EEG-based Automatic Emotion Recognition: Feature Extraction, Selection and Classification Methods

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***Abstract*—Automatic emotion recognition is an interdisciplinary research field which deals with the algorithmic detection of human affect, e.g. anger or sadness, from a variety of sources, such as speech or facial gestures. Apart from the obvious usage for industry applications in human-robot interaction, acquiring the emotional state of a person automatically also is of great potential for the health domain, especially in psychology and psychiatry. Here, evaluation of human emotion is often done using oral feedback or questionnaires during doctor-patient sessions. However, this can be perceived as intrusive by the patient. Furthermore, the evaluation can only be done in a non-continuous manner, e.g. once a week during therapy sessions.**

In contrast, using automatic emotion detection, the affect state of a person can be evaluated in a continuous non-intrusive manner, for example to detect early on-sets of depression. An additional benefit of automatic emotion recognition is the objectivity of such an approach, which is not influenced by the perception of the patient and the doctor. To reach the goal of objectivity, it is important, that the source of the emotion is not easily manipulable, e.g. as in the speech modality. To circumvent this caveat, novel approaches in emotion detection research the potential of using physiological measures, such as galvanic skin sensors or pulse meters.

In this paper we outline a way of detecting emotion from brain waves, i.e., EEG data. While EEG allows for a continuous, real-time automatic emotion recognition, it furthermore has the charm of measuring the affect close to the point of emergence: the brain. Using EEG data for emotion detection is nevertheless a challenging task: Which features, EEG channel locations and frequency bands are best suited for is an issue of ongoing research. In this paper we evaluate the use of state of the art feature extraction, feature selection and classification algorithms for EEG emotion classification using data from the de facto standard dataset, DEAP. Moreover, we present results that help choose methods to enhance classification performance while simultaneously reducing computational complexity.

I. Introduction

The goal of automatic emotion recognition is the retrieval of the emotional state of a person in a specific point in time given a corresponding data recording. It has great potential for applications in the eHealth domain, such as the early detection of autism spectrum disorder (ASD) [1] or depression [2]. Examples like *Paro*, a robot modeled after a baby seal which is being used in therapy for Alzheimer patients, or *Robear*, a robot designed to help in elderly care, show that emotion recognition is also on the verge of entering the eTherapy domain.

In the process of setting up an automatic emotion recognition system one has to choose the modality for the input, for instance speech, facial gestures or physiological measures. Each is coupled to certain advantages and difficulties. Modalities like speech, facial gestures or body pose are relatively easy to pick up (e.g. via a microphone or a camera) and to interpret by humans. On the other hand, physiological measures are more difficult to interpret by humans (e.g. sweating because of fear or due to temperature?), but much harder to directly manipulate by the sender (e.g. the heartbeat). Therefore, physiological modalities offer a great potential for unbiased emotion recognition.

In this paper we will focus on brain waves, i.e. electroencephalography (EEG), as a way to detect the emotional state of a person. Disadvantages of EEG data are noisy recordings due to artifacts caused by muscular activity and poor electrode contact. Owing to the complexity of the brain, EEG signals are not well understood in regard to emotions. Consequently, EEG-based emotion recognition is a field of active research for which many comparisons of possible algorithms are still to be done. The goal of this work is to evaluate the suitability of different feature extraction methods, EEG channel locations and EEG frequency bands in order to build an EEG-based emotion classification system. Set by another research project this work was conducted in, three disjunct emotion classes are chosen: anger, surprise and other (which includes all emotions except anger and surprise).

In this work Support Vector Machines (SVM) and Random Forests (RF) are applied as two very different state of the art classification algorithms which are trained using features based on statistics, Short-time Fourier Transform (STFT), Higher Order Crossing (HOC) and Hilbert-Huang Spectrum (HHS). Elimination of uninformative features which can result in faster training and classification as well as enhanced classification performance is applied using the mRMR algorithm. On the basis of this we aim to find indications for important frequency bands, feature types and EEG channel locations.

The remainder of this paper is organized as follows: First, related work is discussed in section II. In this section we point out the diversity and complexity of research in this field. Next, we describe the building blocks of our EEG-based emotion recognition system as they were implemented

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using Matlab (see sectionIII). After a short description of the used dataset in section VI, we present the metrics we used in the evaluation and the corresponding results (sections VII and VIII). In section IX, the paper is summarized in a brief conclusion.

II. Related Work

The usage of EEG signals for emotion retrieval was first introduced by [3]. Since then, owing to advances in pattern recognition, machine learning and the availability of lower priced EEG devices, research in this field is becoming more accessible in recent years. In the field's early days signals have been analyzed for linear relationships based on neuro-scientific knowledge. Due to the brain's complexity recent publications [4] consider an increasing amount of non-linear features like Higher Order Crossings [5] or Fractal Dimensions [6]. Still, simple features like band powers have become almost omnipresent notwithstanding the fact, that they are based on different underlying algorithms and sometimes referred to for sole comparison reasons.

A similar picture emerges for feature selection in EEG emotion recognition. The focus shifts from well studied (multivariate) analysis of variance ((M)ANOVA) methods to recent filter methods like (mRMR [7], [8]) or embedded methods like tree-based approaches. Feature selection can be used to find the most informative frequency bands and locations on the scalp ([9], [10]).

Study of related work yields a tough conclusion: despite much effort in the field of EEG-based emotion recognition, it is still a long way for "cookbook recipes" and best practices that could assure high performance. This is owed to a number of factors that make this field particularly complex. For instance, studies about emotion recognition from EEG are very hard to compare. The parameters being optimized or reviewed differ among publications.

Classification accuracy is given by many studies as a means of representing classifier performance. However the class distribution of training and test sets at hand are sometimes not clearly specified (for example [10]), which limits the test reliability of such results. [4] gives a good comparison (using a Naive Bayes classifier) of possible feature extraction and selection methods. However, their study is based on a single dataset for which emotions were induced by showing pictures from the International Affective Picture System to the probands. Though, it can not be fully applied to every use-case. Moreover, it poses another problem: [11] showed that EEG responses are indeed different varying with the modality of induction.

Despite these limitations [4] is the most holistic overview of feature extraction and selection methods we found so far. Thus some choices regarding feature selection and extraction in this work are made with respect to this particular work.

III. Feature Extraction

As a first step towards an EEG-based emotion recognition system the EEG channels and features which are to be extracted from the EEG signal have to be identified. In our work we consider the EEG channel locations AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. This channel locations are widespread, and even available in low cost consumer devices, e.g. the Emotiv EPOC device. In order to evaluate the relevance of different frequency bands, the signals were decomposed into the commonly used θ ((4Hz, 7.5Hz]), α ((8Hz, 13Hz]), β ((13HZ, 30Hz]) and γ ($>$ 30Hz) bands[1]. We omit using the δ ($\leq$ 4Hz) band since this information has been removed in the DEAP dataset [13] which we use in our experiments (see section VI).

From each band statistical, HHS and HOC features were extracted. STFT-based features were obtained from the original signal which is being internally decomposed (see section about STFT). HOC features were additionally retrieved from the original signal.

The following paragraphs give a brief description of each extracted feature.

Butterworth filters are commonly used to extract frequency ranges from a discrete-time signal and have been applied in previous studies on EEG emotion recognition [14], [5], [15]. To retain comparability with these we take advantage of Matlab's `butter` function to design 6^{th} order Butterworth bandpass filters. With the frequency ranges chosen according to the frequency bands, the filters yield four new signals from the original recording.

We apply Short-Time Fourier Tranform (STFT) with the `spectrogram` function that can give a spectrogram representation of the signal as well as power spectral densities of frequency bins. Similar to [4] we apply a Hamming window of 1 second length, that is 128 samples. Since the PSDs are returned for 1 Hz bins, we first sum the PSDs of the according bands. For each resulting band PSD we extract the minimum, maximum and variance as features. Additionally we average over time to arrive at a time-independent representation of band powers which is added to the feature vector as well as the α/β-power ratio.

Similar features as for STFT were produced from the decomposed signals, meaning for each frequency band. Again, the features are minimum, maximum and variance of the signals as well as their mean band powers. We employ the implementation by [16]. With this the intrinsic mode functions (IMFs) are computed. Then the Matlab `hilbert` function is applied to each IMF and the instantaneous frequencies are calculated similarly to [17]. First the instantaneous frequencies are averaged and then the mean (in regard to time) of instantaneous frequencies is computed and used as a feature [4]. This is done for every frequency band.

We implemented simple HOC and execute it for each frequency band signal using the difference filter applied k-times for $k = 1, .., 10$ similarly to [4]. Additionally simple HOCs of the original signal were computed. This decision was made on the fact that the iterative application of the difference filter removes high frequencies in each step, thus

[1]We follow the frequency band definition according to [12]. Different authors use slightly varying definitions between publications.

has the characteristic of a frequency decomposition itself. This process returns ten features for a input signal corresponding to the number of zero crossings for the k-times filtered signal.

IV. Feature Selection

Feature Selection is used to select a relevant subset of all available features which yields not only smaller dimensionality of the classification problem but can also reduce noise (irrelevant features). We further deduce which feature types are suitable for EEG emotion recognition by inspecting features that are being selected by the applied algorithm.

In order to do so, we apply a Matlab implementation [18] of mRMR [7][2]. It being a filter method gives us advantages such as ranked features and classifier-independence while also being less computationally intensive than wrapper methods. [4] and [8] have successfully applied mRMR for EEG emotion classification. Following [19] who report its better stability, we use the Mutual Information Difference version.

Random Forests are also applied for classification (see section V) which is a representative of the feature selection class of embedded methods meaning that these kinds of classification algorithms also do feature selection internally.

SVMs don't perform well on unscaled features since the decision hyperplane can be heavily influenced by just one single feature with large values. RFs do not require this preprocessing step but do not suffer from it either. Thus we first z-normalize and afterwards scale to $[0, 1]$ on the training set and apply the normalization and scaling with the same parameters to the test set. For consistency we use the normalized features for both RF and SVM. For mRMR discretized features are strongly recommended. In order to loose as little information as possible, we deploy discretized (20 steps, similar to [4]) features only for mRMR itself and from its results select a subset of the z-normalized but non-discretized features.

V. Classification

For the classification task, we use two popular algorithms: Support Vector Machines and Random Forests. For the SVM implementation we decided for the widely used LIBSVM [20] of which a Matlab port is freely available. It can also handle multi-class problems by applying the one-against-one method which was shown to give comparable classification performance but shorter training time then one-against-all [21]. The Matlab provided `TreeBagger` class is used for construction of RFs.

Both implementations support cost-sensitive learning which we use to mitigate the problem of imbalanced data. LIBSVM is limited to the assignment of different weights to the classes where `TreeBagger` offers the possibility to define a full cost-matrix. To account for the imbalanced class distribution we choose higher costs/weights for classes *anger* and *surprise* compared to *other*. We tested[3] different costs/weights and chose them such that the diagonal element of each entry of the confusion matrix was the largest per row.

For RF we construct the cost matrix with:

$$C(\text{anger}, \text{surprise}) = C(\text{anger}, \text{other}) = 38$$
$$C(\text{surprise}, \text{anger}) = C(\text{surprise}, \text{other}) = 7$$
$$C(\text{other}, \text{anger}) = C(\text{other}, \text{surprise}) = 1$$

and zero cost for correct classification. For SVM $w_{\text{anger}} = 7.7$, $w_{\text{surprise}} = 4.2$ and $w_{\text{other}} = 1.01$ are used.

TABLE I
Values used for mapping from DEAP PAD values ($[0, 9]$) to discrete emotions.

Emotion	Valence	Arousal	Dominance
Anger	< 5	> 5	> 5
Surprise	$[0, 9]$	> 5	≤ 5
Other	$[0, 9]$	≤ 5	$[0, 9]$

VI. Dataset Description

We use preprocessed 128Hz EEG signals from the Database for Emotion Analysis using Physiological data (DEAP) [13] for training and testing. It further offers different biosignals and front face video of participants. In the course of their data acquisition thirty-two subjects were to watch forty one-minute samples of music videos which have been chosen specifically for their high capability of eliciting emotions. After each video the participant gave feedback about their levels of arousal, valence, dominance and liking using the Self-Assessment Manikin (SAM) [22], [23] technique. To yield discrete emotion classes we converted the continuous valence, arousal and dominance values according to Table I.

There are other data sets offering similar data, for example eNTERFACE'06 [24] ($N = 5$, all male) and MAHNOB-HCI [25] ($N = 27$, 11 male). However DEAP has the most participants ($N = 32$) of which 50% are male and eNTERFACE does not include a dominance dimension.

VII. Evaluation Metrics

Depending on the use-case or underlying data different evaluation metrics are used to test the classification performance. While it is often used, accuracy may, depending on the data at hand, not be a suitable representation of classification performance. Due to imbalanced data, meaning that there is not an equal amount of data belonging to each class, this is the case in our work. Hence, we analyse results using *recall*, *precision* and *confusion matrices* according to the following definition of true/false positives/negatives:

Many measures are based on these values but thus are limited to binary classification problems. We extend the definitions in a one-vs-all manner to account for multi-class problems as well. The definitions are therefore always relative

[2]Due to an error in the source code, the implementation can not be compiled right away but all calls to `log` have to be passed a `float` or `double` in the C++ source files. To fix this, every occurrence of `log(2)` was replaced by `log(2.0)` and the source files subsequently recompiled.

[3]This was done using 10-fold cross-validation on the top 100 features as determined by mRMR.

to the examined class i. Given the examined class i a true positive (TP) is thus the number of instances that have been predicted correctly as an instance of class i, a false positive (FP) corresponds to a instances of true class j with $j \neq i$ and predicted class i. Consequently, a true negative (TN) is an instance of true class j with $j \neq i$ and predicted class t with $t \neq i$. In conclusion a false negative (FN) is an instance of true class i and predicted class j with $i \neq j$. Given a sequence of true labels and predicted classes the total number for one of these measures is computed as the sum of the values for the particular measure over all classes.

In order to evaluate the importance of different feature bands, feature types and EEG channels, we first run the mRMR feature selection ten times each on a random subset of 90% (that equals 1152 instances) of the data and record the number of occurrences of the according property for each run. From this the mean and standard deviation of the number of occurrences is computed. A corresponding bar plot can then give indication whether the different selection frequencies are significant. Each feature corresponds to either one of the frequency bands or the original signal. For a feature chosen by the feature selection the corresponding band count is then simply incremented. Features linked to the different θ- and γ-bands are represented in equal amounts but since the α/β-ratio features are linked to these two bands, we count these for both bands as well. To account for these differences, we plot the occurrences and standard deviations divided by the number of feature types that are based on a particular band.

We analyze the types of features returned by feature selection with the help of histograms that are scaled to clarify which types were favored and which were disfavored. The procedure is equivalent to the steps applied for comparison of the frequency bands.

For each EEG channel location an equal number of features are extracted therefore we simply present histograms with the absolut number of occurrences and standard deviations as well as topographic heat maps to convey which scalp locations were selected more often.

VIII. Results

Based on the results of the mRMR feature selection this section highlights the most important features in regard to extraction methods, frequency bands and EEG locations.

In Figures 1 and 2 it can be seen that classification for SVM is the most robust and successful between the top 80 and top 125 features (as selected by mRMR) but tends to decline when using a larger amount of features. This presumably arises from the sensitivity of SVMs to noise (e.g. irrelevant features). Precision, recall and accuracy values (Figure 1) show that from the top 5 to top 125 features, classification performance improves for both SVM and Random Forest indicating that features which are not in any of these sets have low or no relevance for EEG emotion recognition. Random forests show very robust results even when adding all up to 900 features which is indication of the robustness of RFs to non-relevant

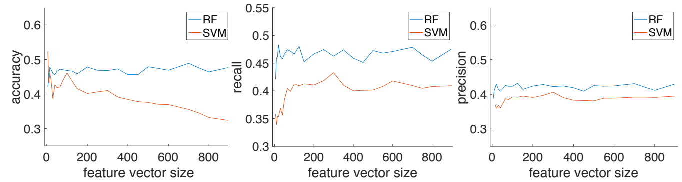

Fig. 1. From left to right: Classification accuracy, recall and precision values based on the mean of 10-fold CV for the top N features.

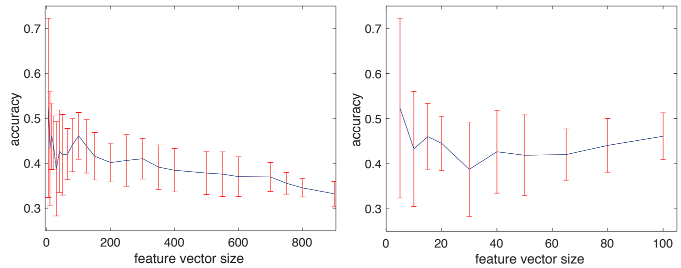

Fig. 2. Classification accuracies for SVM and corresponding standard deviations for the top N features.

features. Overall, standard deviations of measurements were smaller for Random Forests than for SVMs.

Figure 4 shows that γ-band features are strongly represented in the top features selected by mRMR. Up to the top 50 features θ-band features are slightly favored over α and β. For even larger feature subsets there is no big difference between the selection frequency of θ and α. Further the selection of only few features based on the original signal is easily recognizable up to the top 200 features. Starting from the plot for the top 30 features, standard deviations are rather small compared to the corresponding histogram bar which supports the significance of the previous statements.

The main point that can be taken from these results is an increased importance of the γ band for emotion recognition given the emotion classes defined in this work. Figure 6 supports this: classification performances are overall worse when removing γ band features. This coincides with results from [14] and [4] but are inconsistent with work by [9] who consider α and β to be more suitable for EEG emotion recognition.

Furthermore these results indicate that frequency band decomposition can be beneficial since features based on the original signal were seldom selected in for the top features.

The topographic heat maps in figure 5 show a tendency of mRMR to select features linked to the (pre)frontal lobe, especially from the left hemisphere. Features corresponding to the T7 location, that is from the left temporal lobe, are strongly represented in the top 30 to top 600 features. The indication of these locations being suitable for EEG emotion recognition agrees with results by [14] and findings from neuroscience [26]. However standard deviations are rather high up to the selection of top 100 features, especially for features from the F7 location. It should be noted though that (pre-)frontal locations are prone to recording Electrooculogram

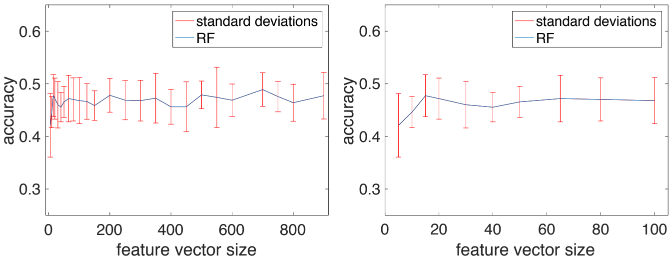

Fig. 3. Classification accuracies for RF and corresponding standard deviations for the top N features.

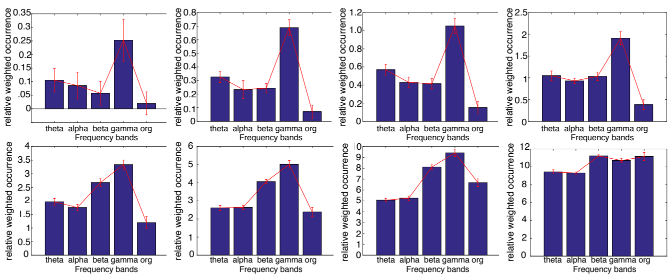

Fig. 4. Weighted relative occurrences of frequency bands in the top N features selected by mRMR. From upper left to lower right corresponding values are $N = 10, 30, 50, 100, 200, 300, 600, 900$.

(EOG) artifacts [27] which may not be perfectly removable although attempted in the DEAP data [28]. Thus classification may to some degree be based on eye movements rather than brain activity.

During our experiments we found that mRMR favors STFT-based features heavily compared to their statistical counterparts when choosing the top 10 to top 200 features. Especially up to the top 50 features, STFT band minimums are represented very frequently. Classification performance in figure 7 after removal of the STFT minimum features support the increased importance of these features as indicated by the mRMR selection. While RFs are not significantly influenced by this removal SVMs show much weaker performance especially in terms of classification accuracy. HHS-based features are dominant from the top 30 to top 300 features. When removing HHS-based features from the top feature sets (see figure 8) the best classification performance (which is similar to the performance using all feature types) is between 200 and 250 features for both SVM and RF. This indicates that the loss of information from removing HHS features can be compensated for by adding other features.

From the set of statistics-based features, band powers are the most frequently chosen features in the top 10 to top 300 features however, from the top 100 features on there is not much difference to band variances. HOC features, statistical band minimums, maximums and α/β-ratios are sparsely represented in the top 10 to top 300 features. From the differences between the distribution of features in the top 600 and top 900 sets can be taken that HOCs are predominantly in the lower midfield of the mRMR ranking. As most of the statistical features are added between the top 300 and top 900

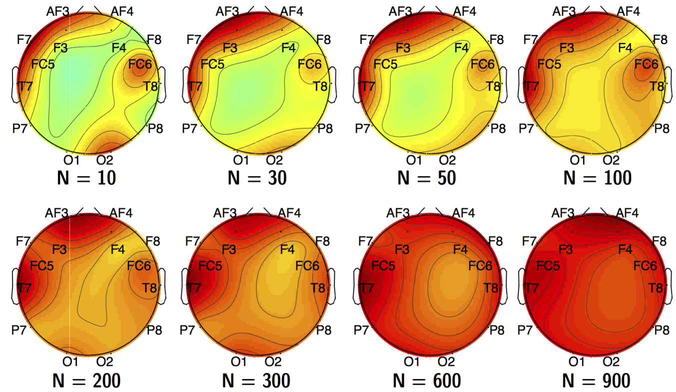

Fig. 5. Topographic heat maps showing how many features based on the particular EEG channel were chosen during mRMR feature selection for the top N features. The color green represents none selected and dark red that many were chosen.

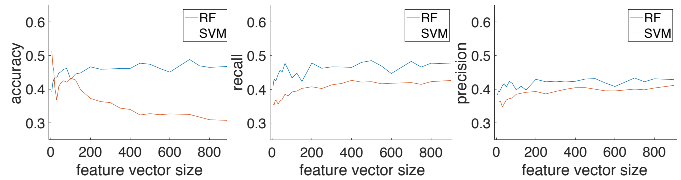

Fig. 6. From left to right: Classification accuracy, recall and precision values based on the mean of 10-fold CV for the top N features after removing features based on the γ band.

features, they are also mostly in the (according to mRMR) worse half of features. It is also striking that even in the top 900 features STFT-based band variances hardly occur, thus they are very low in the mRMR ranking.

IX. Conclusion

In this paper, we tested different frequency bands, EEG channel locations and feature extraction algorithms for their

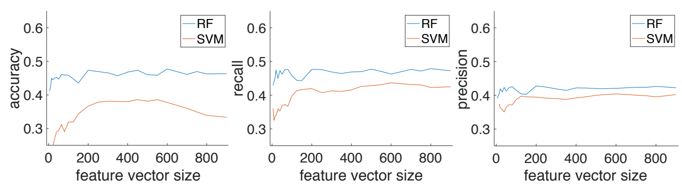

Fig. 7. From left to right: classification accuracy, recall and precision values based on the mean of 10-fold CV for the top N features after removal of STFT minimum features.

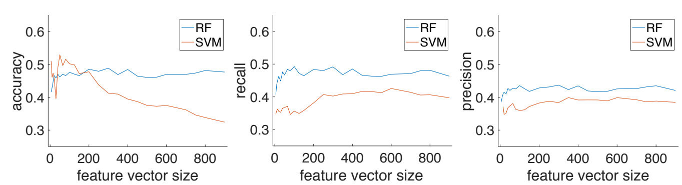

Fig. 8. From left to right: classification accuracy, recall and precision values based on the mean of 10-fold CV for the top N features after removal of HHS features.

suitability in EEG-based emotion recognition. Various feature extraction algorithms were applied, mRMR was used for feature selection and classification was done using SVM an Random Forests. HHS- and STFT-based features were found to be valuable feature extraction algorithms for classifying EEG data according to emotions felt.

Further we showed the increased importance of γ features and EEG locations corresponding to the (pre-)frontal and left temporal lobe for EEG emotion classification which coincides with findings from neuroscience [26] and related work [14], [4]. In the course of this work we have also found Random Forests to be much more robust and simpler to use than Support Vector Machines for the use-case of EEG emotion recognition.

In our future work, we will expand EEG-based emotion recognition to continuous automatic depression detection, which will be done with the authors of [2]. This research will then be evaluated within a clinical trial.

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