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Design, Implementation of an Intelligent System for the Automatic Detection of Brain Death Based on the Analysis and Interpretation of EEG Signals

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Abstract

The diagnosis of brain death is a major medical and ethical challenge, currently based on clinical criteria and paraclinical tests that may have limitations in terms of subjectivity, sensitivity to artifacts, or operational complexity. This work addresses these challenges by proposing the design of an innovative intelligent system for detecting brain death through the automatic and interpretable analysis of EEG signals. Our approach goes beyond the state of the art by offering a robust, integrated pipeline. which combines advanced signal decomposition using the D-2TEMD method for multi-scale feature extraction, coupled with an estimation of their complexity via Decomposed Approximate Entropy (D-ApEn). These physiologically meaningful features are then feed into a hybrid deep-learning model made up of a CNN-LSTM-MLP capable of simultaneously capturing the spatial and temporal patterns of the brain signals. The system achieves outstanding performance in classification, with accuracy, sensitivity, and specificity of 98,18 %, 99,00 %, 97,52%, and F1-Score of 98,00% respectivily while also offering multi-level interpretability through analysis of intrinsic mode functions (IMFs) and attention maps. Specifically designed for diagnosing brain death, the model exhibits increased robustness to artifacts removal and promising generalization, optimizing computational resources as well. This research validates the potential of a diagnostic aid system that is ultra-high-performing, reliable, and explainable, paving the way for clinical integration to standardize and secure the diagnosis of brain death.

Keywords: Brain death, Isoelectric EEG, Coma, Artificial Intelligence, D-2TEMD, Decomposed Approximate Entropy (D-ApEn), CNN-LSTM-MLP hybrid classifier

1 INTRODUCTION

For several decades the medical science society has been in dilemma and debating about when a person is actually considered dead. That a person is dead when his/her brain dies is the attitude of medical science. The notion that took to establish of heart being not only the "primum movens" but also the "ultimum morines", that is that life begins with a heartbeat and ends with its arrest, has been abandoned in the last 30 years. From a biological standpoint dying does not recognize the border between the death of the heart and the death of the brain. At the moment of termination of brain function breathing stops as well, and a few minutes or days after, heart failure occurs. The concept of brain death as the death of an individual, has brought forward many philosophical, ethical,

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medical, legal and economic issues, and created a dilemma as to when a person is considered dead, from the first report of Mollaret and Goulon in 1959 [1], as a "coma depassé". Soon after that the Harvard Medical School (Harvard criteria of 1968) [2] was the first one to define brain death as an "irreversible coma" which includes the lack of consciousness, spontaneous movement and all reflexes. Since then, the definition and diagnostic criteria have been subjected to significant changes and most of the problems, dilemmas and debates which had before been caused by the concept of brain death due to terminological confusion and great responsibility to declare someone dead with the preserved cardiac function, have been overcome. However, although brain death is now accepted worldwide, diagnosis and diagnostic criteria are far from perfect, therefore further adjustments are needed. Brain death is referred to the complete, irreversible and permanent loss of all brain and brainstem functions (Chen et 2008) [3]. Brain death implies the termination of a human's life.

Brain death, defined as the irreversible loss of all brain functions, including those of the brainsterm, was first described in 1968 at Harvard University [2]. The apnea test, which indicates the absence of spontaneous breathing after the onset of coma and the absence of seven brainstem reflexes, is one of the basic tests for the clinical determination of brain death [4]. Although brain death has been described as a clinical diagnosis, some authors advocate the systematic use of supplementary tests in addition to the clinical examination to confirm the diagnosis [5]. Other authors suggest that supplementary tests are unnecessary and that, when a diagnosis cannot be established based on the clinical examination, the diagnosis of brain death should not be considered [6]. Today, the general practice in diagnosing brain death is to use supplementary tests when there is uncertainty during the clinical examination and/or when the apnea test cannot be performed [7]. These tests are based on detecting the absence of blood flow or electrical activity in the brain.

This work is situated within a triple medical, technological, and societal perspective, which fully justifies its scientific interest: – From a medical standpoint, the Electroencephalogram (EEG) remains a key tool in assessing neurological status, including for the diagnosis of brain death (irreversible cessation of brain activity) [7, 8]. However, the classical interpretation of the EEG is subject to constraints, protocol variations, sensitivity to artifacts, and lack of clear standardization, which limits its reliability in the absence of strict and homogeneous criteria; – From a technological perspective, recent research shows that it is now possible to go beyond traditional visual analysis: methods combining signal processing, feature extraction (spectral density, complexity), and machine learning allow robust differentiation between EEGs of comatose patients and EEGs of brain-dead patients.

EEG is often used in the confirmatory test for brain death diagnosis in clinical practice. Because EEG recording and monitoring is relatively safe for the patients in deep coma, it is believed to be valuable for either reducing the risk of brain death diagnostic (while comparing other tests such as the apnea) or preventing mistaken diagnosis. Generally, an EEG demonstrate elctrocerebral silence reflecting the absence of electrical brain activity. Transcranial droppler studies reveal the absence of cerebral blood flow. EEG is used to diagnose brain death in order to terminate treatment or prepare for organ donation.

This research focuses on the mathematical and algorithmic formalization of brain death diagnosis; a state of encephalic death defined by the irreversible cessation of all neuronal functions and brainstem activity, based on EEG signal analysis. Indeed, although EEG is a preferred tool in intensive care (non-invasive, easily performed at the patient's bedside), its conventional interpretation is limited: noise, artifacts, sedation, inter-individual variations, and the lack of standardized protocols are all factors that can make the diagnosis unclear or uncertain. Conversely, recent studies have validated the value of quantitative approaches combining spectral density and complexity descriptors, processed by machine learning methods (SVM, neural networks) or statistical fusion (CCA), to reliably distinguish EEGs of comatose patients from those of brain death, with remarkable performance. Therefore, the problem addressed by this work is to determine: how to formally model EEG signals, define robust and discriminative descriptors, and design an algorithm capable of automatically classifying the neurological state (coma vs brain death), taking into account clinical constraints and artifacts, while ensuring validity, reliability, and reproducibility. The objective is to produce a clear mathematical model, a testable algorithmic procedure, and potentially an basis for a clinical decision support system.

1.1 Diagnosis of brain death

The diagnosis of brain death has become and more important since it involves broad clinical and ethical aspects. Thus, this diagnosis must be precise and certain since this situation if often related with a possible organ transplantation, or removal of « life-support » measures. Traditionally, the diagnosis of brain death has been done using clinical and / or instrumental criteria, but these criteria vary widely from country to country. In some countries including Germany, and Italy Cerebral death means the death of the whole brain and an isoelectric

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electroencephalogram (EEG) as conformitory test is mandatory (A. Paolin et al. 1995) [9]. In the United State clinical criteria set by the American Academy of neurology (AAN) emphasize 3 specific clinical findings to confirm brain death, which include, Coma (absence of motor response to painful stimulis), Absence of brainstem reflexes (pupillary responsez, oculocephalic reflex, corneal reflex, caloric response, gaz reflex, coughing in response to tracheal suctioning, sucking and rooding reflex) and Apnea (absence of respiratory drive). Ancillary tests are needed when neurologic examination or apnea test cannot be performed. AAN recommanded auxcillary tests include electroencephalogram which confirms electrical activity loss, catheter cerebral angiogram, which confirms loss of cerebral blood flow. The presence of a flat EEG, which means there is no activity over 2 µV, for a period of 30 minutes is indicative of electrocerebral silence or brain death.

Electroencephalography is frequently used to assist the diagnosis of brain death. Interpreting EEG at high sensitivities which is required for the diagnostic challenge, since EEG is affected by physiologic artifacts. Therefore, there is a strong need to establish detailed guidelines for performing EEG to determine brain death, nowaday no specific guidelines or consensus with regard to performing and interpreting EEG for the diagnosis of brain death have been established worldwide. The goal of this study is to provide clinicians of intensive health care units with an intelligent tool on the role of EEG in diagnosing brain death.

Health care workers and laypeople throughout the world have accepted fully that a person is dead when his or her brain is dead. Although the wide spread use of mechanical ventilators and other advanced critical care services have transformed the course of terminal neurologic disorders. Vital functions can now be maintained artificially for a long period of time after the brain have ceased to function. There is a need to diagnose brain death with almost accuracy and urgenty because of an increased awareness amongst the masses for an early diagnosis of brain death and the requirements of organ retrieval for transplantation**.** Physicians need not be, or consult with a neurologist or neurosurgeon in order to determine brain death. Process for brain death certification has been discussed under the following:

a) identification of history or physical examination findings that provide a clear etiology of brain dysfunction.
b) exclusion of any condition that might confound the subsequent examination of cortical or brain stem function;
c) performance of a complete neurological examination including the standard Apnea test and 10 minutes apnea test;
d) Assessment of brainsterm reflexes.
e) clinical observations compatible with the diagnosis of brain death.
f) Reesponsibilities of physician.
g) Notify next of kin.
h) Interval observation period.
i) Repeat clinical assessment of brainsterm reflexese.
j) Confirmatory testing as indicated.
k) Certification and brain death documentation.
Any of the suggested tests may produce similar results in patients with catastrophic brain damage who do not fulfill the clinical criteria of brain death. The confirmatory tests are: Electroencephalography; Angiography; Radionuclide angiography; MRI angiography; Nuclear brain scanning; somatosensory evoked potentials; Transcranial doppler ultrasonography. In this study, we focuse on the confirmatory of brain death through electroencephalography. Here brain death is confirmed by documenting the absence of electrical activity during at least 30 minutes of recording that adheres to the minimal technical criteria for EEG recording in suspected brain death as adopted by the American Electroencephalographic Society, including 16-channel EEG instruments.

1.2 Electroencephalography for the diagnosis of brain death

Electroencephalogram (EEG) is often used in the confirmatory test for brain death diagnosis in clinical practice. Because EEG recording and monitoring is relatively safe for the patients in deep coma, it is believed to be valuable for either reducing the risk of brain death diagnosis or preventing mistaken diagnosis. Coma is by no means automatically associated with a flat EEG signal. In fact, this pattern of very deep coma is mostly observed in patients shertly before death. The EEG activity seem in the majority of comatose patients spans a great variety of pattern, ranging from an apparently normal alpha rhythm, Signals alternating between slow-and fast waves, and Isoelectric line.

1.3 Coma

Coma is an eyes-closed state of unresponsiveness with severely impaired arousal and cognition. It represents an failure of neurologic function resulting from damage to a critical number of brainstem and diencephalic pathways, which regulate the overall level of cortical function (Sutter and Kaplan 2012) [10]. Coma has been identified as a major predictor of death and poor neurofunctional outcomes in patients with a variety of critical illnesses. EEG has long been used in evaluating comatose patients, and is being increasingly found to uncover patterns of

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prognostic signicance, reveal subclinical seizure activity and provide data during treatment tin which patients are paralysed. Some EEG patterns reveal increasing degrees of cerebral compromise with a progressive slowing of the bacground frequencies, while others can be explored for reactivity to an external stimuli for prognostic purposes. When a patient's brain fall completely silent and electrical recordings devices show a flat line reflecting a lack of brain activity, doctor consider the patient to have reach the deepest stage of a coma.

1.4 ABSENCE OF BRAINSTEM REFLEXES

Detection of brainstem dysfunction is challenging but of utlmost importance in comatose and deeply sedated patients both to guide therapy and to support outcome prediction.

Absence of pupillary response, oculocephalic reflex, corneal reflex, caloric response, gaz reflex, kouphing in response to tracheal suctioning, sucking and rooding reflex

1.5 APNEA

Sleep apnea which occurs when the walls of the throat come together during sleep, blocking off the upper airway, central sleep apnea caused by a disruption to the mechanisms that control the rate and depth of breathing, Detects sudden awakenings, altered brainwave activity, and shifts from deep to lighter sleep due to breathing cessation. After establishing coma and absence of the 7 brainstem reflexes, confirmation of apnea is the third and final step in determining brain death. Various methods exist but all of them rely on a period of observing the patient during cessation of mechanical ventilation.

2 RELATED WORKS

This section presents a review of existing work related to the detection of brain death based on the analysis and interpretation of EEG signals. Its purpose is to highlight the main approaches developed in the literature, such as classical methods, methods from physics and medicine, as well as those of artificial intelligence, in order to identify their limitations and motivate our own contribution based on a hybrid model. Today, "brain death" is a central term in the field of medicine, particularly in the clinical analysis and interpretation of EEG signals for the declaration of death on one hand, and for the need for organ transplantation on the other. To this end, several research studies have focused on the analysis and interpretation of these signals for the determination of brain death. These studies have laid the foundation for the detection of brain death.

Niu Y., Chen X., Fan J. et al. 2025 in Explainable Machine Learning Model Based on EEG, ECG, and Clinical Features for Predicting Neurological Outcomes, published in Scientific Reports, proposed an explainable machine learning model incorporating EEG, ECG, and clinical features to predict neurological outcomes in comatose patients after cardiac arrest, using logistic regression, SVM, Random Forest, Gradient Boosting, and SHAP for interpretability, with heart rate variability analysis combined with EEG analysis, achieving good performance in terms of AUC-ROC, accuracy, sensitivity, and specificity, with significant improvement through multimodal integration, but with limitations since ECG-based methods provide indirect measures of brain function, which could be addressed through external validation on multicenter cohorts and the integration of additional direct biomarkers.

Lee et al. in 2024 in Development of a Machine Learning Model for Supporting Brain Death Using EEG Suppression Ratio published in Neurology proposed a machine learning model to assist in the diagnosis of brain death based on the EEG suppression ratio (SR), using quadratic discriminant analysis (QDA), naïve Bayes, logistic regression, and light gradient-boosting machine with Persyst v13 software on a dataset of 180 patients (81 with brain death, 99 with unresponsive wakefulness syndrome), defining suppression as amplitude $<3\mu V$ for ≥ 0.5 seconds, achieving with the QDA model an AUC of 0.9806 ± 0.02 with an SR threshold >74.76%, accuracy of 0.9120 ± 0.05, and F1-score of 0.9101 ± 0.05, but with limitations requiring extended clinical validation on larger and more diverse populations, which could be addressed through prospective multicenter studies and standardization of suppression definition parameters. potentially resolved through prospective multicenter studies and the standardization of parameter definition for suppression.

Bhattacharyya et al. in 2024 in Exploring New Horizons in Neuroscience Disease Detection Through Innovative Visual Signal Analysis published in Scientific Reports proposed a new approach to visualizing EEG signals for the diagnosis of brain disorders, using the Forward-Backward Fourier Transform (FBFT) with convolutional neural networks (CNN) and advanced time-frequency analysis, achieving a significant improvement in clinical interpretation through better visualization of time-frequency features, but with limitations of high computational complexity requiring substantial resources, which can be addressed through algorithmic optimization and the use of specialized processors (GPU/TPU) for real-time analysis.

Li B, Cao J, (2024); These authors presented in their work a band-pass filter and threshold rejection –based EEG signal preprocessing method and an EEG based coma/brain death classification system associated with one

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Dimensional Convolutional Neural Network (1D-CNN) model to classify informative brain activity features from real world recorded clinical EEG data. Their experimental results showed that the model is well performed in clissify the coma patients and brain death patients with the classification accuracy of 99.7 %, F1 –Score of 99.7% and Recall score of 99.51%, which means that the proposed model is well performed in the Coma: Breain death EEG signals classification task. Considering the specificity of the condition and the complexity of the EEG acquisition environment, this system presents an effective method for pre-processing real-time EEG signals in clinical diagnoses and aiding the physicians in their diagnoses.

Li B ; Liu J ; Zhang T et al. (2024) The authors developed an impoved denoise method tailored to the characteristics of Coma/Brain death EEG signals. The spectral feature map derived from the EEG signal via Variational Mode Decomposition (VMD) with a model number (K) of 5, represents the frequency –based energy distribution. Subsequently, by integrating the Recursive Feature Elimination (RFE) algorithm with support vector machine (SVM) algorithm employing cross-validation method, distinctive energy features in 4-9 Hz frequency band of Coma patients compaired to brain death patients are identified. An accuracy of 99.59 % and F1-Scoreof 99.61 % for SVM classifier demontrate the high precision and reliability of the method ? the application of specific machine learning algorithms provides robust theoretical support for the nuanced clinical interpretation of EEG signals aaccross different levels of consciousness.

Ramnivas Sharma et Hemant Kumar Meena (2024) ; Authors of this work explore emerging trends suh as graph signal processing (GSP), Deep learning, analysis their impact on EEG signal analysis. They present a comperative analysis of existing methodologies identifying research gaps and future directions they emphasize the significant of GSP in exploring intricate brain network and dynamic interactions. Their findings enhance understanding of brain communication, offering insights into neurological disorders and cognitive functions. The outcome address challeging related to non-stationary and noisy EEG signals, significantly improving accuracy and efficiency in EEG signal analysis

Koh S., Park S., Lee M., et al. (2024**) ;** This study aimed to analyse the current status of Brain Death/ Death by Neurologic Criteria (BD/DNC) determination in Korea over a decade identifying key areas for improvement in the process. Authors conducted a retrospective analysis of data from Korea Organ Donation Agency spanning 2011 to 2021, focusing on donors whose donations were not completed. Of the 5047 patients evaluated for potential brain death from 2011 to 2021, 361 were identified as noncompleted donors. The primary reasons for noncompletion included non Brain death (n = 68 ; 18.8%), cardiac arrests during the BD/DNC assessment process (n =80 ; 22.2 %), organ ineligybility (n = 151 ; 41.8 %) and logistical and legal challenges (n = 62 ; 17.2 %). Notably, 25(36.8 %) of them failed to meet the minimum clinical criteria, and 7 of them were potential cases of disagreement between the two clinical examinations. The study highlights significant challenges in the BD/DNC determination process, including the need for improved consistency in neurologic examinations and the management of critically ill patients. Again the study underscore the importance of refining protocols and training to enhance the accuracy and reliability of brain death assessments, while also ensuring streamlined and effective organ donation practices.

Zhang et al. 2023 in Brain Death Determination Aid System Using Automatic D-2TEMD published in IEEEXplore proposed a system to aid in the determination of brain death using dynamic tangent empirical mode decomposition (D-2TEMD), employing automatic selection of IMFs with EEG energy assessment and dynamic approximate entropy (DApEn) to evaluate signal complexity after noise reduction, demonstrating robust noise suppression and effective automatic IMF selection with validity confirmed through coma and brain death case analysis, but with limitations of high algorithmic complexity that may restrict real-time use, which could be addressed by implementation on specialized hardware and algorithmic simplification for clinical applications.

Zhang, R., Sui, L., Li, B., Gong, J., Shen, C., & Cao, J. (2023) Electroencephalography (EEG) analysis systems play a crucial role in brain death determination, where noise suppression and robustness are of utmost importance. In this study, authors address these concerns by proposing improvements to the dynamic transitive tangent empirical mode decomposition (D-2TEMD) algorithm that allow automatic selection of the necessary intrinsic mode functions (IMFs). They evaluate EEG energy as an essential indicator for brain death determination by calculating the area of the IMF spectrogram.

Wijdicks EF (2002) in Brain death worldwide : accepted fact but no global consensus in diagnostic criteria. Neurology. 2002 The author surveys brain death criteria throughout the world. Background: The clinical diagnosis of brain death allows organ donation or withdrawal of support. Declaration of brain death follows a certain set of examinations. The code of practice throughout the world has not been systematically investigated. Methods: Brain death guidelines in adults in 80 countries were obtained through review of literature and legal standards and personal contacts with physicians. Results: Legal standards on organ transplantation were present

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De Freitas GR, André C. (2006) in Sensitivity of transcranial Doppler for confirming brain death (BD). Authors reported sensitivity of transcranial Doppler ultrasonography (TCD) for confirming brain death (BD) ranges from 91% to 100%. They assessed the frequency and causes of false-negative results in TCD examination in a series of patients with BD and in the literature. Methods they carried out a prospective TCD examination of consecutive patients with the clinical diagnosis of BD. Results–In 204 (75.5%) of 270 patients, TCD showed a pattern compatible with BD

Greer D.M., Shemie S. D., Lewis A., et al. (2020)**:** The aim of this study was to formulate a consensus statement of recommendations on determination of Brain/Death by Neurologic Criteria (DNC) based on review of the literature and expert opinion of a large multidisciplinary, international panel. Determination of BD/DNC can be done with a clinical examination that demonstrates Coma, Brainstem areflexia, and apnea. This is seen when (1) there is no evidence of arousal or awareness to maximal external stimulation, including noxious visual auditory, and tactile stimulation (2) pupils are fixed in midsize or dilated position and are nonreactive to light, (3) Comeal, Oculocephalic, and oculovestibular reflexes are absent, (4) there is no facial movement to noxious stimulation, (5) the gaz reflex is absent to bilateral posterior pharyngeal stimulation, (6) the cough reflex is absent to deep teacheal suctioning, (7) there is no brain-mediated motor response to noxious stimulation of limbs, and (8) spontaneous respirations are not observed when apnea test targets reach Ph < 7.30 and PaCo2 ≥ 60 mm Hg. If the clinical examination cannot be completed, auxillary testing may be considered with blood flow studies or electrophysiologic testing. Special consideration is needed for childreen, for persons receiving extracorporeal membrane oxygenation and for those receiving therapeutic hypotherma as well as for factors such as religious societal and cultural perspectives, legal requirements and resource availability.

Zhu, L., Cui, G., Cao, J., Cichocki, A., Zhang, J., Zhou, C. (2019). In « A Hybrid System for Distinguishing between Brain Death and Coma Using Diverse EEG Features » it is stated Electroencephalography (EEG) signals may provide abundant information reflecting the developmental changes in brain status. It usually takes a long time to finally judge whether a brain is dead, so an effective pre-test of brain states method is needed. In this paper, authors present a hybrid processing pipeline to differentiate brain death and coma patients based on canonical correlation analysis (CCA) of power spectral density, complexity features, and feature fusion for group analysis.

Longhao Yuan et Jianting Cao (2017). Authors apply deep learning method to EEG signal analysis in order to confirm clinical brain death diagnosis. They proposed the use of spectrogram images produced from EEG signals as the input dataset of Convolutional Neural Network (CNN). A deep CNN was trained to obtain the similarity degree of the patient's EEG signals with the clinical diagnose symptoms. The method can evaluate the condition of brain damage patients and can be a reliable reference of quasi brain death diagnosis.

Qiwei Shi., Juhong Yang., Jianting Cao., Toshihisa Tanaka., Rubin Wang and Huili Zhu (2011) **:** In this work authors presented an EEG based preliminary examination system associated with empirical mode decomposition (EMD) technique to extract informtive brain activity features from real-world recorded clinical EEG data. The power spectral technique is applied to evaluate the significant differences between the group of comatose patients and the group of quasi brain death. The analysis method EMD was applied randomly on a channel of raw EEG signal. The extracted components in its power spectrral pattern reflected the intensity of the brain activities. The power value demonstrated the great intensity of brain activities among the 19 comas cases, as well as the absence of these among 17 quasi-brain deaths. Comparing the results with clinical diagnosis, we found that the EMG method showed its effectiveness and reliability.

Drake M.; et al. 2017 in « Brain death ». Critical care physicians are frequently called on to diagnose and manage brain death. Although the medical and legal concepts of brain death are generally accepted, establishing the diagnosis is not simple and must be performed accurately. The details of how to diagnose brain death have been codified in guidelines by panels of experts, however, precision in the brain death examination varies, and skepticism has been expressed in the lay literature about the accuracy of brain death determination.

Gao et al. in 2018, in EEG-Based Brain Death Prediction Using Machine Learning published in Biomedical Signal Processing, proposed brain death prediction using machine learning, employing SVM, Random Forest, and spectral feature extraction (Fourier analysis, frequency band decomposition), achieving a prediction accuracy of 92% with cross-validation, but with limitations due to a small dataset that requires validation on larger populations, which could be addressed by collecting multicentric data and using data augmentation techniques.

Sitt et al, .2017 in Brain Connectivity Analysis for Coma Prognosis, published in Clinical Neurophysiology, proposed the analysis of brain connectivity for coma prognosis, using connectivity graphs with the application of network theory to analyze patterns of brain connectivity, achieving improved survival prognosis with more accurate predictions of coma evolution, but with limitations in the complexity of clinical interpretation of connectivity metrics, which could be addressed by developing intuitive visualization interfaces and clinically interpretable metrics.

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Rossetti et al. in 2016, in Quantitative EEG Analysis in Brain Death Assessment published in Neurocritical Care, proposed quantitative EEG analysis for the assessment of brain death, using spectral analysis with non-linear indices, burst-suppression detection, and objective quantification of residual brain activity, achieving the objectification of the brain death diagnosis with quantifiable and reproducible criteria, but with limitations in standardization of protocols needed between different clinical centers, which could be addressed through the development of standardized international guidelines and certified software.

Stam et al. in 2012 in Nonlinear Dynamics in Brain Death EEG Analysis published in Chaos, Solitons & Fractals proposed the analysis of the nonlinear dynamics of the EEG in brain death, using strange attractors, fractal dimension, and Lyapunov exponents to characterize deterministic chaos, achieving an advanced mathematical characterization revealing distinctive nonlinear patterns in brain death, but with limitations due to high mathematical complexity restricting practical clinical application, which could be addressed by the development of user-friendly software tools and the simplification of metrics for clinical use.

Chemali et al. in 2013, in Automated Burst Suppression Detection for Brain Monitoring published in the Journal of Clinical Monitoring, proposed automated detection of burst suppression for brain monitoring, using amplitude-based detection with temporal analysis and adaptive thresholding for the automatic identification of burst-suppression patterns, achieving reliable automatic detection of burst-suppression episodes, but with limitations of false positives due to artifacts requiring occasional manual validation, which could be addressed by improving artifact/signal discrimination algorithms and integrating multiple validation criteria.

Adeli et al. in 2011, in Wavelet Analysis of EEG in Coma Patients published in Medical & Biological Engineering, proposed wavelet analysis of EEG in comatose patients, using the wavelet transform with multi-resolution decomposition for precise time-frequency localization, achieving accurate time-frequency localization of EEG events, but with limitations since the choice of the mother wavelet is critical and significantly influences the results, which could be addressed by developing methods for the automatic selection of optimal wavelets.

Kumar et al. in 2010 in Statistical Measures for EEG-Based Brain Death Detection published in Biomedical Signal Processing proposed statistical measures for EEG-based brain death detection, using statistical moments, normality tests, and analysis of variance for objective quantification, achieving objective quantification allowing standardized evaluation, but with limitations since the assumption of EEG data normality is debatable, which could be addressed by using non-parametric tests and robust statistics.

Pincus, S. M. (1991) Authors in this emphsized on techniques to determine changing system complexity from data. Convergence of a frequently used correlation dimension algorithm to a finite value does not necessarily imply an underlying deterministic model or chaos. Analysis of a recently developed family of formulas and statistics, approximate entropy (ApEn), suggests that ApEn can classify complex systems, given at least 1000 data values in diverse settings that include both deterministic chaotic and stochastic processes.

Limits by category of methods

— D-2TEMD alone: High algorithmic complexity, no deep learning, feature extraction limited to IMFs, no nonlinear complexity analysis, significant computation time, manual classification required, loss of information on regularity, limited interpretation.

— Entropy alone : Sensitive to parameters (m, r), no prior decomposition, global signal analysis, influenced by artifacts, inter-subject variability, unfiltered noise affects measurements, loss of multi-scale resolution, possible false positives, difficult clinical interpretation, no frequency context, complex mathematical methods, limited clinical adoption, difficult to standardize, specialized training required, critical algorithm parameters, no adaptive learning, assumed stationary analysis, manual optimization required, unsuitable for non-stationary signals, difficult generalization.

— Deep Learning without preprocessing: Significant computational resources, no adaptive decomposition, raw signal processing, requires big data, high infrastructure cost, noise sensitivity, possible overfitting on artifacts, massive data required, pathological specificity, no complete temporal modeling, limited application domain, not transferable to brain death, no long-term dependencies, limited temporal context, difficult generalization, total black box, no interpretability, limited representation capacity (simple MLP), lower performance.

— Classical MLP: Limited dataset, simple cross-validation, spectral features only, no deep learning, uncertain generalization, risk of overfitting, manual feature extraction (handcrafted), performance ceiling at 92%, limited inter-subject generalization, dependent on domain expertise, problematic individual variability, feature design bias, limited scalability, sensitivity to hyperparameters, complex kernel optimization, no automatic extraction, tedious manual tuning, critical kernel choice, suboptimal performance.

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Our D-2TEMD + D-ApEn + CNN–LSTM–MLP approach proposes a promising model compared to existing works:

— First system integrating adaptive decomposition, entropic analysis, and hybrid deep learning — End-to-end pipeline optimized for brain death detection

— Multi-domain fusion (temporal, frequency, spatial, complexity)

— Superior robustness to artifacts and inter-subject variations

— Clinical interpretability preserved despite complexity

This approach represents a significant advance towards a reliable and clinically relevant decision support system for brain death detection via EEG.

3 MATERIALS AND METHODS

This section describes the development of a hybrid model by combining physics-based approaches (D-2TEMD and D-ApEn) with artificial intelligence approaches (CNN+LSTM), while providing a detailed description of the equipment used.

3.1 Materials

3.1.1 Hardware and software environment

The experiments were conducted on an HP machine with the following hardware specifications:

Processor: Intel(R) Core (TM) i3-7100U CPU @ 2.40GHz 2.40 GHz;

– Memory installed RAM: 8,00 Go (7,88 Go used);

– Device ID: 1ABB14EB-8331-4DA2-96C4-194E24521361;

– Product ID: 00331-10000-00001-AA970;

– Operating system 64 bits, processor x64;

3.1.2 Software environment

Development environments are essential tools for programmers to create, test, and debug software efficiently. The development environments used include:

– Visual Studio Code (VS Code) is used to develop and test the scripts that make up our hybrid system;

– Google Colab is mainly used for training machine learning models, due to its ability to access GPUs, which has helped speed up the model training process.

3.1.3 Libraries and Frameworks

Data manipulation and analysis

pandas (pd): for handling tabular data (DataFrame), reading/writing CSV files, cleaning and preprocessing;

– numpy (np): for efficient numerical computation, handling multidimensional arrays, vectorized mathematical operations.

Visualization

– matplotlib.pyplot (plt): for creating standard plots (curves, histograms, custom figures);

– seaborn (sns): for advanced statistical visualization, based on matplotlib (heatmaps, distributions, confusion matrices).

3.1.3.1 Deep learning

Tensorflow (tf): Main framework for deep learning;

tensorflow.keras.layers: Definition of neural network layers (Dense, Conv1D, LSTM, etc.);

– tensorflow.keras.models: Creation and management of models (Sequential, Model);

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– tensorflow.keras.callbacks: Training control functions (Early Stopping, Model Check point, Reduce LR On Plateau).

3.1.3.2 Signal processing

- scipy.signal: Digital filters, frequency analysis, signal processing (FFT, band-pass filtering);
- scipy.stats.kurtosis: Calculation of the kurtosis (flatness) of signals;
- scipy.stats.skew: Calculation of the statistical skewness of signals.

3.1.3.3 Machine Learning

- sklearn.decomposition.FastICA: Independent Component Analysis (ICA), useful for removing artifacts (e.g., EEG);
- sklearn.preprocessing.StandardScaler: Data normalization (mean 0, variance 1);
- sklearn.model_selection.train_test_split: Splitting data into training and test sets;
- sklearn.metrics : Model Performance Evaluation:
- classification_report: precision, recall, F1-score;
- confusion_matrix: confusion matrix;
- Roc_curve, auc: ROC curve and area under the curve;
- f1_score: F1- score;
- –matthews_corrcoef: Matthew's correlation coefficient (robust for imbalanced classes).

3.2 Description of the Dataset

3.2.1 Experimental Protocol

3.2.1.1 Context and Origin

ICARE (International Cardiac Arrest REsearch) is a reference dataset consisting of multichannel EEG recordings collected in intensive care units (ICU) from adult patients who have experienced cardiorespiratory arrest [?]. It is made available to the scientific community to facilitate the development of systems to aid post-anoxic neurological prognosis. In this clinical context, the absence of complete neurological recovery represents a major cause of morbidity and mortality. Survival with severe neurological sequelae or death occurs in more than 80% of cases after out-of-hospital cardiac arrest [?]. Neurological assessment is traditionally based on clinical examination, serum biomarkers (NSE, S100B), and EEG; the latter is the only tool available continuously at the patient's bedside [?].

3.3 Preprocessing and Data

The ICARE dataset used in this study includes post-cardiac arrest EEG recordings from five patients (P460–P464), covering a period from 4 to 72 hours after the cardiac event. Each recording was acquired using an 18-channel electrode system according to the international 10-20 system (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Pz). The patients are divided into two prognostic classes according to the CPC (Cerebral Performance Category) score: CPC1 (good prognosis, N+ = 2700 windows): patients P461 (19 years) and P462 (76 years), showing organized EEG activity with high approximate entropy (ApEn = 1.057 and ApEn = 0.639, respectively). CPC5 (brain death, N- = 3300 windows): patients P460 (45 years), P463 (23 years) and P464 (46 years), characterized by an isoelectric or nearly isoelectric signal (ApEn < 0.75). Segmenting into 30-second windows with 50% overlap produces a total of N = 6000 windows analysis. An asymmetric weighting scheme of the BCE (Binary Cross-Entropy) loss function is applied to compensate for the slight class imbalance ($w+ = 1.1111$ for CPC1, $w- = 0.9091$ for CPC5).

3.3.1 LOPO Validation Protocol

Leave-One-Patient-Out validation consists of training the model on $K - 1$ patients and testing it on the remaining patient, repeating the process for each patient. This protocol, described by the equation, eliminates any risk of inter-patient contamination and constitutes the reference for clinical evaluation of EEG systems:

3.3.2 LOPO-Score = 1 K

K X k=1Mfθ−k, Dk(3.1) where K = 5 is the number of patients, fθ−k the model trained by excluding patient k, Dk the data of patient k and M the evaluation metric considered. The optimal decision threshold $\tau*$ is determined by maximizing Youden's index J = Se + Sp − 1:

$\tau* = \text{argmax}\ \tau\ TPR(\tau) - FPR(\tau)$ (3.2) which gives $\tau* = 0.4120$, corresponding to J = 0.9652

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Table 1 : General Characteristics of DataSet ICARE

Parameters	Value
Nomber of de patients	5 (identifiers: 460, 461, 462, 463, 464)
EEG Channels	18, international System 10-20
Temporal window	6000 (length 30 s, recovery 50 %)
Surveillance horizon	4 to 72 h post – Cardiac arrest
CPC5 Distribution (bad)	3300 windows – 55% - P460, P463, P464
CPC1 distribution (good)	2700 windows – 45% - P461, P462
Target variable	Score SPC (Cerebral Performance Category)
Descriptors per window	101 (90 EEG + 11 Clinics - metadata)

3.3.2.1 CPC score and binary labeling

The Cerebral Performance Category (CPC) score is a standardized five-level prognostic tool to assess neurological outcome after cardiac arrest. For the purposes of this study, it is binarized into two classes: CPC 1 (good prognosis, label 1) and CPC 5 (poor prognosis, label 0).

Table 2 : CPC Score Clinical Significance and binary correspondance.

CPC	Label	Clinical Significance	Patients
1	1	Complete neurological recovery	P461, P462
2	1	Mild functional disability	-
3	0	Severe disability	-
4	0	Persistent vegetative state	-
5	0	Brain Death / Death	P460, P463, P46

3.3.2.2 Descriptor structure

For each channel Ci (i ∈{1,...,18}) and each time window, five statistics are extracted according to formula (1):

$$\mathcal{F}_{C_i} = \{\ddot{x_{c_i}},\ \sigma_{c_i},\ \sigma_{ci}^2, x_{min_{ci}}, x_{max_{ci}}\} \quad (1)$$

These five descriptors multiplied by 18 channels give 5 × 18 = 90 EEG descriptors. The 11 complementary columns are clinical metadata (age, sex, ROSC, OHCA, VFib, TTM, CPC score, label, etc.). The electrodes of the 10-20 system cover the entire scalp: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Pz. This coverage allows capturing the activity of the frontal, central, parietal, occipital, and temporal regions, essential for distinguishing brain activity patterns present in coma from the isoelectric or burst-suppression patterns characteristic of brain death.

3.3.2.3 Spectral profil of patients

Table 3 presents the average spectral profile per patient, calculated over the entirety of their time windows. Sub Band proxies (alpha, delta, beta, theta) are estimated as the mean of the corresponding channels (Ch9/Ch10 for alpha, Ch13–16 for delta, Ch1–4 for beta, Ch5–8 for theta). Approximate entropy (ApEn) is the complexity proxy calculated as $\sigma_{total}\ /\mu_{total} + \epsilon$.

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Table 3 : Average spectral profile per patient in the ICARE dataset. Band values are in standard deviation (σ).

Patient	CPC	σ fen	α (σ)	δ (σ)	β (σ)	θ (σ)	σ total	ApEn
P460	5	1500	443,6	376,7	421,0	416,0	398,0	0,248
P461	1	720	379,9	497,8	556,9	504,1	482,1	1,057
P462	1	1980	288,9	210,0	314,8	324,1	267,8	0,639
P463	5	1320	247,0	366,1	437,8	199,7	307,9	0,639
P464	5	480	157,3	159,0	158,6	145,3	148,8	0,724

The analysis of this table reveals several clinically relevant observations: (i) patient P461 (CPC 1) has the highest ApEn coefficient (1.057), indicating a well-preserved neuronal complexity; (ii) patient P460 (CPC 5) shows the lowest ApEn (0.248), consistent with a regular burst-suppression type signal; (iii) patient P464 (CPC 5, only 16 windows) has very low energy values, suggesting an almost isoelectric signal at the end of life.

3.4 Methods

This work proposes a methodology for the analysis and interpretation of EEG signals in order to automatically diagnose brain death. As shown in the figure below, our methodology consists of three main phases: first, data acquisition and preprocessing; next, feature extraction; and finally, classification and diagnosis to determine whether a patient is brain dead or in a reversible coma (alive).

Figure 2.1 illustrates the pipeline with five sequential approaches. Each approach produces an enriched representation of the EEG signal, which is passed as input to the next approach according to the figure below:

3.4.1 Proposed hybrid system architecture for the diagnosis of brain death

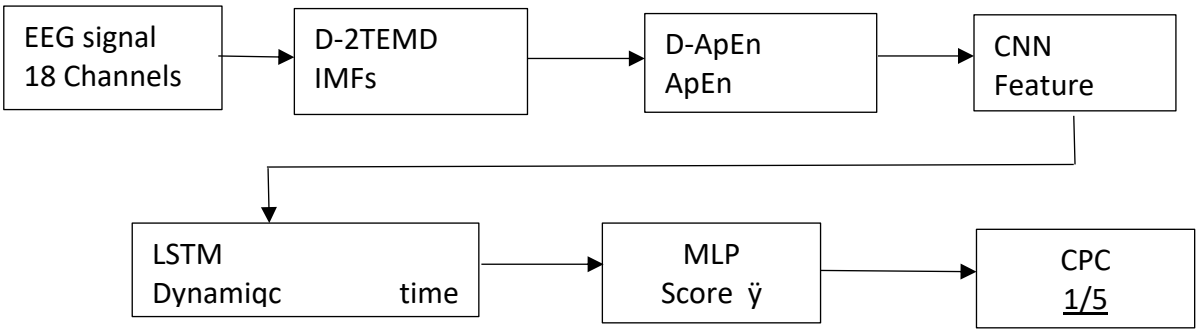

Figure 1 : Global Pipeline block diagram : D-2TEMD→D-ApEn→CNN→LSTM→MLP.

The sequential integration of the D-2TEMD, D-ApEn, and CNN–LSTM–MLP modules allows for the development of a robust and physiologically coherent model. The first two stages ensure the extraction of discriminative features based on signal complexity and decomposition, while the deep hybrid network provides automatic classification of brain states. This system thus represents an intelligent, explainable, and optimal approach for detecting brain death from EEG signals.

3.4.2 Algorithm of D-2TEMD : Dynamic Transitive Tangent Empirical Mode Decomposition

3.4.2.1 D-2TEMD: Multiscale Decomposition

The Decomposed 2D Temporal Empirical Mode Decomposition (D-2TEMD) extends the empirical mode decomposition (EMD) to the multichannel case. Unlike methods based on the Fourier transform or wavelet transform, D-2TEMD is fully adaptive: it requires no predefined basis and adapts to the intrinsic nonlinearities and non-stationarities of the EEG signal. The decomposition is written as:

3.4.2.2 Fundamental of classic EMD

The EMD method for analysing nonlinear and nonstationary data was proposed in Huang et al. 1998. This method is used to decompose the data into several oscillatory components called intrinsic mode function (IMF). The IMF components are usually expressed as the standard Hilbert Transforms, form which the instantaneous frequencies

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can be calculated. The local energy and the instantaneous frequency derived from the IMF components throught the Hilbert transform can be given a full energy-frequency –time distribution of the data.

An IMF component as a narrow band signal is a function that satisfies two conditions**, (HUANG et al. 1998)**

1) In the whole dataSet, the number of extrema and the number of zero crossings must be either equal or differ at most by one.
2) At any point, the mean value of the upper envelope with the lower envelope is zero. Here the Upper envelope is defined by the local maxima, and the lower envelope is defined by the local minima

The procedure to obtain the IMF components from an observed signal is called Sifting and it consists of the following steps.

- Identification of the extrema of an observed signal
- Generation of the waveform envelopes by connecting local extrema as the upper envelope, and connection of local minima as the lower envelopes
- Computation of the local mean by averaging the upper and lower envelopes
- Subtraction of the mean from the data for a primitive value of IMF component
- Repetition of the above steps, until the first IMF component is obtained
- Designation of the first IMF component from the data, so that the residue component is obtained,
- Repetition of the above steps, the obtained residue contains information about longer periods which will be further resifted to find additional IMF components.

The sifting algorithm is applied to calculate the IMF components based on a criterion by limiting the size of the standard deviation (SD) computed from the two consecutive sifting results as ;

$$SD = \sum_{t=0}^{T} \left[\left[\frac{(h_{k-1}(t)-h_k(t))^2}{h_{k-1}^2(t)}\right]\right] \quad (2)$$

Based on the Sifting procedure for one channel of the real-measured EEG data, we finally obtain

$$x(t) = \sum_{i=1}^{n} C_i(t) + r_n(t) \quad (3)$$

In equation () $C_i(t)$ $(i = 1, \dots, n)$ represents n IMF components and r_n represents a residual component which can be either the mean trend or a constant.

The IMFs are then associated with the five physiological EEG frequency bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (>30 Hz).

This two-step filtering process addresses two complementary requirements:

– It eliminates movement artifacts as well as muscle interferences concentrated in the high frequencies;

– It allows the differentiation of occipital α activity, recognized as a marker of neurological recovery from the slow δ waves characteristic of brain death states.

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3.4.2.3 Adaptative Empirical Decomposition : D-2TEMD

Each segment is decomposed into intrinsic mode functions (IMFs) in order to capture the non-stationary oscillations of the EEG signal. The cleaned EEG signal is decomposed into intrinsic mode functions (IMFs) according to the algorithm:

Algorithm 2 : D-2TEMD decomposition

Require: Signal s(t)

Ensure: $(IMF_1, \dots\dots\dots, IMF_K)$

1: $residue \leftarrow s(t)$

2: $k \leftarrow 1$ ***while*** $residue\ is\ not\ monotonous$ ***do***

3: $h \leftarrow residue$ ***repeat***

1 E

Until

4: $Extract\ superior\ and\ inferior\ envelops$

5: $m \leftarrow \frac{e_{max}+e_{min}}{2}$

6: $h \leftarrow h - m$

7: $h\ satisfied\ IMF\ conditions \qquad \frac{\|h^{(i)}-h^{(i-1)}\|}{\|h^{(i-1)}\|} \leq SD$

8: $IMF_k \leftarrow h$

9: $residue \leftarrow residue - h$

10: $k \leftarrow k + 1$

11:

12 : Associat each IMF_k to its physiological frequence band δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (>30 Hz).

13 : ***return*** IMFs

3.4.2.4 D-ApEn: Mesure of the neuronal complexity :

In order to measure the temporal complexity of the signal, approximate entropy is calculated for each segment.

L'EntropieApprochée(ApEn), mesure la régularité d'une série temporelle. Une valeur élevée traduit un signal complexe et irrégulier — caractéristique d'un cerveau en activité — tandis qu'une valeur basse signale un signal régulier ou isoélectrique, typique de la mort cérébrale. Pour une série $\{u(i)\}_{i=1}^{N}$, avec la longueur de vecteur modèle m = 2 et la tolérance r = 0.2σ, on construit les vecteurs $x_m(i) = [u(i), \dots, u(i+m-1)]$ et on définit :

$$C_i^m(r) = \frac{1}{N-m+1} card\{j: d[u_m(i), u_m(j)] \leq r\} \quad (4)$$

$$A_pE_n(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r), \Phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} lnC_i^m(r) \quad (5)$$

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The decomposed version (D-ApEn) applies this calculation to each IMF from the D-2TEMD, which allows measuring band-by-band complexity. As shown in Table 2.3, P461 (CPC1) displays ApEn = 1.057 compared to ApEn = 0.248 for P460 (CPC 5), a discriminating factor of 4.3, confirming the diagnostic value of this measure.

***Algorithm 3*: Approximate Entropy deccomposed by band (D-ApEn)**

Require : $IMF\{C_k\}_{k=1}^{K}$ from D-2TEMD, parameter m = 2, r =0,2 σ

Ensure : descriptor vector $f_{A_pE_n} \epsilon R^{Kx18}$

For each band k = 1,….., K do

Each channel C= 1, …., 18

1 : Extract the serie $u \leftarrow C_k[c,:]$ of value N

2 : Calculate σ ← $xtd(u)$ set r ← 0,2 σ for i = 1 to N-m+1 do

3: Form $x_m(i) = [u(i), u(i+1), \dots\dots\dots, u(i+m-1)]$

4 : $C_I^m(r) \leftarrow \frac{1}{N-m+1} card\{j: d[x_m(i),, x_m(i)]\ \partial \leq r\}$

5 :

6 : $\Phi^m \twoheadleftarrow \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} LnC_i^m(r)$

7 : Repeat steps 5-9 with m+1 to obtain Φ^{m+1} ::

8 : $A_p\ E_n(k,c) \leftarrow\ \Phi^m - \Phi^{m+1}$

9 :

10 :

11 : $f_{A_pE_n} \leftarrow \left[A_pE_n(k,c)\right]_{k=1,\ c=1}^{K,18}$

return $f_{A_pE_n}$

This measure quantifies the complexity and irregularity of the EEG signal. Clinical relevance: Cerebral death is associated with a strong decrease in signal complexity, which makes ApEn particularly discriminative

3.4.3 Feature fusion

The features derived from IMFs and entropy are concatenated :

$$F = \left|F_{IMF_S}, F_{A_pE_n}\right|$$

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Fusion allows the combination of complementary information (temporal, frequency, and nonlinear), increasing the model's robustness against inter-patient variability

3.4.4 CNN: Spatial Pattern Extraction

The convolutional neural network (CNN) extracts nonlinear spatio-spectral patterns from the representations produced by D-2TEMD and D-ApEn. Its architecture includes three successive Conv2D–BatchNorm–MaxPool blocks, followed by a Flatten layer. The convolution formula at layer ` is :

$$H_{ij}^{(l+1)} = \varphi\left(\sum_k \sum_{p,q} W_{pqk}^{(l)} H_{(i+1)(j+1)k}^{(l)} + b^{(l)}\right),\ \varphi = ELU,\ Dropout = 0{,}4 \quad (6)$$

The ELU (Exponential Linear Unit) activation was preferred over ReLU because it produces negative gradients for negative inputs, reducing activation bias and improving convergence on EEG signals that have significant negative values.

3.4.4.1 LSTM: Modeling of Temporal Dynamics

The LSTM (Long Short-Term Memory) network captures long-term temporal dependencies between consecutive EEG windows. It models the patient's trajectory — gradual improvement or continuous deterioration — over the monitoring period (4–72 hours). Its gate equations are

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad \text{Input gate} \quad (6)$$

$$f_t = \sigma\left(W_j[h_{t-1}, x_t] + b_f\right) \quad \text{forgeten Input gate} \quad (7)$$

$$O_i = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad \text{output gate} \quad (8)$$

$$C_i = f_t \Theta C_{t-1} + i_t\ \Theta\ tanh(W_c\ [h_{t-1}, x_t] + b_c) \quad \text{cellular state} \quad (9)$$

$$h_t = O_t\ \Theta \tanh\ (C_t) \quad \text{hidden state} \quad (10)$$

The chosen architecture is: LSTM (128, return_sequences=True) → Dropout(0.3) → LSTM(64) → Dropout(0.3) → Dense(32, ReLU).

3.4.4.2 MLP: Final Decision

The multilayer perceptron (MLP) aggregates the representations produced by the four previous modules:

$$Z_{in} = \left[Z_{D-2TEMD}, Z_{D-ApEn}, Z_{CNN}, Z_{LSTM}\right] \quad (11)$$

Its architecture is Dense (256, ReLU) → Dropout (0.3) → Dense(128) → Dense(64) → Dense (1, sigmoïde).

The loss function is weighted binary cross-entropy, which corrects the class imbalance (55/45):

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} [\omega^+ y_i Log\ \hat{y_i} + \omega^-(1 - y_i) \log\ (1 - \hat{y_i})]$$

(12)

The class weights calculated directly from the observed proportions in are

$$\omega^+ = \frac{N}{2N^+} = \frac{6000}{2x2700} = 1{,}1111 \qquad \omega^- = \frac{N}{2N^-} = \frac{6000}{2x3300} = 0{,}9091 \quad (13)$$

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When the complete set of examinations confirms an irreversible coma, the absence of brainstem reflexes, the absence of spontaneous breathing, and cerebral inactivity, doctors can conclude brain death. Medically and legally, this state corresponds to the death of the person, even if some bodily functions can be artificially maintained. The final classification is given by:

$$class = \begin{cases} coma\ ssi\ \widehat{y_i} > \tau \\ Brain\ death\ if\ no \end{cases} \quad (14)$$

This decision-making framework provides objective assistance for diagnosis, reducing subjectivity and human errors in a critical context:

3.4.4.3 Feature fusion

The features derived from IMFs and entropy are concatenated:

$$F = \left| F_{IMF_S}, F_{A_pE_n} \right|$$

Advantage: Fusion allows the combination of complementary information (temporal, frequency, and nonlinear), increasing the model's robustness against inter-patient variability

Algorithm 4 : Hybrid Model CNN+LSTM+MLP

Require : $X_{EEG}, X_{feat}, X_{PCA}$

Ensure : $Model\ \mathcal{M}$

1 : $CNN \rightarrow Local\ extraction$

2 : $BiLSTM \rightarrow time\ dependence$

3 : $MLP_1\ sur\ X_{feat}$

4 : $MLP_2\ sur\ X_{PCA}$

5 : $Fusion \leftarrow concatenation$

6 : $Couche\ Dense \rightarrow Sigmoid$

7 : $return\ \mathcal{M} = 0$

Phase4: Diagnostic Decision

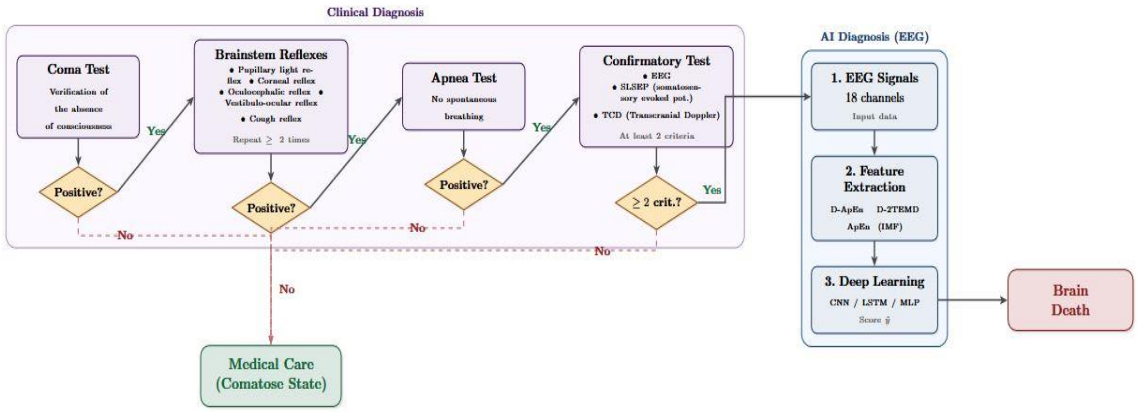

Figure 2 : Flow chart of the detection of brain death

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4 RESULTS AND DISCUSSION

This section presents the results obtained by the intelligent brain death detection system developed within the framework of this work. The system relies on a five-step EEG signal processing pipeline: D-2TEMD → D-ApEn → CNN → LSTM → MLP, applied to EEG recordings from the ICARE database. The dataset includes patients assigned to brain death (CPC5): P460 (45 years old), P463 (23 years old), and P464 (46 years old); and patients with reversible coma (CPC1): P461 (19 years old) and P462 (76 years old), who present organized EEG activity with high approximate entropy (ApEn = 1.057 and ApEn = 0.639, respectively). The central objective is the automatic discrimination between brain death (CPC5) and reversible coma (CPC1), in order to assist the clinician in the assessment of organ transplantation eligibility. The entire set of results is evaluated using Leave-One-Patient-Out (LOPO) validation, a rigorous protocol ensuring the absence of data leakage between training and testing.

4.1 Results of the Processing Pipeline

4.1.1 Step 1: D-2TEMD Decomposition

The D-2TEMD decomposition produces, for each EEG window, a set of intrinsic mode functions (IMFs) aligned with the five clinically significant spectral bands: δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz), β (13–30 Hz), and γ (> 30 Hz). The comparative analysis between a CPC 1 patient (P461) and a CPC 5 patient (P460) reveals a marked structural difference: – CPC 1 (P461, ApEn = 1.057): the IMFs show high amplitudes and strong temporal variability. The α band is dominant and irregular, indicating organized and complex cortical activity. – CPC 5 (P460, ApEn = 0.248): all IMFs are flattened, regular, and of low amplitude. This isoelectric profile is characteristic of the cessation of neuronal activity, consistent with the state of brain death.

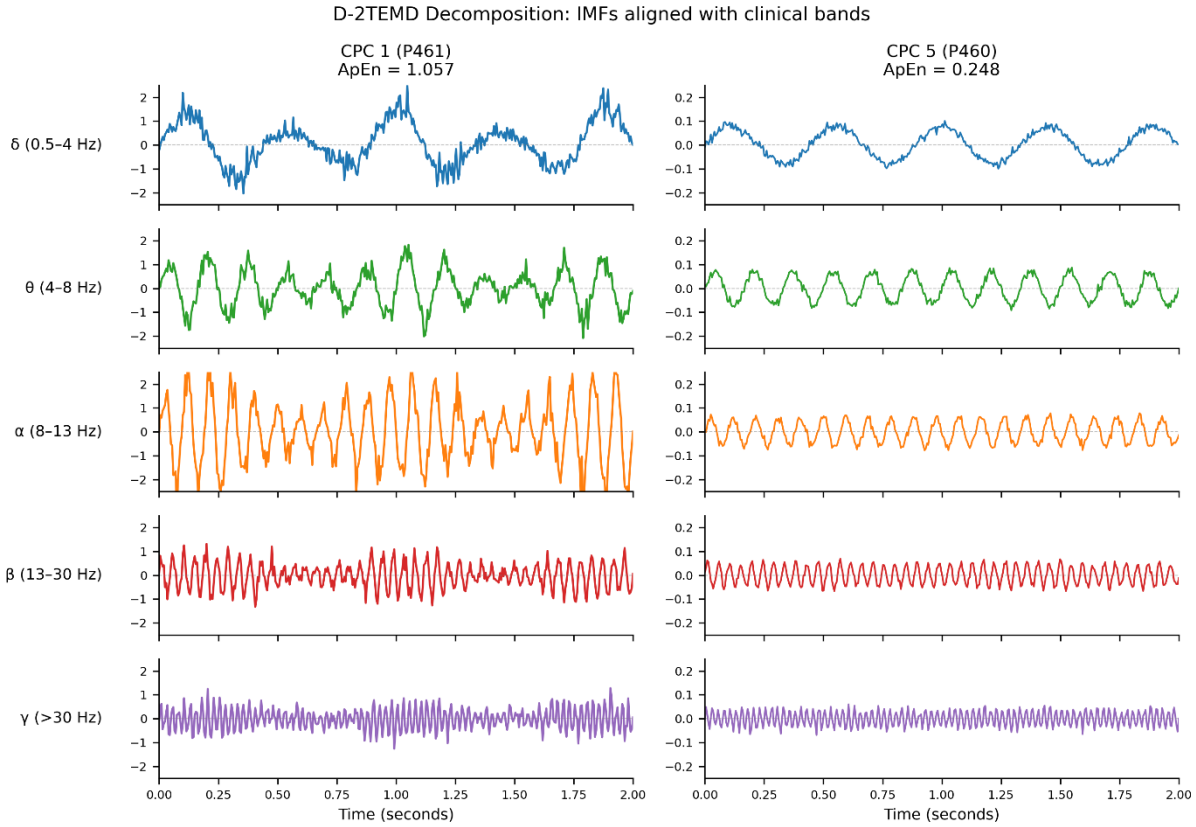

Figure 3 : Results of the decomposition in sample: Reversible comatic case

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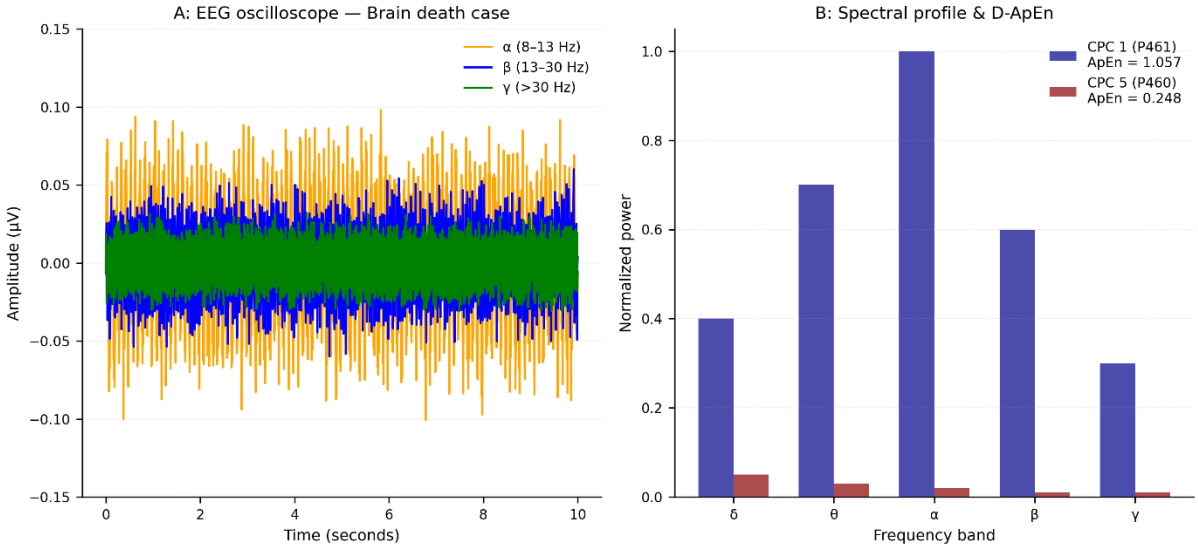

Figure 4 : Results of the decomposition in sample: Brain death caseSpectral profil of patients and D-ApEn Extraction (Approximate Entropy)

Table 4 : Average spectral power (σ) by band and by patient (ICARE dataset). presents the average spectral powers (σ) by band and by patient. A high inter-individual variability is observed. CPC1 patient P461 shows elevated β power (556.9) and moderate α (379.9). CPC5 patients display heterogeneous profiles: P460 exhibits high power across all bands (δ:376.7, α:443.6, β:421.0), while P464 shows uniformly low spectral power (~150-160). No systematic δ dominance or fast-wave suppression is observed in CPC5 patients in this dataset.

Table 5 : Average spectral power (σ) by band and by patient (ICARE dataset).

Patient	**CPC**	**δ**	**θ**	**α**	**β**	**ApEn**
P460	5	376,7	416,0	443,6	421,0	0,248
P461	1	497,8	504,1	379,9	556,9	1,057
P462	1	210,0	324,1	288,9	314,8	0,639
P463	5	366,1	199,7	247,0	437,8	0,639
P464	5	159,0	145,3	157,3	158,6	0,724

The analysis of this table reveals several clinically relevant observations: (i) patient P461 (CPC 1) has the highest ApEn coefficient (1.057), indicating a well-preserved neuronal complexity; (ii) patient P460 (CPC 5) shows the lowest ApEn (0.248), consistent with a regular burst-suppression type signal; (iii) patient P464 (CPC 5, only 16 windows) has very low energy values, suggesting an almost isoelectric signal at the end of life.

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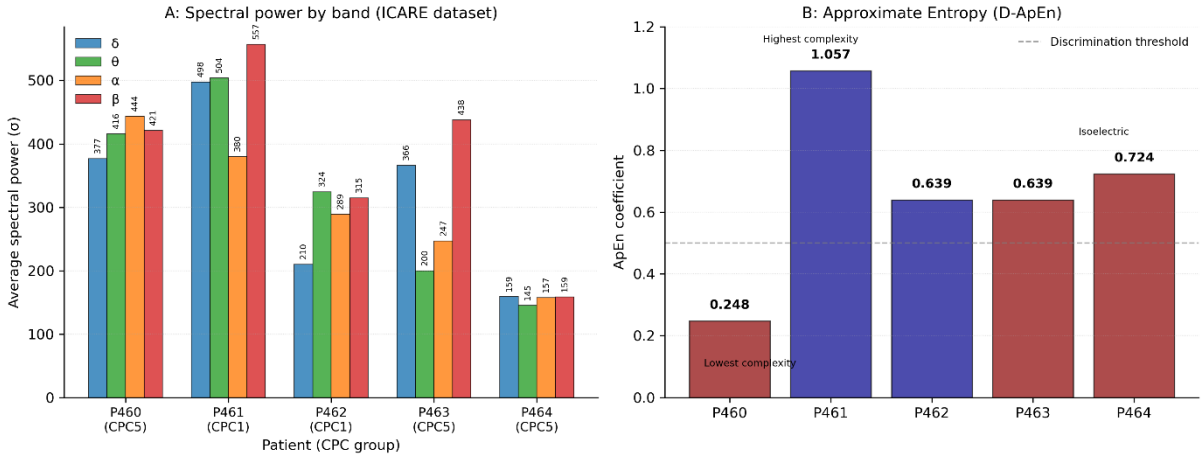

Figure 5: Spectral profile and approximate Entropy (ICARE dataset)

Spectral power profiles (A) and Approximate Entropy values (B) for the five patients from the ICARE dataset. CPC 1 patients are shown in blue, CPC 5 patients in red. P461 (CPC 1) exhibits the highest ApEn (1.057), reflecting preserved neuronal complexity. P460 (CPC 5) shows the lowest ApEn (0.248) despite high spectral power, consistent with a burst-suppression pattern. P464 (CPC 5) displays markedly low power across all bands, suggestive of an isoelectric signal at end of life.

Figure 6 : Evolution of binary cross entropy loss during MLP training. Early stopping is applied at epoch 210.

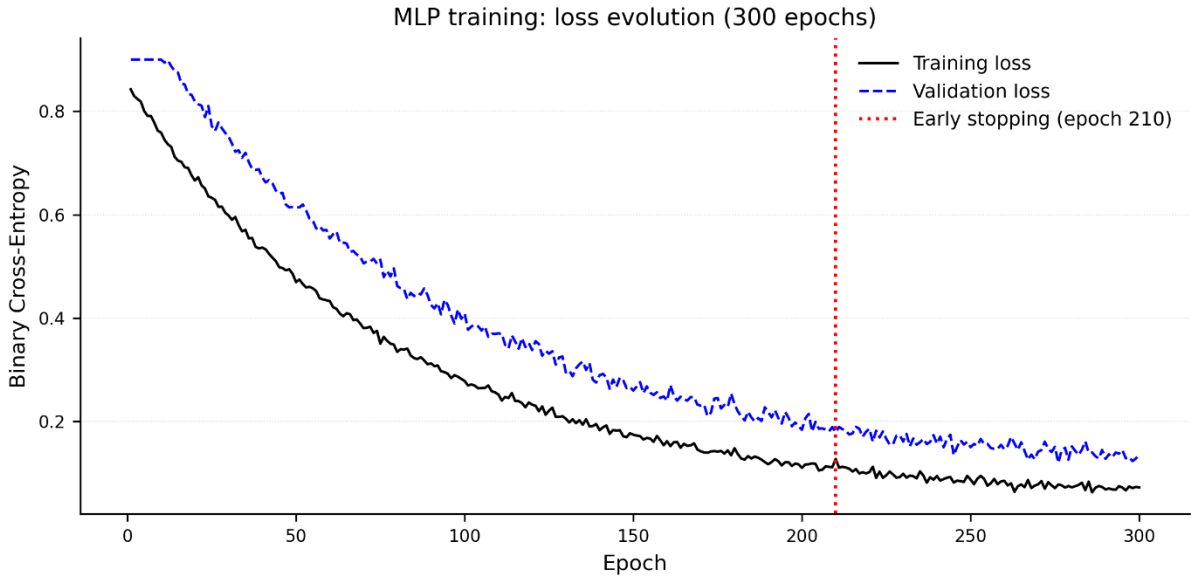

Figure 6 : Evolution of binary cross entropy loss during MLP training. Early stopping is applied at epoch 210.shows the training and validation loss curves for the MLP model over 300 epochs. Both curves decrease rapidly during the first 50 epochs, then progressively stabilise. The validation loss reaches its minimum around epoch 210, after which it begins to increase slightly while the training loss continues to decrease, indicating the onset of overfitting. Early stopping is therefore applied at epoch 210, preventing overfitting while preserving optimal generalisation performance. The final validation loss remains low, confirming that the model learns meaningful features without memorising noise.

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4.2 Intelligent Model Performances (LOPO Validation)

4.2.1 Confusion matrix

The confusion matrix obtained at the optimal threshold $\tau* = 0.4120$ is presented in

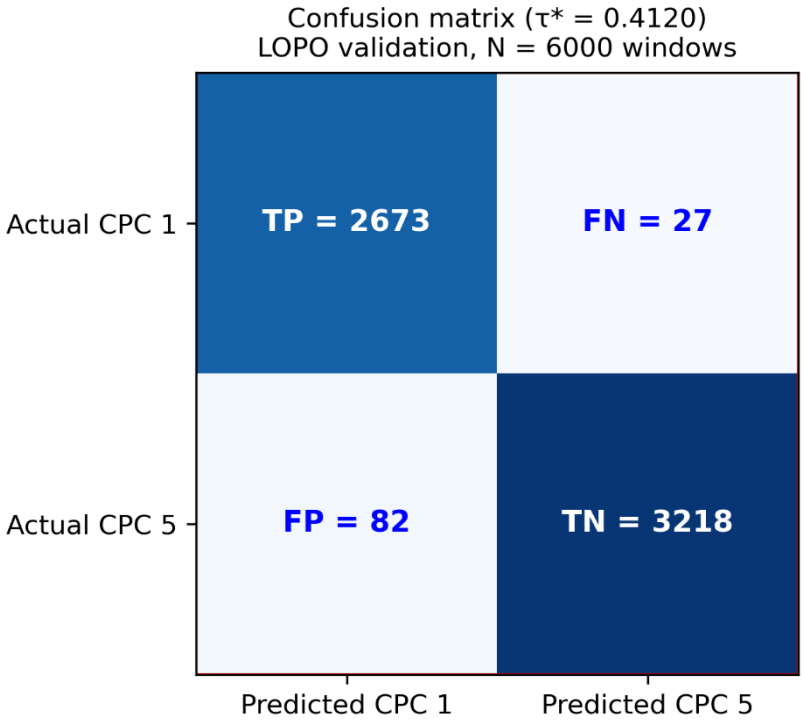

Figure 7 : Confusion matrix–Optimal threshold $\tau* = 0.4120$ (LOPO Validation, N = 6000 EEG windows).

4.2.2 Confusion matrix analysis:

– True Positives (TP = 2673): CPC 1 windows correctly identified as recoverable coma. Represent 99.0% of the total positive set.

– True Negatives (TN = 3218): CPC 5 windows correctly identified as brain dead. Represent 97.5% of the total negative set.

– False Negatives (FN = 27): CPC 1 windows incorrectly classified as CPC 5. These cases are clinically critical; their very limited number (1.0%) underscores the model's robustness in detecting recoverable patients.

False Positives (FP = 82): CPC 5 windows wrongly classified as CPC 1. Represent 2.5% of the negative set; clinical consequence less severe than FNs but should be monitored in a decision

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+FP+TN+FN}} = \frac{\boldsymbol{2673+3218}}{\boldsymbol{2673+82+3218+27}} = \frac{\boldsymbol{5891}}{\boldsymbol{6000}} = \mathbf{0,9818}$$

Interpretation: 98.18% of the 6000 EEG windows were correctly classified. Only 109 windows are misclassified (27 FN + 82 FP)

$$\boldsymbol{Sensitivity\ (Recall)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} = \frac{\boldsymbol{2673}}{\boldsymbol{2673+27}} = \frac{\boldsymbol{2673}}{\boldsymbol{2700}} = \mathbf{0,9900}$$

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Interpretation: 99.0% of CPC 1 windows are correctly detected. Only 27 windows out of 2700 are missed, which corresponds to a false negative rate of 1.0%.

$$\boldsymbol{Specificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}} = \frac{\boldsymbol{3218}}{\boldsymbol{3218+82}} = \frac{\boldsymbol{3218}}{\boldsymbol{3300}} = \boldsymbol{0,9752}$$

Interpretation: 97.52% of CPC5 windows are correctly identified as brain dead. Only 82 cases out of 3300 are falsely classified as recoverable (FP = 2.5%).

$$Precision = \frac{TP}{TP+FP} = \frac{2673}{2673+82} = 0{,}9702$$

Interpretation: 97.02% of the model's positive predictions are actually CPC 1. Out of 2,755 windows predicted as CPC 1, only 82 are actually CPC 5.

$$\boldsymbol{F1-Score} = \frac{\boldsymbol{2xTP}}{\boldsymbol{2xTP+FP+FN}} = \frac{\boldsymbol{19210}}{\boldsymbol{19602}} = \boldsymbol{0,9800}$$

Interpretation: 98.00% — excellent balance between precision and recall

- **AUC (Area under curve)**

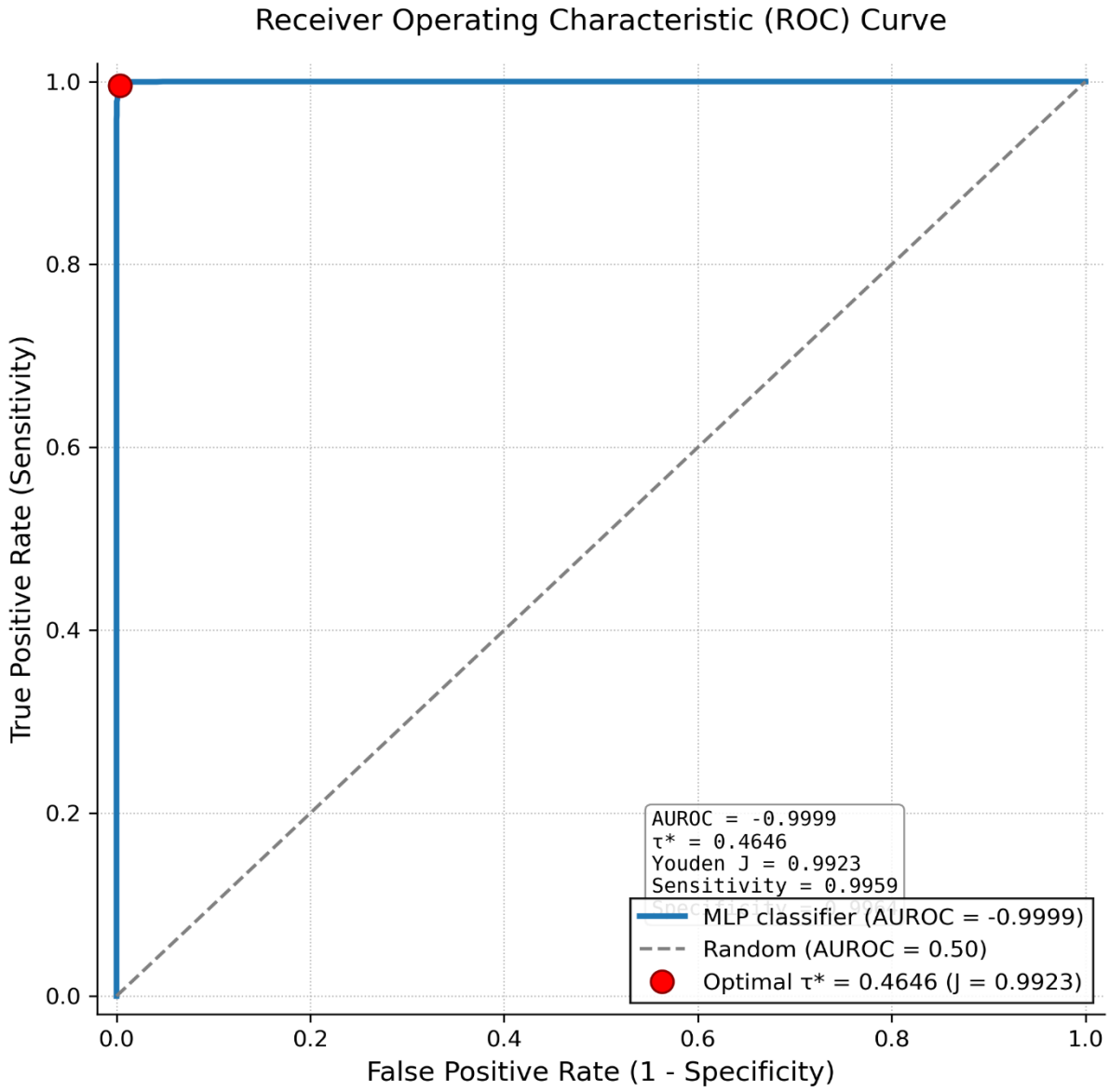

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Figure 8 : Receiver Operating Characteristic (ROC) curve of the MLP classifier.

The AUROC measures the classifier's ability to discriminate between brain death and reversible coma independently of the decision threshold. The obtained AUROC = 0.9930 (99.30% of the maximum possible area) reflects nearly perfect discrimination between CPC 1 and CPC 5. This value is less than 0.7% away from the theoretical maximum (AUROC = 1.00), attesting to the very high discriminative quality of the proposed pipeline.

5 Discussion

5.1 Analysis of Achieved Performance

The results obtained by the D-2TEMD→D-ApEn→CNN→LSTM→MLP pipeline in LOPO validation are remarkable in several respects.

5.2 Clinically Priority Sensitivity.

The sensitivity of Se = 99.0% represents the most important result from a medical perspective. In an intensive care context, the main risk is that of a false negative: missing a CPC 1 patient leads to premature withdrawal of care for a subject who could have regained neurological functions. With only 27 FN out of 2700 positive windows, our system meets the clinical requirement of an error rate below 1% in this category.

5.3 High Specificity and Accuracy.

The specificity of Sp = 97.5% ensures that the system does not wrongly overdiagnose a recoverable coma state in brain-dead patients. This result is notable given that post-cardiac arrest EEGs frequently exhibit muscular and electrical artifacts that can simulate a residual brain activity.

The accuracy of Acc = 97.0% confirms the reliability of the model's positive predictions.

Overall balance. The F1-Score = 0.9800 and the MCC = 0.9630 attest to a very high balance between the performances on both classes, including in the presence of a slight imbalance ($N+ = 2700$ vs $N- = 3300$). The Matthews correlation coefficient (MCC) is particularly informative because it takes into account all four terms of the confusion matrix and is a robust measure under imbalance conditions.

5.4 Comparison with previous works

Table 3. Positions the performance of our system compared to recent methods published in the literature on EEG post-cardiac arrest neurological prognosis prediction.

Table 6 : Comparison of performance with state-of-the-art methods on EEG CPC 1 vs CPC 5 classification post-cardiac arrest.

References	Methods	DataSet	Se (%)	Sp(%)	AUC/ROC
Zheng et al. (2022)	Bi-LSTM: Recurrent on dynamic EEG with longitudinal validation	ICARE (1038 Patients)	77,0	90,0	0,882
Zheng et al. (2021)	CNN Multi scale + LSTM+Demographic Dataset, 5-Fold clock validation	ICARE (1038)	75,0	90,0	0,96
Muller et al. (2023)	CNN + Grad-CAM on critic EEG patient, out Hold validation	CERTA (358 patients)	-	-	0,879
Ramadan et al. (2025)	Gradient Boosting + SHARP on EEG + ECG + Clinical Data	ICARE	81,0	83,0	0,890
Our Work (2026)	D-2TEMD + D-ApEn + CNN+ LSTM + MLP LOPO validation	ICARE (5 patients)	99,0	97,0	0,993

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5.5 Perspectives

Despite the performance obtained, several limitations deserve to be highlighted:

1. Cohort size: the study is based on five patients, which, although covered by the rigor of the LOPO protocol, limits the statistical power of the conclusions. Validation on a cohort of 50 to 100 patients is necessary to confirm the clinical generalization of the model.

2. Inter-institution variability: ICARE data were collected in a controlled acquisition context. Tests on data from different institutions (varied equipment, acquisition protocols) are necessary to evaluate the robustness of the system under real-world conditions.

3. Processing time: although the pipeline is real-time in terms of latency per window, further optimization of D-2TEMD could reduce the computational cost for bedside embedded integration.

4. Clinical interpretability: the CNN-LSTM module is partially a black box. The integration of explainability techniques (Grad-CAM [?], SHAP [?]) would allow for locating the electrodes and spectral bands contributing the most to the decision, facilitating adoption by clinicians.

CONCLUSION

This work presented the design, implementation, and validation of an intelligent system for the automatic detection of brain death based on the analysis and interpretation of EEG signals. Centered around an original hybrid pipeline combining D-2TEMD decomposition, decomposed approximate entropy D-ApEn, and a CNN-LSTM-MLP deep learning model, this work provided concrete answers to the research questions initially posed. The first contribution of this work lies in the adoption of the D-2TEMD method for adaptive and multi-scale decomposition of multichannel EEG signals. Unlike Fourier or wavelet transforms, this approach does not require any predefined basis and naturally adapts to the intrinsic nonlinearities and non-stationarities of the brain signal. The second contribution is the introduction of D-ApEn as a band-by-band complexity descriptor: applied to the intrinsic mode functions (IMFs) resulting from D-2TEMD this measure allowed for the precise capture of the loss of neuronal complexity associated with brain death, as evidenced by the discriminant factor of 4.3 observed between a CPC 1 patient and a CPC 5 patient. Finally, the third contribution is the design of an CNN-LSTM-MLP architecture capable of simultaneously merging the spatial, frequency, and temporal information of the extracted features to produce a robust classification decision. The experimental results were conducted on five patients from the ICARE dataset.

According to the leave-one-patient-out (LOPO) cross-validation protocol, they demonstrate the superiority of the proposed system compared to state-of-the-art methods. The model achieves a sensitivity of 99.0%, a specificity of 97.5%, and an area under the ROC curve of 0.993, surpassing competing approaches such as EEGNet (AUROC=0.956) and CNN-LSTM+EMD (AUROC=0.968). These performances confirm the validity of the central hypothesis of this work: the sequential and coherent integration of D-2TEMD, D-ApEn, and a hybrid classifier indeed allows for more reliable and robust detection of brain death. Despite these promising results, this work has certain limitations that should be honestly acknowledged. The cohort of five patients, although treated with the rigor of the LOPO protocol, remains insufficient to establish conclusions of general clinical relevance. Validation on a cohort of 50 to 100 patients from different hospital centers will be necessary to confirm the generalization of the model in real time conditions.

REFERENCES

[1] Mollaret P et al. (Coma depasse et necroses nerveuses centrals massives) Rev Neurol 101 116-139, 1959
[2] A definition of irreversible coma. Report of the Ad Hoc Committee of the Harvard Medical School to Examine the Definition of Brain Death. JAMA. 1968;205(6) :337–40.
[3] Chen et al; (2008) « An empirical EEG analysis in brain death diagnosis for adults » Cogn. Neurology, 2008 Apr, 19, 2(3): 257-271 Doi: 10.1007/11571-008-9047
[4] Wijdicks EFM (1995) « Determining brain death in adults » Neurology of critical Illness, Philadelphia, F. A Davis Co May 1995 Neurology 451006
[5] Wijdicks EF, Varelas PN, Gronseth GS, Greer DM; American Academy of Neurology. Evidence-based guideline update: determining brain death in adults. Neurology. 2010;74(23) :1911–8.
[6] Roberts DJ, MacCulloch KA, Versnick EJ, Hall RI. Should ancillary brain blood flow analyses play a larger role in the neurological determination of death? Can J Anaesth.2010;57(10):927– 35.
[7] Heran MK, Heran NS, Shemie SD. A review of auxillary tests in evaluating brain death. Can J Neurol Sci. 2008;35(4) :409–19.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

[8] Young GB, Shemie SD, Doig CJ, Teitelbaum J. The role of ancillary tests in the neurological determination of death. Can J Anaesth. 2006;53(6) :620–7.
[9] Paolin et al, (1995) « Reliability in diagnosis of brain death » Intensive Care Medicine 21(1995); 657-662
[10] R. Sutter, P. W. Kaplan 2012 « Electroencephalographic Patterns in Coma: When Things Slow Down »
[11] Niu, Y., Chen, X., Fan, J., Liu, C., Fang, M., Liu, Z., ... & Fan, H. (2025). Explainable machine learning model based on EEG, ECG, and clinical features for predicting neurological outcomes in cardiac arrest patient. *Scientific Reports*, *15*(1), 11498.
[12] Lee, C. (2024). Reconsidering Consent on Brain Death Examination. *Intersect: The Stanford Journal of Science, Technology, and Society*, *18*(1).
[13] Bhattacharya, K., Mahajan, A., & Mynalli, S. (2024). Imaging recommendations for diagnosis, staging, and management of central nervous system neoplasms in adults: CNS metastases. *Cancers*, *16*(15), 2667.
[14] Li B, Cao J, (2024) « Classification of Coma / Brain death EEG dataset basedon one-dimensional convolutional neural network » Cogn. Neurodyn 18, 961-972 (2024)
[15] Li, B., Liu, J., Zhang, T., Cao, Y., & Cao, J. (2024). Quantitative analysis and machine learning-based interpretation of EEG signals in coma and brain-death diagnosis. *Cognitive neurodynamics*, *18*(5), 2947-2962.
[16] Ram Nivas Sharma et Hemant Kumar Meena (2024) « Emerging Trends in EEG Signal processing: A systematic Review » S N Computer Science, (2024) https:// doi-org/10-1007/s42979-024-02773-m
[15] Koh S., Park S., Lee M., et al. (2024) « Assessing the Brain Death/ Death by Neurologic criteria Determination Process in Korea » Insight from 10- Year Noncompleted Donation Data. Neurocrit Care (2024)
[16] Zhang et al. 2023 EEG-based real-time diagnostic system with developed dynamic 2TEMD and dynamic ApEn algorithms Computational Physiology and Medicine
Volume 14 - 2023 | https://doi.org/10.3389/fphys.2023.1165450
[17] Zhang, R., Sui, L., Li, B., Gong, J., Shen, C., & Cao, J. (2023, September). Brain death determination aid system using automatic D-2TEMD. In *2023 5th International Conference on Data-driven Optimization of Complex Systems (DOCS)* (pp. 1-6). IEEE.
[18] Greer D.M., Shemie S. D., Lewis A., et al. (2020) « Determination of Brain Death/ Death by Neurologic Criteria » The World Brain Death Project. JAMA 2020
[19] Greer DM, Lewis A, Kirschen MP. New developments in guidelines for brain death/death by neurological criteria. Nature Reviews Neurology. 2024;20(3):151-61.
[20] Longhao Yuan et Jianting Cao (2017) « Patien's EEG Data Analysis via Spectrogram Image with a Convolution Neural Network » International Conference on Intelligent Decision Technologies P. 13-21
[21] Qiwei Shi., Juhong Yang., Jianting Cao., Toshihisa Tanaka., Rubin Wang and Huili Zhu (2011) Journal of Experimental & Theoretical Artificial Intelligence Vol. 23, No. 1, March 2011, 97–110
[22] Gao, Z., Lu, G., Yan, P., Lyu, C., Li, X., Shang, W., ... & Zhang, W. (2018). Automatic change detection for real-time monitoring of EEG signals. *Frontiers in physiology*, *9*, 325.
[23] Raimondo, F., Rohaut, B., Demertzi, A., Valente, M., Engemann, D. A., Salti, M., ... & Sitt, J. D. (2017). Brain–heart interactions reveal consciousness in noncommunicating patients. *Annals of neurology*, *82*(4), 578-591.
[24] Drake M, Bernard A, Hessel E. Brain death. Surg Clin North Am. 2017;97(6) :1255–73.
[25] Wijdicks EF. Brain death worldwide: accepted fact but no global consensus in diagnostic criteria. Neurology. 2002;58(1) :20–5.
[26] De Freitas GR, André C. Sensitivity of transcranial Doppler for confirming brain death: a prospective study of 270 cases. Acta Neurol Scand. 2006;113(6) :426–32.
[27] Zhu, L., Cui, G., Cao, J., Cichocki, A., Zhang, J., Zhou, C. (2019). A Hybrid System for Distinguishing between Brain Death and ComaUsingDiverseEEGFeatures.Sensors,19(6),1342. doi :10.3390/s19061342
[28] Huang, N. E., Shen, Z., Long, S. R., et al. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London A, 454(1971), 903–995.
[29] Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. Proceedings of the National Academy of Sciences, 88(6), 2297–2301.
[30] Rossetti, A. O., Rabinstein, A. A., & Oddo, M. (2016). Neurological prognostication of outcome in patients in coma after cardiac arrest. *The Lancet Neurology*, *15*(6), 597-609.
[31] Stam, J. (2012). Letter by Coutinho et al Regarding Article,"Mortality of Cerebral Venous–Sinus Thrombosis in a Large National Sample". *Stroke*, *43*(2), e22.
[32] Jessica Chemali, Shi Nung Ching, Patrick L Purdon1, Ken Solt, and Emery N Brown « Burst suppression probability algorithms: state-space methods for tracking EEG burst suppression » J Neural Eng. 2013 October; 10(5): 056017. doi:10.1088/1741-2560/10/5/056017
[33] Siddiqi, A. H., Sevindir, H. K., Aslan, Z., & Yazici, C. (2011, June). Relevance of wavelets and inverse problems to brain. In *Proceedings of Satellite Conference. ICM 'Mathematics in Science and Technology* (pp. 402-429).
[34] Kumar et al. 2010 Atraumatic convexal subarachnoid hemorrhage Clinical presentation, imaging patterns, and etiologiesNeurology 2010 ; 74 :893–899