A Machine Learning Based Classification System for Brain Signals: An Animal Model Application.

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***Abstract*—EEG signals have seen an increase in usage within both research and the medical domain through the improvement of cheaper non-invasive neural signal collection, leading to a a higher rate of application development. Features extracted vary between temporal, spectral, and statistical information; which can then be applied in a number of manners, producing results dependent upon the strengths of a given machine learning architecture. This report shows a comparative study of implementations within those existing domains which make use of machine learning and deep learning as an EEG analysis and classification technique, alongside similar signal processing problems.**

Keywords: EEG, features, signal analysis, machine learning, deep learning.

I. INTRODUCTION

Electroencephalogram, or more commonly referred to as EEG data is a form of measuring electrical signals produced via activity within a living brain; this takes place through the medium of electrodes placed on the subject in question [1], each of which has a predetermined position based upon the 10 - 20 international system [2] (fig. 1). Much of the information found within the signal measures the relationships between physical stimulus and a significant variation in psychological reactions dependent upon individual interactions or substances involved. Digital classification of such differentiation can be an incredibly useful resource when determining prior actions and expected reactions, and has been used in a wide variety of applications to this end.

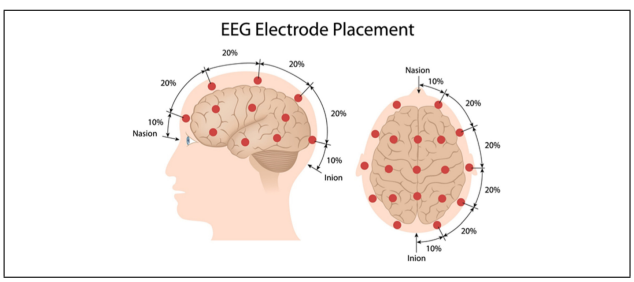

Fig. 1. The international 10-20 system, each segment split into 20% of the skull with the exception of front and back of the head where the segments are at 10% of skull width apart [2] [3].

II. RESEARCH BACKGROUND

There are several varieties of existing applications that deal with EEG signal analysis after it has been extracted, which can take place in one of two major forms. Whilst many research areas cover the human brain, the same techniques are also applicable in many cases to animal EEG.

A. Non-Invasive EEG collection

The brain to computer interface that is required to record EEG data in the first place can be recorded as either invasive or non-invasive. The non-invasive method has a much higher likelihood of large underlying artefacts due to motion or electrode slippage compromising the obtained signals integrity [4], as a trade-off this technique is subsequently both faster and cheaper to obtain data with when compared to the invasive variation; allowing it have a more common application in real world scenarios for both data collection and signal analysis tasks, many of the subsequent literature examples making use of this technique.

B. Invasive EEG collection

Comparatively, invasive EEG methods are required for those areas where precision and detail is a priority due to the severity of the subjects situation, such as epilepsy [5], where alternative forms of localisation have been attempted. For instance in situations where MRI or non-invasive scalp EEG but have presented discordance between the findings. This method is much more extreme and expensive than the prior methodology, requiring surgery and implanting of custom-made electrodes directly onto the brain tissue, often for identification of specific neural locations prior to major operations [6]. Fewer datasets and studies exist when it comes to this variation over data collection for large signal analysis and research due to the severity of the requirements and repercussions.

C. Existing Applications

Several solutions exist in this domain of application which can be used to analyse and understand what the digital representation means. Since the electrodes span the entirety of the scalp for the individual in question, the problem domain becomes one that is multi-channelled (fig. 2). It then must come into consideration which regions of the brain are being affected by the input stimulus relevant to the problem itself. Applications of this technology are present and make use of techniques that have benefits and detriments depending upon the problem requirements.

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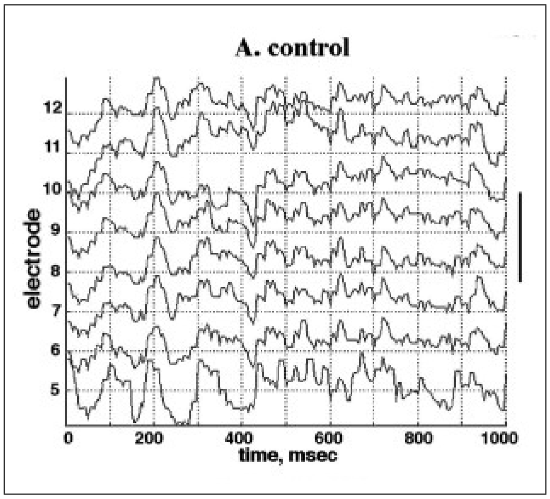

Fig. 2. Raw Multi-channeled EEG signal from several electrodes over a 1000 millisecond duration. From study on the spatial relationship of electrodes for sleep stage analysis [7]

1) Emotion Recognition: Due to continued development within signal processing and electrode efficiency, emotion recognition has become one of the major applications of EEG data analysis [8]. Since emotions can directly impact the relationship that an individual has with concepts and actions, studies showing that classifying the electrical signals that differentiate them is both a plausible and relevant area within both neural-computing and neural-biology. Much of the work in this domain intrinsically take the primary source for EEG stimulus from images (26%), whilst a smaller number (17%) make use of audio signals [9]. It has also been discussed that different specific emotion variations can elicit responses in particular brain regions [10] subsequently translating into a response in fewer channels from which relevant information can be extracted.

Feature extraction of this information has taken a large variety of forms, with spectral domain analysis being at the forefront. Short Time Fourier Transform (STFT) or Fast Fourier transform (FFT) has used for this purpose, extracting the underlying wavelets and frequencies that make up the complex signal. Proposed within one of the earliest instances of mapping emotion based EEG features [11] made use of these techniques, making use of data taken from 76 subjects for a total of 6 possible emotional reactions. This work has then inspired several further studies within the same area [12] [13], then applying the extracted features to their individual classification algorithms. The Discreet wavelet transform has also been used for feature extraction within this domain [14], providing a compact representation of the data, providing insight into energy distribution of the EEG signal in both the time and frequency domains [15].

2) Seizure Detection: Outside of the emotion detection domain, EEG data analysis has been under research via medical imaging processes, with one of the more pressing application areas involving the treatment and detection of seizures within epilepsy patients. Epilepsy is a common neurological problem which has been discussed to have not only the sudden neural impact of the seizure itself, but also retain a close relationship with ongoing brain activity [16] [17], signifying that treatment along behavioural or psychological lines may also assist in this domain. EEG allows the pinpointing of this relationship and can assist in determining common patterns between patients.

The spectral domain again is a strong contender for this problem, both S.H.Lee et al (2014) [18], and more recently Amin et al. (2020) [19] make use of wavelet based analysis with the purpose of producing a highly accurate detection system, which classifies different seizure activities and non-seizure EEG readings; with further more expansive features taken from phase-space reconstruction and fractal intercepts in addition to these [20].

3) Substance Use detection: Another common medical application for EEG signal analysis is for Substance use Disorders (SUD). It is a highly prevalent disorder that involves the neurological side effects of addictive substances such as drugs and alcohol, many of the earlier studies for signal analysis in this domain having real world application for those undergoing alcohol addiction therapy [21]. Studies have included various novel feature extraction techniques [22], of which

4) Sleep Stage detection: Sleep stage analysis is another application for which EEG signals have been used to detect and diagnose sleep disorders within patients as one of several possible classifiers [23]. [7] makes use of sleep stage and wake stage data to test the impact of electrode density upon the problem. Additionally drowsiness, particularly when doing high concentration based activities such as driving can be a great danger, T. Brown (2013) [24] makes use of a wireless headset to track brain signals during a driving simulation.

5) Seismic information: Whilst the medical prominence of this type of signal processing is high, other application areas outside of the medical domain exist, particularly data with this type of imbalance is not unique to brain signals; being present within seismic data, which shows stunning similarities in terms of data type and expected outputs [25]. A high number of data points before the event occurs, followed with a single or many intermittent changes due to that initial event. Data and applications within this domain may very well achieve overlapping goals and procedures which would benefit from considering both domains.

Multiple examples of seismic signal classification make use of random forest (RF) classification with 61 base features [26] including spectral based, waveform based and spectrogram attributes amongst others [26] [27], although the output shares the high successful classification accuracy with the support vector machine (SVM) classification with at or over 98% accuracy, many of the results also return false positive in terms of landslide activity when considering unknown data.

D. Machine learning

Machine learning can generally be split into two major areas, traditional techniques and deep learning techniques which have more recently begun to show massive improvements due to advancements in both hardware and a more extensive understanding of their application, figure 3 shows the distribution of current deep learning algorithms according to A.Craik et al. (2019) [28]. With Convolutional Neural Networks having the highest total usage amongst recent studies (43%) followed by Deep Belief Networks (18%) and Recurrent Neural Networks (10%).

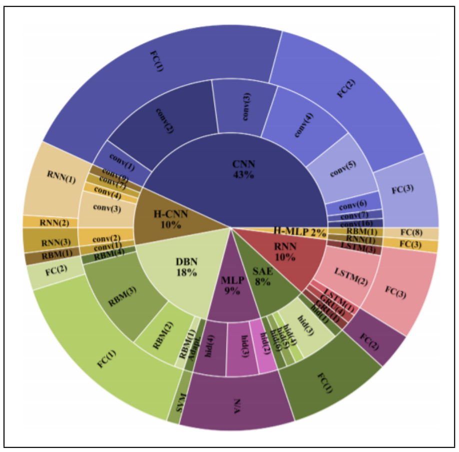

Fig. 3. Distribution of deep learning techniques amongst EEG based research and studies, irrespective of subject area. middle area showing the primary design features and external ring showing secondary design characteristics. Convolutional Neural Networks (CNN) showing the highest implementation distribution followed by Deep Belief Networks (DBN) and Recurrent Neural Networks (RNN) [28] .

1) SVM: Traditional algorithms such as Support Vector Machine's (SVM) have been used within emotion recognition tasks with an 81% classification accuracy for audio data [29] and 87% accuracy regarding video imagery [14]. SVM has been further applied within epileptic seizure detection, using a method based upon many small epochs at a 96% accuracy; this research also discusses that the model does not generalize well towards unknown data that has not been included directly within the training phase[30], causing major issues regarding outliers particularly when considering the medical domain.

The application of SVM is very common within EEG signal analysis, in many cases even when it's not used as the main focus of the research it has been implemented or used in some way as to be comparable to reported algorithms [31] [32] [14], and whilst popular in many early works it is not mutually exclusive. Usage of other algorithms such as KNN (K-Nearest Neighbour) and Adaptive Network-based Fuzzy Inference System (ANFIS) have been used in studies such as C.I.Aci et al (2019) [32] for their comparability to SVM but show reportedly worse results for that data at 77% (KNN), 81% (ANFIS) and 91% (SVM) respectively.

2) CNN: With the ever increasing onset of Convolutional Neural Network (CNN) application and it's ensuing effectiveness regarding image classification; CNN implementation can be seen included within a large quantity of classifications problems for EEG analysis, power spectral density mapping has been identified as a common feature that can be extracted from the signal and interpreted as an image; implementations such as J.Birjantalab et al 2017 [33] show a 95% f-measure classification metric; providing further comparisons via KNN (61%) and SVM (85%) attaining a large performance increase of 10% over the closest competitor.

Additional usage of CNN implementation has been done for previously mentioned sub-domains with varying degrees of outcome accuracy depending upon the problem; for example, [34] implements CNN architecture for an emotion recognition task achieving an 87% classification accuracy. This result is comparable to a CNN implementation for motor impairment classification [35] which only produces a 69% classification accuracy. A number of additional studies have made use of CNN architecture for similar problems but calculated differing metrics to measure the effectiveness, which is an issue regarding direct comparison of algorithms.

3) DBN: Deep Belief Networks (DBN), proposed by G.Hinton (2009) [36] have been applied for EEG analysis as another highly used algorithm depending upon the chosen problem. Turner et al. (2014) [37] proposes the use of such a system for seizure detection due to the high density data-set and computational complexity required. More novel applications for deep belief networks has been seen in feature extraction [38], performing with a 91% sleep stage classification accuracy applied on SVM, KNN and HMM models simultaneously, with the most accurate of the three chosen through an entropy voting principle

4) RNN: Another proposed method makes use of Recurrent Neural Networks (RNN) to classify both seizures [39] [40] and emotions [41] for additional temporal representation during the training phase, of which EEG can take advantage of due to its generally high data quantity per subject. The RNN architecture excels at problems in the time domain, taking into account the previous layers when making a prediction or classification; which can be hugely beneficial for EEG data which has large numbers of continuous data points for individual subjects.

5) Discussion: One of the problems that comes alongside the application of machine learning within this domain, particularly when it comes to the classification algorithms used, is the heavy class imbalance that is representative of this data [42]. The time of which an event does not occur lasts significantly longer than the time which the event does occur, meaning that learning leans towards the non-event data much more frequently and significantly than the data that is relevant to the problem at hand. Additionally while EEG data usually is very large in quantity, spanning hours or days in succession of recorded data, some studies contain data from large numbers of subjects, whereas others contain data taken from very few. This can cause concerns for making a generalized model dependent upon the domain. For example the dataset used by L. Vidyarante (2016) [39] includes 5 subjects for a 34 hour total duration whereas A. Pereira's (2018) [43] dataset includes 66 subjects for a 25.6 hour total duration.

III. Conclusions

The literature included shows that EEG data analysis has been, and continues to be a relevant and evolving area for the application of feature extraction and machine learning techniques to assist in the improvement of the medical domain. Whilst any techniques have been developed and attempted, there exist several gaps in the domain that have not yet been applied past a narrow problems space; where the classification of EEG signals could benefit from the application of existing techniques across both similar problems and completely different domains; which certainly warrants further considerations towards clinical advancements and understanding data in this area. The advancements within non-invasive and wireless hardware allow collection and analysis at a larger scale than that shown within prior studies; potentially granting the ability to improve the corresponding classification accuracy and overall comprehension of those features that represent the data.

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