OPEN ACCESS

Volume: 11

Special Issue: 1

Month: July

Year: 2023

E-ISSN: 2582-0397

P-ISSN: 2321-788X

Impact Factor: 3.025

Received: 11.05.2023

Accepted:13.06.2023

Published: 01.07.2023

Citation:
Gudada, Priyanka V, and R. Varun. "Recognising Consciousness Problems in Brain Injuries Using EEG Coupling and Machine Learning." *Shanlax International Journal of Arts, Science and Humanities*, vol. 11, no. S1, 2023, pp. 271–78.

DOI:
https://doi.org/10.34293/sijash.v11iS1-July.6356

Recognising Consciousness Problems in Brain Injuries Using EEG Coupling and Machine Learning

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Abstract

The cognitive electroencephalogram has lately received a lot of attention for looking into whether EEG properties may be employed as novel predictors for recovery in mild brain damage detection. To solve this issue, this paper proposes a computer-aided technique for automatic DoC identification based on information extracted from electroencephalogram data.It adds a new connection metric called Power Spectral Density Difference, which is based on a recursive Cosine function. The following processing stages.As a result, developing an approach for painstakingly flagging and collecting clean EEG data in order to obtain high-quality discriminative features utilising PCA for feature selection is critical. The technique then uses an ensemble Machine learning approach to classify brain-injured individuals into DoCclasses. Our proposed method for implementing deep learning algorithms with excellent accuracy and prediction status.

Introduction

A Disorder of Consciousness (DoC) in which awareness has been influenced by brain injury. Subtypes include somnolence, stupor, low coma, intermediate coma and profound coma. DoC is common following acute brain traumas such as haemorhages, trauma, and stroke. Accurate DoC diagnosis is critical for informing prognosis counselling and guiding treatment options. Patients suffering from DoC usually encounter major medical issues, which can impede recovery with therapy approaches. Observation in clinical and behavioural examination. Which have a significant test retest and inter examiner variability, have traditionally been used to measure the state of awareness.

The recognition of changes in DoC is mostly determined by the length of time between clinical examinations. For both inpatients and outpatients, such clinical evaluations need a large amount of labour, time, and other resources. Resting state electroencephalography (EEG) monitoring has the potential to help medical practitioners quickly measure DoC following brain trauma. It is typically utilised at a patient's bedside because to its mobility and low cost. EEG brain connectivity which refers to several interconnected features of brain organisation, is a hot issue in EEG research.

It is often classified into three types: anatomical or structural and effective brain connection. We focus on brain connectivity functional in this research, which describes the statistical dependency between signals originating from two or more separate units within a neurological system from single neurons to whole neural networks. Brain networks related with cognitive skills, spontaneous activity, and neurological diseases have been studied using functional brain connectivity.

We use machine learning approaches to gain information from EEG data by then make predictions inferences to accomplish automated categorization of DoC or wakefulness in brain injuries. Machine learning has been used in a variety of medicals and health applications. Examples include the automated identification of movement compensations in stroke patients, the study of sleep phases, the diagnosis cognitive impairment, and the prediction of breast and colon cancers. All of these efforts inspire us to apply machine learning to detect DoC in brain injuries.

Objective of the Work

The purpose of brain injury detection using an EEG dataset is to analyse EEG data in order to identify brain damage detection.

Using DL and ML algorithms to diagnose brain injuries.

To implement the recommended deep learning algorithm of high accuracy and precise forecast of our project's condition.

Problem Statement

One of the most difficult problems in detecting brain damage in EEG datasets is that the ML Algorithm predicts a poor accuracy prediction status.

Literature Survey

Verenna Rasstalked about it. The focus of clinical and animal research in subarachnoid haemorrhage (SAH) has moved in recent years, owing to the link of the early injury pattern (first 72 hours) with subsequent problems and poor prognosis. This stage is often referred to as early brain damage (EBI). We aimed to include generally accepted classifications of EBI, underlying processes, and potential therapeutic implications in this clinical review.We discovered significant variation in the criteria of EBI, which includes clinical symptoms, neuroimaging measures, and sophisticated neuromonitoring approaches. Although specific therapies are not yet available, therapeutic strategies aiming at alleviating EBI by correcting the energy/supply mismatch in the early post-SAH period are being developed.

It can reduce costs and time usage.The disadvantage is that there are too many false negatives. The likelihood of a run to failure is modest.

Joseph T Giacinodiscussed the Report of the American academy of neurology's guideline development, dissemination, and implementation subcommittee; the American congress of rehabilitation medicine; and the national institute on disability, independent living, and rehabilitation research objective: to update the 1995 American academy of neurology (AAN) practise parameter on persistent vegetative state and the 2002 case definition on minimally conscious state (MCS).

Methods

Recommendations were made utilising a modified Delphi consensus process based on systematic review evidence, principle care and inferences from the AAN 2011 process handbook, as revised. Recommendations: To increase diagnosis accuracy in adult and children with extended DoC

(Level B) clinicians should identify and treat confounding factors optimise arousal and undertake serial standardised tests. Clinicians should inform families that in adults, MCS (as opposed to vegetative state [VS]/unresponsive wakefulness syndrome [UWS]) and traumatic (as opposed to nontraumatic) aetiology are associated well outcomes (Level B).

According to Jan Classes, significant progress have been achieved over the last two decades in diagnosing, predicting, and facilitating consciousness recovery in patients with Disorders of Consciousness (DoC) caused by serious brain injuries. Advanced Neuroimaging and Electrophysiological techniques has been revealed new insights into biological mechanisms underlying consciousness recovery, as well as the identification of preserved brain networks in patients who appear to be unresponsive, raising hopes for more accurate diagnosis and prognosis. Emerging research shows that hidden awareness, better known as Cognitive Motor Dissociation (CMD), occurs in up to 15-20% of DoC patients and that detecting CMD in the critical care unit can predict functional recovery one year after injury.

Although basic uncertainties remain concerning which individuals finishedDoCtake a chance of recovery, innovative pharmacological and electrophysiological treatments have demonstrated the ability to reawaken wounded brain networks plus induce awareness re-emergence. This Review focuses on processes of recovery from DoC in the acute alsosubacute-to-chronic stages, as well as current advances in detecting as well as forecasting consciousness recovery. We also discuss advances in pharmacological then electrophysiological therapy that are providing fresh options to enhance the lives of DoC patients.

Predicting unexpected failures is more efficient than signature prediction if the signature detection file is big.Prediction cannot be utilised; signature prediction must be used.The reliability is unknown.

Aurorre Thibout agreed. Recent breakthroughs in functional neuroimaging have shown new possibilities for guiding diagnosis as well as prognosis in the unresponsive restless syndrome and minimally aware states. However this technologies remain prohibitively expensive and complex to implement, limiting the likelihood of widespread therapeutic application in patients. We show here that high density electroencephalography gathered from 104 individuals at rest be able to give useful information about brain connectivity that interacts with behaviour and functional neuroimaging. We visualise and quantify spectral connectivity derived after electroencephalography as a compact brain network using graph theory.

Our findings illustration that important quantitative parameters of this networks correspond through the continuum of behavioural recovery now in patients, ranging from those identified as unresponsive to those who has emerged after minimally conscious to fully conscious locked-in syndrome. A network measure that indexes the existence of highly linked core hubs of connection, in particular, differentiated behavioural awareness with accuracy equivalent to expert evaluation using positron emission tomography. We also show that this measure substantially corresponds with brain metabolism. Furthermore, we predict individual patients' behavioural diagnosis, brain metabolism, and 1-year clinical outcome using classification analysis. Finally, we show that evaluations of brain networks indicate substantial connection in individuals classified as unresponsive by clinical consensus but later rediagnose as minimally conscious with the comma recovery scale.

Each of the misdiagnosed patients was shown to be minimally conscious after a classification study of their brain network, validating their behavioural diagnosis. Such network metrics, if used on the bedside in a therapeutic setting, might supplement systematic behavioural evaluation and assist minimise a high misdiagnosis amount found in this patients. These measurements may also be used to identify individuals who require additional investigation by neuroimaging or traditional clinical Evaluation. Finallythrough providing objective characterisation states of consciousness, frequent evaluations of a network metrics might aid in the longitudinal tracking of individual patients as well as the assessment of a brain responses to therapeutic as well as pharmacological interventions.

A low rate of missing reports; a simple and effective procedure.Must be taught, and trained model must be carefully or false positives occur.

Although the relationship among anaesthesia and consciousness have been studied for decades, our understanding the underlying neural mechanisms of anaesthesia and consciousness remains rudimentary, limiting the development of a systems for anaesthesia monitoring and consciousness evaluation, according to Kangali Don. Furthermore, existing anaesthesia monitoring practises are mostly based on procedures that do not offer appropriate information and may obstruct the exact administration of anaesthesia. Recently there have existed as rising movement to use brain network analysis to uncover anaesthesia processes, with the goal of delivering innovative insights to increase practical application.

This review summarises contemporary research on anaesthesia brain network studies and examines the fundamental neurological processes of awareness and anaesthesia, as well as neural indicators and assessments of the diverse elements of neural activity. We discuss significant approaches and studies involving connection and network analysis, starting with the hypothesis of cortical fragmentation. We show that whole-brain multimodal network data can give valuable additional clinical information. More extremely this paper contends that, if simplified, brain network approaches will likely play a key role in enhancing present clinical anaesthesia monitoring systems.

Rigidity, error tolerance, high sensing quality, cheap cost, and quick deployment are all advantages.Failures are common in nodes.

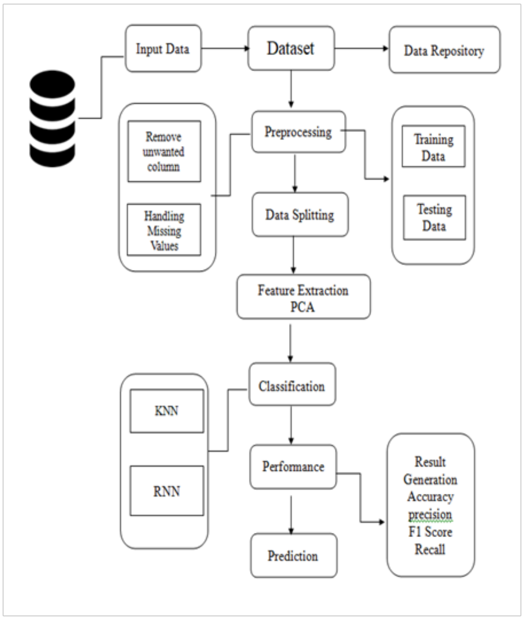

Figure 1 Proposed Architecture

Existing System

In the Current Approach, we use machine learning techniques to collect information from EEG data then generate predictions also inferences to automatically classify DoC or wakefulness in brain injuries. All of these efforts inspire us to apply machine learning to detect DoC in brain injuries.For separating DoC and alertness in brain injuries, a novel functional connectivity metric is presented. Used for the identification of DoCfrom brain damages, an ensemble machine Learning Algorithm is used. The classifier receives connectivity measurements after each pair of electrodes. The classifier's outputs are grouping results, which are a patient's positive, negative, or neutral DoC diagnostic.

When compared to the planned value, the loss value is quite significant.The amount of time required is considerable.Theoretical bound.

Proposed System

To accomplish an automated categorization of DoC or restlessness in brain injuries, we suggest using real-world EEG recordings with imbalances. We use the PCA method for optimum feature selection and Deep Learning approaches to learn from EEG data. The RNN DL method have a high accuracy and prediction rate.

It is efficient for a huge number of datasets; the experimental result is high when compared to the existing system; and the time consumption is minimal.

Implementations

Data Selection

The input data was developed from the internet for the website kaggle.com. This work includes a test dataset and a train dataset, with the test dataset having a 5000 dataset and the train dataset having an 8000 dataset.

This technique read from our obtained dataset using pandas.

Data Preprocessing

The procedure of deleting undesirable data from a dataset is known as data pre-processing. Pre-processing data changing techniques are used to turn the dataset into a machine-learning-friendly structure. This development also includes cleaning the dataset by deleting extraneous or damaged data that might impair the dataset's correctness, creating more efficient.Delete missing dataMissing data removal: This method replaces null values such as missing values and Nan values with 0.Missing and duplicate values were deleted, and the data was thoroughly cleansed of any irregularities.

Data Splitting

- Data are required throughout the machine learning process in order for learning to occur.
- In addition to the data necessary for training, test data are required to evaluate the algorithm's performance, however we offer training and testing datasets separately here.
- In our method, we must separate training and testing into x_train, y_train, x_test, and y_test.
- The process of dividing accessible data into two sections, commonly for cross-validator reasons, is known as data splitting.
- One portion of the data is used to produce a predictive model, while the other is utilised to assess the model's performance.

Feature Classification

- Principal component analysis (PCA) is a method for unsupervised linear transformation that is normally used for feature extraction and dimensionality reduction.
- It seeks the highest variance directions in high-dimensional data and projects the data onto a new subspace with equal or fewer dimensions than the original one.
- Perform one-time encoding to convert a categorical data collection to a numerical data set.
- Split the dataset into training and testing.Normativeize the training and test data sets.
- Fit and convert the training data set to the new feature subspace before altering the test data set.

Classification

The KNN Algorithm

- KNN is an acronym for "K-Nearest Neighbour". It remains a machine learning algorithm that is supervised. The method can handle classification and regression problem statements.
- The sign 'K' represents the sum of nearest neighbours to a new unidentified variable that need be predicted or categorised.
- The KNN algorithm follows the same logic. Its goal is to find all of the nearest neighbours to a new unidentified data point in demand to determine what class it belongs to. It's a method based on distance.

RNN Algorithm

- Recurrent Neural Networks (RNN) are a sort of Neural Network in which previous step's output is known as input to the current phase.
- In typical neural networks, all inputs and outputs are independent of one another; however, when predicting the next word in a sentence, the prior words are necessary, and so the previous words must be remembered.
- Thus, RNN was born, which resolved this problem with the assistance of a Hidden Layer. The Hidden state, which remembers certain information about a sequence, is the core and most essential aspect of RNN.

Result

Accuracy simply methods how often the classifier appropriately predicts. We can define accuracy as the proportion of the number of correct calculations and the total number of predictions. Accuracy explains how many of the correctly predicted cases truly turned out to be positive. Accuracy is useful in the cases where False Positive is a higher concern than False Negatives.It gives a combined idea about Precision and Recollection metrics. It is maximum when Accuracy is equal to Recall. Recallgive details how many of the actual positive cases we were able to forecast correctly with our mode

```
<------dataset------>
********************
    lag1_mean_0  lag1_mean_1  lag1_mean_2  ...  freq_740_3  freq_750_3  Label
0         25.80         33.8        -92.8  ...    0.000325    0.000209    2.0
1         29.40         26.8        417.0  ...    0.000727    0.000801    2.0
2         28.50         31.1         72.2  ...    0.001170    0.000616    2.0
3         21.30         20.0         16.2  ...    0.004550    0.002290    1.0
4         20.40         29.0         27.5  ...    0.006960    0.009840    2.0
5         24.80         33.9       -140.0  ...    0.001090    0.000298    2.0
6          3.29         59.5        -19.4  ...    0.002290    0.001720    2.0
7         26.80         33.3         34.2  ...    0.005970    0.016300    0.0
8         44.60         38.4        -62.4  ...    0.003670    0.003440    2.0
9         32.20         31.0        101.0  ...    0.000375    0.000332    2.0
10        23.10         30.5         26.3  ...    0.015200    0.008290    1.0
11        21.90         26.2         24.0  ...    0.009600    0.009040    1.0
12        28.60         33.4        132.0  ...    0.000544    0.000580    2.0
13        26.90         29.7        -54.6  ...    0.000987    0.000514    2.0
14        20.60         26.0         40.0  ...    0.008350    0.005620    0.0
15        23.30         27.7         86.3  ...    0.000752    0.000922    1.0
16        22.70         15.4         25.5  ...    0.011100    0.013900    0.0
17        30.70         25.7       -122.0  ...    0.001450    0.000749    1.0
18        19.60         16.6         35.6  ...    0.012600    0.004740    0.0
19        31.70         17.1        -61.2  ...    0.010000    0.012200    1.0

[20 rows x 989 columns]
```

Figure 1 Dataset

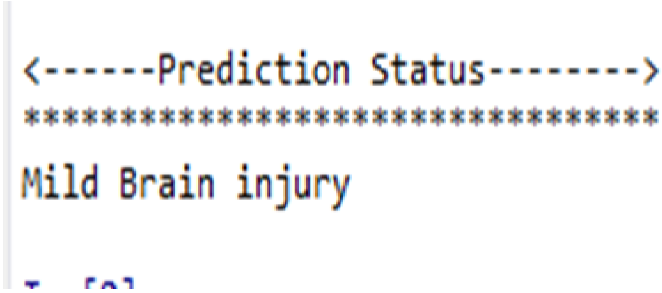

Figure 2 Prediction

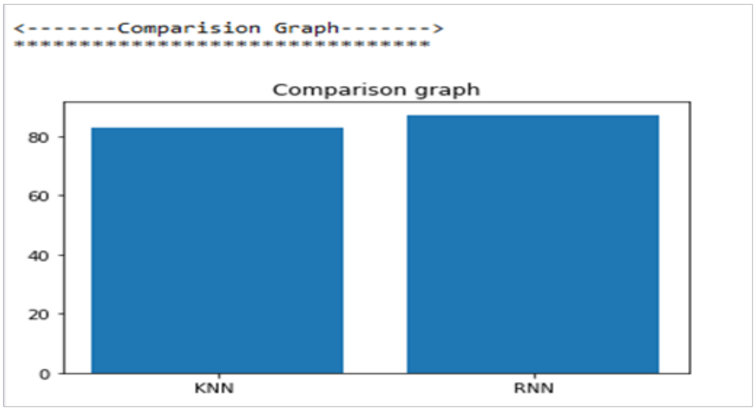

Figure 3 Comparision Graph

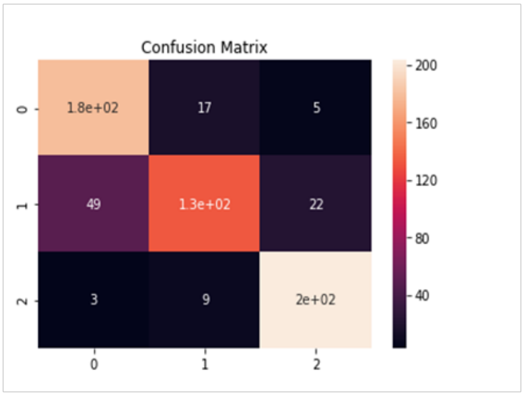

Figure 4 Confusion Matrix

Conclusions

Through EEG connection machine learning and deep learning algorithms, we investigated constant detection of DoC in patients through brain damage. Accuracy, Precision, Recall, and F1 score have all acquired high confidence and accurate prediction level.

Future Work

Additional information will be discovered in the future based on brain damage detection.

We are working on a specific dataset, but now that we have an internet platform, we can work on any dataset.

References

1. J. Claassen et al., “Bedside quantitative electroencephalography improves assessment of consciousness in comatose subarachnoid hemorrhage patients,” Ann. Neurol., vol. 80, no. 4, pp. 541–553, Aug. 2016.
2. S. Chennu et al., “Brain networks predict metabolism, diagnosis and prognosis at the bedside in disorders of consciousness,” Brain, vol. 140, no. 8, pp. 2120–2132, May 2017.
3. B. He et al., “Electrophysiological brain connectivity: Theory and implementation,” IEEE Trans. Biomed. Eng., vol. 66, no. 7, pp. 2115–2137, Jul. 2019.
4. G. Niso et al., “HERMES: Towards an integrated toolbox to characterize functional and effective brain connectivity,” Neuroinformatics, vol. 11, no. 4, pp. 405–434, 2013.
5. J. Cai et al., “Dynamic graph theoretical analysis of functional connectivity in Parkinson’s disease: The importance of Fiedler value,” IEEE J. Biomed. Health Inform., vol. 23, no. 4, pp. 1720–1729, Jul. 2019.
6. A. Zhang, J. Fang, F. Liang, V. D. Calhoun, and Y. Wang, “Aberrant brain connectivity in schizophrenia detected via a fast Gaussian graphical model,” IEEE J. Biomed. Health Inform., vol. 23, no. 4, pp. 1479–1489, Jul. 2019.
7. S. Afshari and M. Jalili, “Directed functional networks in Alzheimer’s disease: Disruption of global and local connectivity measures,” IEEE J. Biomed. Health Inform., vol. 21, no. 4, pp. 949–955, Jul. 2017.
8. C. Gómez, C. J. Stam, R. Hornero, A. Fernández, and F. Maestú, “Disturbed beta band functional connectivity in patients with mild perceptiveinjury: An MEG study,” IEEE Trans. Biomed. Eng., vol. 56, no. 6, pp. 1683–1690, Jun. 2009.
9. F. Li et al., “Differentiation of schizophrenia by merging the spatial EEG brain network forms of rest and task P300,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 4, pp. 594–602, Apr. 2019.
10. C. J. Stam, G. Nolte, and A. Daffertshofer, “Phase lag key: Assessment of useful connectivity from multichannel EEG and meg with reduced bias from mutual sources,” Hum. Brain Mapping, vol. 28, no. 11, pp. 1178–1193, Nov. 2007