Hybrid Deep Learning for Simultaneous Classification of Correlated Biosignals.

Technical Report No. CCC-23-001

by

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January, 2023

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Contents

Abstract

Different systems for biosignals processing and their classification with neural networks and other simple classifiers can be found in the literature. However, the study of these systems, and solving the difficult classification problems that their analysis pose, by applying intelligent hybrid systems in combination with the simultaneous classification of correlated biosignals that helps to discriminate between different states of a system or individual is an area of study still with little exploration. As a contribution to face this challenge, it is proposed to develop a deep fuzzy multimodal neural network with descriptive capabilities based on fuzzy partitions for the characterization and classification of correlated biosignals. Taking into account that the study of different techniques for the characterization of biosignals tends to facilitate and promote improvements in the results of their analysis and classification, this proposal integrates biosignal characterization and description through fuzzy methodologies, like fuzzy granulation, with deep learning since the research carried out so far has shown that this is a promising field of exploration. Through the analysis of biosignals, it is expected to discover the necessary characteristics that allow establishing a deep neural network design with fuzzy multimodal neurons with descriptive capabilities for simultaneous classification of correlated biosignals to clearly delineate when an individual is experiencing different levels of stress. The descriptive output of the proposed model aims to classify correlated biosignals and be able to state with certainty when a stimulus causes the level of stress experienced by a subject to rise or fall.

Keywords: *Hybrid systems, deep learning, biosignals, correlated, multimodal, fuzzy, granulation*

1 Introduction

Deep neural networks are powerful machine learning models. These models use successive layers of nonlinear processing to extract features from the data. Nevertheless, most of the deep learning models are based on stacking simple models, making difficult to improve the efficiency of data processing [1]. Furthermore, deep learning methods are often sensitive to noise in the data, thus not guaranteeing optimal performance [2]. To face the challenges that deep learning proposes, it is necessary to introduce strategies that improve the accuracy and speed of data processing as well as the descriptive capabilities, for example, using fuzzy systems.

Experimental results of fuzzy deep learning models in [3] and [4], like those of other investigations, have shown to be superior to the results obtained using traditional models, mainly when the complexity of the data to be analyzed increases. The development of novel fuzzy deep learning models remains a promising alternative area of exploration. One can consider the introduction of different strategies such as multimodal neurons with fuzzy representations for feature extraction with several layers of hybrid learning models in order to improve accuracy and consistency in classification results. It is also interesting to explore how these new models can contribute to reduce data processing time. Fuzzy granulation provides a new approach to data analysis, it has been used for example to build information granules that describe data structures [5] and to reduce redundant attributes[6].The present proposal poses the development of a model that begins with the application of fuzzy granulation techniques on correlated biosignals, and once the information granules are defined, they would be received by a deep learning system. This proposal aims to explore the performance of multimodal neuron models with descriptive outputs. It is intended to experiment with this hybrid system to provide a pattern recognition tool in which biosignals from different correlated sources would be recibed as input data.

Biosignals, such as electroencephalograms (EEG), have been considered to be the result of random processes or generated by nonlinear dynamical systems exhibiting chaotic behavior. These signals can behave as a deterministic chaotic attractor [7]. Electroencephalogram (EEG) signals can provide an effective representation of the physiological and pathological states of the human being. In recent years the analysis of academic stress through the study of EEG signals has gained importance. Focusing on determining if there are stimuli that allow reduce their levels one can find works as [8]. To establish more precisely whether an EEG signal reflects stress and different levels of it, the simultaneous study of other signals can be introduced. Under stress, the adrenal gland releases cortisol and adrenaline into the bloodstream [9], the heart rate increases, muscle tension increases, and breathing is short and fast [10]. By being able to determine if an individual experiences stress, it is intuited that it is also possible to distinguish among different levels of stress, and to determine different specific stimuli to help reduce this harmful physiological state. Studies such as [8] have managed to find a relationship between listening to music and academic stress generated by a cognitive activity, by observing significant changes in the brain waves of students.

Introducing new methodologies for the characterization of complex and noisy signals is a challenging way to improve EEG analysis and classification. Fuzzy granular clustering provides a new approach to data analysis and discovery of data structures and a fuzzy deep neural network model for simultaneous classification of EEG in combination with other biosignals seems promising to distinguish different levels of stress in a student and whether it experiences variations of this state when perceiving a stimulus, such as listening to music. The present proposal introduces the development of an hybrid deep learning model with a granulation fuzzy layer to characterize multimodal signals and descriptive neurons to overcome the challenge that the analysis and classification of biosignals pose making it possible to specify when stress increases or decreases in a person depending on the stimulus that they perceive.

1.1 Motivation

According to Folkman et. al. [11] stress can be defined as a response to different challenges perceived by an individual as overwhelming, causing physiological arousal. For its part, academic stress refers to this physiological response when a student faces workloads that exceed their adaptive capabilities [12]. Long periods of stress or being under this state continuously can cause serious damage to health, diminish academic performance and provoke maladaptive behaviours [13]. This motivates the development of a solution that allows detecting different levels of academic stress in order to provide tools that allow determining strategies to mitigate its effects.

Emotional states such as stress cannot be distinguished with the naked eye, nor can they be reliably estimated by observing behavior or applying subjective questionnaires, which is why various neuroimaging techniques have been used for their evaluation, including electroencefalograms (EEG). EEG are biosignals that can be analized to detect brain pathologies and different mental states as stress [14]. Because it is a non-invasive technique that has a great capacity to record brain activity with high temporal resolution and because there are portable and inexpensive devices, EEG has an advantage over other techniques such as Near-infrared spectroscopy or Functional magnetic resonance imaging. EEG by nature are considered extremely non-linear and non-stationary and the development of novel fuzzy deep learning models remains a promising alternative area of exploration to overcome the challenges posed by the analysis of this type of signals. Fuzzy models, which apply fuzzy rules, fuzzy logic, and fuzzy measure theory to a fuzzy inference system, provide robust solutions with comparatively lower cost than that of traditional computing techniques [15], and are preferable for processing non-linear and non-stationary signals [14] as EEG and other biosignals. Thus this proposal includes the application of fuzzy granulation for the standardization and interpretation of biosignals.

Unlike other works [16, 17, 18] where only a binary classification is made (stress-no stress) or it is not possible to adequately distinguish multiple levels of stress [19, 20, 21], the model presented in this proposal aims to facilitate the analisys and processing of correlated biosignals through a fuzzy deep neural network applying fuzzy granulation, to precisely frame more than two stress levels that will be classified using multimodal neurons with descriptive outputs, allowing to identify when a stress level is lower or higher than another and thus establish possible stimuli that are opposed to this harmful state for health.

1.2 Justification

Studies related to stress have emerged in recent years and have become relevant with the effects that the COVID-19 pandemic has brought with it [22]. Stress can cause damage to health and is one of the causes of industrial accidents and behaviors that can be classified as dangerous [23]. Academic stress influences student performance and can trigger other deleterious effects. The detection and recognition of stress through electroencephalogram (EEG) signals have become an important area of research, this biosignal contains rich information to assess the level of mental stress in its early stages, and works like [8] have demonstrated that Computational Intelligence and Machine Learning are tools that allow its detection and classification.

Different and sometimes contradictory results in automatic stress classification have been reported in the literature, that can be a consequence of several factors such as lack of standardized protocol to record EEG signals, the brain region of interest, stressor stimuli, experiment duration, proper EEG processing, feature extraction mechanism, and type of classifier used [24]. What's more, most of the studies in the literature assess stress based on self scoring relying on subjective information [25]. Therefore, the construction of a protocol for the sampling of correlated biosignals that allow to clearly and objectively distinguish the presence of more than two levels of stress, observing if a stimulus helps to reduce or increase this harmful state for health, is proposed.

On the other hand, deep neural networks are powerful machine learning models that allows facing the challenges posed by the analysis of chaotic signals such as biosignals, but as deep learning models are based on successive layers of nonlinear processing nodes to extract features from the data and stacking simple models, it is difficult to improve data processing efficiency [1]. It is necessary to implement strategies that improve data processing accuracy and speed, which can be accomplished with fuzzy systems. Furthermore, traditional deep learning models exhibit a black box behavior in which one cannot understand how they arrive at a decision or carry out a classification. The descriptive nature of fuzzy systems allows for a better understanding of the classification process and can be used to provide a mechanism to distinguish between different stress levels as well as whether a specific stimuli is intervening in the increase or decrease of stress.

The research carried out has shown that the majority of the works focus on determining two states of an individual subjected to stressful tasks achieving results ranging from 64% to 97% accuracy. However, when it is desired to determine more than 2 stress levels, these results decrease.

Taking into account that, in general, multimodal approaches have exhibited higher performance classifying medical signals for smart healthcare systems [26] including multimodal data fusion for stress assesment, this proposal presents a model that exploits the descriptive capabilities of fuzzy systems through the design and implementation of a fuzzy deep neural network for multimodal learning with information fusion, including fuzzy granulation to facilitate the standardization of different modalities as well as the extraction of relevant information from biosignals, and descriptive outputs that achieve the identification of more than two stress levels.

During the preliminary investigation, information related to the development of fuzzy deep neural networks for the solution of complex problems and the treatment of highly non-stationary signals [2] has been found, but none directly related to the study of fused biosignals for the recognition of stress levels. Thus, it is proposed to develop a hybrid deep learning system for simultaneous classification of correlated biosignals with descriptive output to classify different levels of stress.

1.3 Problem Statement

The present proposal focuses on three problems related to the classification of multiple stress levels:

- Establish a protocol for acquiring corelated biosignals from different modalities that allow confirmation of a state of stress to prevent subjective results and to reduce the time consumed by the application of questionnaires to confirm the presence of stress.
- Standardize modalities and characterize signals. Biosignals acquired from different

modalities are the result of distinct physiological mechanisms, consequently they are signals with different spatiotemporal resolution that need to be standardized and characterized for their correct analysis and classification.

- Design a model capable of analyzing and processing complex signals to fuse information and perform multimodal learning with descriptive outputs for multi-level stress classification.

1.4 Research Questions

The main questions that arise are:

- What other biosignal, besides the EEG, allows to adequately identify the presence of different levels of stress?
- What protocol will be followed for the simultaneous collecting of EEG signals and other biosignals to confirm a state of stress in an individual?
- How can different physiological signals be mapped and correlated?
- Is fuzzy granulation an appropriate technique for the standardization and characterization of multiple biosignal modalities?
- Is it possible to take advantage of the descriptive properties of neurofuzzy systems to combine modalities and classify multiple levels of stress?

1.5 Hypothesis

As the result of the scientific reading and the experiments carried out so far, the following hypothesis arises:

A deep learning model with fuzzy granulation and layers of fuzzy multimodal neurons allows to combine correlated biosignals for the objective description of stress and to classify multiple stress levels identifying stimuli that intervene in the increase or decrease of stress.

1.6 Objectives

The general objective is: To design and implement a deep fuzzy multimodal neural network with descriptive capabilities based on fuzzy partitions for the characterization and classification of correlated biosignals.

To reach this general objective it is necessary to accomplish specific objectives:

- Design and implement protocols to register correlated biosignals from different modalities that allow the clear identification of the presence of stress and collect correlated biosignals from different modalities.
- Evaluate fuzzy granulation methodologies to select membership functions and clustering techniques to standardize modalities and characterize signals.
- Design a fuzzy deep neural network for multimodal learning with information fusion and descriptive outputs.
- Classify multimodal signals with the designed model for the descriptive classification of stress levels and identify whether a stimulus intervenes in the increase or decrease of stress.

1.7 Scope and Limitations

The proposed research has the following limitations:

- The sampling protocol is intended to be performed in a controlled environment.
- Preprocessing, characterization and classification of the samples will be performed offline.
- Initially, it is proposed to combine only two modalities to classify only three levels of stress.

1.8 Expected Contributions

As a result of the culmination of the proposed research, the following main contributions are expected:

- Establishment of a protocol to simultaneously record signals from different physiological sources that objectively represent at least three different stress levels.
- Determine a useful fuzzy granulation technique to characterize and standardize different biosignal modalities.
- A neurofuzzy deep learning model with multimodal neurons with descriptive capabilities for descriptive multi-level stress classification.

2 Background

The word ”stress” has its origin in Physics, describing the magnitude of forces that cause deformation. Its incorporation into medicine was thanks to Hans Selye, when he observed that his patients, regardless of their illness, presented a certain state and universal reactions to being sick. He described this state as a non-specific response of the body to any demand such as irregularities in normal body functions, and called it ”stress”. His concept of stress had repercussions in different fields, including social psychology [27].From here, the study of stress gains interest and other possible causes of stress, besides physical illness, were questioned. The body reacts in similar way to physical, mental or emotional pressure by increasing the heart rate and raising blood glucose concentrations as a result of stress hormones release [28].

On a daily basis, people are exposed to different stimuli that provoke emotional responses. Throughout the day we can experience various emotions, from the most pleasant to the most disturbing. All of these are reflected in the activities we carry out and in the way we relate to others. Stress is the body’s response that occurs as a physiological arousal due to the perception of challenges that exceed a person’s capabilities. Academic stress is the perception of this physiological sensation triggered by workloads and threats that a student faces in his school environment. Mental stress is considered as one of the serious factors that lead to many health problems [24].

When a person experiences stress, cortisol is released into the bloodstream and distributed to different tissues. Cortisol is essential for the regulation of metabolism, blood pressure, the immune system, among other important physiological functions, therefore, inadequate cortisol levels can cause serious damage to health. Currently, the increase in cortisol levels caused by stress is considered a public health concern, since in the long term it can cause negative changes in the human body. Cortisol monitoring can be carried out through samples of sweat, hair, saliva, and blood; in practice, these types of samples are not easy to take or analyze, the intervention of a specialized laboratory is necessary. In addition electrochemical techniques have been developed for cortisol monitoring, however, they are still in their experimental stage and are not commercially available [29].

Various methods have been developed to assess stress in its early stages to prevent its negative consequences. Questionnaires have been developed for an individual to self-assess their stress condition. However, these methodologies lack objectivity, since each individual perceives stress in different ways and sometimes people are not totally honest, or aware of their stress condition, when answering this type of questionnaires. Physiological signals such as those obtained through electrocardiograms (ECG), electrodermal activity (EDA, sometimes known as galvanic skin response, or GSR), surface electromyogram (sEMG), functional near-infrared spectroscopy (fNIRS), encephalograms (EEG), have shown to be a more reliable source and provide objective information for stress assessment [24]. Therefore, to provide tools for the early detection of stress states that can be harmful to health it is proposed the combination of EEG signals with other biosignals like GSR or ECG.

The first record of an electroencephalogram dates back to 1929 with the work of Berger [30] and it remained a rough science until the 1960's. Algorithms like Fast Fourier Transform (FFT) were developed allowing to see what frequencies were present in the EEG signal and find some correlation with specific mental states. Later, and thanks to the emergence of computers, it was possible to analyze the electroencephalographic activity in greater depth [31]. In the 1970s, the first works related to the computational analysis of EEG signals for feature extraction and automatic classification emerged, but it was not until 2010 when EEG signals began to be used for stress assessment [19]. However, in the last 10 years EEG analysis has undergone great changes thanks to: portable low-cost electronics, various techniques for preprocessing and feature extraction, and machine learning algorithms.

Different studies have been carried on the analysis of biosignals through machine learning and computational intelligence techniques, in the literature it can be found that three main types of characteristics have been used for its procesing: time-domain, frequency-domain and time-frequency analysis [32]. According to the research carried out so far, most of the works found focus on the binary classification of stress, and the works classifying multiple stress levels do not help to determine the conditions that can cause variations in the level of stress, they do not provide an objective confirmation of which stimuli can influence the increase or decrease of stress. Reyes [21] carried out a research to study the decrease in academic stress levels through listening to music. A protocol for obtaining EEG signals was followed while a student performed a cognitive test in three different scenarios: in silence, with relaxing music, and with music rated by the student as the prefered one. Using a random forest classifier, he manages to distinguish between these three scenarios by classifying the EEG signals obtained from 12 participants. This allows us to propose that labeling more than two stress levels is possible.

On the other hand, the introduction of soft computing techniques such as fuzzy logic and deep learning have shown encouraging results in the analysis of various signals for the diagnosis of stress in humans [33], however, very little has been found on the analysis of EEG signals through these techniques and no applications of this type have been found to determine more than two levels of stress. No fuzzy deep network model has been found where fuzzy granulation is integrated for sample characterization and then to use multimodal neurons with descriptive outputs. The design of this model aims to simple data processing and achieve at least results comparable to the state of the art which is reviewed in the next section.

3 Related work and State-of-the-art

Emotional states such as stress, despite being harmful to health, are not easily detectable, and their diagnosis can become subjective, therefore the use of correlated biosignals that allow us to distinguish these types of states can be a valuable tool for its diagnosis in early stages. Multimodal data fusion can help us to attain a reliable identification of a specific emotion [34]. The foundations of modern data fusion can be traced back to the work of Hotelling in 1936 [35] where the study of relationships between two sets of variables is introduced. Since then, different works have shown that the combination of complementary information is useful for solving complex problems, such as the study of chaotic signals. A chaotic signal is an extremely non-linear and non-stationary signal; biosignals exhibit behaviors that can be classified as chaotic. The nature of this type of signals has motivated its study through different approaches of computational intelligence such as Multimodal Machine Learning, Deep Learning for Multimodal Data Fusion, and Fuzzy Deep Neural Networks.

Regarding multimodal data fusion, Gonzalez et. al. [36] analysed the combination of EEG and ECG signals to distinguish stress and non-stress states in 24 healthy individuals. EEG signals were decomposed using Discrete Wavelet Transform (DWT) and then artefacts were removed from the N level decomposition for DWT using independent component analysis (ICA). K-means was proposed as a strategy to identify groups of characteristics in EEG signals that allow distinguishing stress and non-stress periods. For ECG signals RR (inter-beat) intervals were computed after DWT was applied. General model (considering all subjects) and subject-oriented classification strategies were considered, for each strategy five different classifiers were tested: k Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN). In the case of subject-oriented classification, the classifier that yielded the best results was ANN, with an average accuracy (Acc.) percentage around 85%. The results of the general model register a lower classification percentage, reaching up to 79.91% Acc. with SVM.

Betti et. al. [37] carried out a study to distinguish between conditions of stress and relaxation in a work environment. They used wearable sensors to measure EEG signals, electrodermal activity (EDA), heart rate variability (HRV), confirming the stress presence by levels of cortisol in saliva . They worked with 5 characteristics from each of the recorded signals concatenated in a single vector. To classify the subjects as stressed or not stressed a SVM was used implementing 5 -fold cross-validation. The results obtained in this study to distinguish whether or not a person was stressed were reported as performances summed up in 84.0% sensitivity, 90.0% specificity and 86.0% overall Acc.

Secerbegovic, A. et al. [38] worked in the differentiation between relaxed and high mental workload states, by means of combining single-channel EEG, EDA, and ECG signals. To reduce the total number of features to be used for classification of two mentioned states Minimum Redundancy Maximum Relevance (mRMR) was applied, ten top-ranked features were obtained as result of this process. The classification stage was performed using Naive Bayes (NB) and SVM methods. Combined features from three signals recordedresulted, in general, in highest classification Acc., 83.33%.

In [39] the authors fused EEG and functional Near-Infrared Spectroscopy (fNIRS) modalities to detect stress by differentiating two states: control condition and stress condition. Signals were co-registered into three PFC scalp quadrants: Frontopolar area (FPA), Ventrolateral prefrontal area (VLPFC) and Dorsolateral prefrontal area (DLPFC). To permit data fusion Canonical Correlation Analysis (CCA) of EEG and fNIRS data was performed. SVM was used for classifying stress and control state in sole EEG (85.8% Acc.), sole fNIRS (82.9% Acc.) and fusion of EEG-fNIRS (97.7% Acc.).

Table 1: Related work. Multimodal Machine Learning, Deep Learning for Multimodal Data Fusion, Fuzzy Deep Neural Networks and Multiple classes in biosignals.

Ref.	**Year**	**Problem**	**Approach**	**Acc. %**
[36]	2021	Stress/Non-stress	EEG, ECG ANN, SVM, DT, RF, KNN	85
[37]	2018	Stressed/Not stressed	EEG, EDA, HRV SVM	86.0

Table 1 continued from previous page

[38]	2017	Relaxed/high mental workload	ECG, EDA, EEG SVM, NB	83.33
[39]	2017	Control condition/Stress condition	EEG and fNIRS. CCA, SVM	97.7
[34]	2021	Emotion recognition: 4 classes	EEG, Facial image, CNN, SVM, Monte Carlo	83.33
[18]	2021	Stress-Relaxation	EEG: TFR images CNN	87.5
[17]	2019	Stress-Relaxation	Lower body signals, EEG CNN	90
[16]	2019	High stress-Low stress	EEG, Cortisol labeling DNN, CNN	86.62
[40]	2021	Emotion recognition: 6 classes	Facial images, EEG 3D-CNN, FT2FDNN	87.58
[41]	2021	Subject identification	EEG FSF, LSTM	94.96
[42]	2018	Intention Recognition: 5 classes	EEG 3D-CNN, DQN(FIO)	93.02
[20]	2021	Resting-Stressful-Attention	EEG, ECG, RS, BVP RF	84.3
[21]	2021	3 stress scenarios.	EEG RF	96.89
[19]	2017	Binary comparison: 4 stress levels	EEG LR	83.43

Biosignals can generate large amounts of data and deep learning for multimodal data fusion has been applied to deal with the challenges of combining data of different types and distributions. In [18],Kaminska et. al. proposed the use of a Convolution Neural Network (CNN) to assign EEG signals to two classes: stress and relaxation. The samples were collected under a VR protocol where stressful and relaxing scenes were presented. Authors used a CNN based on raw signal and frequency information, having time-frequency representation (TFR) images as input, which were generated using a Morlet wavelet transform. The CNN reports a 82.1% of classification accuracy

In [17] the authors developed a wireless sensor model that records physiological and neural signals from the brain, called brain signal; heart, respiration and skin conductance, named lower body signals of a human body. The signals were recorded in two phases, the first one registering the lower body signal and the second one monitoring brain signals. The activities were divided into two classes: stress class and non-stress class. The signals were classified using a CNN, separately, lower body signals (84% Acc.) and brain waves (87.5% Acc.), finally a classification was performed combining heart, respiration, skin conductance and brain signals (90% Acc.).

Jebelli et. al. [16] worked on a model for mobile EEG-based workers' stress recognition by using Deep Neural Networks. They classified EEG signals that were collected at real construction sites. Authors registered EEG signals from 10 workers using a wearable EEG headset. Different construction tasks were labeled as low or high stress based on cortisol levels measured in workers' saliva samples. Collected signals were preprocessed to eliminate artifacts and the classification was carried out by two different classifiers: a Fully Connected Deep Neural Network (DNN) reaching 86.62% Acc. and a Convolutional Deep Neural Network (CNN) achieving 64.20% Acc.

Different works can be found related to the analysis of EEG signals with the aim of detecting stress, these are generally focused on a binary classification: relaxation and stress, therefore the use of fuzzy classifiers is proposed in order to provide descriptive information on different states of stress. In this sense, works related to the analysis of EEG signals through fuzzy deep learning have been reviewed, and according to the research carried out so far, no works have been found directly focused on the study of stress under this approach. Nevertheless, other studies show that Fuzzy Deep Learning is a promising approach to deal with EEG signal irregularities modeling uncertainty with rigorous mathematical tools in order to solve multiclass problems offering a better interpretability.

Ghosh et. al. [40] propose a fused type 2 fuzzy deep neural network (FT2FDNN) that integrates the brain signal processing approach by a general type 2 fuzzy set induced reasoning algorithm (GT2FS) with the image processing approach using a 3D-Convolutional Neural Network (3D-CNN). FT2FDNN uses multiple modalities to extract emotional change information of android-gamers by decoding their brain signals and facial images simultaneously during playing video games. The 3D-CNN and GT2FS outputs are fused using Multimodal Neural Network structure with dense-connected fusion layers. The fused information is connected with a dense layer for classification into its corresponding emotion classes: happiness, sadness, surprise, anger, disgust and neutral reaching 87.58% Acc.

Adhikary et. al. [41] developed a system to identify an individual using a Deep Learning Recurrent Neural Network model based on Long Short-Term Memory Network (LSTM). The *GAMEEMO* database which stores EEG signals from 28 subjects collected to track 4 different moods arisen while playing video games was used.The signal of each participant, numbered from 1 to 28, were passed through a Fuzzy Sigmoid Function (FSF) and the respective outcomes were mapped as the identity of the subject, i.e. the result obtained from the FSF is the expected output of the network for a particular person.

Zhang et. al. [42] proposed a Fuzzy Integral Optimization (FIO) with Deep Q-Network for EEG-Based Intention Recognition. The proposed approach was evaluated using the EEG dataset *EEGMMIDB* from PhysioNet for EEG-based movement intention recognition with 5 different classes: imagine opening and closing left fist, right fist, both fists, both feet, and think nothing with eyes closed. Classification reached 93.02% Acc.

Even when last three works summarized here fall under the category of application of fuzzy deep learning to analyze EEG signals, these are not directly related to stress. However, they reveal the possibility of achieving good results in the classification of multiple biosignals, and therefore could yield good results in the classification of EEG signals to recognize multiple classes.

Throughout the research carried out, it has been found that stress brain signals usually are classified in two main categories: relaxation and stress, reaching results between

64% and 97% Acc. Very little information has been found on the classification of various levels of stress using EEG signals with relevant results, classification accuracy decreases when data processing aims to detect at least 3 levels of stress. Works that report accuracy above 90% in the classification of three stress levels do not provide an analysis of the intra class performance or do not clearly express the segmentation and filtering process applied to the biosignals used. Some indicate train-test contamination, which increases the accuracy of the classification.

It can also be noticed that in general, the combination of different biosignals helps to achieve better classification results, with which it is shown that multimodal data fusion is a propitious strategy for the processing of biosignals for the recognition of more than two stress levels.

The reviewed literature demonstrates that when working with biosignals, a significant number of processing steps are required to extract features, most related works are based on frequency domain features, and after multimodal data fusion, some works obtain vectors with hundreds or thousands of attributes, such as that of Zanetti [20], where vectors with 3481 features are calculated for the representation of four levels of stress, which are then classified into groups of two classes. Regarding the classifiers SVM has a lot of presence, as well as CNN, on the other hand, the combinations of fuzzy logic and deep learning pose a promising path for biosignal analysis and processing . This proposal aims to take advantage of its descriptive nature to characterize, standardize signals and recognize patterns of more than two stress levels. No work has been found in which electroencephalography and galvanic skin response signals are combined, characterized through fuzzy granulation and then processed by a deep fuzzy network with descriptive outputs for the distinction of at least 3 stress levels.

4 Research Proposal

The present proposal poses as principal aim to design and implement a deep fuzzy multimodal neural network with descriptive capabilities based on fuzzy granulation for the characterization and classification of correlated biosignals.

4.1 Methodology

A methodology with three principal phases is proposed: Acquiring correlated biosignals, the design of fuzzy deep neural network for multimodal learning, and implementation and validation of the designed model to classify multimodal signals for the recognition of stress levels. Each of these phases are composed of different tasks, in particular, the design of fuzzy deep neural network for multimodal learning requires the biosignals characterization and standarization through fuzzy granulation, the fusion of biosignals, and the development of the learning mechanism of the fuzzy deep neural network. The proposed methodology is described below.

4.1.1 Acquiring correlated biosignals.

It is necessary to design and implement protocols to acquire correlated biosignals from different modalities that will be used to determine different stress levels. In [43] different protocols for the experimental induction of stress are discussed, including from the most traditional ones such as the Trier Social Stress Test (TSST) protocol to the most innovative ones supported by the use of new technologies such as virtual reality.

Since the interest of this proposal is to classify levels of academic stress, it is expected to use a protocol based on the one presented in [21], with the inclusion of new biomarkers in addition to EEG.

The collected biosignals must go through at least basic preprocessing so that they provide relevant information, eliminating certain inherent noise. After simple prepocessing a phase of general feature extraction will be carried out observing the most characteristic

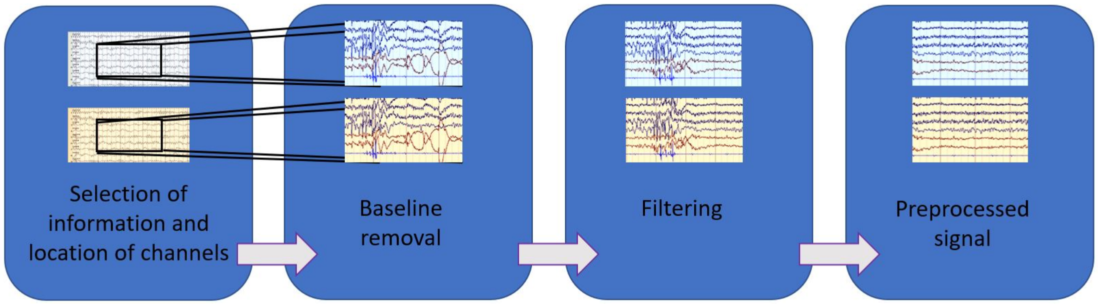

Figure 1: General steps for signal preprocessing.

aspects of the biosignals that could indicate the presence of stress (Figure 1).

4.1.2 Desing of fuzzy deep neural network for multimodal learning.

Taking into account the advantages of fuzzy deep neural networks and the results in classifing biosignals a fuzzy deep neural network for multimodal learning with information fusion will be designed. The proposal is to design a model based in works like [3] and [4] adapted to have multimodal neurons. The expectation is that the model will be able to discriminate among at least three different classes based on correlated biosignals. Different information fusion techniques will be explored as early information fusion and late information fusion [44, 45].

Correlated biosignals characterization and standarization. Since it is intended to use the complementary information of different modalities to correctly describe different levels of academic stress, the compatibility of the different signals recorded must be ensured and a clear correlation between them must be established.

Fuzzy granulation techniques will be applied in order to discover a family of information granules to characterize the input space [46]. It is expected that information granules help to standardize the number of characteristics (granules) presented as fuzzy sets. The aim is to overcome discrepancies in the length of signals coming from different modalities and other inconveniences related to having inputs from different sources as scales and timing. Our proposal is to apply Fuzzy Granulation through clustering techniques on a set of previously extracted features.

According to the research carried out so far, fuzzy granulation is a technique that has not been involved in EEG-based multilevel stress classification, but it has been applied to time series modeling [3, 47, 48, 49, 50]. From here we propose the idea of using fuzzy granulation to represent the extracted features, reducing and standardizing the number of features that are used as inputs for biosignal classification. We propose to order the biosignal time series to compute fuzzy granules with different membership functions.

Fuzzy Granulation. In general, when we break down an object, problem, or concept into simpler parts, it is easier to represent the object, to solve the problem, or to understand the concept. Granulation allows the decomposition of a whole into parts and fuzzy granulation represents an analogy to how human reasoning tends to describe entities with terms that do not have precise limits: close, far, almost, enough, etc. This type of decomposition is useful to represent changes in time series. According to [47] time series granulation can be seen as a process composed by four layers: discretization, granulation, linguistic description and prediction. We propose fuzzy granulation as a feature extraction strategy based in the first three layers of the mentioned framework. For granulation and linguistic description we propose to adapt the methods presented in [3] not for time series prediction but for feature extraction taking only tree layers described as follows (Figure 2):

1. Discretization. This layer is responsible for dividing the time series into windows of the same size. Having a time series $T = \{t_1, t_2, ..., t_{n-1}, t_n\}$ and $1 <= l <= n$ the size of the window, if $l = n$ then the time series is represented by 1 window, if $l = 1$ then T is discretized in n windows. Once l has been set, time series T can be split into windows $W_1 = \{t_1, t_2, ..., t_l\}, W_2 = \{t_{l+1}, t_{l+2}, ...t_{2l}\}, ..., W_l = \{t_{n-l+1}, ..., t_{n-1}, t_n\}$.

2. Granulation. This process consists in extracting granules of the segmented windows from the previous layer which are distributed throughout the time window. Granules are a representation of the data in windows using intervals, rough sets, or other type of sets. The interest of this proposal is in using fuzzy sets for extracting granules since they provide information with different level of detail of problems with imprecise

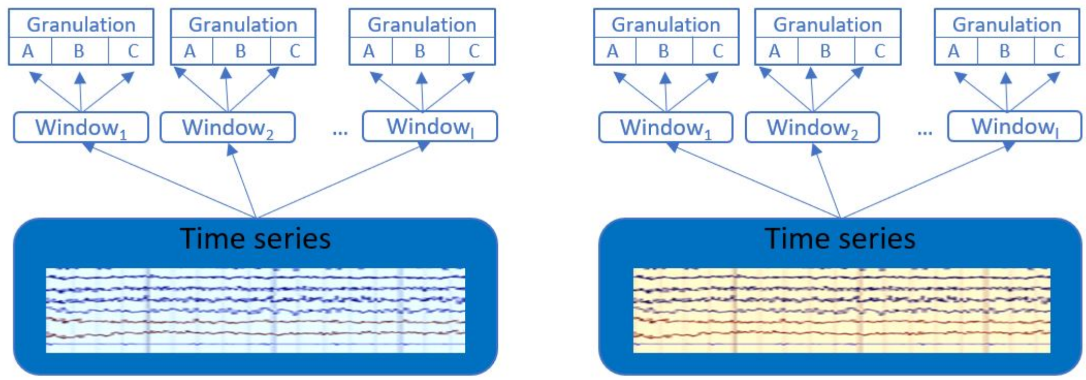

Figure 2: Fuzzy granulation process.

information. Fuzzy membership functions are applied to granulate the values in each window.

3. Linguistic description. In this layer, each granule is associated with a linguistic term that describes it. A time series could be granulated using linguistic terms as high amplitude, medium amplitude and small amplitude, each of them calculated for each window W_i.

This granulation process is expected to be useful to characterize and standardize EEG an EDA modalities thus avoiding more complex calculations and keeping the number of features to a minimum to represent different stress levels.

Information Fusion. It is necessary to explore different information fusion techniques. One approach is to use techniques such as correlation matrix computation to find aspects in the characteristics of signals coming from different modalities called co-regularization. The goal of this matrices is to represent fused information minimizing the distance among objects of the same class while maximizing the distance among objects of different classes.

Co-regularization style algorithms are based on integrating different views into a unified representation. One simple approach is Concatenating the features of each view and then run a standard classification algorithm. There are other strategies summarized in [51] like constructing a transformation, linear or non-linear, from the original views to

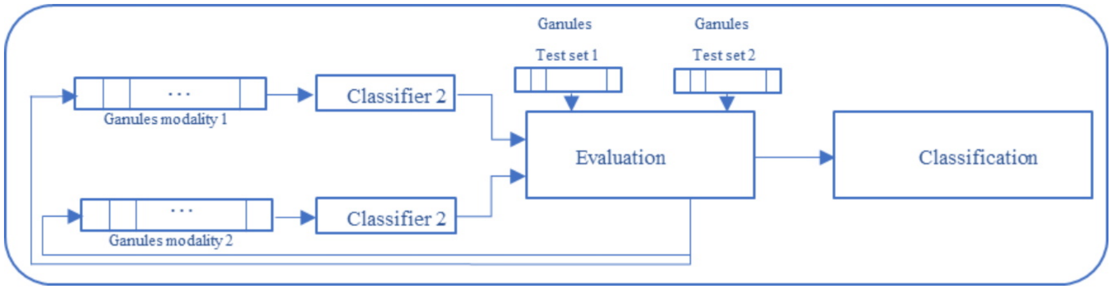

Figure 3: Co-training approach.

a new representation, or including label information to the transformation to add intra-class and inter-class constrains, also combining the data and label information by the use of classifiers pursuing that the results obtained from different views be as consistent as possible [52, 53].

Another approach is to build classifiers for each modality and then to combine the results obtained from each classifier. Co-training was proposed to combine labeled and unlabeled data from different views of an object (Figure 3). This technique has shown that even when there are no naturally different views to describe an object, generate these views and combine them by Co-training can improve the results of other classifiers not using different views[54]. According to [55] there are two main considerations in Co-training: each set of features is sufficient for classification, and the two feature sets of each instance are conditionally independent given the class.

Research on multi-view supervised learning is comparatively less than multi-view semi-supervised learning, but Co-training can be adapted for supervised learning [56]. Various experiments testing the suggested fusion information techniques on EEG databases were carried out during the preparation of this research proposal. The one that best adjusts to the multimodal data gathered throughout the scheduled stress research study will be picked.

Fuzzy deep neural network. The proposal is to base the architecture of the fuzzy deep neural network in a Mamdani fuzzy inference system. In [57] a three layers network is presented having a feedforward architecture, the layers are: input, hidden and output.

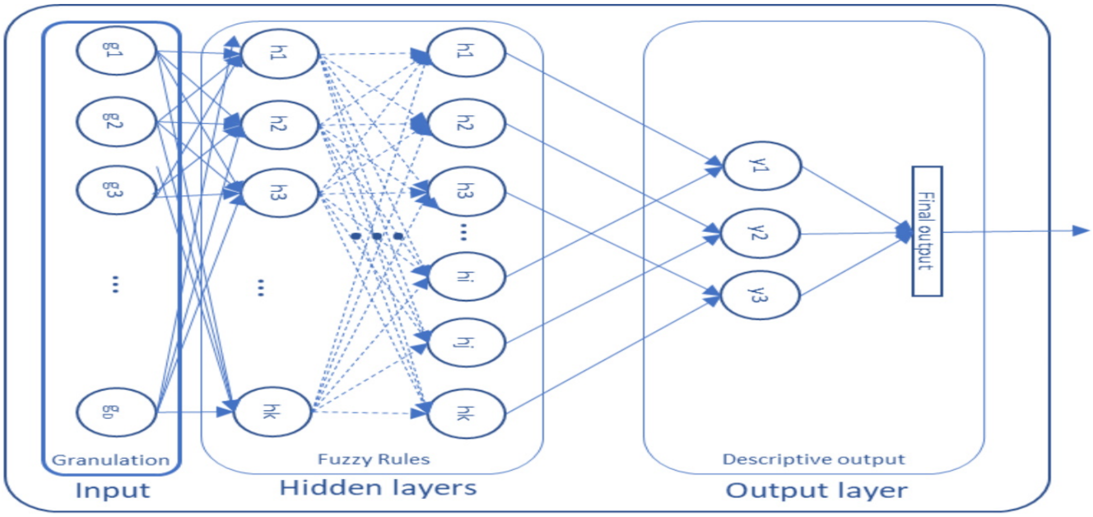

Figure 4: Proposed Fuzzy Deep Neural Network basic architecture.

This model is going to be taken as a generic one that can be modified to represent more complex fuzzy rule base system. Adding hidden layers to the model as well as hidden nodes and output nodes it is possible to adapt the generic architecture to represent multiple rules that help us to recognize different stress levels.

The input layer is going to be in charge of fuzzy granulation, hidden layers will describe fuzzy rules, each of them composed of a premise (IF) and a consequent (THEN): $R_{hi} = IF\ g_1$ is $G_1, ..., AND\ g_D$ is $G_D\ THEN\ Sample$ is Y_i; where R_{hi} is the rule i of the hidden unit h, g_i is the input granule, G_i is the corresponding fuzzy membership function, Y_i is the descriptive output representing the consequent. The final layer consists of output units, one for each class. Figure 4 shows a general representation of the model to be built.

Self-adaptive neuro fuzzy systems have two learning elements: parameter learning and structural learning, incorporating at least one of these two learning aspects is what makes them self-adaptive [58]. To train the network the proposal is to experiment with supervised rule learning algorithm [57] to adapt fuzzy rules as it runs cyclically through all of the training set, and with the the Gradient Descent for all model parameters modification [59]. The trade-off between computational complexity and performance will be considered while selecting one of the above strategies.

4.1.3 Implementation and validation.

Once the model has been designed experiments will be conducted to classify, at first, two levels of stress, and later to classify at least three stress levels. The results will be analyzed and the necessary adjustments to the proposed model will be made. The model implemented will be evaluated with the collected database using standard metrics to determine its performance such as precision, accuracy, recall, f1 measure.

- Precision: This metric represents the number of true positives that are actually positive compared to the total number of predicted positive values, taking into account false positives (FP) and true positives (TP). For the present proposal, a true positive represents a level of stress correctly identified by our model, a false positive is a test sample classified as the specific level of stress observed but really belonging to a different stress level. $Precision = TP/(TP + FP)$

- Accuracy: Indicates the number of items correctly classified compared to the total number of classified samples. $Accuracy = TP/(Total number of samples)$

- Recall: Calculates the proportion of true positives (TP) that the model has classified based on the total number of positive values, including false negatives (FN). For the present proposal, given an specific level of stress, a FN represents a sample belonging to the given stress level but classified by the model in a different stress level. $Recall = TP/(TP + FN)$

- F1-score: Summarizes accuracy and sensitivity in a single metric. A model that works correctly for the classification task for which it was developed looks for an F1 score close to 1. An F1 score close to 0 indicates that the model is not correctly solving the classification task for which it was designed. $F1 = 2 * (Recall * Precision/Recall + Precision)$

The designed model also will be tested using public data bases as *DEAP* [60], *SEED* [61] and *PASS* [62] to compare its performance with other state-of-the-art works.

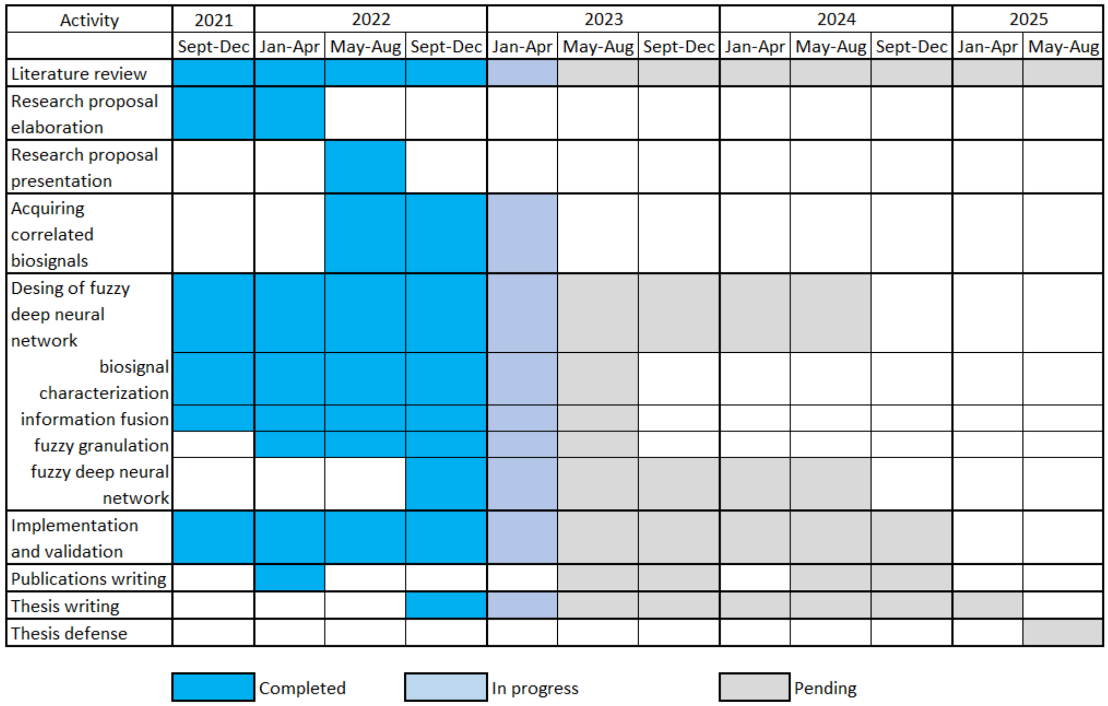

Figure 5: Work plan schedule

4.2 Work Plan

Figure 5 presents the activity schedule for the accomplishment of the objectives of this research.

4.3 Publications Plan

The planned publications are listed below:

1. Conference article: This publication will be oriented to show the advances in the application of fuzzy granulation for biosignal representation and the exploration of different information fusion algorithms. Estimated submission date: 2023

2. Journal article: The aim here is to publish discoveries related to the results obtained through the hybrid deep learning designed model for simultaneous classification of correlated biosignals. Estimated submission date: January 2024

3. Conference article: The principal objective is to publish the final remarks of the designed model. Estimated submission date: August 2024

5 Preliminary Results

In order to test the feasibility of fuzzy granulation and information fusion techniques for the treatment of biosignals such as EEG, experiments were carried out in these two areas: Multi-view learning for EEG signal classification and fuzzy granulation for feature extraction in EEG-based stress level recognition.

5.1 Information Fusion: Multi-view learning for EEG signal classification

Multi-View Learning (MVL) has the objective of combining the information that describes an object from different groups of characteristics. This paradigm of computational learning has proven useful to improve generalization performance of classifiers by taking advantage of the complementary information from different views of the same object. Two approaches of MVL have been explored: Co-training and Co-regularization to classify EEG signals of imagined speech. Two different views were used to characterize these signals, extracting Hjorth parameters and the average power of the signal. Six different implementations of MVL have been tested, the first three techniques: Basic Co-training, Simple Co-training, and Majority Vote Co-training; are based in the algorithm proposed originally in [55] (Table 2). The last three techniques are based in Co-regularization style algorithms: Concatenation, MULDA [52] and SVM-2K [53]. As the objective of this experiments was to identify information fusion strategies we use Random Forest (RF) as base classifier.

1. Basic Co-training. In this approach separate RF for each view were trained, the most confident model was used to label a new example, then this new labeled example is added to the training set of individual models and iterated until there are not unlabeled (test) objects. To stablish which is the most confident model we use the misclassification probability of each tree in the ensemble (RF). We select the tree with the minimum misclassification probability to label test samples of each view.

2. Simple Co-training (SCT). This is a slight variation of basic Co-training algorithm. We worked with two views, and we modeled a different Random Forest algorithm for each. We observed the resulting models and the more confident was used to

Table 2: The Co-training algorithm [55].

Given: a set L of labeled training examples, a set U of unlabeled examples
1:Create a pool U' of examples by choosing u examples at random from U
2:for k iterations:
3: Use L to train a classifier that considers only the x1 portion of x
4: Use L to train a classifier h2 that considers only the x2 portion of x
5: Allow h1 to label p positive and n negative examples from U'
6: Allow h2 to label p positive and n negative examples from U'
7: Add these self-labeled examples to L
8: Randomly choose 2p+2n examples from U to replenish U'

classify the whole test data set. As in the previous approach we select the most confident model according to misclassification probability, but in this case, there are not incremental construction of the models. Each model is trained just once with the corresponding training set, then for each test object the most confident model is used to label it.

3. Majority Vote Co-training (MVCT). This approach has an initial stage as the previous variation presented. Two different RF are modeled, one for each view, then each model classifies the complete test set. This process is repeated through a ten-fold cross validation schema, meanwhile the label assigned to each sample is stored. Finally stored labels are used to emit a vote, and test samples are classified according to the most voted class.

4. Concatenation (CC). Given Xi and Xj, two views of EEG signals, we concatenated them into a single set Xij = [Xi, Xj]. This set is divided into training, validation and testing subsets to model a RF for classification of EEG signals.

5. MULDA. The purpose of this method, introduced in [52], is to take advantage of Canonical Correlation Analysis (CCA) and Uncorrelated Linear Discriminant Analysis (ULDA), so that useful features can be exploited for Multi-view applications.

Through optimizing the corresponding objective, discrimination in each view and correlation between two views can be maximized simultaneously. Given Xi and Xj, two views of EEG signals, the characteristics are combined in correlation matrices, then features containing minimum redundancy are extracted. The resulting set of features are divided into training, validation and testing subsets to model a RF for classification of EEG signals. Table 15 presents a simplified version of MULDA algorithm.

6. SVM-2K In [53] the authors trained a Support Vector Machine from each individual view and then regularized the consistencies across different views. Assuming that given two views of the same data, one expressed through a feature projection ϕ_A with corresponding kernel K_A and the other through a feature projection ϕ_B with kernel K_B. A combined data set is then given by a set:

$$S = (\phi_A(x_1), \phi_B(x_1)), ..., (\phi_A(x_\iota), \phi_B(x_\iota)) \tag{1}$$

Where ϕ_A and ϕ_B are feature vectors associated with view A and view B, respectively. Also, each data item is labeled.

Kernel Canonical Correlation Analysis (KCCA) algorithm projects training data onto directions where the vectors for each view are maximally correlated. KCCA would typically find a sequence of projection directions that can be used as the feature space for training a SVM.

SVM-2K combines two stages by introducing the constraint of similarity between two 1-dimensional projections identifying two distinct SVMs one in each of the two feature spaces. The extra constraint is chosen as an ϵ-insensitive 1-norm using slack variables to measure the amount by which points fail to meet ϵ similarity:

$$|\langle w_A, \phi_A(x_i)\rangle + b_A - \langle w_B, \phi_B(x_i)\rangle - b_B| <= \eta_i + \epsilon, \tag{2}$$

where w_j, b_j are the weight and threshold of each SVM. Having $\hat{w}_j$, $\hat{b}_j$ solutions to the optimization problem stated for the previous SVMs, the final SVM-2K decision function is then $h(x) = sign(f(x))$, where

$$f(x) = 0.5(\langle \hat{w}_A, \varphi_A(x)\rangle + \hat{b}_A - \langle B, \varphi_B(x)\rangle - \hat{b}_B) = 0.5(f_A(x) + f_B(x)) \tag{3}$$

The data base used to explore Multi-view learning consists of EEG signals from 27 subjects. For acquiring EEG signals an EMOTIV kit was used. This is a wireless kit and consists of fourteen channels whose frequency sample rate is 128 Hz. According to the international 10-20 system, channels are named: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. Each subject imagined 5 words: “arriba” *(“up”)*, “abajo” *(“down”)*, “izquierda” *(“left”)*, “derecha” *(“right”)*, “seleccionar” *(“select”)*. Samples collected include 33 repetitions(epochs) of each word. Detailed information of data base can be found in [63].

Two representative feature extraction methods were used to generate two different views of the original EEG signals: Hjorth parameters [64] and average power. The objective was to analyze the signals in both time and frequency domains.

- Hjorth parameters are three characteristics extracted from a signal. They were designed to obtain important information from EEG signals in time domain. These characteristics are Activity, Mobility and Complexity.
  - Activity. This parameter represents the variance of the time function giving a measure of the squared standard deviation of the amplitude of the signal. Having x, the signal vector, Activity parameter is computed following the next formula:
$$Activity(x) = var(x) \tag{4}$$
  - Mobility. This parameter is defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal. Mobility parameter is computed according to the following formula:
$$Movility(x) = \sqrt{var(x')/var(x)} \tag{5}$$
  - Complexity. This parameter indicates how the shape of a signal is similar to a pure sine wave. The value of Complexity converges to 1 as the shape of signal gets more similar to a pure sine wave. Complexity parameter is computed according to the next formula:
$$Complexity(x) = Movility(x')/Movility(x) \tag{6}$$

- Average band power. A common way to analyze EEG data is to decompose the signal into functionally distinct frequency bands. To move the EEG signal from time domain to frequency domain we used Fast Fourier Transforms (FFT). Once in frequency domain, average band power (AVP) was computed, which consists in computing a single number that summarizes the contribution of the given frequency band to the overall power of the signal [18]. Having x, the EEG signal vector:

$$AVP(x) = bandpower(FFT(x)) \tag{7}$$

5.1.1 Experiments and Results

To build a data corpus for the experiments, EEG signals from 27 healthy individuals (S1-S27) were used, 2 of them are left-handed and the rest are right-handed. The corpus has 33 samples for each of the words(“arriba”, “abajo”, “izquierda”, “derecha”, “seleccionar”), imagined by each individual. The first experiment seeks to evaluate different classifiers to select one of them to apply Multi-view Learning. For this, the recorded EEG epochs go through a feature extraction process, each imagined word is described by a vector consisting of 14 characteristics, plus its class tag, for each view. View 1 was taken as the Average Band Power of signal and View 2 was taken as the Activity Hjorth parameter. MATLAB and EEGLAB toolbox were used to extract characteristics. We use Weka to classify the signals, each view separately, and discovered that the classifier with higher percentage of accuracy, was Random Forest (RF) with 50 trees.

The percentages of accuracy are obtained by ten-fold cross validation. These results are consistent with [63]. To explore the different approaches of Co-training and Co-regularization of Multi-view Learning the discussed methods were implemented in MATLAB. Regarding Co-training, MVCT is the approach that yields the best results.

Table 3: Single view, Co-training and Co-Regularizacion compared with Torres et. al. [63] Acc. %

Subj	Avp	Act	BCT	SCT	MVCT	CC	SVM-2K	MULDA	[63]
1	33.5	62.5	49.09	62.42	60.61	56.1	74.33	16	80
2	31.88	43.63	34.12	49.09	58.18	45.4	54.49	16	49.1
3	54.38	73.13	57.51	61.45	80	73.1	64.2	17	63.1
4	61.75	74.75	66.11	57.58	86.06	84	62.31	16	57.9
5	34.5	55.63	48.98	36.97	85.45	56.5	59.35	16	67.7
6	28.63	33.5	31.5	32.73	75.15	39.5	65.72	16	43
7	39.38	75	65.22	75	84.24	76.9	69.19	16.03	63.9
8	39.63	72.25	67.61	72.12	81.82	70	68.3	16	86.1
9	37.25	56.5	52.28	56.97	80.61	55.3	64.18	16	62.5
10	44.88	71.38	64.74	75.76	86.06	74.1	64.62	16	61
11	42.5	66	56.17	61.82	86.06	58.8	66.88	16	83.6
12	53.38	73.25	56.48	51.44	77.16	70.9	74.33	17	60.6
13	40.25	60.38	51.1	46.67	71.07	55.5	71.64	16	65.6
14	23.5	46	40.38	44.85	69.54	43.1	63.56	16	43.2
15	37.38	67.13	57.55	60.61	78.17	68.9	65.32	16	60.6
16	27.5	52.88	53.04	48.8	75.13	49.5	68.64	16	51
17	57.63	66	56.33	56.97	79.7	68.9	65.13	16	67.3
18	38.75	53	44.18	48.48	76.14	56.8	43.21	16	71.9
19	23.63	37	29.45	26.67	66.5	38.9	69.86	16	51.5
20	36.5	43.38	34.88	38.79	61.42	43.3	72.06	16	76.3
21	38.5	52.63	38.82	50.91	65.48	61.5	67.06	16	36.8
22	31	62.25	55.15	63.64	73.1	64.5	70	16	65.3
23	39.13	53.5	44.36	46.67	74.62	58.6	59.85	16	54.1
24	44.25	40.5	45.22	43.98	73.1	57.4	69.03	17	45.6
25	33.38	41.88	34.58	38.79	69.04	44.6	61.1	16	43.6
26	31.13	58	51.49	55.95	69.04	54.3	63.3	16	52.7

Table 3: Single view, Co-training and Co-Regularizacion compared with Torres et. al. [63] Acc. %

Subj	Avp	Act	BCT	SCT	MVCT	CC	SVM-2K	MULDA	[63]
27	28.63	42.38	38.69	37.2	64.97	45	53.44	16.03	59.2
Avg	38.25	56.83	49.08	51.94	**74.39**	58.19	**64.86**	16.11	**60.11**

Within the co-regularization strategies, it can be observed that the approach with the greatest accuracy is SVM-2K. This algorithm manages to project the characteristics of each view to spaces in which the highest correlation between them is ensured. Considering that for some subjects the CC approach achieves better results, it is important to note that SVM-2K, on average, has a higher accuracy.

We can see the comparison of Multi-view Learning approaches explored with results reported in [63] (Figure 6), where the same problem, EEG imagined speech signals classification, using the same data base, is addressed but using a single view. For practically each subject, MVCT always achieves better results. SVM-2K has higher average precision than the results shown in [63], although they are very close.

The results shown here help to conclude that it is possible to improve classification accuracy of imagined speech by combining the information from different views. Over all the experiments with MVL, Majority Vote Co-training is the approach that reaches the highest average accuracy (74.38%), followed by SVM-2K (64.86%). It is important to highlight that the feature extraction process was made over EEG signals without any extra preprocessing since the main objective of this work was to study Multi-view Learning performance.

5.2 Automatic Selection of View Combination

We combined features in the time domain with features in the frequency domain by means of Multi-view learning techniques for the classification of EEG signals, two sets of features were extracted for each domain. In frequency domain, Absolute Power of Theta, Alpha

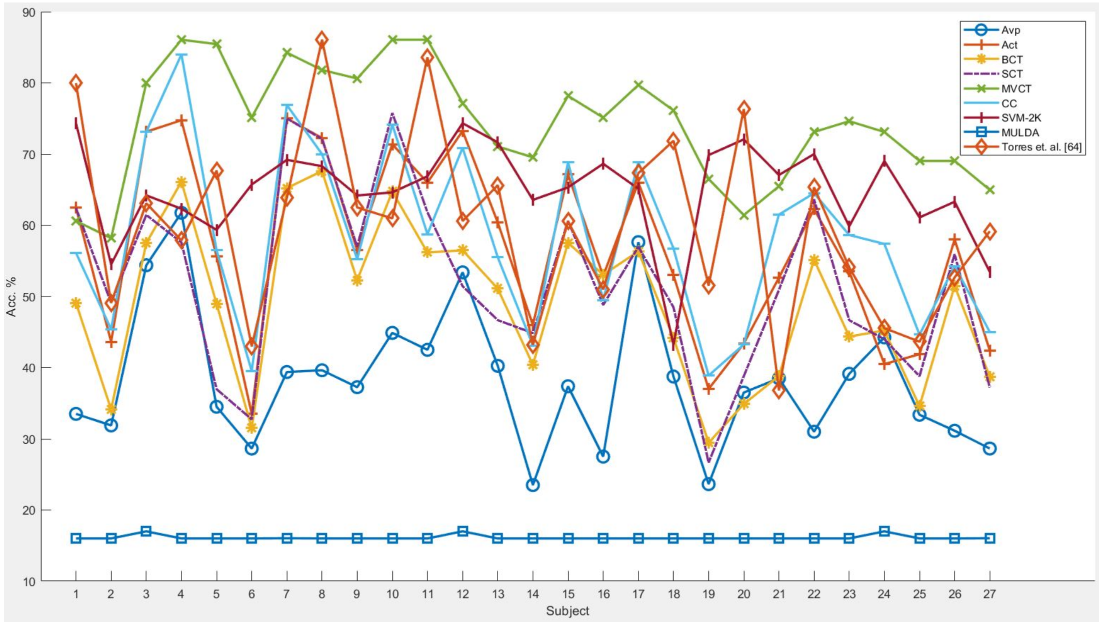

Figure 6: Comparison of accuracy reached by Multi-View Learning approaches explored and results achieved in Torres et. al. [63]

and Beta bands (ABP); and Intensity Weighted Mean Frequency (IWMF) were extracted. In frequency domain we extracted Activity, Movility and Complexity Hjorth parameters (HjPa); and Shannon Entropy (ShEn).

We design a model capable of selecting different subsets of views, ensuring the combination of time and frequency domain features, while evaluating the different MVL techniques explained above. The model identifies the MVL method and the set of views that achieve the highest accuracy in pattern recognition in EEG signals. This model is divided in five stages: multidomain feature set generation (S1), selection of a MVL approach (S2), evaluation of the combination of selected views and MVL approach (S3), performance comparison (S4) and finally, identification of views and MVL approach with highest accuracy (S5). A general description of the proposed model is showed in Fig.7.

In S1 stage a subset of Multi-view features is selected, the views are not combined or fused, they are included as input information for the subsequent stage. The subsets that this stage generate consist of four views: {ABP, IWMF, HjPa, ShEn}; three views{ABP, IWMF, ShEn}, {ABP, IWMF, HjPa}, {ABP, HjPa, ShEn}, {IWMF, HjPa, ShEn}; and

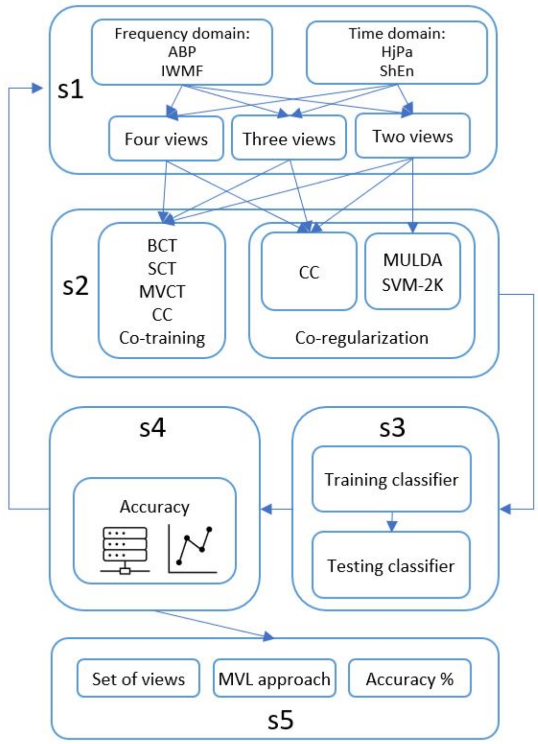

Figure 7: Proposed model for automatic selection of views and MVL approach.

two views: {ABP, HjPa}, {ABP, ShEn}, {IWMF, HjPa}, {IWMF, ShEn}. Each subset includes the objects (EEG signals), described by the corresponding features and labels to identify the objects.

Stage S2 is in charge of selecting a MVL technique compatible with the number of views selected. Co-training approaches as well as CC Co-regularization technique are able to work with any subset o views generated in previous stage S1. MULDA and SVM-2k given the characteristics of the algorithms, are selected just for subsets of two views.

Stage S3 receives the information from S2 about which MVL technique in going to be applied as well as the combination of views to be used. S3 applies 10-fold cross validation, this stage divides the subset of views in ten random sections, nine of them are taken as train samples and the one that has not been selected is used as the set of test samples, then the MVL algorithm is executed, this process is repeated ten times. The result of this stage is the classification assigned to the test samples and is received by S4.

In stage S4 the accuracy of the MVL technique applied to the subset of views is computed. This metric is stored as well as the corresponding subset of views and the MVL approach applied. After this stage the model iterates until all the combinations of views subsets and MVL techniques are tested. This stage draws a graph to observe the results of each combination of views with the selected multi-view approach.

Finally, stage S5 compare all the results stored in stage S4, it is responsible of displaying the findings indicating the MVL approach and the subset of views with higher accuracy.

5.2.1 Experiments and Results

The exploration of Multi-view learning was motivated as a promissory alternative to achieve better results in classifying imagined speech and in stress pattern recognition. While other machine learning approaches have been applied to the analysis of imagined speech and EEG stress signals [65, 66, 67, 68], MVL is a less explored approach. The experiments performed with stress EEG signals are described below.

Electroencephalogram (EEG) signals contain relevant information that can be used to represent physiological and pathological states of the human being and in recent years the analysis of academic stress through the study of EEG signals has gained importance. By being able to determine if an individual experiences stress, it is intuited that it is also possible to distinguish between different levels of stress, and maybe to determine different specific stimuli to help reduce this harmful physiological state. Studies such as [5] have managed to find a relationship between listening to music and academic stress generated by a cognitive activity, by observing significant changes in the brain waves of students, reaching up to 93% correct classification when distinguishing three stress scenarios.

We worked with a corpus of electroencephalographic signals from 12 participants under different sound stimuli recorded with a commercial EEG headband (Epoc+ from EMOTIV). The signals were acquired with a sampling frequency of 128 Hz. The channels that record the biosignal in the device used are based on the international 10-20 system;

AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4.

The sampling of this database was carried out in a controlled environment and each subject participated in three sessions: one in total silence, another with relaxing music and another with pleasant music chosen by the subject participating in the session. In each session, participants are asked to keep their eyes closed for 40 seconds, then open them and do basic multiplication exercises for 5 minutes. To induce a state of emotional stress, each exercise must be solved within a time limit of less than 5 seconds and if the answer is wrong, the participants get negative feedback. At the end of the mathematical test, the participants close their eyes for another 30 seconds to finish taking the sample. The objective of the analysis of the EEG signals obtained with these experiments is to determine if it is possible to discriminate these three stress scenarios: Stress while listening to music rated by the participant as pleasant, stress while listening to music identified as relaxing, and stress while in silence. For details of this database, consult [5].

The whole signal has a duration of almost 7 minutes, but the interest is in one minute of the signal, from second 240 to second 300 as this is the segment when the participants are more concentrated on the mathematical task. Features ABP, IWMF, HjPa and ShEn, were extracted from each one second of the signal, and then for each 10 seconds of the signal, statistical measures were obtained: average, maximum, standard deviation, variance, skewness, and kurtosis. As ABP and HjPa include three different measures, Theta, Alpha and Beta bands; Activity, Movility and Complexity; respectively, each sample is represented by 252 characteristics in these two views. Samples have 84 features in IWMF and ShEn views.

Table 4: Accuracy % reached with subsets of two views and MVL approches

MVL	**Subset of views**	**Accuracy %**
BCT	ABP, HjPa	92.81
BCT	ABP, ShEn	85.74
BCT	IWMF, HjPa	89.23

Table 4: Accuracy % reached with subsets of two views and MVL approches

MVL	**Subset of views**	**Accuracy %**
BCT	IWMF, ShEn	90.92
SCT	ABP, HjPa	92.31
SCT	ABP, ShEn	89.74
SCT	IWMF, HjPa	85.13
SCT	IWMF, ShEn	92.31
MVCT	ABP, HjPa	92.27
MVCT	ABP, ShEn	92.31
MVCT	IWMF, HjPa	92.82
MVCT	IWMF, ShEn	94.36
CC	ABP, HjPa	74.88
CC	ABP, ShEn	75.62
CC	IWMF, HjPa	70.37
CC	IWMF, ShEn	73.75
MULDA	ABP, HjPa	60.67
MULDA	ABP, ShEn	28.57
MULDA	IWMF, HjPa	44.44
MULDA	IWMF, ShEn	45.21
SVM-2k	ABP, HjPa	50.00
SVM-2k	ABP, ShEn	54.67
SVM-2k	IWMF, HjPa	50.00
SVM-2k	IWMF, ShEn	56.28

Once feature vectors were computed the model propossed for automatic selection of views was applied. Random Forest (RF) with 50 trees was selected as base classifier because the exploratory experiments showed that it was the classifier that achieved highest accuracy. Table 4 shows an example of part of the values stored in stage S4 of the model.

In this table we can see how MVCT with {IWMF, ShEn} set of views is the combination which results achieve the highest accuracy in classification (94.36%).

The results with three views for each of the possible subsets are very close to those obtained with two views, in some cases obtaining results with a lower accuracy than with two views. Fig.8 shows the graph obtained at the end of stage S4 of the built models where the results obtained with different numbers of views can be quickly compared.

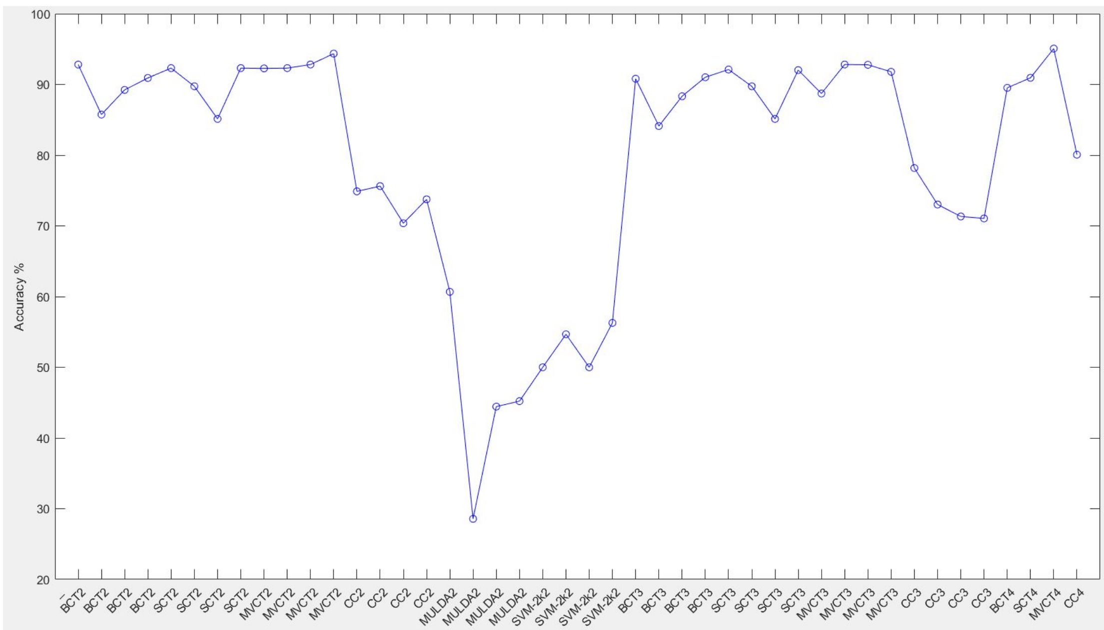

Figure 8: Classification accuracy % achieved by all the combinations tested by the proposed model

In Table 5 another section of the results stored in stage S4 of the model is showed, in this case, one can see an example of the results achieved by the combination of the four views {ABP, IWMF, HjPa, ShEn} and the MVL approaches. Majority Vote Co-training is the Multi-vie learning technique that obtains the higher accuracy.

The final stage of our model, S5, showed as output that the best combination of views is ABP,IWMF,HjPa,ShEn and the Multi-view learning approach that achieves the best results is MVCT with 95.07% accuracy in recognizing three different stress patterns. Comparing our results with the results achieved by Reyes in [5] it can be observed that the application of MVL is usseful to achieve higher accuracy in discriminating among tree

Table 5: Accuracy percentages achieved using four views

MVL	**Subset of views**	**Accuracy %**
BCT	ABP,IWMF,HjPa,ShEn	89.52
SCT	ABP,IWMF,HjPa,ShEn	90.94
MVCT	ABP,IWMF,HjPa,ShEn	95.07
CC	ABP,IWMF,HjPa,ShEn	80.07

different stress scenarios: Silence, listening to pleasant music and listening to Relaxing music (Table 6).

Table 6: Accuracy % comparison of MVL approach and single view approach in [5]

{IWMF, ShEn} MVCT	{ABP,IWMF,HjPa,ShEn} MV	[5]
94.36	95.07	93.00

5.3 Work in progress

Motivated by the results obtained with granulation and data fusion, it is proposed to continue with the refinement of different granulation techniques, addressing Fuzzy Clustering for time series and experimenting with different membership functions and using the extracted granules to merge information from different biosignal modalities.

The analysis of different databases related to biosignals and stress, as well as the study of different protocols for the collection of correlated biosignals, is one of the tasks that is being carried out to propose our own protocol and start with the necessary sampling to generate our own database that allows putting into action all aspects of the methodology described in this proposal. At the same time, basic familiarization tests have been carried out with the devices proposed for taking samples: NeXus-10 and EMOTIV EPOC+.

6 Final Remarks

During the preparation of this proposal, it has been confirmed that the development of a robust system for the detection and quantification of stress remains an open problem that requires the identification of specific stressors that allow determining the presence of this harmful state for health, likewise, it is necessary to include multimodal signals collected consistently and reliably for an objective description of different stress levels. The collection of this data is an important challenge, as well as its proper characterization and standardization, since the synchronization of the sensors, the noise in the signals, the mixing of the data, increase the complexity of the analysis and processing that must be faced for the correct recognition of different levels of stress. Therefore, the exploration of new ways to characterize and merge biosignals, the use of deep learning and the inclusion of a descriptive system understandable by human reasoning that introduces ease of processing can constitute an appropriate system for the classification of correlated biosignals for the determination of different levels of stress levels.

This document proposes the development of a fuzzy deep neural network that allows characterizing correlated biosignals and classifying them to distinguish multiple levels of stress. Preliminary results show that fuzzy granulation of time series is an approach that allows finding relevant information in electroencephalographic signals recorded in different stress scenarios. These feature extraction proposal leads to encouraging results in multilevel stress classification. Experimentation with information fusion techniques have also been done, the results of these experiments allow us to reaffirm the possibility that the inclusion of multimodal information will help to confirm the presence of stress and correctly classify multiple stress levels.

The research carried out so far allows us to conclude that it is possible to work with biosignals from different acquisition methods and that through fuzzy granulation the recorded signals can be characterized, breaking down the data into simpler problems and eliminating irrelevant information, reducing the number of attributes needed for classification. The information fusion techniques will allow the implementation of multimodal neurons and fuzzy representations introduce logical interpretability of information processing these are necessary components for the implementation of a hybrid deep learning model for simultaneous classification of correlated biosignals capable of recognize multiple levels of stress.

Further testing and research regarding fuzzy granulation and multimodal learning is still needed to test other combinations of parameters. Fuzzy deep learning network design has not started yet. Work will continue to investigate existing models to be better documented and thus initiate the necessary work for this phase of the proposal.

References

[1] S. Dong, P. Wang, and K. Abbas, “A survey on deep learning and its applications,” *Computer Science Review*, vol. 40, p. 100379, 2021.

[2] R. Das, S. Sen, and U. Maulik, “A survey on fuzzy deep neural networks,” *ACM Comput. Surv.*, vol. 53, no. 3, 2020.

[3] R. Zhang, F. Shen, and J. Zhao, “A model with fuzzy granulation and deep belief networks for exchange rate forecasting,” in *2014 International Joint Conference on Neural Networks (IJCNN)*, pp. 366–373, 2014.

[4] G. Sideratos, A. Ikonomopoulos, and N. D. Hatziargyriou, “A novel fuzzy-based ensemble model for load forecasting using hybrid deep neural networks,” *Electric Power Systems Research*, vol. 178, p. 106025, 2020.

[5] T. Ouyang, W. Pedrycz, O. F. Reyes-Galaviz, and N. J. Pizzi, “Granular description of data structures: A two-phase design,” *IEEE Transactions on Cybernetics*, vol. 51, no. 4, pp. 1902–1912, 2021.

[6] Z. Huang and J. Li, “Feature subset selection with multi-scale fuzzy granulation,” *IEEE Transactions on Artificial Intelligence*, pp. 1–1, 2022.

[7] J. Pijn, J. Van Neerven, A. Noest, and F. Lopes da Silva, “Chaos or noise in eeg signals; dependence on state and brain site,” *Electroencephalography and clinical neurophysiology*, vol. 79, no. 5, p. 371–381, 1991.

[8] R. Reyes Galaviz, C. A. Reyes-Garcia, and L. Villaseñor-Pineda, “Análisis de la escucha de música para el estudio de estrés académico con electroencefalografía,” *4to Congreso Nacional de Investigación Interdisciplinaria*, vol. 4, 11 2020.

[9] O. Parlak, S. T. Keene, A. Marais, V. F. Curto, and A. Salleo, “Molecularly selective nanoporous membrane-based wearable organic electrochemical device for noninvasive cortisol sensing,” *Science Advances*, vol. 4, no. 7, p. eaar2904, 2018.

[10] E. Smets, W. De Raedt, and C. Van Hoof, "Into the wild: The challenges of physiological stress detection in laboratory and ambulatory settings," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 463–473, 2019.

[11] S. Folkman, "Coping and emotion in stress and coping: An anthology , eds. monat a., and lazarus rs," 1991.

[12] S. E. Wilks, "Resilience amid academic stress: The moderating impact of social support among social work students," *Advances in Social Work*, vol. 9, no. 2, p. 106–125, 2008.

[13] R. Vermunt and H. Steensma, "How can justice be used to manage stress in organizations?," in *Handbook of Organizational Justice :*, pp. 383–410, Leiden University, The Netherlands, 2005.

[14] X. Gu, Z. Cao, A. Jolfaei, P. Xu, D. Wu, T.-P. Jung, and C.-T. Lin, "Eeg-based brain-computer interfaces (bcis): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 5, pp. 1645–1666, 2021.

[15] S. Sharma, G. Singh, and M. Sharma, "A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans," *Computers in Biology and Medicine*, vol. 134, p. 104450, 2021.

[16] H. Jebelli, M. M. Khalili, and S. Lee, "Mobile eeg-based workers' stress recognition by applying deep neural network," *Advances in Informatics and Computing in Civil and Construction Engineering*, p. 173–180, 2018.

[17] K. Masood and M. A. Alghamdi, "Modeling mental stress using a deep learning framework," *IEEE Access*, vol. 7, pp. 68446–68454, 2019.

[18] D. Kamińska, K. Smółka, and G. Zwoliński, "Detection of mental stress through eeg signal in virtual reality environment," *Electronics*, vol. 10, no. 22, 2021.

[19] A. R. Subhani, W. Mumtaz, M. N. B. M. Saad, N. Kamel, and A. S. Malik, "Machine learning framework for the detection of mental stress at multiple levels," *IEEE Access*, vol. 5, pp. 13545–13556, 2017.

[20] M. Zanetti, T. Mizumoto, L. Faes, A. Fornaser, M. De Cecco, L. Maule, M. Valente, and G. Nollo, "Multilevel assessment of mental stress via network physiology paradigm using consumer wearable devices," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 4, p. 4409–4418, 2019.

[21] R. S. Reyes Galaviz, "Item 1009/2048: Repositorio inaoe," Apr 2021.

[22] M. Mosanya, "Buffering academic stress during the covid-19 pandemic related social isolation: Grit and growth mindset as protective factors against the impact of loneliness," *International Journal of Applied Positive Psychology*, vol. 6, no. 2, p. 159–174, 2020.

[23] D. Shon, K. Im, J.-H. Park, D.-S. Lim, B. Jang, and J.-M. Kim, "Emotional stress state detection using genetic algorithm-based feature selection on eeg signals," *International Journal of Environmental Research and Public Health*, vol. 15, no. 11, p. 2461, 2018.

[24] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, "A review on mental stress assessment methods using eeg signals," *Sensors*, vol. 21, no. 15, p. 5043, 2021.

[25] A. Arsalan, S. M. Anwar, and M. Majid, "Mental stress detection using data from wearable and non-wearable sensors: A review," *CoRR*, vol. abs/2202.03033, 2022.

[26] G. Muhammad, F. Alshehri, F. Karray, A. E. Saddik, M. Alsulaiman, and T. H. Falk, "A comprehensive survey on multimodal medical signals fusion for smart healthcare systems," *Information Fusion*, vol. 76, pp. 355–375, 2021.

[27] S. Tan and A. Yip, "Hans selye (1907–1982): Founder of the stress theory," *Singapore Medical Journal*, vol. 59, no. 4, p. 170–171, 2018.

[28] U. D. of Health and N. C. I. Human Services, “Psychological stress and cancer,” Dec 2012.

[29] M. Zea, F. G. Bellagambi, H. Ben Halima, N. Zine, N. Jaffrezic-Renault, R. Villa, G. Gabriel, and A. Errachid, “Electrochemical sensors for cortisol detections: Almost there,” *TrAC Trends in Analytical Chemistry*, vol. 132, p. 116058, 2020.

[30] H. J. a. Britton JW, Frey LC, “NCBI - Electroencephalography (EEG): An Introductory Text and Atlas of Normal and Abnormal Findings in Adults, Children, and Infants [Internet].,” 2016.

[31] J. Flood, “A History of Modern EEG,” 09 2020.

[32] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, “A review on mental stress assessment methods using eeg signals,” *Sensors*, vol. 21, no. 15, 2021.

[33] S. Sharma, G. Singh, and M. Sharma, “A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans,” *Computers in Biology and Medicine*, vol. 134, p. 104450, 2021.

[34] Y. Tan, Z. Sun, F. Duan, J. Solé-Casals, and C. F. Caiafa, “A multimodal emotion recognition method based on facial expressions and electroencephalography,” *Biomedical Signal Processing and Control*, vol. 70, p. 103029, 2021.

[35] H. Hotelling, “Relations Between Two Sets of Variates,” *Biometrika*, vol. 28, pp. 321–377, 12 1936.

[36] L. Gonzalez-Carabarin, E. Castellanos-Alvarado, P. Castro-Garcia, and M. Garcia-Ramirez, “Machine learning for personalised stress detection: Inter-individual variability of eeg-ecg markers for acute-stress response,” *Computer Methods and Programs in Biomedicine*, vol. 209, p. 106314, 2021.

[37] S. Betti, R. M. Lova, E. Rovini, G. Acerbi, L. Santarelli, M. Cabiati, S. D. Ry, and F. Cavallo, “Evaluation of an integrated system of wearable physiological sensors

for stress monitoring in working environments by using biological markers," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 8, pp. 1748–1758, 2018.

[38] A. Secerbegovic, S. Ibric, J. Nisic, N. Suljanovic, and A. Mujcic, "Mental workload vs. stress differentiation using single-channel eeg," *IFMBE Proceedings*, p. 511–515, 2017.

[39] F. Al-Shargie, T. B. Tang, and M. Kiguchi, "Assessment of mental stress effects on prefrontal cortical activities using canonical correlation analysis: an fnirs-eeg study," *Biomed. Opt. Express*, vol. 8, pp. 2583–2598, May 2017.

[40] L. Ghosh, S. Saha, and A. Konar, "Decoding emotional changes of android-gamers using a fused type-2 fuzzy deep neural network," *Computers in Human Behavior*, vol. 116, p. 106640, 2021.

[41] S. Adhikary, K. Jain, B. Saha, and C. Koner, "Fuzzy logic on long short-term memory for smart person-identification system through electroencephalogram," in *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*, pp. 609–613, 2021.

[42] D. Zhang, L. Yao, S. Wang, K. Chen, Z. Yang, and B. Benatallah, "Fuzzy integral optimization with deep q-network for eeg-based intention recognition," *Advances in Knowledge Discovery and Data Mining*, p. 156–168, 2018.

[43] S. O. Ferreira, "Activación emocional en sujetos humanos: Procedimientos para la inducción experimental de estrés," *Psicologia USP*, vol. 30, 2019.

[44] D. Lahat, T. Adali, and C. Jutten, "Multimodal data fusion: An overview of methods, challenges, and prospects," *Proceedings of the IEEE*, vol. 103, no. 9, pp. 1449–1477, 2015.

[45] T. Baltrusaitis, C. Ahuja, and L. Morency, "Multimodal machine learning: A survey and taxonomy," *CoRR*, vol. abs/1705.09406, 2017.

[46] O. F. Reyes-Galaviz and W. Pedrycz, "Granular fuzzy models: Analysis, design, and evaluation," *International Journal of Approximate Reasoning*, vol. 64, pp. 1–19, 2015.

[47] W. Lu, W. Pedrycz, X. Liu, J. Yang, and P. Li, "The modeling of time series based on fuzzy information granules," *Expert Systems with Applications*, vol. 41, no. 8, pp. 3799–3808, 2014.

[48] J. Ruan, X. Wang, and Y. Shi, "Developing fast predictors for large-scale time series using fuzzy granular support vector machines," *Applied soft computing*, vol. 13, no. 9, pp. 3981–4000, 2013.

[49] H. Guo, L. Wang, X. Liu, and W. Pedrycz, "Information granulation-based fuzzy clustering of time series," *IEEE Transactions on Cybernetics*, vol. 51, no. 12, pp. 6253–6261, 2021.

[50] Y. Hao, S. Jiang, F. Yu, W. Zeng, X. Wang, and X. Yang, "Linear dynamic fuzzy granule based long-term forecasting model of interval-valued time series," *Information Sciences*, vol. 586, pp. 563–595, 2022.

[51] J. Zhao, X. Xie, X. Xu, and S. Sun, "Multi-view learning overview: Recent progress and new challenges," *Information Fusion*, vol. 38, pp. 43–54, 2017.

[52] S. Sun, X. Xie, and M. Yang, "Multiview uncorrelated discriminant analysis," *IEEE Transactions on Cybernetics*, vol. 46, no. 12, pp. 3272–3284, 2016.

[53] J. Farquhar, D. Hardoon, H. Meng, J. Shawe-taylor, and S. Szedmák, "Two view learning: Svm-2k, theory and practice," in *Advances in Neural Information Processing Systems* (Y. Weiss, B. Schölkopf, and J. Platt, eds.), vol. 18, MIT Press, 2005.

[54] K. Nigam and R. Ghani, "Analyzing the effectiveness and applicability of co-training," in *Proceedings of the Ninth International Conference on Information and Knowledge Management*, CIKM '00, (New York, NY, USA), p. 86–93, Association for Computing Machinery, 2000.

[55] A. Blum and T. Mitchell, "Combining labeled and unlabeled data with co-training," in *Proceedings of the Eleventh Annual Conference on Computational Learning Theory*, COLT' 98, (New York, NY, USA), p. 92–100, Association for Computing Machinery, 1998.

[56] Q. Chen and S. Sun, "Hierarchical multi-view fisher discriminant analysis," in *Proceedings of the 16th International Conference on Neural Information Processing: Part II*, ICONIP '09, (Berlin, Heidelberg), p. 289–298, Springer-Verlag, 2009.

[57] D. Nauck, U. Nauck, and R. Kruse, "Generating classification rules with the neuro-fuzzy system nefclass," in *Proceedings of North American Fuzzy Information Processing*, pp. 466–470, 1996.

[58] V. Ojha, A. Abraham, and V. Snášel, "Heuristic design of fuzzy inference systems: A review of three decades of research," *Engineering Applications of Artificial Intelligence*, vol. 85, pp. 845–864, 2019.

[59] Y. Chai, L. Jia, and Z. Zhang, "Mamdani model based adaptive neural fuzzy inference system and its application in traffic level of service evaluation," in *2009 Sixth International Conference on Fuzzy Systems and Knowledge Discovery*, vol. 4, pp. 555–559, 2009.

[60] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A Database for Emotion Analysis ;Using Physiological Signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, 2012.

[61] W.-L. Zheng, W. Liu, Y. Lu, B.-L. Lu, and A. Cichocki, "EmotionMeter: A Multimodal Framework for Recognizing Human Emotions," *IEEE Transactions on Cybernetics*, vol. 49, no. 3, pp. 1110–1122, 2019.

[62] M. Parent, I. Albuquerque, A. Tiwari, R. Cassani, J.-F. Gagnon, D. Lafond, S. Tremblay, and T. H. Falk, "PASS: A Multimodal Database of Physical Activity and Stress for Mobile Passive Body/ Brain-Computer Interface Research," *Frontiers in Neuroscience*, vol. 14, 2020.

[63] A. Torres-García, C. Reyes-García, L. Villaseñor-Pineda, and J. Ramírez-Cortés, "Análisis de señales electroencefalográficas para la clasificación de habla imaginada," *Revista mexicana de ingeniería biomédica*, vol. 34, pp. 23 – 39, 00 2013.

[64] B. Hjorth, "EEG analysis based on time domain properties," *Electroencephalography and Clinical Neurophysiology*, vol. 29, no. 3, pp. 306–310, 1970.

[65] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, "A review on mental stress assessment methods using eeg signals," *Sensors*, vol. 21, no. 15, p. 5043, 2021.

[66] D. Lopez-Bernal, D. Balderas, P. Ponce, and A. Molina, "A state-of-the-art review of eeg-based imagined speech decoding," *Frontiers in Human Neuroscience*, vol. 16, 2022.

[67] S. Sharma, G. Singh, and M. Sharma, "A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans," *Computers in Biology and Medicine*, vol. 134, p. 104450, 2021.

[68] A. A. Torres-García, C. A. Reyes-García, and L. Villaseñor-Pineda, "Chapter 12 - a survey on eeg-based imagined speech classification," in *Biosignal Processing and Classification Using Computational Learning and Intelligence* (A. A. Torres-García, C. A. Reyes-García, L. Villaseñor-Pineda, and O. Mendoza-Montoya, eds.), pp. 251–270, Academic Press, 2022.