ALFABEATS: A Machine Learning Based Decision Support Platform for Biomedical Time Series Analysis

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Abstract. Most AI tools for biomedical time series analysis are designed as engineering toolkits, requiring technical expertise. While effective in research, they are rarely usable by clinicians. ALFABEATS is a modular, web-based decision support platform that bridges this gap. It integrates advanced machine learning and deep learning models for classifying signals like EEG and ECG, while abstracting technical complexity via an intuitive interface. Unlike conventional toolboxes, ALFABEATS automates preprocessing, model selection, inference, and interpretability, thus enabling clinicians to make informed decisions without ML expertise. As a case study, we demonstrate its application in detecting major depressive disorder (MDD) from EEG data using several trained models. The platform supports end-to-end workflows, including data ingestion, prediction, and post hoc explanations.

Keywords: Biomedical time series · Clinical decision support · EEG · Machine learning · Explainable AI

1 Introduction

Analysis of biomedical time series (BTS), such as ECG, EEG, and EMG, poses challenges, including non-stationarity, nonlinearity, inter-subject variability, low signal-to-noise ratio, and the need for real-time interpretability [14,39]. Building effective decision support systems for BTS has been a long-standing medical goal [2, 16]. Despite recent progress in machine learning and signal processing [29], few accessible online tools exist for clinicians to analyse BTS data quickly, securely, and efficiently. Barriers include inconsistent data formats, proprietary systems, and methodological complexity.

* This work has been fully supported by the Croatian Science Foundation under the project number IP-2022-10-8241. The funder played no role in the study design, data collection, data analysis and interpretation, or the writing of this manuscript.

This paper introduces ALFABEATS, a web-based, machine-learning-driven decision support platform for BTS analysis. Designed for medical professionals, ALFABEATS abstracts technical complexity while integrating state-of-the-art models for the classification of biomedical signals. The platform runs remotely, minimising infrastructure needs on the client side, and provides end-to-end functionality—data ingestion, preprocessing, model selection, inference, and post hoc interpretability.

We demonstrate its capabilities through a case study on major depressive disorder (MDD) detection from EEG signals. MDD presents subtle and heterogeneous electrophysiological patterns, making it a challenging test case for BTS analysis. The study showcases how integrated machine learning models can aid in clinical decision-making for affective disorders [1, 25].

The remainder of the paper covers related work, platform functionalities, and case study methodology and results, concluding with a discussion of future directions.

2 Related Work

2.1 Platforms for Biomedical Signal and Image Analysis

Several open-source platforms, libraries, and toolboxes support biomedical data analysis, though many remain domain-specific, lack modularity, or pose usability challenges.

NeuroKit2 [21] is a Python toolbox focused on feature extraction and signal quality assessment but lacking integrated classification or decision support. BioSPPy [5] extends basic analysis with synthetic signal generation and clustering-based outlier detection. Most similar toolboxes focus on preprocessing and feature extraction, typically support only a few signal types, and rarely implement machine learning-based analysis [5]. BioSig [38] is one of the few actively maintained libraries that covers multiple formats and includes functions for preprocessing, feature extraction, classification, statistical testing, and visualization.

Standalone applications with graphical interfaces have also emerged. BioLab [17] enables real-time streaming and basic analysis of ECG, EMG, and EEG but lacks advanced analytics. PyBioS [33] supports nonlinear cardiovascular signal analysis, with a machine learning module under development. MULTISAB [13] is a web platform for multivariate biomedical signal analysis using domain-specific frameworks and ML-based model construction. However, it remains inaccessible to the public due to challenges in deploying online ML models [15].

In imaging, a related field, tools such as ImageJ [31] are widely used for segmentation, registration, and visualization, with plugin support for tasks like MRI [30], cardiac studies [27], CT [19], and bone analysis [10]. Specialized tools like MONAI [7] provide a deep learning infrastructure for MRI/CT segmentation, while RECOMIA [37] offers a cloud-based platform for AI-supported radiological research.

2.2 Classification Models for Biomedical Time Series

Numerous algorithms have been proposed for time series classification (TSC), often evaluated on synthetic or general-purpose datasets [24]. HIVE-COTE v2 [23] is a leading meta-ensemble-based method that combines multiple ensembles and model types (e.g., shapelet, interval, dictionary) and consistently achieves high accuracy, but it is computationally intensive and difficult to interpret. HYDRA [9] is a fast dictionary-based approach that uses competing convolutional kernels, effectively blending the strengths of ROCKET and classical dictionary methods. Its combination with MultiRocket, referred to as HydraMultiRocketPlus [24], offers state-of-the-art performance with high speed.

InceptionTime [12], a deep learning model based on convolutional inception blocks, captures multiscale temporal features and performs particularly well on long, noisy signals such as EEG. Hybrid LSTM-CNN architectures [18, 41] are also common in biomedical TSC, although their adoption is limited by long training times and complex tuning. Transformer-based models [8, 35] have recently been adapted for EEG analysis, but remain challenging to train on small datasets and are often hard to interpret. Finally, interpretable models such as OCT-H trees [4] offer transparent decision paths, though typically with lower predictive performance when compared to black-box models.

3 Platform Description

ALFABEATS is a modular Python-based decision support platform for biomedical time series, currently focused on EEG and ECG. It follows a client-server architecture with distinct backend and frontend components (Figure 1). The backend is implemented in Django and uses PostgreSQL database to manage user accounts, medical metadata, and model artefacts. It handles data preprocessing, model training, and inference, organized into independently configurable modules. Core functionalities include:

- **Data ingestion and preprocessing**– accepts raw biomedical time series data in EDF format and applies comprehensive preprocessing using `MNE` and `mne-icalabel`, including filtering, ICA-based artefact rejection, epoching, and normalisation.
- **Model integration** – supports state-of-the-art time series classification models implemented with `scikit-learn`, `sktime`, `torch`, and `tsai`. Pretrained models currently include ROCKET, HydraMultiRocketPlus, HIVE-COTE v2, and InceptionTime, optimized for detecting major depressive disorder (MDD) from EEG data. The platform is being extended to support both EEG and ECG modalities, with ongoing integration of advanced deep learning models, including transformer-based architectures, while maintaining a strong focus on explainability.
- **Inference and pipelining** – inference is handled through `joblib` to enable pipelined execution and concurrent processing.

- **Explainability** – includes Shapley values, feature permutation importance, and saliency maps to support transparent and informed clinical decisions.
- **REST API** – exposes backend functionalities for seamless web/mobile frontend integration.

Core components such as preprocessing, segmentation, and model selection are implemented in a modality-agnostic manner, enabling adaptation across biomedical signal types with minimal code modification.

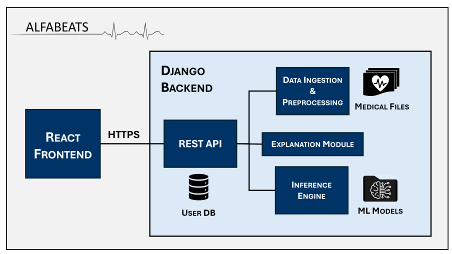


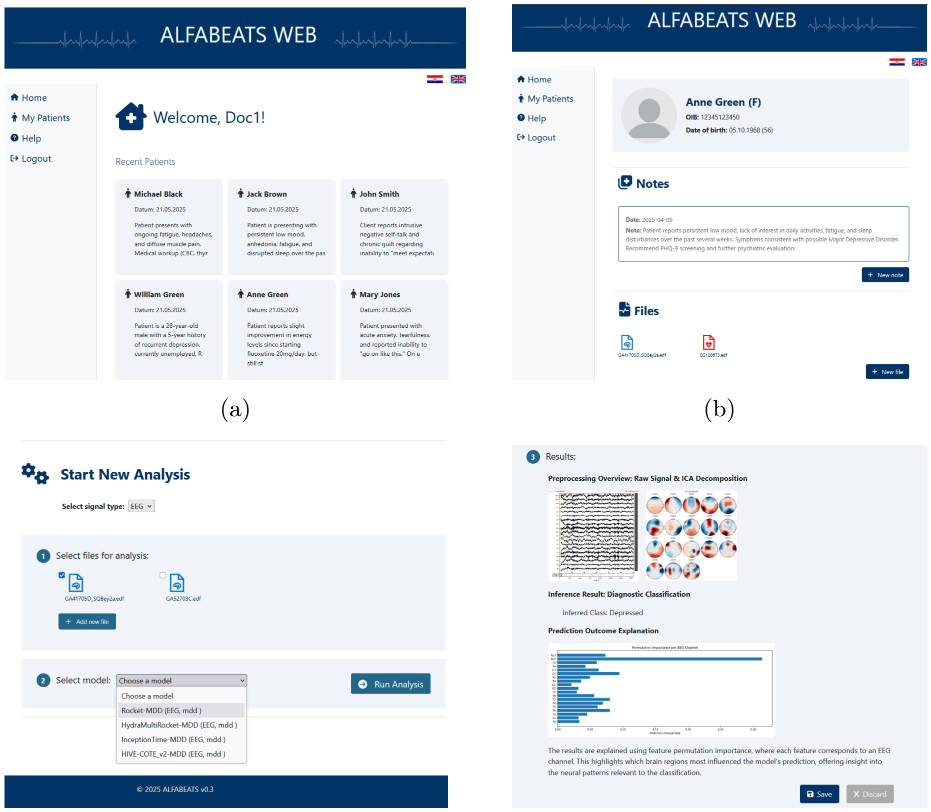
Fig. 1: ALFABEATS modular platform architecture

The frontend is implemented in React and provides a responsive, intuitive interface tailored to clinical workflows. After login, users see recent activity (Figure 2a) and can access patient records or create new ones. Each patient view (Figure 2b) presents a history of diagnostic entries alongside associated with associated predictions and a file panel listing uploaded signals (EEG/ECG) and metadata.

New data and analyses can be added directly through the interface, which also supports reanalysis of existing signals. The analysis workflow (Figure 2c) allows model selection and evaluation configuration. Upon completion, results are presented in an interactive dashboard (Figure 2d) with preprocessing snapshots (e.g. raw traces, ICA), diagnostic predictions with confidence scores, and interpretability outputs, each supported by brief clinical guidance.

Data privacy and compliance: While the current version operates in a research setting, ALFABEATS is built following GDPR-aligned best practices. Data is anonymised before processing, and authenticated access is enforced via time-limited tokens and role-based controls. Future deployments will add audit logging, encrypted storage, and formal risk assessment procedures to meet clinical certification standards.

Security features include authentication, access control, session/token handling, and CORS protection. A mobile app is under development. For reproducibility and clinical traceability, configurations, parameters, and session logs are persistently stored in structured format.



(a) (b) (c) (d)

Fig. 2: Overview of key ALFABEATS interface screens: (a) home screen with recent activity; (b) patient overview with diagnostic history and uploaded recordings; (c) configuration interface for launching analysis; (d) inference results with prediction and feature importance visualization.

4 Case study

4.1 Dataset Description

To demonstrate the ALFABEATS workflow and evaluate its performance in a realistic clinical scenario, we conducted a case study on detecting major depressive disorder (MDD) using resting-state EEG data. The dataset includes 140 anonymized EEG recordings from the University Psychiatric Hospital Vrapče [25], evenly split between patients diagnosed with depressive disorders (70) and healthy controls (70), matched by age and sex. Each subject underwent a 30-minute resting-state EEG session using a standard 10–20 electrode montage. Recordings included eyes-open/closed rest, photostimulation, and hyperventilation protocols, sampled at 200–256 Hz.

Recordings were downsampled to 200 Hz and bandpass filtered (0.1–40 Hz). Signals were rereferenced to the average reference, and artefacts were removed using ICA followed by ICLabel [28]. From each subject, the first 5 minutes post-cleaning were retained and segmented into non-overlapping 2-second windows, yielding 150 epochs per subject. All channels were z-score normalized to improve convergence and reduce inter-channel variance. The preprocessing step resulted in over 20,000 labelled EEG epochs, balanced across classes. The dataset was split into a training and test set with an 80/20 ratio, where the split was stratified and subject-wise.

4.2 Modeling and Explainability

To evaluate the classification performance on EEG data, ALFABEATS integrates four state-of-the-art time series models: ROCKET, HydraMultiRocket-Plus, HIVE-COTE v2, and InceptionTime. These models were selected based on their reported performance in the literature, suitability for short-length biomedical time series, and availability of robust open-source implementations. Transformer-based models were not included in this evaluation, as they typically require extensive pretraining or task-specific fine-tuning, which falls outside the scope of this benchmarking-focused study, the aim of which was to evaluate integrated workflows under realistic, reproducible conditions.

All models were trained and evaluated using an 80/20 stratified subject-level split to prevent data leakage and ensure realistic performance estimates. Reported metrics include accuracy, F1-score, precision, recall, and AUROC.

The platform incorporates multiple post hoc explainability methods to support clinical insight into model decisions. Feature permutation importance [6] is applied across all models to assess the influence of individual EEG components. For kernel-based models (ROCKET, HydraMultiRocketPlus), SHAP (SHapley Additive exPlanations) [20] is used to estimate per-feature contributions for each prediction, enabling clinicians to identify which EEG features influenced the model most. For deep learning models such as InceptionTime, saliency maps [34] highlight temporal regions of the signal that had the greatest impact on the classifier's decision.

5 Evaluation

5.1 Classification Performance

Table 1 presents test-set evaluation metrics for the four classification models used in ALFABEATS. The training of all models was conducted on a workstation equipped with an Intel(R) Core(TM) i9-14900HX 2.20 GHz, 32 GB RAM, and an NVIDIA RTX 4090 Laptop GPU (used only for the InceptionTime model).

HydraMultiRocketPlus achieved the highest overall performance, with an accuracy of 94.0% and an AUROC of 0.964, indicating strong discriminative power. RocketClassifier followed closely with 92.0% accuracy, while offering significantly

Table 1: Classification performance and training times for evaluated models

Model	**Accuracy**	**F1-score**	**Precision**	**Recall**	**AUROC**	**Training Time**
HydraMultiRocketPlus	0.940	0.932	0.926	0.938	0.964	2h 15m
RocketClassifier	0.920	0.915	0.912	0.918	0.950	18m
HIVE-COTE v2	0.893	0.885	0.877	0.890	0.935	72h
InceptionTime	0.793	0.780	0.765	0.782	0.875	8m (GPU)

faster training—18 minutes versus over 2 hours—making it well-suited for time- or resource-constrained deployments.

HIVE-COTE v2 performed competitively (89.3% accuracy) but required more than 70 hours of training, limiting its practicality in clinical workflows. InceptionTime achieved 79.3% accuracy, with lower F1 and AUROC scores, suggesting difficulty in capturing consistent discriminative patterns from noisy EEG signals. However, its training time was only 8 minutes (GPU), showing promise for future use with larger datasets and additional optimization.

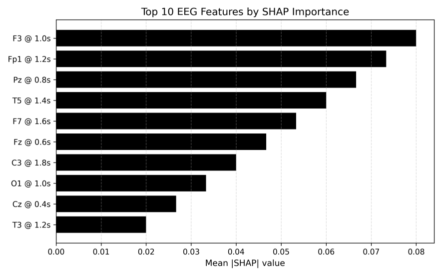
These results highlight tradeoffs between accuracy, efficiency, and interpretability. HydraMultiRocketPlus offers a strong balance across all dimensions, while RocketClassifier provides near-equivalent performance with lower computational cost. HIVE-COTE v2 remains a useful benchmark, and InceptionTime demonstrates the potential (and limitations) of deep learning in small-scale EEG analysis.

5.2 Explainability

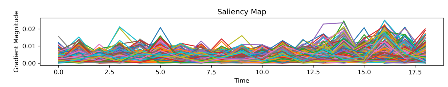
ALFABEATS integrates post hoc explainability tools adapted to each model type. For HydraMultiRocketPlus, SHAP was used to quantify feature contributions. Since direct SHAP support for sktime's RocketClassifier is unavailable, SHAP values were computed using a logistic regression model on ROCKET-transformed features. As shown in Figure 3a, the most influential features originated from frontal and parietal electrodes in the 200–600 ms range, consistent with known MDD biomarkers such as frontal asymmetry and altered alpha activity [22].

For InceptionTime, saliency maps based on input-output gradients were used to identify temporally relevant regions (Figure 3b). These maps revealed distributed influences across the full epoch, with peaks around 1.0 s, 5.0 s, and 12.5 s, suggesting a reliance on extended temporal dynamics, which aligns with the diffuse and heterogeneous neural signatures observed in affective disorders [36].

To illustrate clinical relevance, consider a case where an EEG segment is classified as "Depressed" with high confidence. SHAP values attribute the decision to decreased alpha and increased theta activity in frontal electrodes (e.g., Fp1, F3, Fz), aligning with established MDD biomarkers. Such feedback may help clinicians assess physiological plausibility. These examples are being explored in collaboration with clinicians to evaluate the interpretability of model outputs in practice.



(a)



(b)

Fig. 3: Interpretability outputs for EEG-based MDD classification: (a) SHAP summary for RocketClassifier highlights frontal-parietal features; (b) saliency map from InceptionTime shows distributed temporal contributions across the epoch.

5.3 Discussion

Table 2 compares EEG-based MDD classification models across studies. Most studies, except Zhang et al. [42] and our work, use fewer than 100 subjects, increasing the risk of overfitting, especially with segment-wise splits. Zhang et al. report the lowest accuracy (75.29%), while other studies, including ours, achieve over 90%. Our best-performing model, HydraMultiRocketPlus, reached 94% accuracy on a larger dataset, using subject-wise splitting to prevent data leakage.

Unlike many prior studies, the ALFABEATS platform achieves comparable accuracy while leveraging a substantially larger dataset and employing subject-wise data splitting, thereby minimizing data leakage and reducing the risk of overfitting. However, the current evaluation is limited to a single disorder (MDD) and one modality (EEG). Broader validation across diverse datasets, integration of other biosignals (e.g., ECG, EMG), and clinical testing are essential next steps to assess generalizability and real-world diagnostic utility.

To complement the proprietary dataset used in ALFABEATS development, core models were benchmarked on the CHB-MIT Scalp EEG dataset [11], a widely used reference for seizure detection. It contains EEG recordings from 24 pediatric patients with intractable epilepsy, sampled at 256 Hz using the 10–20 system, with expert-annotated seizure events. Signals were segmented into non-overlapping 10-second epochs, yielding 19,379 segments, including 39 seizure events. Compared to the 2-second ICA-cleaned segments used in the Vrapče dataset, CHB-MIT preprocessing was limited to 1–40 Hz bandpass filtering due to its lower channel count and seizure-specific focus. The same classification pipeline was applied, with results shown in Table 3, illustrating ALFABEATS' ability to generalise across diverse EEG tasks while retaining strong performance.

Table 2: Comparison of Different Models

Paper	Dataset	EEG Setup	Sample Size	Model	Acc (%)
Acharya et al. (2018) [1]	15 MDD, 15 H	2 Ch (bipolar EEG)	4,384	13-layer CNN	95.96
Mumtaz, Qayyum (2019) [26]	33 MDD, 30 H	19 Ch, 1s non-overlapping	∼37,800	1D-CNN+LSTM	98.32
Zhang et al. (2020) [42]	81 MDD, 89 H	3 Ch, 4s non-overlapping	1,700	1D-CNN	75.29
Seal et al. (2021) [32]	15 MDD, 18 H	19 Ch, 4s with 3s overlap	17,307	DeprNet (18-layer CNN)	91.40
Xu et al. (2023) [40]	41 DD, 34 H	6 Ch, 4s non-overlapping	16,797	MRCNN-RSE	98.48
Anik et al. (2024) [3]	34 MDD, 30 H	19 Ch, 15s with 1s overlap	∼1,280	Ex-1DCNN	99.60
Our work (2025)	70 MDD, 70 H	19 Ch, 2s non-overlapping	∼20,000	HydraMulti-RocketPlus	94.00

Table 3: Performance of ALFABEATS models on CHB-MIT dataset

Model	Accuracy	F1-score	Precision	Recall	AUROC	Training Time
HydraMultiRocketPlus	0.868	0.83	0.79	0.88	0.894	3h 24min
InceptionTime	0.842	0.81	0.77	0.85	0.876	28 min (GPU)
RocketClassifier	0.825	0.78	0.73	0.82	0.853	31 min

6 Conclusion

ALFABEATS is a fully integrated platform for biomedical time series classification, developed with a strong focus on clinical usability and interpretability. Its modular architecture and interactive dashboard enable clinicians and researchers to evaluate, compare, and interpret multiple machine learning models using real-world data.

While formal clinical trials are beyond the scope of this study, the platform was designed with clinical applicability as a central goal. Preliminary feedback from collaborators at the University Psychiatric Hospital Vrapče, the Polyclinic for Cardiovascular Prevention, and the Traumatology Clinic Zagreb highlighted the value of explainability features (e.g., SHAP visualisations, saliency maps) for diagnostic support and longitudinal assessment. Suggestions such as simplified real-time dashboards have informed plans for a pilot usability study with medical staff.

Planned extensions include support for additional models (e.g., OCT-H, Transformers), integration of multimodal signals, and clinical trials to assess diagnostic impact. The platform—currently in active development—will support multiple medical scenarios across at least two signal modalities. Access will be granted via approval-based registration to ensure responsible use. A comprehensive public release, including documentation and access details, is planned within two years. By bridging technical sophistication with clinical practicality, ALFABEATS aims to accelerate the adoption of machine learning in routine diagnostic workflows.

Acknowledgment We thank the University Psychiatric Hospital Vrapče, Zagreb, for providing the dataset for this study.

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