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RESEARCH PAPER

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BIG FIVE PERSONALITY TRAIT ANALYSIS FROM RANDOM EEG SIGNAL USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: Personality can be characterized as a remarkably steady form of theorizing, feeling and acting. These forms can be clarified by methods for the possibility of character attributes – hidden components that cause variation in perceptible personality traits. As indicated by a prevailing Five-Factor model (FFM), perceptible personality is generally decided by means of five fundamental properties – Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. Automated recognition of an individual's personality traits has numerous applications. In the proposed method the brain activity has been analyzed to detect big five personality traits by gathering publicly available random EEG signal datasets taken from different subjects using a convolutional neural network (CNN). Five different networks with same architecture have been used to train the system for the five personality traits. The outcomes surpass the current state of the art for each of the five patterns.

Keywords: Five-Factor model (FFM); convolutional neural network (CNN); EEG signal; Neuroticism; Extraversion, Openness, Agreeableness, Conscientiousness

I. INTRODUCTION

The study of human personality and the appearance of it and their impact on each person is intriguing. Most experts and psychologists concur that individuals might be portrayed based on their personality inclinations. Various analysts found and characterized the five expansive propensities dependent on observational, information-driven research.[5] This five-factor model of personality shows five center propensities that communicate to shape human personality.[1] The five components are: Openness to experience (creative/inquisitive vs steady/careful), Conscientiousness (methodical/efficient vs agreeable/reckless), Extraversion (active/dynamic vs lonely/reticent), Agreeableness (cordial/empathetic vs challenging/confined), Neuroticism (touchy/stressed vs secure/phlegmatic). Each of the five personality components constitutes a span between two extremes. For instance, extraversion represents perpetuity between extreme extraversion and inordinate introspection. In the real world, almost all individuals lie someplace in the middle of the two polar parts of each dimension.

If personality trait precisely contemplates discrete variance in tonic brain function, then the baseline measurement of the brain activity may give an immediate way for personality assessment. In our model, we endeavored to analyze the brain activity to identify the big five personality traits by gathering publicly available random EEG signal datasets taken from different subjects. EEG is one of the most widely used non-invasive neuroimaging strategies and is particularly acceptable for application-oriented personality evaluation due to its adequately less expensive and fair. The EEG signal comprises of among the useful data, which permit researchers to see the cerebral intrigue, redundant or clamor data.

Five different networks with same architecture has been used to train the system for the five personality traits. Each system was a binary classifier that prognosticates the equivalent attribute to be positive or negative.

Most implementation of the Big Five adaptation depends on self-expressed scales which require the respondents to contemplate proclamations or descriptive words which they judge with regards to their character and report their level of agreement[6]. These self-reported scales, simultaneously as having the advantages of straightforwardness and cost-viability, are inclined to predispositions comprising of the social allure of self-presentational concerns. This hindrance restrains the technique's adequacy in certain application settings.

Lately, the acquaintance of the machine learning methods into psychological science has unfurled new possibilities for verifiable personality measures [7]. The machine learning approach to deal with personality assessment focuses on creating automated algorithms to anticipate one's personality from certain data sources, and the algorithms are generally cross-validated to ensure their simplification of new samples. As of late, there have been reports of accomplishment in the application of this method on person's digital footprints on web-based networking media sites [8] For instance, Wu et al. [9] created machine learning method to predict individual's levels on the Big Five traits from Facebook "Preferences". The exactness of their adaptation's forecasts, assessed towards self-expressed personality scores and prescient legitimacy forever conclusive outcomes factors, turned out to be better than the decisions made by means of human informants.

Be that as it may, for the intention of becoming neural-based personality measures, the current research is kept in manners. First, many of the findings were gotten by method for procedures that incorporate functional magnetic resonance imaging (fMRI), which as a result of their expensive charges and fixed status, are not suitable in application settings. Second, the greater part of these

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analyses took a correlational strategy, wherein the focused trait was related to explicit neural features. These correlations confided in-sample population inference and were presently not necessarily generalizable to out-of-sample individuals [10]. Conversely, predictive machine-learning inspired enlivened structure would employ cross-validation systems to ensure generalizability, hence might be progressively ideal for application outcomes that require accurate personality forecasts from novel samples.

II. DATA ACQUISITION

This research adopts the random EEG dataset to evaluate the proposed methods. We have used publicly available EEG dataset which may or may not contain peripheral physiological signals. In this research, the multimodal system with auditory, visual, and somatosensory stimuli has been used at the same time the dataset contains 64-channel EEG recordings from 108 subjects and 12 runs on each subject have also been used.

III. PREPROCESSING & FEATURE EXTRACTION

A. *Preprocessing*

After collecting the EEG signals from the different data source, the raw file has been converted to the EDF file where the multichannel data and different sample rates for each signal have been stored. Subjectively it comprises a header and at least one data record. The header contains some extensive information and specialized specs of each signal (alignment, sampling rate, separating, ...), coded as ASCII characters.

B. *Signal Space Projection (SSP)*

After converting the file, a noise cancellation approach has been used. Here Signal Space Projection (SSP) [4] approach has been used as it defines a linear operation applied spatially to EEG data. Contrasting to numerous other noise-cancellation methodologies, SSP does not require extra reference sensors to record the unsettling influence fields. Rather, SSP depends on the reality that the magnetic field distributions created by method for the sources inside the brain have spatial distributions adequately remarkable from those produced by external commotion. Moreover, it is certainly expected that the linear space spanned by the notable external commotion styles has a low measurement. A projection operator is applied to each of the data and the forward operator for source confinement. EEG normal referencing might be finished using such a projection operator.

C. *Power Spectral Density (PSD)*

Using the power spectral density (PSD) the plotting has been done for each sensor type. Here in the PSD plot, only frequencies below 50 Hz is plotted. The Power Spectral Density (PSD) computes the signal's power content versus frequency. The amplitude of the PSD is normalized by spectral resolution utilized to digitize the signal. Figure 1 shows the result generated after applying PSD.

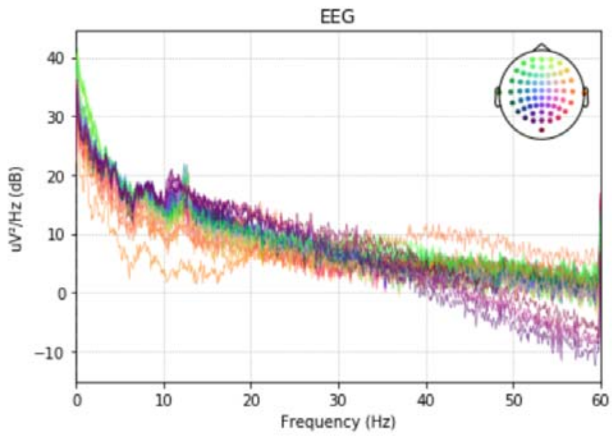

Figure 1. Spectral Density of EEG Signal

D. *Independent components analysis (ICA)*

Disintegrating data by ICA includes a linear difference in the basis of information gathered at single scalp channels to a spatially changed "virtual channel" basis. The cleanup task has been done to the information by executing independent components analysis (ICA). As is commonly done with ICA, the information is first scaled to unit deviation and whitened using principal components analysis (PCA) before executing the ICA decomposition. Figure 2 shows fitting ICA to data using 364 channels. Plotting has been done to show multitaper spectrum estimation in figure 3.

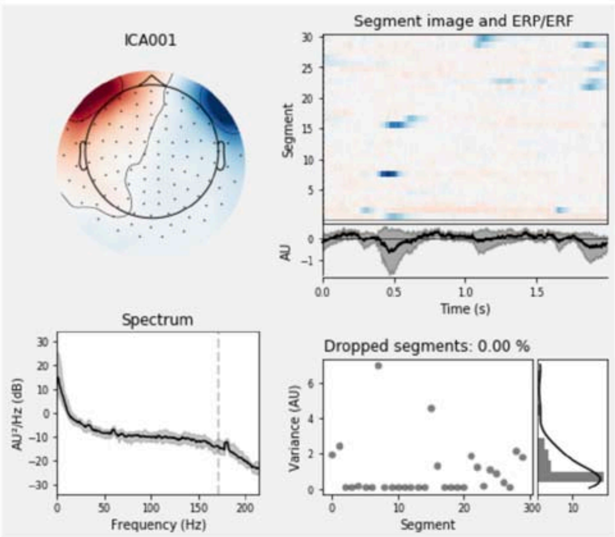

Figure 2. Fitting ICA to data using 364 channels.

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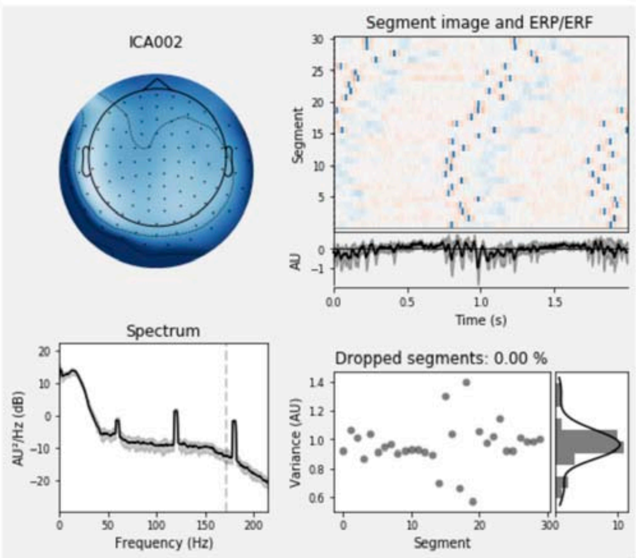

Figure 3. Multitaper spectrum estimation

IV. METHOD

For the classification purpose, we use a Deep Convolutional Neural Network. Deep Learning is turning into an exceptionally mainstream subset of machine learning because of its inordinate level of performance across numerous sorts of data. A good method to apply deep learning to categorized images is to develop a convolutional neural network (CNN). Deep learning models perform exceptionally better and show potential ability in order to work with multichannel EEG-based applications over traditional machine learning. The DL model is the utilization of Convolutional Neural Network (CNN) layers for learning information on summed up characteristics and dimension reduction, whereas a traditional Fully Connected (FC) layer is used for classification. With a CNN, each progressive convolutional layer will expand filters in order to have the option to see progressively additional complex features in the EEG data.

Together they build a coalesce end-to-end model that might be actualized to raw EEG signals. Participants' ERP reactions were used as features to train five predictive models, one for each of the Big Five traits, using a nested cross-validation approach with versatile net regularized regression analyses. To research, the predictive models' general execution of basic ERP features held notwithstanding at finally used for the sparse-regression-based trait predictive models. These had been put not only inside the time windows of those emotion-related ERP segments yet additionally reached out to the pre-stimulus periods (< 0 ms), notwithstanding the late processing stages. The applied classification model depends absolutely on shallow CNN. It incorporates two 1-D convolutional layers with 40 filter kernels per layer. While the first layer applies convolution along with the time axis, the subsequent layer learns a spatial filter along with the EEG channel dimension, which makes weighted linear combinations of the single-channel values. That is, this layer reduces the dimensionality of the data along with the EEG channel dimension to one. From there on temporal mean pooling is executed to reduce the length of the data correspondingly sooner than the signal is passed to a completely connected layer for classification.

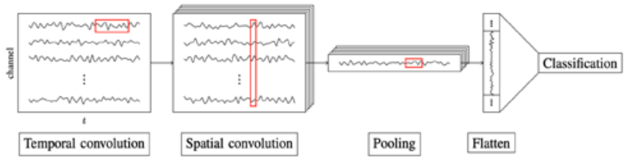

Figure 4. Convolutional neural network model

V. RESULT

The vast majority of the current studies in this field corresponds to character attributes that have been carried out in a hypothesis-driven way. The objective of the present method is to use data-driven techniques to generate a relevant outcome that relates in an extensive and systematic manner. To that end the classifiers, scientific models have been used that map input data to a set of classes or labels, to predict personality traits from EEG signals.

In the accompanying, we present and analyze various segments of the executed classification performance and the learned model parameters. The notable ERP segments evoked through the stimuli included two positive peaks at 200-300ms and 400-500ms, and two negative peaks at 100-200ms and 300-400ms, comparing to the emotion-related ERP components of N100, P200, N400 and late positive complex (LPC).

The temporal area scores for agreeableness ($r = -.18$, $p < .05$). For conscientiousness, higher rankings had been related inside the frontal and right temporal area ($r = -.15, -.15$, respectively, every $p < .05$). For neuroticism, higher rankings had been identified with larger N100 in the central area ($r = -.16$, $p < .05$), larger N100 in the left temporal area ($r = -.15$, $p < .05$), larger N100 inside the frontal, central, left temporal ($r = -.16, -.17, -.17$, respectively, all $p < .05$), larger N400 inside the frontal, central, left temporal and right temporal areas($r = -.20, -.15, -.15, .20$, respectively, all $p < .05$), larger LPC inside the frontal, central, left temporal and right temporal areas($r = .15, .15, .17, .20$, respectively, all $p < .05$). For openness, higher evaluations had been related with littler P200 inside the central and left temporal area ($r = -.14, -.16$, respectively, every $p < .05$).

For extraversion, better scores had been identified with littler N100 in the central area ($r = .15$, $p < .05$), littler P200 inside the central, left temporal and right temporal areas ($r = -.16, -.19, -.16$, respectively, all $p < .05$), littler N100 inside the frontal and central areas ($r = .18, .14$, respectively, both $p < .05$), littler P200 in the central, left temporal and right temporal areas ($r = -.21, -.18, -.18$, respectively, all $p < .05$), and littler N400 in the left temporal area ($r = .15$, $p < .05$).

The selected global classifier arrived at 80.38%, 69.82%, and 58.58% mean correctnesses for datasets with two, three, and four classes, individually, validated using 5-fold cross-validation. As a novel methodology in this context, transfer learning was used to adjust the global classifier to single individuals improving the general mean accuracy to 86.49%, 79.25%, and 68.51%, respectively. The global models were trained in 3s portions of EEG records from various subjects in comparison to they have been tested on, which demonstrated the speculation generally execution of the model. The results are comparable with the articulated

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precision values in related research and the presented model surpasses the outcomes in the literature on the equivalent underlying data.

VI. ACKNOWLEDGMENT

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