Time for an Explanation: A Mini-Review of Explainable Physio-Behavioural Time-Series Classification

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Abstract

Time-series classification is seeing growing importance as device proliferation has lead to the collection of an abundance of sensor data. Although black-box models, whose internal workings are difficult to understand, are a common choice for this task, their use in safety-critical domains has raised calls for greater transparency. In response, researchers have begun employing explainable artificial intelligence together with physio-behavioural signals in the context of real-world problems. Hence, this paper examines the current literature in this area and contributes principles for future research to overcome the limitations of the reviewed works.

CCS Concepts

• **Mathematics of computing → Time series analysis**; • **Computing methodologies → Knowledge representation and reasoning**; *Supervised learning by classification*; • **Human-centered computing → Ubiquitous and mobile computing**; *Visualization design and evaluation methods.*

Keywords

explainable artificial intelligence; time-series classification; physio-behavioural signals; ubiquitous computing; design principles

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1 Introduction

Since Mark Weiser's seminal article on ubiquitous computing "The computer for the 21st century" [31], embedded computers have found their way into all kinds of everyday devices within human environments and enabled the collection of an enormous amount of time-series data [25]. There has thus been considerable interest in applying Machine Learning (ML) to automatically classify this data, which is known in the literature as Time-Series Classification (TSC) [8]. Deep-learning models in particular have achieved high performance on various tasks, yet are often considered as "black boxes" [17]. Consequently, eXplainable Artificial Intelligence (XAI) has gained traction as a means to shed light on these models [15].

Although there are existing surveys discussing eXplainable TSC (XTSC) [27, 29], those focusing specifically on applications using physiological and behavioural (physio-behavioural) signals are scarce. Therefore, this paper aims to fill this gap and is structured as follows: Section 2 provides a brief overview of model explanations and how these can be evaluated; Section 3 presents the results of the literature review; Section 4 constitutes the main contribution of this paper in the form of a set of principles for future research to address the limitations in the reviewed works.

2 Explainable Artificial Intelligence

As Artificial Intelligence (AI) is deployed in domains with stringent safety requirements such as health care, it is increasingly important to be able to explain models to justify decisions, prevent misinterpretations, identify shortcomings and increase knowledge [4]. Nauta et al. [22] treat explanations as "a presentation of (aspects of) the reasoning, functioning and/or behavior of a ML model in human-understandable terms." These can be in the form of visualizations, textual descriptions, simplified models, data examples or relevance scores and serve different purposes depending on the audience [3], who can be split into novice users, data experts and AI experts [21]. Ideally, an explainable system would present its explanations appropriately to address the needs of the intended target group.

Due to the many factors that influence the effectiveness of explanations, it is necessary to evaluate the chosen methods to ensure that these align with the expectations of the target users. This can be achieved using human-centred methods, such as quantitative and qualitative surveys, or objective metrics [30]. The importance of the latter is in comparing and benchmarking different methods and as optimization criteria during model training [22]. Consequently, several approaches for evaluating XAI methods for TSC have been developed. For instance, Fouladgar et al. [10] formulate multiple sensitivity-based metrics specifically tailored for time-series data and Fauvel et al. [9] propose a framework to systematically assess the performance and explainability of ML models and benchmarked several multivariate time-series classifiers. Readers are referred to Nauta et al. [22] for a comparison of evaluation methods.

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3 Literature Review

Explainability is crucial in many practical applications of TSC where sensitive personal data collected from wearable and ambient sensors is used to make important decisions pertaining to those individuals. This section reviews and summarizes the recent literature regarding applications of XTSC using physio-behavioural signals.

As shown in Table 1, many of the papers reviewed focused on disease diagnosis, such as detecting arrhythmia, strokes, seizures and psychotic disorders. Other applications included sleep diagnosis, human activity recognition and affect and emotion recognition. The majority of papers dealt with only a single modality, the most common of which was electroencephalogram (EEG), but electrocardiogram (ECG), electrodermal activity (EDA) and accelerometer (ACC) sensor data also appeared several times.

The majority of papers utilized Convolutional Neural Network (CNN) architectures, followed by those based on Tree Ensemble (TE) methods. Recurrent Neural Network (RNN) and the related Echo State Network (ESN) and Residual Network (ResNet) architectures saw surprisingly little use despite their inherent suitability for sequential data. SHapley Additive exPlanations (SHAP) were the most popular explainability method, followed by Local Interpretable Model-agnostic Explanations (LIME) and Gradient-weighted Class Activation Mapping (Grad-CAM).

3.1 Disease Diagnosis

The aim of disease diagnosis is to identify abnormal patterns in sensor data that are indicative of particular diseases and conditions. For instance, Cesarelli et al. [6] propose an explainable CNN architecture for discriminating regular and irregular heartbeats from spectral centroid images extracted from phonocardiograms (PCG) and visualize which sections of these images contribute to the classification using Grad-CAM. Alamatsaz et al. [2] look at the same problem, but combine CNN with Long Short-Term Memory (LSTM) and use SHAP instead of Grad-CAM. Similarly, Islam et al. [13] and Bouazizi and Ltifi [5] both investigate detecting stroke from EEG signals. The former paper explains predictions from various TE models with LIME and Eli5, including Adaptive Gradient Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost) and Light Gradient-Boosting Machine (LightGBM), whilst the latter paper uses Ensemble ESN (E-ESN) and SHAP.

Al-Hussaini and Mitchell [1] suggest a TE architecture with Categorical Boosting (CatBoost) for detecting seizures trained on an EEG data set augmented with Fourier-transform surrogates, claiming that the glass-box model has performance similar to black-box models. They use SHAP values to visualize the contributions of each value to the predictions. In comparison, Halimeh et al. [12] use ACC, EDA and Heart Rate (HR) signals and feed each of these directly into residual blocks to perform automatic feature extraction. The authors use Uniform Manifold Approximation and Projection (UMAP) to visualize discriminatory power at the individual level and SHAP to determine which features are most informative during seizure events. Finally, Misgar and Bhatia [20] present a dual-branch CNN architecture with a Multi-Headed Attention (MHA) mechanism using Grad-CAM for explaining depression and schizophrenia detection from motor activity data, where one branch processes daytime activity and the other nighttime activity to deal with different data distributions during these time periods.

3.2 Sleep Diagnosis

In the category of sleep diagnosis, Dutt et al. [7] combine 1-D CNN with Conditional Random Fields (CRF) to identify stages of the sleep cycle from EEG signals extracted from a polysomnogram and use Grad-CAM to identify which time intervals correspond to different stages. The paper by Jany et al. [14] is similar, but the authors use TE models, including Random Forest (RF), Gradient Boosting (GB) and XGBoost, along with SHAP instead of Grad-CAM. In contrast, Rossi et al. [26] provide a CNN architecture to discriminate three breathing-related patterns (normal, apnoea and irregular) during sleep from somnographic signals, including Breathing Rhythm (BR), Chest Effort (CE), Body Position (BP), Mechanical Vibration (MV) and peripheral oxygen saturation (SpO_2). For each prediction, the authors calculate a Confidence Interval (CI) and heat maps for visualization of time intervals pertinent to the classification.

3.3 Human Activity Recognition

The objective of human activity recognition is to determine which actions human agents are performing in real time from sensor readings. To this end, Yuan et al. [32] design an explainable multimodal sensor-fusion system comprised of three RNN models with LSTM units trained on Passive InfraRed (PIR), Passive Radio Frequency (PRF) and mixed data sets. They use a transparent model, Support Vector Machine (SVM) with a linear kernel, for decision-level fusion and produce SHAP plots to show the relative weights of each RNN prediction to the final decision. Mekruksavanich et al. [19] similarly propose a multichannel CNN architecture with LSTM layers, where convolution is performed separately over each input variable and the intermediate features are concatenated before being classified in a fully connected layer. The authors employ t-distributed Stochastic Neighbour Embedding (t-SNE) to visualize the features extracted by the model.

3.4 Affect and Emotion Recognition

Affect and emotion recognition represents a significant research area whose goal is to automatically identify various human psychological states with technology. Pan and Rahman [23] take an interesting approach to recognize stress by training an Artificial Neural Network (ANN) on EEG data, using a Genetic Algorithm (GA) for feature selection, and then extracting rules for explaining the model behaviour through sensitivity analysis. In a similar vein, Tervonen et al. [28] focus on discriminating between physical and psycho-social stress from ECG, EDA, electrooculogram (EOG) and Brain Beat (BB) signals using a variety of classifiers: k-Nearest Neighbours (k-NN), Linear and Quadratic Discriminant Analysis (LDA, QDA), SVM, Decision Tree (DT), RF and XGBoost. They use SHAP values to discover the most influential features for classification. Lastly, Lin et al. [18] propose a Multimodal-Multisensory Sequential Fusion (MMSF) model to distinguish between neutral, stress and amusement states from ACC, EDA, ECG, electromyography (EMG), Blood Volume Pulse (BVP), respiration (RESP) and temperature (TEMP) signals. They perform late fusion using Linear

Table 1: XTSC Applications Using Physio-Behavioural Signals

Reference	Domain	Modalities	Architecture	Explanation
Cesarelli et al. [6]	Arrhythmia	PCG	CNN	Grad-CAM
Alamatsaz et al. [2]	Arrhythmia	ECG	CNN+LSTM	SHAP
Islam et al. [13]	Stroke	EEG	AdaBoost, LightGBM, XGBoost	Eli5, LIME
Bouazizi and Ltifi [5]	Stroke	EEG	E-ESN	SHAP, LIME
Al-Hussaini and Mitchell [1]	Seizure	EEG	CatBoost	SHAP
Halimeh et al. [12]	Seizure	EDA, ACC, HR	ResNet	SHAP, UMAP
Misgar and Bhatia [20]	Psychosis	ACC	CNN+MHA	Grad-CAM
Dutt et al. [7]	Sleep Stage	EEG	CNN+CRF	Grad-CAM
Jany et al. [14]	Sleep Stage	EEG	XGBoost, GB, RF	SHAP
Rossi et al. [26]	Sleep Event	BR, CE, BP, MV, SpO_2	CNN	CI, Heat Map
Yuan et al. [32]	Human Activity	PIR, PRF	RNN+LSTM+SVM	SHAP
Mekruksavanich et al. [19]	Human Activity	ACC	MC-CNN-LSTM	t-SNE
Pan and Rahman [23]	Stress	EEG	ANN+GA	Rules
Tervonen et al. [28]	Stress	ECG, EDA, EOG, BB	k-NN, LDA, QDA, DT, SVM, RF, XGBoost	SHAP
Lin et al. [18]	Affect	ACC, ECG, EMG, EDA, BVP, TEMP, RESP	MMSF (LR, SVM, RF)	FI, Ablation

Regression (LR), SVM and RF classifiers on the outputs of several submodels, providing explanations for the fusion and individual predictions through Feature Importance (FI) scores and an ablation experiment, respectively.

4 Discussion

In this section, the deficiencies of the current literature are discussed and used to derive a set of principles to guide researchers interested in XTSC and physio-behavioural signals.

4.1 Deficiencies

4.1.1 Lack of clarity. In many of the papers reviewed, explainability was presented almost as an end in itself or an afterthought without a specific context or audience in mind. The problem with this is that the requirements for model explanations strongly depend on the audience's particular interests and level of AI proficiency [3]. For example, Lin et al. [18] raise the inability of humans to understand model predictions as a hindrance to the adoption of deep learning models in affect recognition and attempt to overcome this limitation through an explainability analysis. They conclude that EDA from chest signals contribute most to model predictions, but do not elaborate on the concrete uses or explanatory value of their results for practitioners. In contrast, Alamatsaz et al. [2] discuss the use of Shapley values for clinicians during the differential diagnosis process and to ensure that the model concentrates on features that are consistent with clinical expertise. Researchers should, thus, take care to clarify how and by whom model explanations are intended to be used.

4.1.2 Lack of relevance. Following from the previous point, it was noted during the review that XAI models were often developed in isolation from those who have an interest in or would be affected by its use. In one of the papers, Bouazizi and Ltifi [5] present a decision support system software to support clinicians with stroke diagnosis, including a panel for visualizing explanations using LIME plots and SHAP values and recommendations for diagnostic tests. It is not clear, however, whether clinicians were consulted in the design process of the software's user interface. Similarly, in the paper by Yuan et al. [32], although the dependence of explanations on the needs of the users is acknowledged, no attempt to elicit explainability requirements from the users was made. The benefit of involving relevant stakeholders in the design of the system is that it provides an opportunity to obtain feedback that can be used to tailor the explanations and their presentation to the expectations of the recipients [16].

4.1.3 Lack of interpretability. Another issue present in the reviewed works that limits the utility of model explanations is the insufficient consideration given to domain-specific nuances of the time-series data. Notably, many real-world time series have temporal patterns that are often non-obvious, hidden or contaminated by noise, making interpreting the raw data directly difficult [24]. This is exemplified in Fig. 7–9 of the paper by Misgar and Bhatia [20], where heat maps highlight the regions of the feature maps learnt by the model that contribute most to its prediction. However, these visualizations do little to identify the reasoning behind the prediction in the absence of easily recognizable and well understood patterns in the feature maps. Researchers should consider providing explanations in terms of handcrafted features extracted during the data processing stage where appropriate, as argued by Geurts [11]. Islam et al. [13] and Jany et al. [14] make use of this approach by splitting the input EEG into frequency subbands corresponding to different types of brain waves. This makes it easier to see the link between the provided explanations and existing knowledge about the brain waves associated with each class.

4.1.4 Lack of validity. Of particular concern were missing evaluation procedures to validate the effectiveness of model explanations in real-world scenarios. Similar to the standard practice of evaluating model performance using metrics such as F1 score, accuracy, precision and recall, explanations should also be subject to the same rigour [22]. However, many authors appeared to rely primarily on intuition based on a few arbitrary examples to determine the acceptability of the explanations, which was also raised as an issue by Nauta et al. [22]. For example, in the paper by Cesarelli et al. [6], the authors only mention that the heat maps generated using Grad-CAM seem to coincide with peaks in the spectral centroid without further elaboration. Some authors relate the explanations to existing theory to show that these are sensible, but do not attempt an empirical validation. This is the case in the paper by Alamatsaz et al. [2], where the authors compare the explanations to clinically

Table 2: Evaluation of Literature through DEEP Principles

Reference	Define	Engage	Embed	Prove
Cesarelli et al. [6]	N	N	Y	N
Alamatsaz et al. [2]	Y	N	N	N
Islam et al. [13]	N	N	Y	N
Bouazizi and Ltifi [5]	Y	N	Y	N
Al-Hussaini and Mitchell [1]	Y	N	Y	N
Halimeh et al. [12]	Y	N	N	N
Misgar and Bhatia [20]	N	N	N	N
Dutt et al. [7]	Y	N	N	N
Jany et al. [14]	N	N	Y	N
Rossi et al. [26]	N	N	Y	N
Yuan et al. [32]	Y	N	N	N
Mekruksavanich et al. [19]	N	N	N	N
Pan and Rahman [23]	N	N	Y	N
Tervonen et al. [28]	Y	N	Y	N
Lin et al. [18]	N	N	N	N

relevant EEG characteristics for various types of abnormal heart rhythms. As mentioned in Section 2, researchers can take advantage of existing human-centred and objective evaluation metrics for explainability methods to demonstrate that their proposed explainable models will perform as intended.

4.2 Principles

In Figure 1, a list of four principles are presented to help future researchers avoid the common pitfalls noted in the prior discussion: Define, Engage, Embed, Prove. Using these principles, the reviewed works were evaluated to obtain Table 2, where an item was determined to have been satisfied (Y) if the authors made an effort to address the related issue or not satisfied (N) otherwise.

DEFINE purpose and target audiences of explanations at the start of the study.
ENGAGE stakeholders throughout system design to obtain regular feedback.
EMBED domain knowledge when selecting appropriate input features.
PROVE validity of explanations using theoretical and empirical evaluation.

Figure 1: DEEP (Define, Engage, Embed, Prove) Principles

As can be seen in Table 2, whilst almost half of the papers stated the purpose and audience of their system's explanations, the remainder did not address this point at all. None of the papers involved stakeholders in the system design process except occasionally during data collection. The papers were approximately evenly split between those that presented explanations in terms of intuitive features and those that did not. Although some papers attempted to show that explanations aligned with theory, none performed a thorough empirical evaluation.

5 Conclusion

In this paper, a brief overview of explainability and evaluation methods were given and the current literature on applications of XTSC using physio-behavioural signals were reviewed. The deficiencies of the reviewed works were discussed and a set of principles were presented to combat these. In particular, it was shown that there was an absence of stakeholder participation in the research and empirical evaluation of explanations. Future efforts should aim to follow these principles to address these limitations.

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