Abstract—Obesity is a serious issue in the modern society since it associates to a significantly reduced quality of life. Current research conducted to explore the obesity-related neurological evidences using electroencephalography (EEG) data are limited to traditional approaches. In this study, we developed a novel machine learning model to identify brain networks of obese females using alpha band functional connectivity features derived from EEG data. An overall classification accuracy of 90% is achieved. Our finding suggests that the obese brain is characterized by a dysfunctional network in which the areas that are responsible for processing self-referential information such as energy requirement are impaired.

I. INTRODUCTION

Obesity is a world-wide health problem today and obesity-related diseases such as Type 2 diabetes now threaten to reach epidemic proportions in many countries [1]. In recent decades, an increasing number of studies have investigated the brain activities of obese individuals with an aim to understand obesity-related neurological characteristics [2], [3]. As a non-invasive technique, the electroencephalography (EEG) technology is one of the most intensively used approach for brain activity measurement. In the EEG session, one’s electrical activities of the brain is recorded in high temporal resolution through the electrodes placing on the scalp [4].

This study focuses on understanding the neurological effect of obesity by investigating obese individuals and healthy (i.e. lean) individuals’ EEG data using machine learning approaches. The analysis first involves extracting the lagged coherence features from the source-localized EEG signal. A novel feature selection method is then applied, where each coherence feature is evaluated by its enhancement of the validation score versus its potential redundancy to other features. Multiple experiments are then conducted and by integrating the results of all experiments we obtained the final selected feature set. The experimental results demonstrated the effectiveness of our model, which successfully identified 90% of the obese subjects.

The paper is organized as follows: Section II briefly reviews some related work; Section III gives details about the subject groups participating in our experiment and the EEG data recording procedure; The source localisation protocol, lagged coherence features, and the proposed machine learning model applied in this study are introduced in Section IV. Then in Section IV, the results of obesity classification are discussed. The paper is concluded in Section V.

II. OBESITY-RELATED WORK

Abnormalities have been observed in various regions that are encoded to process self-referential information and information regarding the environmental context in the obese brain [5]–[7]. Apart from the study [8] that used a machine learning framework to identify the neurological characteristic of Binge Eating Disorder patients, to our knowledge no research has been conducted to retrieve EEG-based direct obesity-related neurological evidences using a machine learning driven approach. In this study, we proposed an effective machine learning model to explore the characteristics of obese brain using source-localized EEG features.

III. DATA ACQUISITION

A. Subjects

Thirty obese females and thirty lean (i.e., healthy) females between 25 to 65 years old have participated in our study. Subjects who have a Body Mass Index (BMI) higher than 30 are defined as obese individuals and those who have a BMI lower than 25 are defined as lean individuals. Participants who have obesity associated co-morbidities, which include diabetes, obstructive sleep apnoea, pregnancy, centrally acting medications, previous head injury or neurological/psychiatric disorders, or significant weight loss or gain in the previous 6 months, are excluded from this study.
### B. EEG Data Recording

The EEG data used in our study was recorded through the international 10–20 system. During the recording session, the lab environment and EEG recording devices were controlled to be in the same condition for all the subjects. EEG data are recorded at nine time-points during eye-closed resting state. This is illustrated in Fig. 1. The first EEG dataset was captured when all subjects were on empty stomachs. The second EEG dataset was captured 15 minutes after a liquid meal was given. The other seven EEG datasets were then captured between various time intervals after the second liquid meal was given.

| Time (Minutes) | EGG Consumed | EGG Consumed | EGG Consumed | EGG Consumed | EGG Consumed | EGG Consumed |
|---------------|--------------|--------------|--------------|--------------|--------------|--------------|
| <0            |              |              |              |              |              |              |
| 0+15          |              |              |              |              |              |              |
| +15 +30       |              |              |              |              |              |              |
| +30 +45       |              |              |              |              |              |              |
| +45 +60       |              |              |              |              |              |              |
| +60 +90       |              |              |              |              |              |              |
| +90 +120      |              |              |              |              |              |              |
| +120 +180     |              |              |              |              |              |              |
| +180 +240     |              |              |              |              |              |              |

Fig. 1: The 9 time-points for EEG capture.

### IV. Method

#### A. Data Pre-processing

The first five seconds of each EEG recording were discarded as they usually contain a high level of noise. The EEG recordings were then resampled to 128Hz, and band-pass filtered to 0.1Hz - 45Hz. We then cut each EEG time series into consecutive 20-second segments.

#### B. Source Localization and Feature Extraction

Source localization was performed using the Low-resolution Electromagnetic Tomographic Analysis (LORETA). The Regions of interest (ROI) selected for the process were based on the Brodmann brain atlas, which has been widely used to represent the localization of brain function. We further divided the Brodmann areas no.53 and no.54 into 3 sub regions to improve the resolution of the brain map. Totally, 88 ROIs are localized for further feature computation.

It is suggested that the lagged components of functional connectivity (i.e. lagged coherence) are minimally affected by the low scalp spatial resolution, thus containing high quality physiological information. Based on initial evaluation across different frequency bands, the lagged coherence features in the alpha band (8-13Hz) were employed in our study for obesity classification. Between the 88 pairs of ROI voxels, $88 \times 87/2 = 3828$ distinct lagged coherence features are used in this study.

#### C. Subject-based Cross Validation

The lagged coherence feature set with a size of 540 (9 time points $\times$ 60 subjects $= 540) \times 3828$ is split for training and testing using subject-based 10-fold cross validation. Specifically, each “experiment” consists of 10 trials (i.e., folds). In each of the 10 trials, we select 54 subjects’ data, which includes 54 $\times$ 9 = 486 samples for training and validating, and 6 subjects’ data, which includes 6 $\times$ 9 = 54 samples for testing. No subjects are selected for both training or testing, i.e., testing is always done on external subjects. The number of obese subjects and lean subjects selected for training or testing is equal.

#### D. Feature Selection

To effectively select features from the high dimensionality (3828), a new feature selection method is proposed. It involves several key steps explained as follows.

1) Feature Preselection: We firstly reduced the size of the feature set using a Random Forest classifier validated by the 10-fold cross validation and selecting the top 100 features with the highest importance scores.

2) Feature selection: In this step, we propose a novel maximum performance gain and minimal correlation (MPGmC) method for feature selection. Denote the reduced feature set as $F_0$. We start with an initial selection $F_1 = \{f_1\}$, where $f_1$ is the feature in $F_0$ that has the highest importance. Our goal is to select features using a classifier, assessing the merit scores of all the other features not yet selected, by looking at their potential gain in classification performance versus their correlation with the existing feature selection and selecting the best features incrementally. Specifically, suppose at $m$-th step we have selected feature set $F_m$, and we want to We define the merit score for a feature candidate $f_i$ as:

$$\mu(f_i, F_m) = \frac{\phi(F_m \cup f_i) - \phi(F_m)}{|F_m|}$$

where $\phi(.)$ gives the classification accuracy obtained from one fold of training and testing, $f_i \in F_0 \setminus F_m$. We then pick the best feature with the top score:

$$f_s = \arg \max_{f_i \in F_0 \setminus F_{m-1}} R(f_i, F_{m-1}),$$

and update the feature selection by

$$F_m = F_{m-1} \cup f_s,$$

if the best merit score is higher than a threshold $T$: $\mu(f_s, F_m) > T$; otherwise we terminate the feature selection procedure.

The MPGmC algorithm, with core algorithmic steps outlined as above, is presented in Algorithm 1. Each feature contained in $F_0$ is therefore assessed and potentially added to the selected feature pool progressively. For each iteration, a 10-fold cross validation score is computed using the Support Vector Machine (SVM) with the radial basis function (RBF) kernel as the classifier.

The above steps are then performed iteratively on each of the 10 trials and 10 feature selection pools are obtained. Next, we re-rank all the selected features in a descending order according to the number of times they are selected across all 10 trials.

3) Classification: A properly tuned SVM with RBF kernel is fitted on the training data to predict the label of each sample. Since each subject has 9 samples that are generated from the data of 9 different time points, we then determined the final label of each subject by counting how many samples that
belong to the subject are classified as obese and how many are classified as lean.

Algorithm 1: MPGmC Feature Selection

Data: Initial feature set $F_0$, threshold $T$

Result: Selected feature set $F$

1. Assign the best feature to selection: $F \leftarrow f_1$;
2. for $f_i$ in $F_0 \setminus F$ do
3. Calculate score $R_m(f_k), \forall f_k \in F_0 \setminus F$ using Eq. 1;
   Pick the top-score feature $f_s$ according to Eq. (2)
   if $R_m(f_s) > T$ then
5. $F \leftarrow F \cup f_s$;
6. else
7. Break;
8. end
9. end
10. Return $F$;

4) Running the experiment multiple times: The entire process which starts from train and test split following by the feature selection and classification steps described above is called an experiment. In order to improve the reliability of our results, we then conducted the experiment for 9 more times, each time the input dataset is shuffled. Fig. 2a shows the selected lagged coherence features by overlaying the results of all 9 experiments. A thicker line between two brain regions means the coherence feature has been selected in more experiments, thus having more contribution to yield a reliable classification result.

We then constructed the final selected feature pool by integrating the results obtained from the 9 experiments in two ways:

a) Using the SVM classifier with RBF kernel to select the final feature set: In this method, we ranked each selected feature according to the number of times it has been selected across all the 9 experiments. Then incrementally add one feature for a 10-fold cross validation.

b) Picking the most commonly selected features: Based on the lagged coherence features visualized in Fig. 2a, we picked the 7 most commonly selected features (i.e. 7 thickest lines).

V. RESULTS AND DISCUSSION

The feature selection outcome are given in Fig. 2. All selected features form a complex mesh as shown in Fig. 2a, the final 19 selected features are shown in Fig. 2b, and the top-7 connectivity pattern is visualized in figure Fig. 2c.

The test scores obtained across the 9 experiments using the SVM selected features and the commonality-based selected features are demonstrated in Fig. 3. Furthermore, we compared our feature selection model with the Minimum Redundancy and Maximum Relevance (mRMR) feature selection method [10]. The experimental result obtained using the mRMR method is also shown in Fig. 3. An overall accuracy of 0.90, 0.88, and 0.90 are achieved for the SVM selected feature set, the commonality-based selected feature set, and the mRMR selected feature sets, respectively. T-tests are then performed and a $p$-value of 0.18, 0.64, and 0.25 is obtained between each two selected feature set. This suggests that the classification performances on the three selected feature sets are not significantly different. We therefore will discuss only the commonality-based selected features in the following paragraphs.

On the other hand, comparing to the mRMR method which selected 100 features to achieve a classification accuracy of 0.9, our method demonstrated its higher efficiency by using only 7 features to achieve a similar performance.

![Fig. 2: Selected lagged coherence features obtained from 9 experiments: (a) all features; (b) 19 features selected by SVM; (c) 7 lagged features selected on a commonality basis.](image)

![Algorithm 1: MPGmC Feature Selection](image)

![Fig. 3: Violin plots of test scores obtained across 9 experiments by using SVM selected feature set and commonality based selected feature set.](image)

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etal and inferior parietal area, and the parahippocampal area in obese women. The connection between the temporo-occipital junction and the parahippocampal area which can be observed in healthy brain is also missing in obese brains. Since these areas work together for individuals to process environmental cues and adapt their behaviors accordingly, we can then infer that contextual information may influence obese women less than lean women, potentially explaining the impaired ability of predicting energy requirement of obese women. [13]. [14].

VI. CONCLUSION

In this study, we have investigated the obesity-related neurological characteristics in resting-state EEG signals using a machine learning approach. Using a new feature selection scheme, the large dimensionality of the source connectivity features were reduced effectively, and distinctive functional connectivity patterns were found between obese females and lean females. The distinction primarily associates to the impairment of brain areas which encode to evaluate energy requirement. For future work, we intend to collect more EEG data from subjects of both sexes and apply our method to identify reliable diabetes neural signatures, which may pave the way for effectively diagnosis as well as interventions.

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