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Towards PTSD Diagnosis Through ECG Anomaly Detection based on Autoencoders

Vasileios Skaramagkas[1,2,*], Ioannis Kyprakis[1,2], Georgia S. Karanasiou[3,4], Dimitris I. Fotiadis[3,4], Manolis Tsiknakis[1,2]

[1]Biomedical Informatics and eHealth Laboratory, Dept. of Electrical and Computer Engineering, Hellenic Mediterranean University, Heraklion, 71410 Crete, Greece
[2]Institute of Computer Science, Foundation for Research and Technology Hellas (FORTH), Heraklion, 70013 Crete, Greece
[3]Unit of Medical Technology Intelligent Information Systems, University of Ioannina, Ioannina, 45110, Greece
[4]Biomedical Research Institute, Foundation for Research and Technology Hellas (FORTH), Ioannina, 45110, Greece

Abstract

INTRODUCTION: Post-Traumatic Stress Disorder (PTSD) is a debilitating mental health condition that can develop after exposure to traumatic events, often resulting in symptoms that severely impair daily functioning. Current diagnostic methods largely rely on subjective assessments, highlighting the need for objective, non-invasive tools to improve diagnostic precision.
OBJECTIVES: This study aims to develop and validate an innovative deep learning approach using autoencoder neural networks to detect PTSD through analysis of electrocardiography (ECG) signals. The goal is to provide a reliable and sophisticated diagnostic method that bridges computational and clinical domains.
METHODS: We employed autoencoder neural networks to analyze ECG data collected from wearable heart zone sensors. This unsupervised learning model was trained to detect subtle anomalies in the ECG signals that may serve as biomarkers for PTSD. The methodology was evaluated using data collected from individuals with and without PTSD symptoms.
RESULTS: The proposed model demonstrated strong potential as an objective diagnostic tool, successfully identifying patterns in ECG signals associated with PTSD. The analysis confirmed the model's ability to distinguish PTSD-related anomalies with 83% accuracy.
CONCLUSION: This research introduces a novel, non-invasive diagnostic methodology for PTSD using deep learning and wearable ECG data. The findings support the model's value as a potential objective biomarker, contributing to more precise psychiatric diagnostics and expanding the role of machine learning in healthcare.

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1. Introduction

The field of medical diagnostics has seen a transformative change with the introduction of sophisticated data analysis methods, namely in the domain of mental health conditions like Post-Traumatic Stress Disorder (PTSD). PTSD is a mental disorder that arises from a significant psychological trauma of a threatening or catastrophic nature and is characterised by recurrent exposure to components of a traumatic incident, accompanied by feelings of worry, panic, wrath, guilt, and a strong urge to avoid stimuli linked to the source of stress [1]. Its prevalence is notable among individuals with chronic diseases, including breast cancer, where treatment-induced cardiac toxicity can exacerbate PTSD symptoms, affecting patients' overall quality of life [2]. The current method of diagnosing PTSD relies on self-reports, which may be susceptible to inaccuracies, particularly in individuals, including children and adults, who display avoidance signs [3].

*Corresponding author. Email: vskaramag@ics.forth.gr

Given the intricate nature of the problem, it is crucial to employ inventive methods to achieve precise and unbiased detection. To this goal, machine learning methods have been taught to accurately assess the severity of PTSD by analysing signals, such as electroencephalography (EEG), and extracting relevant information [4]. Additionally, electrocardiography (ECG), a readily accessible and non-invasive technology that can be obtained even from wearable devices, provides valuable insights into the complex interaction between the heart and the neurological system. In PTSD, these variations in ECG rhythms have the potential to function as biomarkers for the condition, providing a new and unbiased diagnostic tool [5].

Within the rapidly growing domain of deep learning (DL) applications in medical diagnostics [6, 7], there is a noticeable deficiency: the absence of models explicitly tailored to identify PTSD through the analysis of ECG data, especially in populations with co-existing conditions like breast cancer [8]. Although there has been notable progress in creating advanced DL models for diagnosing different mental disorders [9], PTSD has not received the same amount of focus, especially when it comes to using ECG inputs. The absence of ECG analysis in diagnosing PTSD is significant, considering its ability to uncover the physiological foundations linked to this condition [10]. This highlights a promising yet unexplored approach for an objective and non-intrusive diagnosis, which could complement the existing dependence on self-reported symptoms and clinical evaluations.

This work aims to capitalize on recent novel computational approaches with clinical diagnoses for PTSD, in order to address the existing gap. Our objective is to utilise autoencoders to analyse ECG data and create a model that can detect the tiny irregularities which can be characteristic of PTSD, particularly for breast cancer patients dealing with complex health challenges. This technique not only provides the potential to improve the precision of PTSD identification, but also makes a valuable contribution to the wider field of diagnosing psychiatric disorders, where there is a pressing demand for objective biomarkers.

We introduce a complete methodology that utilises autoencoder-based anomaly identification for the analysis of ECG data. Our approach is founded on a thorough understanding of both the clinical aspects of PTSD and the technological complexities of machine learning models. Our model, validated with an extensive dataset from wearable devices, offers insights into enhancing PTSD diagnosis in patients with breast cancer [11].

2. Related Work

2.1. PTSD Diagnosis Based on Machine Learning

Machine learning approaches have been developed alongside traditional interview-based and evidence-based diagnostic methods to diagnose symptoms of PTSD [12]. Convolutional Neural Networks (CNN) have been employed to diagnose PTSD by analysing keywords extracted from Twitter [13]. Their approach achieved 91.00% accuracy within the group of cancer survivors. Lekkas *et al.* [14] conducted an experiment on female trauma witnesses, focusing on the duration of their absence from home. By inputting the information from the global positioning system (GPS) into an XGB classifier, they obtained AUC value 0.82 and accuracy rate 77.00%. Finally, a recent study successfully employed RF classifiers to examine medical records for automated diagnosis of PTSD, resulting in impressive accuracy rate 99.00% and AUC 0.89 [15].

Moreover, multiple research papers have explored the diagnosis of PTSD by employing machine learning methods on neuroimaging data. In [16], researchers employed a deep learning approach to achieve diagnostic accuracy 71.20%. They utilised neural fingerprints from important brain regions. Zhu *et al.* developed a deep learning graph-theoretic approach to distinguish between PTSD and trauma exposed non-PTSD groups. They achieved an accuracy of 80.00% by analysing brain network graphs [17]. Furthermore, Gong *et al.* employed a SVM classifier using gray and white matter metrics. They achieved an accuracy of 91.00% in differentiating individuals with PTSD from healthy controls. Additionally, they achieved an accuracy of 67.00% in separating those exposed to trauma but without PTSD. This demonstrated the effectiveness of magnetic resonance imaging (MRI) data in identifying PTSD [18].

2.2. Autoencoders Towards the Detection of Mental Disorders

Autoencoders are employed in the domain of mental disorders for several objectives. In a recent study, a novel autoencoder model that utilises variational mode decomposition and mutual information techniques to identify depression from speech data in the DAIC-WOZ dataset was presented [19]. The proposed model achieved accuracy 78.95% and f1-score 0.76. Moreover, scientists in [20] utilised an autoencoder, to precisely forecast missing responses in depression research. The findings demonstrated the superior accuracy of this approach compared to alternative models, enabling its application in accurately forecasting patients' depression status with minimal error rate 2.85%.

Regarding other mental disorders, Sewani *et al.* [21] developed a combination of unsupervised autoencoder and supervised CNN in order to deliver a proficient diagnosis of autism spectrum disorder, particularly

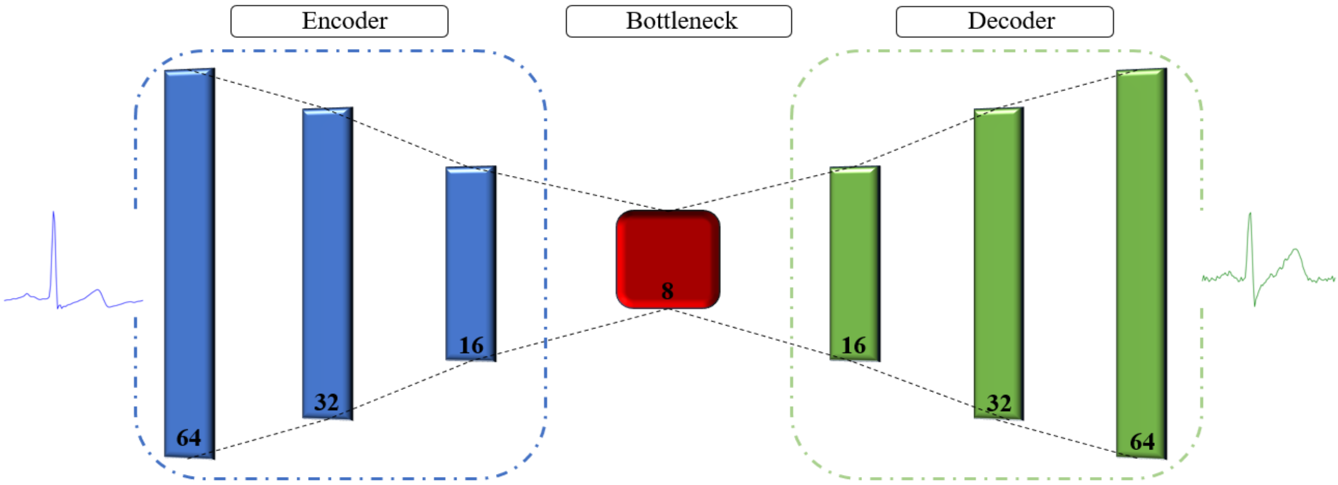

Figure 1. Architecture of the built autoencoder model used for ECG anomaly detection.

for children. Their model yielded high level of performance, obtaining accuracy 84.05% and AUC value 0.78. A CNN-based autoencoder was also developed in [22] to forecast individuals with suicidal tendency by analysing their structural brain imaging. The findings indicated that a specific arrangement of brain structures in various areas can effectively differentiate those with suicidal thoughts from those without such thoughts and healthy controls, with 85.00% accuracy. The effectiveness of a 3D convolutional autoencoder (3D-CAE) in extracting features associated with schizophrenia, without relying on diagnostic labels was examined in [23]. The features obtained using 3D-CAE preserved their correlation with clinical data and it was found that the developed model might potentially be used to extract features to predict medication dosage and symptom severity in schizophrenia. These studies illustrate the effectiveness of autoencoders in comprehending and tackling mental problems.

3. Methodology

3.1. Dataset description

ECG signals were obtained from 42 patients in two clinical centers in Greece (No. 683/22-11/2022, 31557/27-12-2022) and one in Cyprus (No. EEBK/EP/2022/58) during the period 06.2023 - 12.2023 in the framework within the CARDIOCARE's Clinical Study [11]. The study aims to improve patients' participation in their care process and improve their physical condition and psychological adaptation to the disease by implementing an individualised care plan. This plan is based on monitoring the patient's health status using a mobile platform including a smartwatch, a heart zone sensor, and a mobile phone (mobile-Health monitoring system), as well as to collect new biomarkers.

In this context, each patient was provided with a Polar H10 Heart Rate Sensor and was instructed to perform a 30 min. long ECG every two weeks. ECG signals were recorded from the Polar belt at a 146 Hz and were uploaded as 5 min. segments on the CARDIOCARE platform through a mobile app. Moreover, the patients completed the IES-R questionnaire during their tactical visits at the clinical centers. In total 5,285 5 min. ECG segments were uploaded on the platform during the 6-month period and were used for the preprocessing stage as described in 3.2. Additionally, based on their answers, the 10 patients with IES-R scores of 33 and above were labeled as class 1: "likely PTSD" and the rest 32 with scores below 33 as class 0: "no or few PTSD symptoms".

3.2. Data Acquisition and Preprocessing

We imported long-term ECG signals using the Python data analysis tool, *Pandas*. After loading the data, preprocessing was essential in preparing the dataset for analysis. Initially, we utilised a data cleaning procedure and eliminated noise and the baseline wander from the ECGs. Next, we divided the ECGs from each patient into separate heartbeats, 100-point length each, by utilising *neurokit2* [24]. Subsequently, the dataset was partitioned into two distinct subsets: the feature set, which encompasses the ECG signal data, and the label set, which encompasses the related labels. To reduce the impact of varying sizes and distributions in the data, we implemented normalisation procedures. The *MinMaxScaler* from Scikit-Learn was employed to standardise the data, which is crucial for optimal model training and analysis.

3.3. Dataset Partitioning

The preprocessed data were divided into separate training and testing sets. The dataset was partitioned using Scikit-Learn's *train_test_split* function, with 80% assigned for training and 20% set aside for testing. The random state parameter was configured to guarantee the replicability of our findings. The processing stage included the categorization of our data into normal (class 0) and anomalous (class 1) groups for both training and testing, according to the label set, as described in detail in section 3.1. Finally, our data comprised of a total of 70,095 heartbeat samples: 46,025 normal training, 11,557 normal testing, and 12,513 anomalous testing samples respectively. It is important to mention that the normal samples belong to the 32 patients with no sings of PTSD, whereas the anomalous to the rest 10 patients who is likely to have PTSD, according to IES-R.

3.4. Model Architecture and Training

The focal point of our methodology revolved around the development and training of an autoencoder model. The autoencoder, a type of neural network, was designed to learn efficient encodings of the input ECG data. Its architecture (Fig. 1) consists of an encoder and a decoder, with a critical bottleneck layer. The encoder employs a series of four dense layers, each consisting of 64, 32, 16, and 8 neurons respectively, all utilising "ReLU" activations. This process effectively reduces the dimensionality of the input data from its original 100 to 8. Moreover, the 8-neuron layer serves as the bottleneck of the model, capturing the most compact representation of the input data. The decoder subsequently restores the data by progressively increasing its dimensionality through layers containing 16, 32, and 64 neurons, culminating in a final layer that matches the input size and utilises "sigmoid" activation.

The training process of our autoencoder model was performed using *TensorFlow* and *Keras*. The model is configured to use early stopping through a callback that monitors the validation loss, ceasing training if there's no improvement for two consecutive epochs. This is set up to minimize loss, a common practice to avoid overfitting.

3.5. Performance Evaluation

After the training session, we assessed the model's performance on the anomalous group's data. The evaluation measures were centred on the model's capacity to precisely recreate the ECG data and detect anomalies that are suggestive of PTSD. Specifically, the model initially forecasts the restoration of the normal test data, producing results that ideally should nearly mirror the original inputs if the model is functioning effectively. Next, the mean absolute error (MAE) is calculated between these reconstructions and the actual normal test results. This MAE serves as a metric for the reconstruction error of each sample. The threshold is established by determining the 90^{th} percentile of these reconstruction errors. Subsequently, this threshold is employed to identify anomalies by forecasting the reconstructions for the anomalous dataset and computing their MAE. Instances from the anomalous dataset that possess a reconstruction error over the threshold are very probable to be anomalies, as their error is larger than that of the bulk of the normal data. Ultimately, the model's efficacy is assessed based on its accuracy in properly detecting abnormal heartbeats as well as the f1-score.

4. Results

4.1. Impact of Event Scale - Revised (IES-R)

The IES-R is a commonly employed psychological tool developed to evaluate the personal discomfort resulting from traumatic situations [25]. The self-report measure assesses three primary elements of PTSD: hyperarousal, intrusion, and avoidance, encountered within the previous seven days. The scale comprises 22 items, with each item being evaluated on a five-point scale that ranges from 0 ("not at all") to 4 ("extremely"). The IES-R yields a total score ranging from 0 - 88, where 33 is the optimal threshold for a likely diagnosis of PTSD.

4.2. Experimental setup and implementation

The implementation and experiments were carried out in a virtual environment using Python version 3.9.7, installed on a personal computer equipped with a GTX GeForce 750 Ti GPU, an Intel(R) Core(TM) i7-6700 CPU with a clock speed of 3.40 GHz, and 32 GB of RAM. To create, train, and evaluate the autoencoder model, many frameworks and libraries are utilised, such as TensorFlow-GPU version 2.5.0 with the Keras-GPU frontend. The model employs a MAE loss function and an Adam optimizer with initial learning rate 10^{-4}. The loss of the model is calculated and its weights are adjusted during training. Furthermore, the suggested model underwent training with minibatches having size 128 for duration 8 epochs, resulting in a completion time of around 2 minutes. Furthermore, *NumPy* is employed for a multitude of mathematical computations, including the manipulation of array shapes and the concatenation.

4.3. Experimental Results

Fig. 2 exhibits six ECG traces categorised into two groups: regular (normal) and abnormal (anomalous)

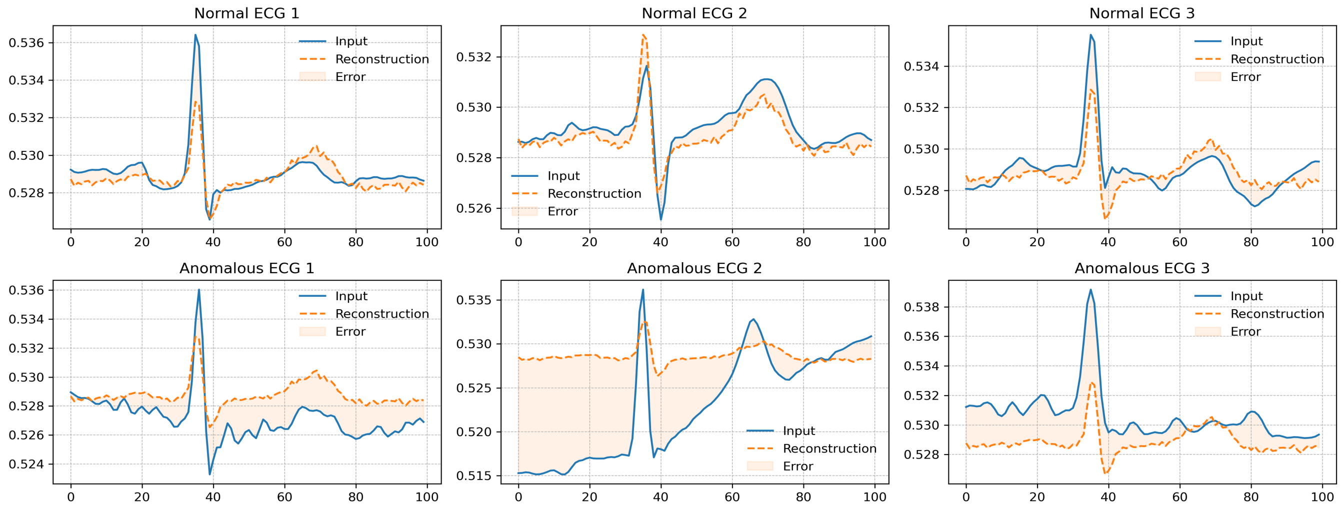

Figure 2. Indicative normal and anomalous ECG heartbeats along with the model's reconstruction. Each ECG belongs to a different patient (3 with no sings of PTSD, 3 with likely PTSD). Due to the resulting large error, the algorithm correctly detects an anomaly

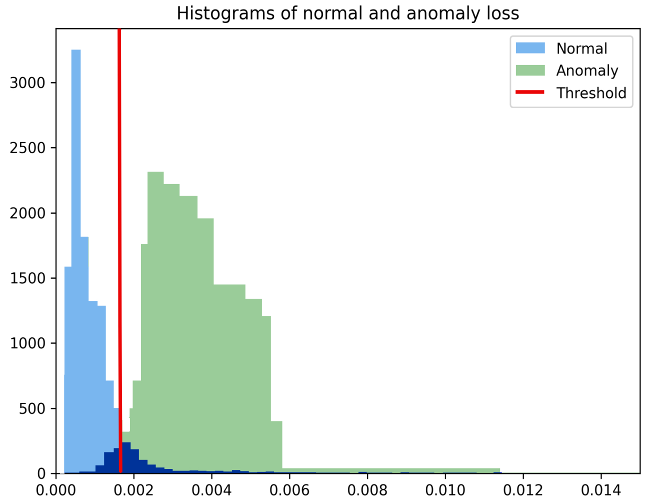

Figure 3. Histograms of normal and anomaly losses along with the computed threshold.

ECG heartbeats that denote to 6 different patients. Three typical ECGs are displayed for each group. The graphs display the original ECG input signal in blue and its reconstruction using the model in orange. The light orange shaded region reflects the discrepancy between the input and the decoder's output, often known as reconstruction error. In the normal ECGs, the reconstruction faithfully replicates the input, leading to a relatively minimal reconstruction error. Nevertheless, in the anomalous ECGs, noticeable disparities between the actual data and the reconstructed data are apparent, especially at the highest points, leading to more pronounced error margins. Therefore, the model's capacity to identify anomalies is demonstrated by the higher reconstruction error observed in the anomalous ECG graphs, which aligns with the anticipated behaviour of an anomaly detection method.

After the model training process, we calculated the threshold based on the normal test data reconstruction error which was found to be 0.0016, as described in Section 3.5. Fig. 3 depicts a histogram that compares the distribution of reconstruction loss for normal and anomalous ECG data after being processed by our model. The black histogram depicts the loss attributed to normal data, whereas the green histogram illustrates the loss incurred by anomalies. A vertical red line, serves as a threshold value that distinguishes between the two. Losses beyond this level are likely to be regarded as anomalies, given that they deviate from the typical range for normal data. The graph indicates that the selected threshold successfully differentiates between normal and anomalous data, as the majority of anomaly losses are observed to exceed this threshold. Notably, our model achieved 82.64% accuracy in detecting anomalous ECG heartbeats based on the computed threshold as well as f1-score 0.82.

5. Discussion

This study's findings illustrate the efficacy of autoencoder-based models in identifying physiological anomalies linked to PTSD through ECG data. The autoencoder achieved a detection accuracy of 82.64% and an f1-score of 0.82 in differentiating abnormal heartbeats from those of patients devoid of PTSD symptoms, according to IES-R thresholds. The results indicate that minor alterations in ECG morphology, likely indicative of autonomic dysregulation frequently associated with PTSD, may be accurately detected and recognized using unsupervised learning algorithms.

The efficacy of the suggested method contributes to the expanding literature endorsing the application of machine learning in mental health diagnostics, especially in instances when subjective self-reporting may prove inadequate or incorrect. In contrast to conventional diagnostic methods that predominantly utilize questionnaires like the IES-R or structured interviews, the ECG-based anomaly detection model offers an objective, non-invasive alternative that may be implemented using wearable technology. This is particularly significant in at-risk groups, such as older breast cancer patients, when comorbidities, weariness, or emotional distress may hinder precise self-evaluation.

The architecture's dependence on standard (non-PTSD) data for training significantly improves its generalizability in anomaly detection contexts, where acquiring extensive, well-annotated clinical datasets is frequently problematic. Utilizing solely the normal class for model training, the method builds a physiological baseline to identify variations that may suggest PTSD. This anomaly-based approach is consistent with the clinical goal of early warning and monitoring rather than definitive diagnostic classification.

Nonetheless, several limitations must be acknowledged. The sample size, while adequate for preliminary assessment, was comparatively limited (n=42), exhibiting an imbalance between the PTSD (n=10) and non-PTSD (n=32) cohorts. This may constrain the statistical power and generalizability of the findings. The dependence on IES-R as a benchmark entails intrinsic constraints linked to subjective self-report instruments, notwithstanding its clinical validity. Subsequent research should focus on corroborating results with larger, more heterogeneous populations and including further objective measures of PTSD, like hormone biomarkers or multimodal physiological data (e.g., EEG, GSR).

Moreover, the model's existing framework presupposes a binary classification (presumably PTSD vs non-PTSD), thus oversimplifying the continuum of PTSD severity and symptomatology. Integrating continuous severity scores or multi-class outputs may improve therapeutic relevance and customisation. Finally, although anomaly detection is effective for recognizing anomalies, its interpretation necessitates meticulous contextualization to prevent overdiagnosis, especially in individuals with concomitant cardiovascular diseases that may independently affect ECG patterns.

6. Conclusions

In this work, we presented a study that demonstrates a robust autoencoder model designed specifically for detecting anomalies in ECG data, with the potential to identify irregularities connected to PTSD. Particularly relevant to the focus on elderly multimorbid patients with breast cancer, the findings demonstrate that the model successfully differentiates between normal and anomalous ECG signals, supported by the validation of a distinct threshold based on the histograms of reconstruction errors. This strategy shows potential for advancing the diagnosis of PTSD using non-invasive methods, by taking use of ECG data, easily obtained even from wearable devices.

This research adds to the existing knowledge in the field of using machine learning for diagnosing mental health conditions and highlights the possibility of using it in a wider range of clinical settings. Subsequent research might prioritise enhancing the model using larger datasets and investigating real-time anomaly detection, perhaps providing substantial advantages for promptly intervening and monitoring PTSD symptoms.

6.1. Acknowledgements

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6.2. Copyright

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