons and 13 output classes are experimented as given in figure 4.
The randomly initializing weights is trained in a deep learning neural network. A trained neural network has

weights which are advanced at specific qualities that make the best expectation or characterization on our concern. And each time the trained organization will have different sets of weights. In a multi-layer neural network, the principal concealed layer become familiar with some exceptionally simple patterns. Each extra concealed layer will by one way or another have the option to adjust consistently more complicated examples.

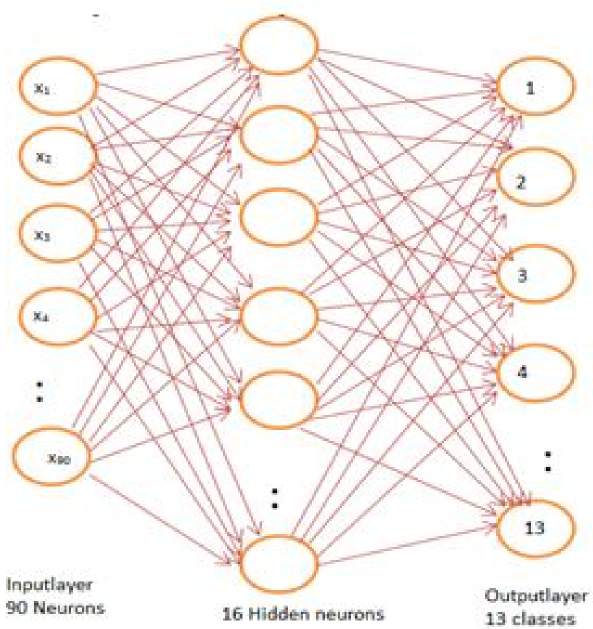

Figure 4: Deep learning MLP for personality profile handwriting recognition

Multilayer perceptron hidden layer is a function f: R^{90} -R^{13} for the given size of input and output vector f(x),

$f(x)= G(b^{(2)} + W^{(2)} (s (b^{(1)} + W^{(1)} x)))$, (1)

where b (1) , b(2) are bias vector and $W^{(1),}$ $W^{(2)}$ exist as weight matrix and G and s are activation functions.

The vector $h(x)=ø(x) = s(b^{(1)} + W^{(1)} x)$ (2)

is a hidden layer, s is tanh function which yields faster training and better to local minima,

$\tanh(a) =(e^{a} - e^{-a})/ (e^{a} + e^{-a})$ (3)

The obtained output vector is

$o(x)= G(b^{(2)} + W^{(2)} h(x))$ (4)

G is chosen as soft max function

The underlying qualities of the hidden layer weights ought to be consistently inspected from a symmetric span that relies upon the activation work. This xavier idealization guarantees that, primal in training preparation, every neuron works enclosed by a system of activation work where data can undoubtedly be proliferated each of two towards a higher level ,initiations spilling out of contributions to yields and in reverse , inclinations spilling out of yields to inputs. One concealed layer MLP, this will convert into a hidden layer with a tanh actuation work associated with the calculated regression layer, the initiation capacity can be supplanted by sigmoid or some other nonlinear function. L1 and L2 regularization is utilized, the L1 standard and the squared L2 standard of the loads W(1), W(2) are determined .Training of this model utilizing stochastic gradient descent with small scale groups is utilized. The cost work is changed to incorporate the regularization term. L1 and L2 are the hyperparameters regulating the heaviness of these regularization terms in that absolute cost function. The boundaries are refreshed for the model utilizing the inclination. Just the quantity of parameters differ in place. To get around , the rundown of boundaries made with the model params are parsed, figuring a slope at each progression. Normal concealed layer of a Multi Layer Perceptron units are entirely connected and have sigmoidal enactment work. At that point stochastic gradient descent optimization improvement for a multilayer perceptron is registered the inclination of cost regarding theta , sorted in params , the subsequent slopes will certainly be be stocked up in a rundown gparams. There is a lot of writing on picking a decent learning rate. The most straightforward arrangement is to just have a steady rate. General guideline: attempt a few log-dispersed qualities (10-1, 10-2,,) and restricted the logarithmic matrix hunt to the area where it is obtained, the most reduced validation error. Diminishing the learning rate after some time is actualized, One basic principle for doing that in the place is $\frac{\mu_0}{1+d\times t}$ where μ_0 is the initial rate, d is called as decrease constant ,which measures the rate after which the learning rate diminishes ,a littler positive number, 10-3 and littler and is the epoch per layer.

A system is adjusted for determining a learning rate for every boundary ,weight in the organization and for picking them dynamically dependent on the error of the classifier. Gradient based learning methods or back propagation learning can be implemented. The way of computing gradient is admitted as back propogation. Stochastic learning is preferred over Batch learning for weight updates. stochastic learning is much faster and gives better solution and used for tracking changes. Non linear networks is usually multiple local minima of different depths, The objective of training is to find one of these minima.Deeper local minima are produced by stochastic learning. Each weight is given its own learning rate. Second order optimization methods are used.If it is unsupervised clustering, RBF network can be used instead of sigmoidal units or ReLU. The breakthrough complete and favorite validation score of 1.82 % obtained at iteration 1070000.New handwritten samples are given as testing input. The prediction of personality traits yields satisfactory result in short time.

4. CONCLUSION

The independent components 70, obtained in analysis of task fMRI and the features obtained 20, hence 90 features by the recognition are fused to classify the emotional state using Deep learning multilayer perceptron as 13 personality traits ,positive nature, negative nature , idealism, broadminded, meanminded, reserved, self centered, roll model, average

,attentive of 129 dataset of different person's handwriting on a phone note or tablet pc. The prediction obtained is almost on par with the ongoing works in deep learning. The obtained emotional state proves to be a basic model for Brain computer interaction. The work can be further extended to analyse the personality traits using the features obtained from facial emotions combined with acquired fMRI features.

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