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Experimental Design of a Model between EEG Signals and Brain Regions Mapping in Anxiety Correlating Factors

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***Abstract*—This paper applies classifying and regression machine learning algorithms within the experimental design of a model based on a holistic methodology to identify, and model EEG signals so that further stages of the experiment can map patterns within the brain in patients with anxiety. The purpose of this research is to propose forms of data analysis that could help medical specialists better diagnose and understand anxiety. This experiment methodology is based on Lean UX and the IBM Data Science Methodology. Algorithmic techniques for classification and categorization were analyzed and compared considering the projects' requirements and constraints. Results from K Means Clustering and ID3/J48 decisions trees were compared to identify control variables and improve data quality in further iterations of the methodology alongside the model and subsequent process outline of the ongoing work.**

***Index Terms*—Data science, data classification, data categorization, correlation model, EEG signals, anxiety.**

I. Introduction

Anxiety disorders are present in 284 million of people with 4.7 percent being women [1], additionally during the pandemic for COVID-19 anxiety disorders on children and teenagers showed an increase [2]. The comprehensive approach provided by a Data Science inspired model based on algorithmic techniques for data classification and categorization is part of a key process for the development of technologies based on the user that can provide further insight regarding the observed data points or cases regarding the use of biological signals such as EEG Signals the activity within brain regions. Is worth nothing that the brain activity can be difficult to monitor, not due to the portability of the device but the occurrence of a panic attack or a surge in anxiety which can present randomly given that the physiological reflex can be affected by internal or external stimuli [3,4], hence a generalized model for the correlation between said events can provide the basis for further experimental designs and case studies.

The experimental design proposed in this article is based on the application of EEG Signals of patients with anxiety factoring the treatment, clinic history, and diagnosis of anxiety disorder particularly panic attacks as to determine the correlation factor between monitored brain activity and statistical techniques oriented to data science to monitor the anxiety constructs and their effect.

II. Literature Review

Algorithmic techniques are the basis on which programming advances and applications can be held and taken to a higher level of implementation given the complexity of the technique itself and the purpose it serves hence, to provide a tailored solution for a problem algorithmic technique must be researched, evaluated, and compared to select the right fit for a set of requirements taking into consideration its mathematical principles and the possibility of causality due to inference [5].

A. Data Science: Algorithmic Techniques

Nowadays there is a wide collection of algorithmic techniques given the influx of information and the advances within their core classification that allow their improvement either as an optimization via the creation of another algorithm based of a certain technique, the combination of techniques or the proposal of new ones; however regardless of the approach taken for it, asides from the requirements of implementation to cover and the selection criteria according to the problem to solve it is important to identify beforehand the area of implementation and the intrinsic characteristics that it will provide.

Within the renowned areas of computer science to cover the demands of the society the branches of Artificial Intelligence and Data Science provide the basis for the development of modern technologies and data driven based solutions [6,7], although they are similar, they are not the same as Data Science encompasses Artificial Intelligence and Big Data among other areas whilst Artificial Intelligence serves specific purposes within said niche; provided the focus on data classification and data categorization as well as the stages posterior to the initial analysis of the data, the approach for the correlation model was based on an earlier implementation of Artificial Intelligence algorithmic techniques for the classification and categorization, and further development within the data science principles by the exploration, cleaning, analysis, processing and profiling of the dataset.

Shown below Table 1 illustrates the algorithmic techniques taken into consideration [8,9], the model they are part of, a brief description, and remarks of the thought process regarding the selection of the supervised learning model and the unsupervised model.

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TABLE I
DATA SCIENCE: AI ALGORITHMIC TECHNIQUES

Type	Model	Description	Remarks
Supervised	Decision Tree	Featured based decision tree.	Use of null values and outliers' sensitivity.
Supervised	Random Forests	Conjunction of trees and its multiple outputs.	High accuracy and training complexity.
Supervised	Gradient Boosting Regression	Predictions ruled out via the weakest learner.	High complexity and computational cost.
Unsupervised	K-Means	Clustering by Euclidian distance.	Tight clusters given a number of K.
Unsupervised	Hierarchical Clustering	Clustering focused on a bottom-up hierarchy.	High complexity that doesn´t select the best cluster.
Unsupervised	Gaussian Mixture Models	Clustering for normally distributed data.	Complex tuning required for optimal results.

Therefore, even though to identify data categories the Random Forests technique provides a higher accuracy it also increases the complexity of its training compared to the decision tree (namely ID3 and J48) regarding the supervised approach [10], whereas for the unsupervised learning approach for the organization of the data the Hierarchical Clustering doesn't always select the best cluster and increases the complexity compared to K-Means that can work with a given number of K that can be scalable and still easy to interpretate for EEG analysis [11].

Data Classification: K Means Algorithm While it is possible to identify patterns within a dataset using a linear regression model, classification techniques are needed to identify characteristics of data clusters that appear within the dataset. K Means allows to identify the centroids of each cluster by measuring the Euclidean distance between different data points, and together, with the Elbow Method, the number of clusters, or K, within the data distribution [12,13]. This approach is key to learning techniques like Random Tree or Bagging; it can also be enhanced with the application of neural networks [14]. The model proposed in this paper focuses on the Elbow Method to identify the number of centroids and observed data tendencies to use this information as control variables and a point of comparison regarding categorization.

Data Categorization ID3 and J48 Algorithm Decision making can be benefited from predefined classes or categorical data within a dataset, thus decision trees require at least one categorical data to create predictions based on the pertaining variables per category; although Random Forest is one of the main techniques applied when a decision tree is required, the core principles of the categorization via the creation of nodes and leaves along with the hierarchy of fathers and sons are optimized through entropy gain to define which variable holds the highest weight so it can be associated with the category with an equally higher rate of accuracy regarding its belonging and the parameters to be considered [15].

The ID3 algorithm deploys a decision tree based on said preamble providing a clear segmentation of the identified relationships, however its results can be improved by applying optimization techniques [16] leading to a better performance and significant reduction of its error rate which is of great importance given the context of health data involved in the proposed model; its optimized version the J48 algorithm improves the acquisition of information, hence the entropy which makes it a differential factor to corroborate the results obtained with the K Means algorithm given its higher precision rate and the possible identification of risks factors and its acute representation in the correlation matrix it can generate [17].

The model proposed in this paper was built with time and use of resources as top priorities which led to the complexity of development and implementation of the algorithmic technique to be regarded as one of the requirements for the selection of the algorithmic techniques to be implemented within the model, thus although neural networks possess a high capability to work with large amounts of data and are highly fitted for the type of problem at hand due to flexibility of its kernel [18], by taking in consideration the requirements previously set on the methodological and instrumental design for the development of the model and its subsequent algorithmic implementation it was disregarded for the current stage of development.

Next, the main algorithms for classification and categorization within the norm were studied to determinate which ones to use to explore the data, find insights, and reshape the dataset, accordingly, given the insights provided after its comparison with a linear regression model the K Means algorithm was selected for its cluster categorization and the corroboration of the right number of clusters given the squared sum of the error (WSS) to determinate K; complemented by the ID3 algorithm which entropy helps to determinate the segmentation of the identified relationships making it a framework of comparison to identify and corroborate the behavior of the dataset and its tendencies whilst its optimized version the J48 algorithm allows to improve the insight acquisition from the information obtained and entropy gain allowing it to be a differential factor to corroborate the obtained results.

III. RELATED WORKS

The uses and applications of EEG signals have been widespread due to the insightful results obtained through the existing techniques for its analysis, and the cost benefit relationship for its implementation in several case scenarios; one of the algorithmic techniques commonly applied for its analysis are the neural networks which can evolve with the use

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TABLE II
EEG SIGNALS AND MENTAL HEALTH: RELATED MODELS AND APPLICATIONS

Reference	Technology	Construct	Description	Approach
Khessiba, S et al. [19]	Deep Learning	Inference	Brain activity study via EEG signals and Deep Learning architectures.	Neural Computing
Hu, G et al. [20]	EEG Signals	Clustering	Evaluation of the stability of NMF algorithms for EEG analysis.	Biomedical Applications
Wang, Q et al. [21]	Autoregressive Model	Bayesian Optimization	Time Varying modeling framework to characterize and analyze EEG signals.	Neural Computing
Suhaimi, N et al. [22]	EEG Signals	Cognition	Identification of human emotional states using EEG signals.	Computational Intelligence and Neuroscience
Akif, M et al. [23]	Global field synchronization	Obsessive-compulsive disorders	Multichannel frontal EEG measurements in obsessive-compulsive disorders.	Biological Engineering and Computing
Song, P et al. [24]	Time-Varying Brain Network Connectivity	Generalized Anxiety Disorder	Effect of low frequency repetitive transcranial magnetic stimulation.	Psychiatry and Neural Computing
Breit, S et al. [25]	Vagal Nerve Stimulation	Nervous System Disorders	Modification of the vagus nerve to reduce the symptoms of the central nervous system disorders.	Psychiatry and Biomedical Applications

Fig. 1. Methodology Design Breakdown. Inspired on Lean UX [27]

of deep learning architectures, or be evaluated through the use of clustering techniques either before or after considering its optimization with Bayesian techniques. Computational Intelligence and Neuroscience along with Psychiatry and Biomedicine are notable opportunity areas in regard of the EEG implementations either to further research on human cognition or to treat specific illnesses associated with the vagal nerve such as anxiety disorders: generalized anxiety disorders and obsessive-compulsive disorders. To elaborate on the related works Table 2 shows the technologies applied to the algorithmic techniques and mental illnesses, in conjunction with the cognitive and emotional processes.

Although the literature review analysis shown above highlight the technological and methodological applications for the identification and treatment of vagus nerve associated illnesses along with the EEG Signals input, is important to highlight that even when Deep Learning approaches are taken as seen with the neural networks they still require optimization and the decision making processes involved make feasible the use of techniques such as decision trees or clustering as proposed in this article, either for initial or later stages of the research. The current model proposal prioritizes the lean approach for the development of software products to integrate the user feedback and the algorithm techniques from artificial intelligence whilst providing a guideline for health specialist based on the insights provided by the methods and iterative products, therefore making it a holistic approach for the implementation of its Brain Computer Interface (BCI) and allowing its exponential growth based on the results obtained through its proposed stages and further input given the biomedical compatibility with other biometric techniques.

IV. EXPERIMENTAL DESIGN

The instrumental design was proposed after analyzing the Lean UX based methodology [26] and its five main stages: segmentation for the exploration and observation of users, the design that covers prototyping and meetings with experts, the data treatment with AI and Big Data Processes, the launching that covers user testing, and the evaluation that ends the cycle with use testing as shown in the Figure 1. Therefore, derived from the stage of treatment in the Figure 2 the core process of

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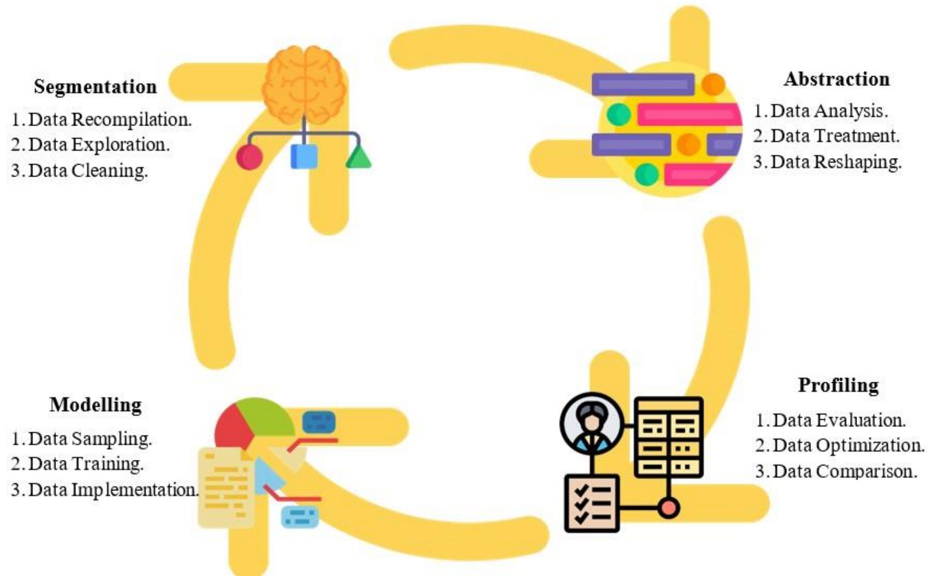

Fig. 2. Instrumental Contextualization of the AI and Data Science Processes

data science was identified along with its main stages: abstraction, profiling, modelling, and segmentation of the data; including respectively three sub-stages oriented to the analysis, treatment, and restructuration of the data, its evaluation, optimization and comparison, sampling, training, and implementation, as well as its recompilation, exploration and cleaning.

A. Data Segmentation

The data segmentation stage represents an initial filter to identify the dataset to work with during the local experimentation phase and as such the type of data to be represented, recollected, and downloaded. To achieve a proper segmentation of the data to evaluate, in the first place a comparison between datasets and databases of EEG Signals took place, from which a dataset was chosen as a sample to work with some of the brain regions areas and the corresponding sensors [28], afterwards the data type of each variable was identified along with its classification and range according to the recorded values and frequencies, followed by the removal of unnecessary variables that contained elements outside the range or null elements.

B. Data Abstraction

The data abstraction involved the preparation of the dataset so the contained data could be processed prior evaluation of the identified variables and classification so the transformation of the hyperparameters within could be normalized and provide the projections of the results given the requirements and specifications to be considered for the algorithmic implementation of the dataset; a subsequent analysis was held to evaluate the structure of the dataset and its segmentation, as for the treatment the names of the variables were changed to reflect not the number of channel, but the sensor and its allocation regarding the brain regions, so the dataset could be reshaped with the inclusion of a control variable for its classification and categorization.

C. Data Modeling

The transformation of the dataset obtained through the abstraction was considered for the application of techniques, thus the specifications and requirements were cross validated given the data to be sampled and trained to make an early evaluation of its implementation. For the data to be modeled accordingly the algorithmic techniques structures and cycles were considered to match the tests and experiments to carry, thereafter from the original dataset a set of the data was chosen to be assigned as a training set for each of the selected algorithms: K Means, ID3 and J48, covering a total of 12 categories to be tested during the implementation of the algorithmic techniques.

D. Data Profiling

Culminating with the instrumental design and the AI and Data Science based model, the modeled data was profiled based on the characterization and values assigned to each of the original sample points within de dataset; the data was evaluated in regards of the results obtained per test, hence analyzing the entropy gain for the decision trees and their accuracy as show in the correlation matrix corroborating the number obtained of K with the Elbow Method for K Means and therefore the classification and categorization of the data, from which opportunity areas where identified as part of the optimization leading to the decision to implement the J48 algorithm instead of the ID3 algorithm due to its improvement in accuracy for the assignation of the data, backed up by a comparison of the original algorithm ID3 and its optimized version J48.

V. Results

A. K Means Algorithm Implementation

The number of K viable groups was identified for the K Means algorithm by applying the Elbow Method in the R Studio Software and the Weka tool to corroborate the results obtained, thus the square sum of the error (WSS) was taken as a basis to

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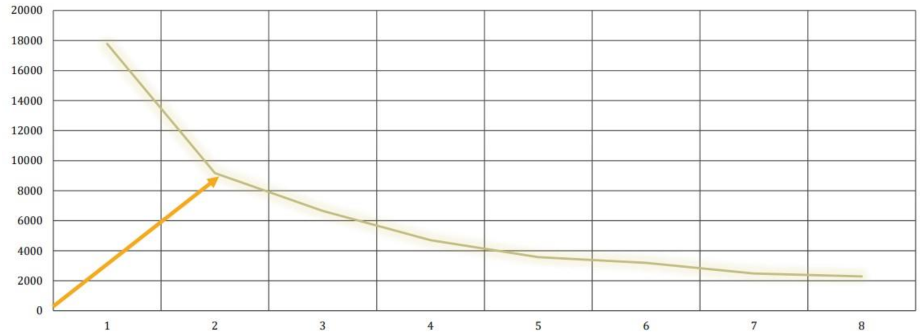

Fig. 3. Determination of K with the Elbow Method

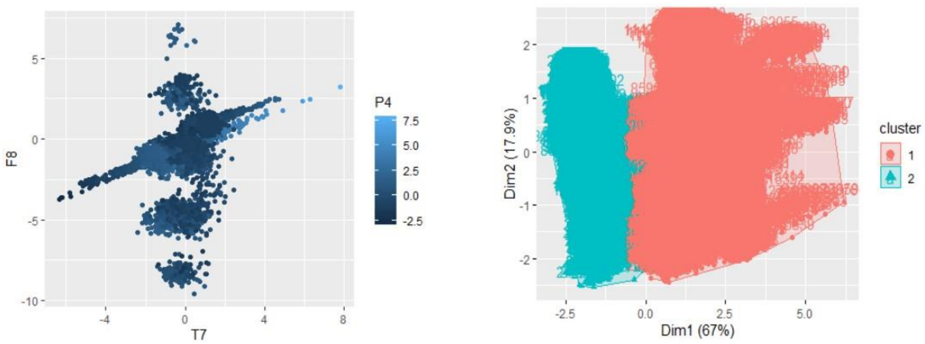

Fig. 4. Data Dispersion and Clusters Aggrupation

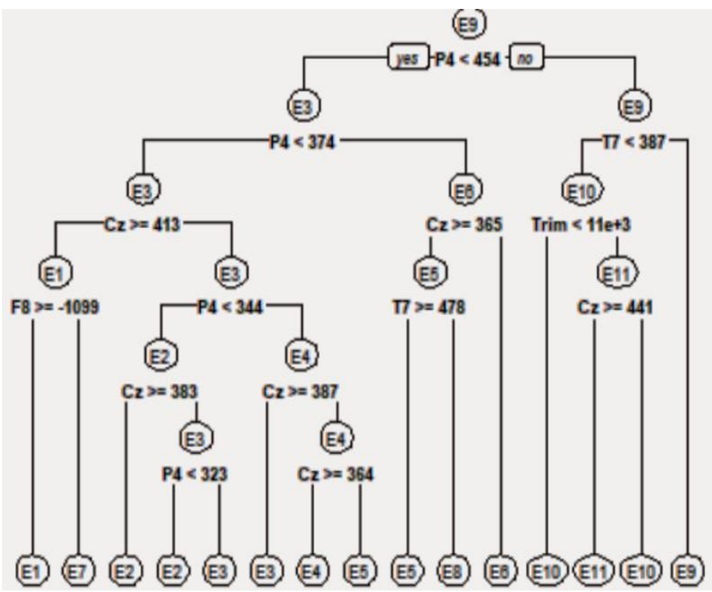

Fig. 5. ID3 Classification Tree

obtain the graphic for which K = 2 was obtained as the best performance which can be observed as a curvature in the data representation in the Figure 3 which exemplifies the number of clusters in the X axis and the obtained values in the Y axis.

Afterwards a dispersion graphic was plotted to visualize the tendency of the raw data from which the data points where distributed in two clusters with 67 and 19 percent of the data respectively as shown in the Figure 4; percentage that was later adjusted to 57 and 43 percent based on the corroboration with the Weka tool and the reshaping of the data in previous stages of the model, highlighting the role of the E4 and E6 records for the classification.

B. ID3 and J48 Algorithms Implementation

The panorama of the data aggrupation was key for the initial stages of data visualization and decision making for the elaboration of the ID3 algorithm as seen in the classification tree obtained in the Figure 5 with the corresponding assignations per category as mentioned in the K Means implementation.

Once the categorical data weights were displayed to corroborate the initial findings, another test was carried out through the computation of the corresponding confusion matrix tested under cross validation with 10 folds which allowed the

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	E1	E10	E11	E2	E3	E4	E5	E6	E7	E8	E9
E1	9706	0	0	956	29	0	0	0	0	0	0
E10	0	11603	2097	20	6	0	14	142	0	130	1279
E11	0	2335	5719	4	9	0	9	27	0	102	486
E2	1600	0	0	12074	1026	31	130	0	0	0	30
E3	64	0	0	1705	12895	2376	238	5	3	4	1
E4	0	0	0	0	1190	12056	3443	1	0	0	1
E5	0	0	0	1	38	1060	10877	1713	0	2	0
E6	0	0	0	0	2	0	1558	14129	0	1	1
E7	3	0	0	7	0	0	33	0	6410	38	0
E8	0	154	35	0	8	1	25	0	183	4428	1657
E9	0	723	26	0	0	0	0	0	0	63	17278

a	b	c	d	e	f	g	h	i	j	k	<-- classified as
17908	0	0	0	68	0	0	0	17	0	97	a = E9
0	16428	354	3	0	466	32	2	0	1	5	b = E3
0	268	16050	2	0	4	366	0	0	0	1	c = E4
0	3	3	15596	1	0	87	0	0	0	1	d = E6
74	0	0	0	14325	0	0	0	874	0	18	e = E10
0	531	4	0	0	14213	0	143	0	0	0	f = E2
0	15	373	70	0	0	13233	0	0	0	0	g = E5
0	0	0	0	0	165	0	10526	0	0	0	h = E1
40	0	0	0	897	0	0	0	7741	0	13	i = E11
0	4	0	0	0	0	0	4	0	6477	6	j = E7
136	0	1	2	44	1	2	0	15	4	6286	k = E8

Fig. 6. ID3 and J48 Comparison Matrixes

identification of the precision behavior and tendencies, with a percentage from 50 up to 80 percent of accuracy that after evaluating the acquisition based on the entropy gain was replaced in the final model with its optimized version: the J48 algorithm; hence, the final results were from 89 up to 96 percent of accuracy as it can be seen in the Figure 6 thus reinforcing the importance of the adjustments to objective functions to improve the precision of the algorithms and therefore contribution to the aggrupation and classification of the dataset for decision making in conjunction with the support of a mental health specialist during the user observation and test application.

VI. Conclusions and Future Work

The experiments proposed in this article attempted to analyze EEG signal patterns to extrapolate the algorithmic techniques on data of patients with anxiety, factoring in treatment, clinical history, and specific events such as panic attacks. In doing so, we hope to determine correlations between monitored brain activity, and develop statical techniques to monitor artifacts of anxiety and their effect. The methodology proposed of the experimental design for EEG Signals and brain regions was complemented with a design process based on data science and artificial intelligence techniques within the constraints of time and resources available for the development of the project, therefore the results obtained as part of the experimental design allowed to study the behavior of the raw data providing insight on the adjustments required not only to clear and analyze the data, but to process it and interpret the results in each of the algorithms applied being K Means and the optimal number of clusters obtained the basis on which the classification tree and percentage assignation of the J48 algorithm was implemented as an improvement over the ID3 algorithm; subsequently the corresponding categorization and classification will be used for the launching and evaluation stages of the methodology, particularly in the data profiling and modelling thus contributing to the design and verification of the instrument to obtain data from patients that have had anxiety or currently have anxiety, and as such stablishing training and control samples within the stablished population targeting anxiety, generalized anxiety, and the presence and likability of panic attacks.

Further research should cover the validation and verification stages of the methodology applied to the results of the early implementation of the instrument based on a training set to be compared on later stages of the data recollection once the instrument is finished so the control, training and raw data can be analyzed, compared and processed to explore the correlation between the EEG signals and the brain regions in future works based on the behavior tendencies to be evaluated with the algorithmic techniques and taking into consideration the training methods provided its specifications to potentially find correlations between said events in a way that can enhance our medical understanding, whilst providing a guideline for the constructs to be targeted during the stages of user testing; thus reinforcing the development of technologies that can provide further insight about anxiety.

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