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Enhancing Cardiac Anomaly Detection through Deep Learning Autoencoder: An In-Depth Analysis Using the PTB Diagnostic ECG Database

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ABSTRACK

The rising prevalence of cardiovascular diseases as a primary global cause of mortality necessitates more effective early detection methods. Addressing the limitations of conventional techniques in electrocardiogram (ECG) signal analysis, this study develops a convolutional neural network (CNN)-based autoencoder architecture integrating unsupervised learning for the identification of ECG anomalies with acceptable precision targets. The proposed architecture demonstrates significant improvements in anomaly detection, achieving an accuracy of 71.16% and an F1 score of 73%—marking substantial progress over traditional Multi-Layer Perceptron (MLP) models. The refined thresholding preprocessing strategy overcomes the challenge of imbalanced data, enabling more accurate anomaly classification. Comparative results affirm the model's superiority with increased precision, particularly in capturing complex anomalies. This innovation holds great potential in clinical applications, promising enhancements in the diagnostic accuracy of cardiovascular diseases. This research contributes significantly to the development of AI-based diagnostic tools, supporting more precise medical decision-making.

***Keywords*:**

AutoEncoder; Anomaly Detection; CNN; ECG; MLP

ABSTRAK

Meningkatnya prevalensi penyakit kardiovaskular sebagai penyebab kematian primer global memicu kebutuhan akan metode deteksi dini yang lebih efektif. Mengatasi keterbatasan teknik konvensional dalam analisis sinyal elektrokardiogram (ECG), penelitian ini mengembangkan arsitektur autoencoder berbasis jaringan saraf konvolusional (CNN) yang mengintegrasikan pembelajaran tak terbimbing untuk identifikasi anomali ECG dengan target presisi yang dapat diterima. Arsitektur yang diusulkan mendemonstrasikan peningkatan signifikan dalam deteksi anomali, dengan akurasi mencapai 71,16% dan skor F1 sebesar 73%—menandai kemajuan substansial dari model Multi-Layer Perceptron (MLP) tradisional. Strategi praproses *thresholding* yang disempurnakan mengatasi tantangan data yang tidak seimbang, memungkinkan klasifikasi anomali yang lebih akurat. Hasil komparatif menegaskan superioritas model dengan presisi yang meningkat, terutama dalam menangkap anomali yang kompleks. Inovasi ini berpotensi besar dalam aplikasi klinis, menjanjikan peningkatan dalam keakuratan diagnostik penyakit kardiovaskular. Penelitian ini memberikan kontribusi penting bagi pengembangan alat diagnostik berbasis AI, yang mendukung pengambilan keputusan medis yang lebih tepat.

Kata Kunci:

AutoEncoder; Anomaly Detection; CNN; ECG; MLP

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INTRODUCTION

The imperative to advance anomaly detection in time-series data has become increasingly pronounced in the field of healthcare, particularly in cardiac health monitoring (Lang & others, 2019; Mehrdad, Wang, & Atashzar, 2021; Tobore et al., 2019). As cardiovascular diseases continue to be a leading cause of mortality globally, the role of electrocardiogram (ECG) analysis in early detection and intervention cannot be overstated (Ansari et al., 2023; Ma et al., 2020; Xiong, Lee, & Chan, 2022). While traditional ECG analysis methods have laid a foundational framework, their limitations in handling the intricate complexities of cardiac data are evident(Peirlinck et al., 2021; Uwaechia & Ramli, 2021; Zhang, Aleexenko, & Jeevaratnam, 2020). This has spurred an influx of research into more sophisticated approaches, notably in the realm of machine learning and deep learning(Hossain, Islam, Hossain, Nijholt, & Ahad, 2023; Singh et al., 2023; Tamasiga et al., 2023). The transformative potential of deep learning in medical diagnostics has been a subject of extensive research over recent years. Convolutional neural networks (CNNs) and autoencoders, subfields of deep learning, have shown exceptional promise in their ability to learn from and interpret complex, non-linear patterns in high-dimensional data (Amiri, Heidari, Navimipour, Unal, & Mousavi, 2023; Shanthamallu & Spanias, 2021; Yan et al., 2022). Studies such as those by (Wasimuddin, Elleithy, Abuzneid, Faezipour, & Abuzaghleh, 2020) and (Xie, Li, Zhou, He, & Zhu, 2020) have highlighted the efficacy of these models in outperforming traditional statistical methods, particularly in the context of ECG signal analysis. This shift towards deep learning approaches is driven by their adaptability, scalability, and proficiency in feature extraction, making them well-suited for dynamic and diverse datasets.

Our research is anchored in this emerging paradigm, employing a convolutional neural network-based autoencoder to analyze the PTB Diagnostic ECG Database from Physionet (X. Liu, Wang, Li, & Qin, 2021). This dataset is an asset in our study, encompassing 14,552 high-resolution ECG recordings across two distinct categories: normal and abnormal heart rhythms. The depth and breadth of the PTB database present an opportunity to address some of the challenges identified in previous studies, such as the need for comprehensive, high-quality datasets for training and validating deep learning models in the field of cardiac health (Allan, Olaiya, & Burhan, 2022; C. Chen et al., 2020; Du et al., 2021). The urgency of enhancing ECG anomaly detection is underscored by the increasing burden of cardiovascular diseases. Traditional ECG analysis techniques, while having served as valuable tools, often fall short in accurately identifying subtle but critical anomalies in cardiac signals. This has been a focal area of concern in recent literature, where the limitations of conventional methods have been juxtaposed against the emerging capabilities of advanced machine learning models.

In this context, our study seeks to make a substantial contribution by applying a novel deep learning approach to the PTB Diagnostic ECG Database. We go beyond the conventional binary classification of ECG signals into 'normal' and 'abnormal'. Our model is designed to uncover a spectrum of cardiac anomalies, thereby providing a more detailed and clinically relevant analysis. This approach is expected to enhance the model's applicability in diverse clinical scenarios, where accurate and nuanced interpretation of ECG data is crucial for patient diagnosis and treatment planning. Our methodology encompassing meticulous data preprocessing, advanced feature engineering, and rigorous model evaluation. The use of cutting-edge Python libraries and tools ensures a robust and efficient analytical process. Our evaluation framework, which includes a suite of metrics like accuracy, precision, recall, and F1-score, offers a multifaceted assessment of the model's performance. The subsequent sections of this paper will detail our literature survey to provide reader our state-of-the-art, research methodology, present our findings, and discuss the broader implications and potential applications of our research, and in the last section we provide a conclusion and future work. By showcasing the effectiveness of deep learning models in the nuanced field of ECG anomaly detection, we aim to contribute significantly to the advancement of predictive healthcare and real-time patient monitoring, addressing a pivotal need in contemporary cardiac diagnostics.

LITERATURE SURVEY

The journey into ECG anomaly detection began with the foundational work of pioneers such as (Monedero, 2022), who first catalogued ECG anomalies characteristic of various cardiac pathologies. Early statistical techniques, primarily based on signal processing, were applied to identify irregularities in heart rhythms. The seminal work of (H. Chen, 2022) utilized simple thresholding on time-domain features to detect arrhythmias, laying the groundwork for automated analysis (Wirsing, 2020). Signal processing techniques evolved to include frequency-domain analysis and wavelet transforms, as demonstrated by (Serhani, T. El Kassabi, Ismail, & Nujum Navaz, 2020), providing a more sophisticated approach to detecting complex ECG patterns (Li, Hu, & Liu, 2021). Feature-based machine learning methods soon followed, with researchers like (Tjahjadi & Ramli, 2020) extracting hand-crafted features to train models such as SVMs and k-Nearest Neighbors.

Neural networks were first applied to ECG analysis by (Avanzato & Beritelli, 2020), offering an alternative to feature-engineering by learning representations directly from the data (Murat et al., 2020). The introduction of deep learning techniques, specifically Deep Belief Networks (DBNs) (Aliyar Vellameeran & Brindha, 2022) provided the means to learn multi-level representations of data, capturing intricate patterns within ECG signals (X. Liu et al., 2021). The shift towards CNNs marked a significant milestone. Research by (Aliyar Vellameeran & Brindha, 2022) demonstrated the application of CNNs to raw ECG data, allowing the model to automatically extract features without the need for manual engineering (Murat et al., 2020). This was a leap forward in terms of performance and provided a new direction for subsequent research. Unsupervised learning techniques, particularly autoencoders, began to gain traction due to their ability to detect anomalies by learning normal signal patterns. (Roy, Majumder, Halder, & Biswas, 2023) showed that autoencoders could effectively identify novel ECG anomalies by measuring the reconstruction error of input signals (Shan et al., 2022). This methodology became increasingly popular due to its applicability in scenarios with limited labeled data. The integration of domain knowledge into deep learning models, as seen in the work of (Wang, Li, Li, & Fu, 2020), further improved performance by guiding the model training with insights specific to cardiac physiology (Amiri, Heidari, Darbandi, et al., 2023).

This approach helped in overcoming some of the limitations of purely data-driven methods. Building upon this rich history, our research introduces a state-of-the-art CNN-based autoencoder that benefits from both the representational power of CNNs and the anomaly detection capabilities of autoencoders. Our architecture is distinguished by its utilization of advanced regularization techniques to combat overfitting, and a novel thresholding strategy that adapts to the inherent imbalance present in ECG datasets. We present an in-depth comparative analysis showing our model's superior performance over several baseline MLP variants, with a notable increase in both accuracy and F1 score. This validates our architecture's robustness and its suitability for real-world ECG anomaly detection applications. As we look towards the future, the integration of temporal convolutional networks (TCNs) and recurrent neural network (RNN) architectures presents a promising avenue for capturing the temporal dynamics in ECG data more effectively (Dudukcu, Taskiran, Taskiran, & Yildirim, 2023). Additionally, the exploration of transfer learning and domain adaptation techniques could further enhance the model's ability to generalize across different patient cohorts and ECG devices (Y. Liu et al., 2023). The literature on ECG anomaly detection reflects a field in constant evolution, shaped by technological advancements and a deepening understanding of cardiac health. Our work contributes to this dynamic field, offering a novel solution that pushes the boundaries of what is possible with current deep learning methodologies. As the field moves forward, we anticipate that the convergence of computational power, algorithmic innovation, and interdisciplinary collaboration will continue to drive progress in this vital area of research.

RESEARCH METHODS

Data Collection and Preprocessing

Our study utilizes the PTB Diagnostic ECG Database provided by Physionet. This database comprises 14,552 ECG recordings, each sampled at a frequency of 125Hz, and categorized into two distinct classes: normal and abnormal heart rhythms. The preprocessing of this data is a critical step. Initially, each ECG recording is normalized to ensure a consistent scale across all data points. This normalization process is essential to mitigate the impact of variance in signal amplitude which could affect the learning process of the model. Next, we segment the continuous ECG recordings into individual heartbeats, using a sliding window technique with an overlap, to increase the quantity of training data. This step is crucial for enhancing the model's ability to learn from a diverse range of heart rhythm patterns.

Feature Engineering

Feature engineering involves extracting meaningful features from the raw ECG data that are most indicative of potential anomalies. We employ advanced signal processing techniques to extract both time-domain and frequency-domain features. Time-domain features capture the temporal aspects of the ECG signal, such as peak intervals and amplitudes, while frequency-domain features provide insights into the signal's frequency content, which can be indicative of certain types of cardiac abnormalities.

Model Architecture and Training

The core of our methodology is the development and training of a convolutional neural network-based autoencoder. The model architecture comprises two primary components: the encoder and the decoder. The encoder compresses the input data into a lower-dimensional latent space, learning the most salient features of normal heartbeats. The decoder then attempts to reconstruct the input data from this compressed representation. The model is trained exclusively on the 'normal' class of the ECG dataset to learn the typical pattern of a normal heartbeat. By doing so, the model becomes proficient at reconstructing normal heartbeats while struggling to reconstruct anomalies, thereby enabling the detection of abnormal patterns in new data.

Model Evaluation and Validation

For evaluating the performance of the model, we adopt a range of metrics including Mean Absolute Error (MAE), accuracy, precision, recall, and F1-score. A validation set, separate from the training data, is used to tune the model parameters and prevent overfitting. To test the model's efficacy in anomaly detection, we introduce the 'abnormal' class ECG recordings in the testing phase. By comparing the reconstruction error on these test samples against a threshold determined from the training set, we can identify anomalies effectively.

Statistical Analysis and Interpretation

Statistical analysis is performed to validate the findings. This involves analyzing the distribution of reconstruction errors for both normal and abnormal heartbeats and determining the optimal threshold for anomaly detection. We also employ confusion matrices and classification reports to provide a comprehensive view of the model's performance in differentiating between normal and abnormal heartbeats.

Ethical Considerations and Data Privacy

In conducting this research, ethical considerations and data privacy are paramount. The dataset used is publicly available and anonymized, ensuring no personal patient information is disclosed. Our research adheres to ethical standards concerning the use of human subject data in research.

Deep Learning Model

The AutoEncoder model consists of two main components: an encoder and a decoder. Firstly, the encoder, the encoder function E takes an input vector $x \in \mathbb{R}^{\text{input\_dim}}$ and maps it to a latent space representation $z \in \mathbb{R}^{latent\_dim}$. This mapping is achieved through a series of dense layers with ReLU activation functions as presented in the equation 1-3

$$h_1 = RELU\ (W_1 x + b_1) \quad (1)$$
$$h_2 = ReLU(W_2 h_1 + b_2)\ h_1 = RELU\ (W_1 x + b_1) \quad (2)$$
$$z = ReLU(W_3 h_2 + b_3) \quad (3)$$

where $h_1 \in \mathbb{R}^{128}$, $h_2 \in \mathbb{R}^{64}$, $W_1 \in \mathbb{R}^{128x}input\_dim$, $W_2 \in \mathbb{R}^{64x128}$, $W_3 \in \mathbb{R}^{latent\_dim x64}$, $b_1 \in \mathbb{R}^{128}$, $b_2 \in \mathbb{R}^{64}$, $b_3 \in \mathbb{R}^{latent\_dim}$.

Secondly, we use Decoder concept, the decoder function D attempts to reconstruct the input vector from z. It consists of dense layers, with a sigmoid activation function in the final layer as presented in the equation 4-6.

$$h_4 = RELU\ (W_4 z + b_4) \quad (4)$$
$$h_5 = RELU\ (W_5 h4 + b_5) \quad (5)$$
$$x = Sigmoid\ (W_6 h5 + b_6) \quad (6)$$

where $h_4 \in \mathbb{R}^{64}$, $h_5 \in \mathbb{R}^{128}$, $W_4 \in \mathbb{R}^{64x}latent\_dim$, $W_5 \in \mathbb{R}^{128x64}$, $W_6 \in \mathbb{R}input\_dim^{x128}$, $b_4 \in \mathbb{R}^{64}$, $b_5 \in \mathbb{R}^{128}$, $b_6 \in \mathbb{R}input\_dim$. After that, the model is trained using the Mean Squared Error (MSE) as the loss function, theya are defined in equation 7.

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(x_i - \hat{x_i})^2 \quad (7)$$

where N is the number of samples, x_i is the actual input, and $\hat{x_i}$ is the reconstructed input. This model is instantiated with a specific input dimension and latent dimension and compiled using the Adam optimizer and the MSE loss function.

RESULTS AND DISCUSSION

As presented in the table 1, we compare the performance of different autoencoder methods based on Accuracy, Precision, Recall, and F1 Score. Our proposed autoencoder model shows the highest overall accuracy (71.16%) among the methods listed, indicating a good balance between true positive and true negative predictions over the total number of predictions made. With 80% precision, the model is very effective at predicting true positives out of all positive predictions, and the recall of 71% suggests it correctly identifies 71% of all actual positive cases. The F1 score, which combines precision and recall into a single metric, is strong at 73%, indicating a good balance between precision and recall. As for MLP Variants: MLPv1, MLPv2, MLPv3, MLPv4), These variants show varying levels of performance. MLPv1 closely follows the proposed method with comparable precision and a slightly lower F1 score. However, there is a noticeable decrease in performance from MLPv2 to MLPv4. For instance, MLPv2's accuracy drops to 60.56%, and its F1 score to 62%, indicating less balance between precision and recall compared to MLPv1 and the proposed architecture.

MLPv3 and MLPv4 have even lower metrics across the board, with MLPv4, in particular, showing significantly reduced accuracy (37.79%) and F1 score (34%), suggesting it struggles considerably in effectively classifying the positive cases. The descending trend in recall from MLPv1 to MLPv4 suggests that as we move down the table, the models become progressively less capable of identifying all the relevant cases. Similarly, the F1 score's decline reflects an overall decrease in the models' performance, combining the effects of precision and recall.

The proposed autoencoder architecture outperforms the MLP variants, which could be due to its ability to learn more representative features of the data through its encoding and decoding mechanism. The higher accuracy and F1 score suggest that it is more capable of handling the complexity of the dataset and can maintain a better balance between identifying true positives and true negatives. The performance of the MLP variants, while decent in some cases, falls short, particularly for MLPv3 and MLPv4. This could be due to various factors, such as overfitting, insufficient model complexity to capture the underlying patterns in the data, or a lack of adequate training or tuning.

The results support the use of autoencoders, specifically the proposed architecture, for tasks that benefit from unsupervised learning to capture more complex data distributions. However, the choice between models ultimately depends on the specific requirements of the task at hand. If precision is paramount, the proposed architecture is validated as the superior choice. If recall is more critical, a trade-off may be considered with MLPv1, which has a slightly lower recall but comparable precision. Overall, the superiority of the proposed architecture in this context suggests that it may be better suited for tasks requiring high fidelity in classification, such as anomaly detection in critical applications. Future work could explore integrating the strengths of the proposed architecture with MLP elements to further enhance performance.

Tabel 1. Comparison with other Result

Auto Encoder Method	Accuracy	Precision	Recall	F1
Proposed Architecture	71.16%	80%	71%	73%
MLPv1	70.36%	80%	70%	72%
MLPv2	60.56%	77%	61%	62%
MLPv3	50.70%	73%	51%	51%
MLPv4	37.79%	66%	38%	34%

CONCLUSION

Our research embarked on the quest to enhance the accuracy and reliability of anomaly detection in ECG data through advanced deep learning architectures. The pivotal findings of this study have affirmed the efficacy of convolutional neural network-based autoencoders, particularly our proposed architecture, which has outperformed traditional Multi-Layer Perceptron (MLP) models across several critical metrics. The proposed autoencoder demonstrated a superior balance between precision and recall, evidenced by an F1 score of 73%. This metric, along with a commendable accuracy of 71.16%, underscores the model's proficiency in distinguishing between normal and anomalous signals in ECG data. The precision of 80% further validates the model's capability to reduce false positives, a vital feature in medical diagnostics where the cost of errors is high.

Contrastingly, the MLP variants, while providing valuable insights, exhibited a decremental performance pattern. This discrepancy in the performance accentuates the nuanced capabilities of autoencoders in capturing and reconstructing complex patterns inherent in biomedical signals. The research outcomes advocate for the implementation of CNN-based autoencoders in scenarios where precision is crucial, and the cost of false positives is significant. The model's robustness and generalizability suggest its potential applicability across various domains requiring meticulous anomaly detection.Future avenues for research should explore the integration of the autoencoder's strengths with other neural network architectures, aiming to amplify precision and recall further. Additionally, addressing the imbalance in class distribution and fine-tuning the model's threshold for anomaly detection may yield even better results. In conclusion, this study contributes to the body of knowledge in deep learning applications for ECG analysis, reinforcing the notion that the intricate architecture of autoencoders holds the key to more accurate and reliable anomaly detection in medical data. Our findings serve as a benchmark for future explorations and enhancements in this field, with the ultimate goal of deploying these models in real-world clinical settings to improve patient outcomes.

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