Health Profiling Using Event-Related Potential (ERP) Brain Signals and Spiking Neural Network (SNN)

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Abstract— Unhealthy lifestyles, especially on nutritional factors have become a major problem causing many diseases in Malaysians in recent years. Identification of lifestyle profiles such as preventive for individuals who adopt healthy and curative for individuals who do not maintain their lifestyle is needed to increase their awareness regarding their lifestyle. Because self-assessment is known to be vulnerable to produce response biases that lead to misclassification, identification of profiles based on brain responses needs to be done. An Event-related potential (ERP) is the main tools of cognitive neurologists and make ideal techniques for studying perception and attention. This research captured brain activity using electroencephalography (EEG) during receiving images of healthy and unhealthy foods that act as health-related stimuli. These EEG signals converted mathematically into the ERP signals and entered into the classification interface as input. In terms of classification, the methodology used is a dynamic developing Spiking Neural Network (deSSN) based on the Neucube architecture. ERP analysis results show the mean amplitude of the LPP component in the Parietal and Occipital lobes is higher for healthy food in the preventive group. Whereas in the curative group it has been shown to be higher for unhealthy foods. This result is thought to reflect their preference in choosing food in their daily lifestyle. However, the results of the classification have shown that unhealthy food stimulation in the LPP wave showed superior results compared to data analysis in other conditions. Classification with ERP data is believed to support the results of self-assessment and build methods of making profiles that are more accurate and reliable.

Keywords— Health Profiling, Event-Related Potential, Machine Learning, Spiking Neural Network, Late Positive Potential, LPP

I. Introduction

Nutrition or healthy eating was recognized as a fundamental factor that had a major impact on the healthy lifestyle behaviors of Malaysians [1]. The Global Nutrition Report states that the number of people with diabetes, overweight and obesity in Malaysia has increased in recent years [2], [3]. A report [4] states that Malaysia is the country with the highest obesity rates in Southeast Asia which is mostly caused by unhealthy lifestyles. Also, the unhealthy lifestyle is often the cause of many other chronic diseases such as cancer, stroke, hypertension, and coronary artery disease [5]. Moreover, unhealthy lifestyles hurt health care costs as well, because the data shows that costs for treatment are greater than prevention [6] – [10]. With these negative impacts, it causes an emergence of urgency to increase awareness of the community towards the importance of maintaining lifestyle, especially nutrition.

Regarding psychology, several instruments have been used to assess a person's lifestyle. However, these instruments are generally self-reports that are known to often experience misclassified due to cognitive factors engaged in answering questions [11], [12]. In consideration of that, brain responses or brain activity become another alternative that can be used to identify a person's perceptions and attention [13]. An event-related potential (ERP) is a method for measuring brain activity during cognitive processing. ERP is the average raw EEG signal that can provide insight into cognitive processes which can be an ideal technique for studying individual profile or personality [14], [15].

Recently, ERP studies have used artificial intelligence (AI) techniques that have proven to be useful for classification problems based on brain data with high accuracy [16] – [19]. Evolving spiking neural network (eSNN) is an artificial intelligence technique specifically designed to deal with spatio-temporal brain data (STBD), such as EEG [20]. Thus, the purpose of this research is to identify the characteristic of the individual profile, which consisted of preventive (healthy lifestyle) and curative (unhealthy lifestyle) by using ERP signals. Then for classification, a method to be used is the eSNN that developed from the Evolving Connectionist Systems (ECoS) paradigm.

II. Related Works

In the past few years, there have been many studies that use ERP signals to recognize someone's response to food. ERP is one of the techniques that have the ability to reveal the differences in how the brain processing food images [21]-[23]. Most of the stimuli used in ERP experiments to review dietary decisions are food images. Food images are believed to be a convenient instrument to trigger perceptions and attention of eating patterns because many dietary decisions are made based on the sight of foods [24].

A systematic literature review [14] provides a summary of a collection of studies that conducted ERP related to food experiments. The aim of the study is to investigate the ERP components that need to be highlighted in the correlation to eating habits. The study concluded that ERP showed a convincing ability to extract the feature that relates to human cognition. The stimulus of various types of foods such as healthy and unhealthy food need to be developed to reflect individuals in making dietary decisions in everyday life. Comparing cognitive responses to different types of food will assist researchers and clinicians to understand how people choose and determine which foods to consume.

As stated by the previous studies, it was found that LPP is the one major cognitive components of ERP that are able to show differences in the response of individuals to the processing of attention to visual food images [14], [21], [25], [23], [26]. LPP is a slow positive wave generated around 500 ms after the stimulus is onset until the stimulus is offset [27]. The LPP peaks represent organized attention that is associated with broader allocation or intensity of attention driven by emotional processes and visual image motivation [28].

III. Materials and Methods

A. Participants

Undergraduate student at International Islamic University Malaysia (IIUM) participated with a few exclusion criteria, including eating disorders, substance abuse or addiction, and neurological disorders. The participants were selected and filtered by using the psychology assessment namely Health Promotion Lifestyle Profile-II (HPLP-II) questionnaire [29]. Twenty-two participants (11 females and 11 males) with the highest or lowest score were chosen as representative subjects for preventive and curative group respectively. which was administered as part of an online screening approximately three to five weeks prior to the testing session.

B. Stimuli

The stimulus used in this experiment is consist of a set of food images that present on the screen. Participants view the 60 food images (30 healthy and 30 unhealthy food images). The pictures are displayed in random order for 2000 ms each which is prefaced by a fixation cross (1000-2000 ms) as an intertrial interval (ITI). The presence of ITI is useful for preventing the possibility of alpha oscillations being locked in time during image presentations and contributing to filtering overlapping activities from previous trials [30]. ITI is formed pseudo-randomly between 1000-2000 ms to avoid the response that generates in the elapsed time [31]. Participants are asked to take attention as long as the food picture appears on the screen [21], [23]. Figure 1 shows a chunk of the presentation of the stimulus to each participant.

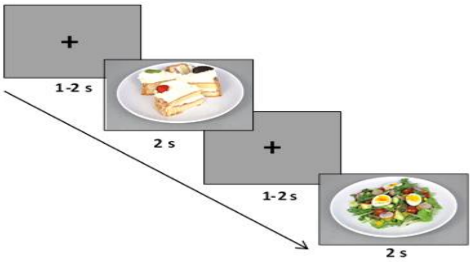

Fig. 1 A representative screen showing a trial in which an image of unhealthy food then followed by healthy food is presented

The food images presented in this experiment were adopted from the Standardized Food Images (SFI) database [24]. In the selection and categorization of food images that represent healthy and unhealthy lifestyles based on the HPLP-II questionnaire, a nutritionist named Dr Nur Fardian, M.Gizi (Indonesia) and Asst. Prof. Dr Nor Azwani Binti Mohd Shukri (IIUM Kuantan, Malaysia) has contributed to completing it.

C. Procedure

Participants were asked not to consume any food other than mineral water (250 ml) within 3 hours before the brain data recording session in order to control hunger levels [32]. This circumstance has the ability to trigger participants' minds to reflect on the food image as their next food in real life. This makes it possible to investigate nerve responses that show how participants choose food in their daily lives.

First of all, participants are given an explanation of the experimental procedure. After understanding and agreeing, participants are required to fill out and sign the consent form as a form of permission to take, store and use their brain data. After that, participants will be told to sit facing the monitor calmly and comfortably. Participants are requested to minimize body movements during signal recording. After adjusting environmental conditions, participants were asked to follow all instructions in accordance with the experimental protocol that had been designed.

IV. Results

A. ERP Results

As a preliminary analysis, MATLAB was implemented to obtain an average ERP waveform in 22 subjects. Grand-averages refer to the waveforms that are built to average together the average waveforms of each subject. Grand-average ERP is done for each group, namely preventive and curative. Grand averages have been made because ERP single subjects are very different from each other. Thus, ERP single-subject analysis is very difficult and complex to capture differences between groups and conditions.

According to the previous study [14], [21], [23], [26] and [33], the Late Positive Potential (LPP; 500-1000 ms) is one of the most powerful ERP components and is generally used in investigating and exploring cognitive functions because this component is strongly related to perception and attention allocation. Thus, the presentation of the results in this study has used the LPP component in the selected waveform and extract it at latency or time duration between 500-1000 ms post-stimulus.

The ERP result is analysed by measuring the mean amplitude at 500-1000 ms for each preventive and curative group. The results of mean amplitude in channels P3, P4, P7, P8, O1, and O2 for the preventive and curative group across condition are shown in Table I and Table II respectively. Table I shows the LPP components in Parietal and Occipital lobe were relatively higher for healthy foods in the preventive groups. Whereas referring to Table II within curative groups, it has been shown roundly higher for unhealthy foods.

TABLE I
MEAN AMPLITUDE OF PREVENTIVE GROUP – LPP IN PARIETAL AND OCCIPITAL LOBE

Channels	Stimuli	
	Healthy Food	Unhealthy Food
P3	0.88	0.87
P4	1.05	1.23
P7	0.69	0.38
P8	1.04	1.32
O1	0.49	0.26
O2	1.47	0.5
Mean	**0.94**	**0.76**

TABLE III
MEAN AMPLITUDE OF CURATIVE GROUP – LPP IN PARIETAL AND OCCIPITAL LOBE

Channels	Stimuli	
	Healthy Food	Unhealthy Food
P3	2.2	2.51
P4	2.89	2.73
P7	2.51	3.12
P8	4.32	4.09
O1	2.76	2.53
O2	2.78	3.7
Mean	**2.91**	**3.11**

B. *PCA Results*

The PCA technique was adopted for visualization purposes by evaluating the distribution of the subject portrayed in 3-dimension graphs. This generated the visual inspection of the performance of the stimulus designed to each subject in extracting the interpretation of the natural brain response to the image.

Three principal components were constructed to visualize the scatter plot. Therefore, Figure 2 presents the distribution of dataset depicted in the form of colored circles, where blue represents subjects with a preventive label and red is a subject with a curative label.

Figure 2.a is a graphical representation created on the data when looking at a collection of images of healthy food. Then Figure 2.b is a demonstration of the distribution of subjects when getting a stimulus in the form of a collection of unhealthy images. Lastly, Figure 2.c is a visualization of the difference wave occurs during 500-1000 ms post-stimulus.

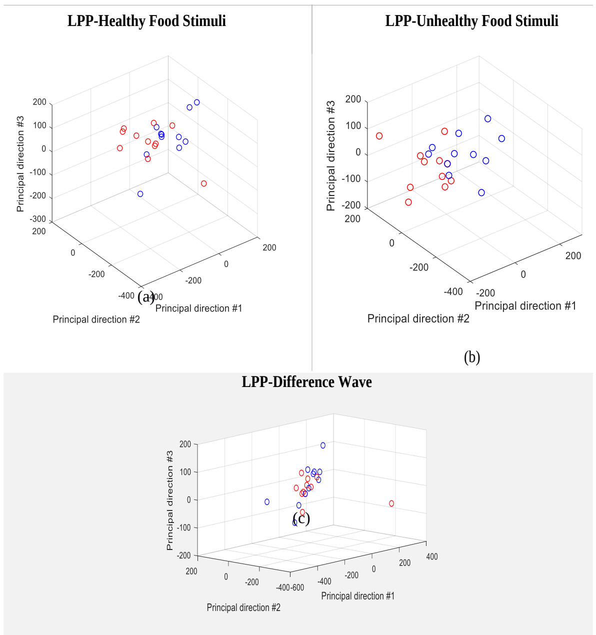

Fig. 2 A representative screen showing a trial in which an image of unhealthy food then followed by healthy food is presented

C. *Classification Results*

Classification by computational methods has been carried out using dynamic spiking neural network (deSNN) techniques. This classification is initialized by categorizing ERP data into a number of desired classes where labels are assigned to each class i.e. preventive and curative. Table III follows the dataset information from input data entered into the classification environment. The sample given is a number of participant data taken namely 22, consisting of 11 data that represent preventive and the remainder representing curative data. Subsequent, the feature used is 19 which means that all sets of channels or electrodes are utilized. Then the length of time is 126 which is the amount of data recorded over 500-1000 ms. Finally, the class information is arranged as much as 2, namely preventive and curative.

TABLE IIIII
DATASET INFORMATION ON LPP WAVE CLASSIFICATION

Dataset Component	Number
Sample	22
Feature	19
Time Length	126
Class	2

ERPs data are analysed based on 3 conditions, namely healthy food stimuli, unhealthy food stimuli, and difference waves (healthy food stimuli - unhealthy food stimuli). Each data condition is applied as input to the environment of this classification method in a separate way or independently. The percentage of the classification accuracy by deSNN techniques of those conditions are listed in Table IV. Class 1 refers to a preventive profile, and class 2 refers to the curative profile.

TABLE IVV
DESNN RESULT ON ERP DATA TIME-LOCKED 500-1000 MS

Accuracy	Healthy Food	Unhealthy Food	Difference Wave
Class 1	27.27%	50.00%	18.18%
Class 2	36.36%	33.33%	45.45%
Average	**31.82%**	**41.67%**	**31.82%**

With reference to the results shown in Table IV, it is acknowledged that the classifications associated to unhealthy food stimuli have achieved the most optimum accuracy compared to other conditions with an average accuracy value is 41.67%. This clarifies that compared to other conditions, unhealthy food stimuli are conceived to be the most qualified to generate characteristics in brain signals that can distinguish both profiles.

V. DISCUSSION

A. ERP Results

The main purpose of the evaluation of ERP is to interpret and examine the relationship between food stimuli and health profiles using brain data. The ERP results show a greater amplitude by the preventive group in responding to healthy foods than unhealthy foods. While the curative group produced a greater amplitude for unhealthy foods compared to healthy food. This result is most likely suspected because the food image is closely related to influencing food choices in daily life. This might reflect their preference in selecting food because in the preventive profile which is more taking care of their health has a greater amplitude in healthy food. As for curative group who do not really protect their daily food, show greater amplitude values when looking at unhealthy foods. Thus, this outcome in line with the literature which states that many food choices in daily life are executed because of the appetizing food scene [34] - [36].

According to knowledge gained from literature which states the amplitude appears greater when the subject allocates more attention to the affective picture [15], [19] [37], [38]. Then these factors support the results obtained from ERP data analysis. The interests and desires that arise when viewing images can provoke appetite and encourage someone to make a decision about the food to be consumed. This desire becomes the cause of the amplitude produced to be greater.

The distinctive ERP wave generated from the two profile groups shows that controlling hunger levels by asking subjects not to eat anything except mineral water as a prerequisite is able to trigger subjects' minds to think according to their food preferences every day. These results also show the contribution of experts in the categorization of giving satisfactory results. Therefore, based on these findings formed a promising initial potential by a stimulus designed to build health profiling from a dietary pattern.

B. PCA Results

Relying on the results of PCA visualization in Figure 2, unhealthy food image came out as the best stimulus in quantifying the profiles, namely preventive and curative. The results of visualization by taking 3 independent components conducted on ERP data on unhealthy food stimuli indicate that there are significant differences in the distribution between the two groups. This is known because the distribution of red and blue circles is in two different regions. The PCA results on unhealthy food stimulation show that the distribution of preventive subjects tends to gather in certain areas. This seems to show a special character in the preventive group against unhealthy foods. Whereas in another condition of ERP data, visually it is difficult to build boundaries that form the boundary between the two groups. This closures with the conclusion that the response when receiving unhealthy food stimuli form the powerful characteristic or feature between preventive and curative subjects.

C. Classification Results

The exposure of the classification results using deSNN aims to perceive the performance of this machine learning technique to recognize, distinguish and understand ERP brain data so as to identify the unique features that distinguish the two healthy lifestyle profiles (preventive and curative). The classification is performed on three ERP data conditions namely healthy food stimulation, unhealthy food stimulation, and waves of difference (healthy waves minus unhealthy waves). The results of this classification can recognize the appropriate protocol or stimuli to differentiate health profiles.

The deSNN has to get involved in learning the patterns of each ERP data for each group and then categorizing and predicting profiles based on input data provided to the classification environment. According to the classification results shown in Table IV, the best classification results were found on unhealthy food stimuli which revealed the highest accuracy results in comparison with other conditions. These results are in harmony with the results of visual examination undertaken by PCA techniques which also demonstrate that unhealthy food stimulation is superior. To summarize, unhealthy food stimulation is considered a promising protocol in triggering distinctive signals between the two profiles. These results are also in line with several previous findings that found significant differences in brain responses in seeing unhealthy and high-calorie foods [39] - [42].

Therefore, with this implementation, it was concluded that the proposed method to do preventive and curative profiling by using ERP data on Neucube framework is working. However, it can also be seen that the accuracy value obtained from the deSNN results tends to be low at below 50%. These results are considered to occur because the samples used in this study need to be added to make better predictions. Because Neucube is known to work better and optimum with a large amount of training data [43] - [46]. Especially in the case of profiling like this study which involves drastic differences between each subject [30].

There are many external factors that influence the variations that occur in the brain's response when dealing with food images. This includes or relates to the character and emotions that are built when the eye captures the image. The factors in question include perception, knowledge, and experience [14]. For example, this research found someone who has a healthy lifestyle and even very eager to choose to eat healthy foods rather than unhealthy food. But he had a bad experience with sour food, like kiwifruit. Even though kiwifruit is considered healthy food in this experiment. As a result, this experience factor will influence the results of ERP signals for that individual which have an impact on the patterns studied by deSNN.

While it is also discovered in the curative group of people who are very fond of eating unhealthy foods, but he extremely likes the taste of dates and has good experience with these dates. Though dates in this experiment are categorized as healthy food. So, the differences in experience and thoughts that are very unique from each of these individuals further strengthen the assumption that more data is necessary to establish the health profiling method. Thus, by learning in a larger dataset, accuracy results are also expected to improve gradually.

Then besides adding more subjects, the classification accuracy is also considered to be increased by upgrading the quality of the selected subject. It means by searching and selecting subjects with extreme results in the HPLP-II questionnaire for each preventive and curative group. In other words, the subject under review really has an extremely healthy and extremely unhealthy lifestyle. This kind of thing is able to produce and extract more valuable information and have an impact on the value of higher classification accuracy. In this experiment, it was found to be difficult to find people with a preventive status in the extreme. Therefore, to overcome this challenge, it is highly recommended to determine the questionnaire distribution environment in advance by setting targets for certain populations. The examples of populations in question include sports fields such as fitness centers, sports fields, etc. Then as for the other alternative target populations are students who are involved in health, nutrition or related fields, such as dietetics or food service system management. Where this population is considered to have an understanding of the importance of adopting healthy lifestyles in their daily lives So the point is, increasing the quality and quantity of the subject is believed to improve the value of accuracy so that a better profiling method is developed.

In the final analysis, the results of this experiment approved that the classification of health profiles can be done by studying ERP brain data. The classification method is capable of extracting information related to cognitive processes to images of food, especially when responding to unhealthy foods. Thus, the establishment of a method for making profiles with ERP brain data can support existing instruments such as HPLP-II in providing stronger decisions. This is due to bias, uncertainty, and errors in the classification of self-assessment believed to be minimized in the presence of other classifications of ERP brain signals.

VI. Conclusions

The greater amplitude produces in the healthy food stimuli by the preventive and in the unhealthy food stimuli by the curative are suspected to be partly because the food image is intimately linked to food choices in daily life. Then, refer to PCA results, it can be interpreted that the unhealthy food stimuli provide an excellent performance and is suitable in distinguishing the profile groups. The finding supported by deSNN result that shows the classification accuracy in unhealthy food stimuli is optimum than another conditions. The accuracy rate might get higher if the number of samples is increased and the quality of the subject is upgraded.

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