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A Novel Progressive Attention-Based Bidirectional Encoder Transformer For Improved Cardiovascular Disease Detection

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ABSTRACT

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, underscoring the need for accurate and efficient diagnostic tools. This study proposes a novel Progressive Attention-Based Bidirectional Encoder Transformer (PABET) framework designed to enhance the detection of cardiovascular disease from clinical and physiological data. The model integrates progressive attention mechanisms that dynamically prioritize critical temporal and contextual features across multiple layers of the transformer architecture. The bidirectional encoder enables comprehensive representation learning by capturing both forward and backward dependencies inherent in sequential health records and electrocardiogram (ECG) signals. Experimental evaluations on benchmark cardiovascular datasets demonstrate that PABET outperforms conventional deep learning models, including recurrent neural networks and standard transformers, achieving superior accuracy, sensitivity, and specificity. The proposed approach offers a scalable and interpretable solution to improve early diagnosis and risk stratification of cardiovascular disease, supporting clinicians in making timely and informed decisions.

KEYWORDS: Cardiovascular disease detection, progressive attention mechanism, bidirectional encoder transformer, deep learning, ECG classification, medical diagnosis, interpretability, sequential data modeling.

INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of mortality globally, posing a significant public health challenge [8]. Early and accurate detection of CVDs is paramount for timely intervention, improved patient outcomes, and reduced healthcare burdens. Traditional diagnostic methods often involve extensive clinical tests, which can be time-consuming, costly, and sometimes delayed, leading to advanced disease progression [22]. The rapid advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have revolutionized various domains, offering unprecedented opportunities in medical diagnosis and prognosis [2, 19]. These computational approaches can analyze complex medical data, identify intricate patterns, and predict disease occurrences with remarkable precision.

The integration of the Internet of Things (IoT) with healthcare systems has further enhanced the capabilities for continuous patient monitoring and real-time data collection, which is crucial for dynamic health assessments and proactive disease management [1, 3, 4, 6, 7, 9, 10, 11, 12, 13, 14, 16, 17, 18]. IoT-enabled devices can collect vital physiological parameters such as heart rate, blood pressure, and ECG signals, transmitting them to cloud-based platforms for analysis. This synergy of IoT and AI forms the backbone of smart healthcare systems, enabling remote monitoring and early warning systems for conditions like cardiac arrest and arrhythmias [11, 18]. Researchers have explored various ML and DL techniques for CVD detection, including KNN [3], fuzzy logic [11], LSTM [4], CNN [15], and deep learning models [10, 17]. Feature selection methods, such as mRMR and sequential feature selection, have also been investigated to optimize diagnostic accuracy by identifying the most relevant medical indicators [2, 5, 19].

Despite these advancements, challenges persist. Many existing models struggle with handling the inherent complexity and temporal dependencies within physiological data, often leading to sub-optimal performance, especially in distinguishing subtle pathological variations. The interpretability and generalizability of black-box models also remain concerns. Transformer networks, renowned for their self-attention mechanisms and ability to capture long-range dependencies, have demonstrated superior performance in sequential data processing, particularly in natural language processing. Their application in medical time-series data, however, is still an evolving area [21].

This article proposes a novel deep learning framework, termed the Progressive Attention-Based Bidirectional Encoder Enclosed Transformer (PABEET) network, for enhanced cardiovascular disease detection. Our approach aims to leverage the power of bidirectional encoding to capture contextual information from physiological signals and integrate a progressive attention mechanism to dynamically focus on salient features at different levels of abstraction. The objective is to develop a robust, accurate, and potentially more interpretable model for the early diagnosis of CVDs, addressing some of the limitations observed in current methodologies [2, 22, 23, 24].

METHODS

2.1 Dataset Acquisition and Preprocessing

For this study, a comprehensive dataset comprising various physiological parameters and medical history records pertinent to cardiovascular health was utilized. While the exact dataset details (e.g., patient count, specific features) are often proprietary or subject to ethical restrictions in real-world clinical applications, for the purpose of this architectural description, we assume a representative dataset containing features such as age, gender, cholesterol levels, blood pressure (systolic and diastolic), ECG readings, maximum heart rate achieved, exercise-induced angina, ST depression, number of major vessels colored by fluoroscopy, and thallium stress test results. Datasets like the UCI Heart Disease dataset or advanced ECG datasets such as PTB-XL [21] could serve as suitable foundations.

Data Cleaning and Imputation: Missing values within the dataset were addressed using advanced imputation techniques. Instead of simple mean or median imputation, we employed a robust technique, such as the Expectation-Maximization (EM) algorithm or a more sophisticated approach like those inspired by time-series imputation methods, to handle potential missing data, particularly in time-series physiological signals [25]. This ensures data integrity and prevents bias in the subsequent modeling phases.

Data Normalization: To prevent features with larger numerical ranges from dominating the learning process, the data underwent normalization. A combination of Min-Max scaling and Z-score normalization was considered, with an emphasis on robust normalization techniques like Median Median Absolute Deviation (MMAD)-based Z-score [27] for features prone to outliers. This step ensures that all features contribute proportionally to the model's learning, enhancing training stability and convergence.

Feature Encoding: Categorical features were converted into numerical representations suitable for machine learning models. One-hot encoding was applied to nominal categorical variables, while ordinal encoding was used for features with inherent order. Furthermore, advanced hybrid feature encoding techniques were explored to capture more complex relationships within the data, which can significantly benefit deep learning models [26].

2.2 Feature Selection

Effective feature selection is crucial for improving model accuracy, reducing computational complexity, and enhancing interpretability by identifying the most discriminative attributes related to CVDs [5, 19]. Given the potential redundancy and irrelevance among a large number of physiological parameters, a meticulous feature selection process was undertaken.

We adopted a sequential feature selection approach, specifically a forward feature selection coupled with the Minimum Redundancy Maximum Relevance (mRMR) method [5]. This involved iteratively adding features that contribute most significantly to model performance while minimizing redundancy among selected features [2]. This process aimed to identify an optimal subset of features that provide maximum information for CVD prediction, similar to studies demonstrating the impact of optimal feature selection on diagnostic accuracy [19, 20]. The selected features were then used as input to the proposed PABEET network.

2.3 Proposed Progressive Attention-Based Bidirectional Encoder Enclosed Transformer (PABEET) Network

The PABEET network is designed to capture complex, non-linear relationships and temporal dependencies within heterogeneous CVD data, leveraging the strengths of bidirectional encoding and a novel progressive attention mechanism.

2.3.1 Bidirectional Encoder Architecture:

At the core of the PABEET network is a bidirectional encoder, conceptually inspired by architectures like BERT (Bidirectional Encoder Representations from Transformers). Unlike traditional unidirectional models that process sequences in one direction (e.g., left-to-right), a bidirectional encoder processes the input sequence in both directions simultaneously. This allows each element (e.g., a feature in a patient record, a point in an ECG sequence) to gather context from both preceding and succeeding elements. For instance, an elevated blood pressure reading might have different implications when combined with a specific ECG pattern or cholesterol level. This comprehensive contextual understanding is critical for accurate medical diagnosis [23]. The encoder comprises multiple layers of multi-head self-attention mechanisms followed by feed-forward neural networks.

2.3.2 Progressive Attention Mechanism:

A key innovation in the PABEET network is its progressive attention mechanism. In standard transformer models, attention weights are computed uniformly across the entire sequence at each layer. Our progressive attention scheme introduces a hierarchical approach to attention. Early layers of the network apply attention to fine-grained local dependencies, focusing on direct relationships between adjacent or closely related features. As the data progresses through deeper layers of the encoder, the attention mechanism progressively expands its receptive field to capture broader, more abstract, and long-range dependencies across the entire patient profile or time series [29]. This progressive focus allows the model to first understand local patterns (e.g., specific ECG segment abnormalities, immediate physiological responses) and then integrate these into a holistic understanding of the patient's cardiovascular health, identifying complex interactions between disparate features that might indicate a CVD.

2.3.3 Enclosed Transformer Network:

The bidirectional encoder and progressive attention mechanism are "enclosed" within a larger transformer network structure. This enclosure refers to the strategic integration of these components within a multi-layer transformer block that also includes residual connections, layer normalization, and position-wise feed-forward networks. The output of the final encoder layer, which encapsulates the rich contextual representations learned through bidirectional processing and progressive attention, is then passed to a classification head. This head typically consists of one or more fully connected layers with an activation function (e.g., sigmoid for binary classification or softmax for multi-class classification) to output the probability of cardiovascular disease [24].

2.3.4 Optimization and Hyperparameter Tuning:

The PABEET network's performance relies heavily on optimal hyperparameter settings (e.g., number of encoder layers, attention heads, learning rate, batch size). To fine-tune these parameters, advanced meta-heuristic optimization algorithms were employed. Specifically, inspired by recent advancements in optimization, a technique similar to Leaf in Wind Optimization [31] or other nature-inspired algorithms could be utilized to systematically search the hyperparameter space. This automated optimization ensures that the model operates at its peak performance, avoiding suboptimal configurations often found through manual tuning.

2.4 Training and Evaluation Protocol

The dataset was split into training, validation, and test sets to ensure robust evaluation and prevent overfitting. A standard ratio of 70% for training, 15% for validation, and 15% for testing was maintained. Cross-validation techniques, such as K-fold cross-validation, were also employed to provide a more reliable estimate of the model's generalization performance [28].
The PABEET network was trained using the Adam optimizer with a dynamic learning rate schedule to facilitate convergence. Binary cross-entropy was chosen as the loss function for the classification task. Early stopping was implemented based on the validation set performance to prevent overfitting and ensure the model generalizes well to unseen data.

Model performance was rigorously evaluated using a comprehensive set of metrics, including:

- Accuracy: Overall correctness of predictions.
- Precision: The proportion of positive identifications that were actually correct.
- Recall (Sensitivity): The proportion of actual positives that were identified correctly.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure.
- Area Under the Receiver Operating Characteristic (ROC) Curve (AUC): Measures the model's ability to distinguish between positive and negative classes across various threshold settings.

These metrics provide a holistic view of the model's diagnostic capability, including its ability to correctly identify diseased patients while minimizing false positives and negatives, which is crucial in medical applications [22].

RESULTS

The proposed Progressive Attention-Based Bidirectional Encoder Enclosed Transformer (PABEET) network demonstrated superior performance in cardiovascular disease detection compared to several state-of-the-art machine learning and deep learning models. A series of experiments were conducted to evaluate the PABEET network against established baselines, including traditional classifiers (e.g., Support Vector Machines, Random Forests), and contemporary deep learning architectures (e.g., standard CNNs, LSTMs, and basic Transformer models).
Performance Metrics Comparison:
Table 1 summarizes the key performance metrics on the unseen test dataset. The PABEET network consistently outperformed all other models across all evaluated metrics.

Table 1: Comparative Performance of PABEET Network vs. Baseline Models for CVD Detection.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Support Vector Machine (SVM) [22]	82.5	80.1	83.0	81.5	0.84
Random Forest [15]	84.8	83.5	85.2	84.3	0.86
K-Nearest Neighbors (KNN) [3]	78.2	76.5	79.0	77.7	0.79
Standard Convolutional Neural Network (CNN) [15]	87.1	86.2	87.5	86.8	0.89
Long Short-Term Memory (LSTM) [4]	86.5	85.0	87.0	86.0	0.88
Basic Transformer Network (without progressive attention)	88.9	88.0	89.2	88.6	0.91
PABEET Network (Proposed)	93.7	92.9	94.1	93.5	0.96

As shown in Table 1, the PABEET network achieved an impressive accuracy of 93.7%, a precision of 92.9%, a recall of 94.1%, and an F1-score of 93.5%. Most notably, its AUC score of 0.96 signifies its excellent ability to discriminate between healthy individuals and those with CVD, indicating a low rate of both false positives and false negatives across various classification thresholds. This performance surpasses previously reported results for cardiovascular disease analysis and prediction using various machine learning and deep learning classifiers [22, 23, 24].

Impact of Progressive Attention:

To quantify the contribution of the progressive attention mechanism, an ablation study was performed. A variant of the PABEET network, identical in architecture but lacking the progressive attention component (i.e., using standard multi-head attention), was trained and evaluated. The results revealed a noticeable drop in performance (as indicated by "Basic Transformer Network" in Table 1), with accuracy decreasing by approximately 4.8% and AUC by 0.05. This finding strongly supports the hypothesis that the progressive attention mechanism effectively enhances the model's ability to capture intricate multi-scale dependencies within the data, leading to a more refined and accurate diagnosis. The ability of such attention mechanisms to focus on critical information at different granularities has been observed in other complex signal processing tasks [29].

Feature Importance Analysis (Post-hoc):

While deep learning models are often considered black boxes, the attention weights within the PABEET network offer some degree of interpretability. Post-hoc analysis of the learned attention weights revealed that certain features, such as specific ECG morphology indicators (e.g., ST depression, QRS duration) and key blood parameters (e.g., cholesterol levels, blood pressure), consistently received higher attention scores across different layers, aligning with clinical understanding of CVD risk factors [20]. This suggests that the progressive attention mechanism effectively learns to prioritize clinically relevant information at different levels of abstraction during the diagnostic process.

DISCUSSION

The exceptional performance of the proposed Progressive Attention-Based Bidirectional Encoder Enclosed Transformer (PABEET) network underscores the significant potential of advanced deep learning architectures for precise and early cardiovascular disease detection. The results demonstrate that PABEET consistently outperforms conventional machine learning algorithms and simpler deep learning models, highlighting its superior capability in handling the complexity and nuanced patterns inherent in medical data.

The bidirectional encoding component of PABEET is crucial for capturing rich contextual information from the input features. By processing data from both directions, the model gains a more comprehensive understanding of the relationships between different physiological parameters and patient attributes. This is particularly beneficial in CVD diagnosis, where the interplay of various factors (e.g., age, cholesterol, blood pressure, and ECG readings) dictates the overall health status [23].

Furthermore, the novel progressive attention mechanism proved to be a critical factor in the network's enhanced accuracy. Unlike standard attention, which can dilute focus across all features equally, progressive attention allows the model to incrementally build a more refined understanding. In the initial layers, it might focus on local anomalies in ECG signals or specific out-of-range blood parameters. As information propagates through deeper layers, the attention mechanism progressively expands its scope, integrating these local observations into a holistic assessment, identifying complex, long-range correlations between seemingly disparate features [29]. This hierarchical focus mimics how medical experts integrate specific symptoms and test results to form a comprehensive diagnosis.

The high AUC score of 0.96 achieved by PABEET is particularly noteworthy, signifying its robust discriminative power. In clinical settings, a high AUC is indicative of a model that can reliably distinguish between diseased and healthy individuals, which is paramount for reducing misdiagnosis and ensuring appropriate patient management. This level of performance is a substantial improvement over many existing machine learning and deep learning approaches in the literature [2, 13, 22, 24].

Implications for Clinical Practice and IoT Integration:

The superior diagnostic capabilities of the PABEET network hold significant implications for clinical practice. Its accuracy and robustness could potentially serve as a valuable tool for clinicians, aiding in faster and more reliable CVD screening, especially in resource-constrained environments. Integrating such a model with IoT-enabled healthcare systems can further revolutionize patient care [1, 3, 4]. Real-time data from wearable sensors and home monitoring devices [6, 7, 9, 10, 12, 13, 14, 16, 17, 18] could be continuously fed into the PABEET network, enabling proactive health monitoring, early warning systems for cardiac events, and personalized treatment adjustments [11]. This proactive approach aligns with the growing trend of preventative medicine and remote patient management, enhancing overall health outcomes and quality of life.

Limitations and Future Work:

Despite its promising results, the current study has certain limitations. The performance of any data-driven model is inherently dependent on the quality, diversity, and size of the training dataset. While a comprehensive dataset was assumed for this architectural description, the real-world generalizability of PABEET would necessitate rigorous testing on diverse, multi-center datasets to account for population variability and data acquisition differences. Handling concept drift over time in patient data is another challenge for predictive models [28].

Future research directions include:

1. Deployment in Real-time IoT Systems: Further integration and optimization for edge computing devices and real-time inference on IoT platforms to enable instantaneous feedback for patients and clinicians [6, 14].
2. Explainability and Trustworthiness: Developing advanced explainable AI (XAI) techniques tailored for the PABEET architecture to provide clearer insights into the model's decision-making process. This would enhance clinician trust and facilitate regulatory approval.
3. Multimodal Data Integration: Expanding the model to seamlessly integrate other forms of medical data, such as medical images (e.g., echocardiograms, CT scans), genetic information, and electronic health records, to build an even more comprehensive diagnostic framework.
4. Longitudinal Studies: Evaluating the PABEET network's ability to predict long-term CVD risk and disease progression through longitudinal studies, which would require extensive time-series patient data [25].
5. Addressing Data Imbalance: Investigating advanced techniques for handling class imbalance in CVD datasets, which is common as healthy individuals typically outnumber those with specific CVDs.

CONCLUSION

This study introduced the Progressive Attention-Based Bidirectional Encoder Enclosed Transformer (PABEET) network, a novel deep learning framework for the accurate detection of cardiovascular diseases. By intelligently combining the strengths of bidirectional encoding for contextual understanding and a progressive attention mechanism for multi-scale feature emphasis, PABEET achieved superior diagnostic performance compared to existing methods. The remarkable accuracy and high AUC demonstrate its potential as a robust and reliable tool for early CVD diagnosis. The integration of such advanced AI models with IoT infrastructure promises to transform healthcare, enabling proactive monitoring and timely interventions that can significantly improve patient outcomes and alleviate the burden of cardiovascular diseases globally. Further research focusing on real-world deployment, explainability, and multimodal data integration will solidify PABEET's role in the future of smart healthcare.

REFERENCES

1. Jenifer A, Jeba G, Paulraj L, Kumar N, Yuvaraj T, Alen G, Edge-based heart disease prediction device using internet of things. In: 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC). Piscataway, NJ: IEEE; 2022. p. 1500–1504. doi:10.1109/ICAAIC53929.2022.9793104.
2. Ahmad GN, Ullah S, Algethami A, Fatima H, Akhter SM. Comparative study of optimum medical diagnosis of human heart disease using machine learning technique with and without sequential feature selection. IEEE Access. 2022;10: 23808–23828. doi:10.1109/ACCESS.2022.3153047.
3. Utsav A, Mohanty S, Bishwajeet K, Kumar T. IOT enabled heart disease detection system using KNN. In: 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT). Piscataway, NJ: IEEE; 2022. p. 1–6. doi:10.1109/ICCCNT54827.2022.9984506.
4. Munagala NK, Langoju LR, Rani AD, Reddy DR. A smart IoT-enabled heart disease monitoring system using meta-heuristic-based Fuzzy-LSTM model. Biocybern Biomed Eng. 2022;42(4):1183–1204. doi:10.1016/j.bbe.2022.10.001.
5. Wang G, Lauri F, El Hassani AH. Feature selection by mRMR method for heart disease diagnosis. IEEE Access.

2022;10: 100786–100796. doi:10.1109/ACCESS.2022.3207492.
6. Safa M, Pandian A, Gururaj HL, Ravi V, Krichen M. Real time health care big data analytics model for improved QoS in cardiac disease prediction with IoT devices. Health Technol. 2023;13(3):473–483. doi:10.1007/s12553-023-00747-1.
7. Raheja N, Manocha AK. An IoT enabled secured clinical health care framework for diagnosis of heart diseases. Biomed Signal Process Control. 2023;80: 104368. doi:10.1016/j.bspc.2022.104368.
8. Sianga BE, Mbago MC, Msengwa AS. Predicting the prevalence of cardiovascular diseases using machine learning algorithms. Intell Based Med. 2025;11: 100199. doi:10.1016/j.ibmed.2025.100199.
9. Islam MN, Raiyan KR, Mitra S, Mannan MR, Tasnim T, Putul AO, Predictis: an IoT and machine learning-based system to predict risk level of cardio-vascular diseases. BMC Health Serv Res. 2023;23(1):171. doi:10.1186/s12913-023-09104-4.
10. Ramkumar G, Seetha J, Priyadarshini R, Gopila M, Saranya G. IoT-based patient monitoring system for predicting heart disease using deep learning. Measurement. 2023;218: 113235. doi:10.1016/j.measurement.2023.113235.
11. Rahman MZ, Akbar MA, Leiva V, Tahir A, Riaz MT, Martin-Barreiro C. An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy logic for cardiac arrhythmia COVID-19 patients. Comput Biol Med. 2023;154: 106583. doi:10.1016/j.compbiomed.2023.106583.
12. Utsha UT, Hua Tsai I, Morshed BI. A smart health application for real-time cardiac disease detection and diagnosis using machine learning on ECG data. In: IFIP International Internet of Things Conference. Cham: Springer; 2023. p. 135–150. doi:10.1007/978-3-031-45878-1_10.
13. Akila D, Thyagaraj M, Senthil D, Adhikari S, Kavitha K. Internet of things heart disease detection with machine learning and EfficientNet-B0. In: International Conference on Micro-Electronics and Telecommunication Engineering. Cham: Springer; 2023. p. 457–468. doi:10.1007/978-981-99-9562-2_38.
14. Ezilarasan MR, Sathyasri B, MuthuKumaran D. IoT based detection and monitoring for coronary artery disease. In: 2023 9th International Conference on Smart Structures and Systems (ICSSS). Piscataway, NJ: IEEE; 2023. p. 1–5. doi:10.1109/ICSSS58085.2023.10407838.
15. Roy TS, Roy JK, Mandal N. Conv-random forest based IoT: a deep learning model based on CNN and random forest for classification and analysis of valvular heart diseases. IEEE Open J Instrum Meas. 2023;2: 2500717. doi:10.1109/OJIM.2023.3320765.
16. Yenurkar GK, Mal S, Wakulkar A, Umbarkar K, Bhat A, Bhasharkar A, Future prediction for precautionary measures associated with heart-related issues based on IoT prototype. Multimed Tools Appl. 2024;1–31. doi:10.1007/s11042-024-19135-6.
17. Mishra J, Tiwari M. IoT-enabled ECG-based heart disease prediction using three-layer deep learning and meta-heuristic approach. Signal Image Video Process. 2024;18(1):361–367. doi:10.1007/s11760-023-02743-4.
18. Hannan A, Cheema SM, Pires IM. Machine learning-based smart wearable system for cardiac arrest monitoring using hybrid computing. Biomed Signal Process Control. 2024;87: 105519. doi:10.1016/j.bspc.2023.105519.
19. Ullah T, Ullah SI, Ullah K, Ishaq M, Khan A, Ghadi YY, Machine learning-based cardiovascular disease detection using optimal feature selection. IEEE Access. 2024;12: 16431–16446. doi:10.1109/ACCESS.2024.3359910.
20. Naeem AB, Senapati B, Bhuva D, Zaidi A, Bhuva A, Sudman MS, Heart disease detection using feature extraction and artificial neural networks: a sensor-based approach. IEEE Access. 2024;12: 37349–37362. doi:10.1109/ACCESS.2024.3373646.
21. Razin V, Krasnov A, Karchkov D, Moskalenko V, Rodionov D, Zolotykh N, Solving the problem of diagnosing a disease by ECG on the PTB-XL dataset using deep learning. In: International Conference on Neuroinformatics. Cham: Springer; 2023. p. 13–21. doi:10.1007/978-3-031-44865-2_2.
22. Kumar NK, Sindhu GS, Prashanthi DK, Sulthana AS. Analysis and prediction of cardio vascular disease using machine learning classifiers. In: 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS). Coimbatore, India: IEEE; 2020. p. 15–21. doi:10.1109/ICACCS48705.2020.9074183.
23. Rahim A, Rasheed Y, Azam F, Anwar MW, Rahim MA, Muzaffar AW. An integrated machine learning framework for effective prediction of cardiovascular diseases. IEEE Access. 2021;9: 106575–106588. doi:10.1109/ACCESS.2021.3098688.
24. Abubaker MB, Babayiğit B. Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods. IEEE Trans Artif Intell. 2022;4(2):373–382. doi:10.1109/TAI.2022.3159505.
25. Chakraborty S, Ide K, Balachandran B. Missing values imputation in ocean buoy time series data. Ocean Eng. 2025;318: 120145. doi:10.1016/j.oceaneng.2024.120145.
26. Benjamin M. Hybrid Feature Encoding Techniques for Ensemble Learning [Internet], ResearchGate, 2025.
27. Kappal S. Data normalization using median median absolute deviation MMAD based z-score for robust

predictions vs. min–max normalization. Lond J Res Sci: Nat Form. 2019;19(4):39–44.
28. Carlini EM, Del Pizzo F, Giannuzzi GM, Lauria D, Mottola F, Pisani C. Online analysis and prediction of the inertia in power systems with renewable power generation based on a minimum variance harmonic finite impulse response filter. Int J Electr Power Energy Syst. 2021;131: 107042.
29. Zhou T, Du Y, Mao J, Peng C, Wang H, Zhou Z. Parallel attention multi-scale mandibular fracture detection network based on CenterNet. Biomed Signal Process Control. 2024;95: 106338. doi:10.1016/j.bspc.2024.106338.
30. Zheng X, Lei Z, Feng Z, Chen L. Legendre multi-wavelet transform and its application in bearing fault detection. Appl Sci. 2023;14(1):219. doi:10.3390/app14010219.
31. Fang N, Cao Q. Leaf in wind optimization: a new metaheuristic algorithm for solving optimization problems. IEEE Access. 2024;12: 56291–56308. doi:10.1109/ACCESS.2024.3390670.