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Detection of Atrial Fibrillation with Custom Designed Wavelet-based Convolutional Autoencoder

Öykü Eravcı[1], Nalan Özkurt[2]*, Özlem Memiş[3], Evrim Şimşek[3]

[1] Graduate School, Yaşar University, Izmir, Türkiye
[2] Dept. of Electrical Electronics Engineering, Yaşar University, Izmir, Türkiye
[3] Dept. of Cardiology Ege University, Izmir, Türkiye
* nalan.ozkurt@yasar.edu.tr
* Orcid No: 0000-0002-7970-198X

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Abstract

Remote monitoring of patients is of great importance in terms of early diagnosis of diseases and improving people's quality of life. With the rapid development of deep learning techniques, wearable health technologies have leaped forward. This has made the automatic diagnosis even more important. In this study, we provide a deep learning approach for classifying Atrial Fibrillation (AF) arrhythmia that uses a customized wavelet-based convolutional autoencoder (WCAE) model. WCAE is employed as an anomaly detector, which combines the time-frequency domain examination ability of wavelet and the data-driven feature learning capability of convolutional autoencoders. The proposed approach received average scores of 95.45%, 99.99%, 90.90%, and 95.23% for accuracy, precision, recall, and F1, respectively, on a large selection of publicly available datasets. The outcomes of the experiments demonstrate the significance of using deep learning-based models in diagnosing AF. Moreover, it is observed that utilization of wavelet methods along with autoencoder model has a great potential for biomedical signal processing systems.

Keywords: Atrial fibrillation detection, ECG, Autoencoder, Deep learning, Discrete wavelet transform

1. Introduction

In the last century, Atrial Fibrillation (AF) has been the most extensively studied heart rhythm disorder, yielding valuable findings [1]. Atrial Fibrillation (AF) is an irregular and rapid atrial rhythm that can occur at a rate of 300-500 beats per minute. In Normal Sinus Rhythm (NSR), the atria conduct electrical impulses smoothly and regularly, initiated by the sinoatrial node. However, AF occurs when there are abnormalities in the generation of impulses or structural abnormalities in the cellular connections, resulting in irregular and chaotic impulses [2]. Clinical practice most commonly manages atrial fibrillation (AF), which is associated with a higher risk of death, stroke, and peripheral embolism, and the incidence of this condition rises with age [1]. According to a 2023 guideline for the diagnosis and management of atrial fibrillation by the American College of Cardiology (ACC) and American Heart Association (AHA), the number of patients with AF in 2010 was estimated that 5.2 million, that is expected to rise to 12.1 million by the year 2030. The number of new AF patients added each year was 1.2 million in 2010, and it is expected that this number will increase to 2.6 million per year by 2030 [2]. The electrocardiogram (ECG) has been a widely used tool in clinical medicine by both cardiologists and non-cardiologists for many years. It is a fast, simple, and inexpensive test available even in settings with limited resources. The test provides insights into the physiological and structural state of the heart and can also provide important diagnostic information for systemic conditions [3]. The condition known as AF is identified by irregular activation of the atrium, which results in reduced heart muscle function. AF can be easily identified on a surface electrocardiogram by the absence of atrial depolarization, represented by a P-wave, and instead showing a quivering isoelectric line. This irregular activation also leads to irregular ventricular activation, which QRS complexes represent, and ultimately impaired muscle contraction [4].

The usual way of diagnosis of arrhythmias is to consider standard electrocardiograms (ECGs), event recorders recordings. This method has limited monitoring periods and occasionally miss intermittent arrhythmic events

among patients who use them. In case of one-day-long ECG recordings of Holter devices, the manual interpretation of ECG data can be time-consuming and subject to human error, leading to potential misdiagnoses [5]. In recent years, extensive work has been carried out to determine the fundamental cellular, molecular, and electrophysiological modifications that make patients more susceptible to the initiation and persistence of AF [6]. With the advent of deep learning methods, studies are focused on automatic detection techniques that can be integrated into wearable devices. Despite advances in cardiovascular disease detection methods, accurately classifying AF is still challenging since the condition can present with varying patterns of arrhythmia, subtle variations in ECG signals, and overlaps with other types of arrhythmias, making it difficult to distinguish using traditional techniques. This makes customized treatment plans and reliable prognostication difficult.
Overall, the literature review demonstrates the advancements in cardiac arrhythmia classification, focusing on the accuracy and scores of recent methods, including deep learning models, autoencoders, and CNN. These studies provide valuable insights into the potential of these techniques for improving ECG arrythmia detection and classification accuracy, although further improvements are still necessary. Therefore, this study aims to establish a custom-designed Wavelet-based Convolutional Autoencoder (WCAE) structure and propose a successful and efficient arrhythmia detection system with machine learning methods. The contributions of this study can be summarized as

- Improving the AF detector performance due to learning the signal pattern with convolution filters of the convolutional autoencoder using only one channel of ECG signal.
- Combining wavelets' multiresolution signal analysis ability with a deep learning algorithm by proposing a WCAE structure.
- Handling the data imbalance problem by training the network with only one type of signal utilizing anomaly detection

Thus, instead of simply categorizing rhythms, this model focuses on spotting abnormalities, offering a fresh perspective on AF detection. Additionally, testing the model on different datasets reveals its flexibility and reliability in various situations. These unique features distinguish this study from others, providing a more thorough approach to AF detection.

2. Literature Review

Recent studies have focused on the accuracy of various atrial fibrillation (AF) classification methods, including autoencoders, convolutional neural networks (CNN), and other deep learning models. Hu et al. [7] proposed a novel frequency-domain feature, specifically the frequency corresponding to the maximum amplitude in the spectrum, to improve atrial fibrillation (AF) detection. By applying a decision tree algorithm to data from the MIT-BIH database, their approach achieved high accuracy (98.9%), sensitivity (97.93%), and specificity (99.63%), highlighting the effectiveness of this method in distinguishing AF signals. Chen et al. [8] proposed a feedforward neural network model for AF detection, achieving an accuracy of 84.00%, sensitivity of 84.26%, specificity of 93.23%, and an area under the receiver operating characteristic curve of 89.40%. Furthermore, Cheng et al. [9] developed a method for AF detection directly from compressed ECG, achieving a varying accuracy with from 91.63% to 98.40% for the signals of 10 seconds. Other studies focusing on deep learning approaches have also shown significant potential in predicting AF accurately. For instance, Wei et al. [10] developed a deep-learning algorithm for atrial fibrillation detection, achieving an F-1 score of 88.2% and accuracy of 97.3%. They utilized spectrograms of pre-processed ECG signals and a fine-tuned EfficientNet B0 model, demonstrating the effectiveness of transfer learning in AF classification. Similarly, Faust et al. achieved an accuracy of 99.09% for AF detection using long short-term memory networks with RR interval signals by only considering the RR irregularity and uses long records to capture 100 RR intervals [11]. Rasmussen et al. [12] proposed a semi-supervised setup using an unsupervised variational autoencoder combined with a supervised classifier to distinguish between AF and non-AF using ECG records, indicating the potential of autoencoders in AF classification with an accuracy of 98.7%. Despite obtaining high accuracy values in these studies, the experiments have been conducted within a limited dataset and focused on lengthy samples. Hence, further development is still required for their applicability in real-life scenarios. To address these limitations, techniques like autoencoders, which are neural networks designed to encode input data into a compressed representation and then decode it back to closely match the original input, offer promising potential for enhancing the robustness and generalizability of these models [13]. The autoencoder is a self-supervised learning system and it aims to minimize the reconstruction error between the input and the output during training [14]. The autoencoder is also employed as a feature extraction as in [15]. The study utilizes an auto-encoder convolutional network (ACN) model based on one-dimensional convolutional neural networks (1D-CNN). These obtained features are then fed into a support vector machine (SVM) classifier, which achieves an overall accuracy of 98.84% in classifying arrhythmia using the MIT-BIH arrhythmia database [15]. Another instance of AE study, Choi et al. [16] proposed an atrial fibrillation (AF) diagnosis system using unsupervised learning with an LSTM-based autoencoder for anomaly detection in ECG segments (PreQ, QRS, and PostS). Their approach, which distinguished between normal and AF segments with AUROC scores up to 0.96, was further validated with an XG-Boosted model, achieving an area under ROC curve score of 0.98 and an F1 score of 0.94.

This method addresses the limitations of supervised learning by providing significant evidence for AF detection based on anomaly scores.

Our previous study proposes an efficient wavelet-based convolutional autoencoder model for the feature extraction of the five arrhythmia types, such as normal sinus rhythm (NSR), right bundle branch block (RBBB), left bundle branch block (LBBB), premature ventricular contractions (PVC), atrial premature contractions (APC) [17]. The study mentioned above used Wavelet-based Convolutional Autoencoder as a feature extractor to classify heartbeats with a Multilayer Perceptron (MLP). The wavelets' success in grasping the time-frequency domain distribution of the signals was integrated into the learning capability of autoencoders. As a result of the analysis with different wavelet families, the Bior 3.5 wavelet produced superior performance compared to the previous studies. The quality and quantity of data is an essential issue in biomedical detection studies. Most of the deep learning models need a vast amount of data that represents the underlying phenomenon. Furthermore, each class should have sufficient data to train the network. In one of the previous studies, the Synthetic Minority Oversampling Technique (SMOTE) was employed to integrate the ECG arrhythmia detection model with the emergent IoT healthcare devices [18]. Then, the performance with different classifiers was compared for two classes, such as cardiovascular disease or not. Another study concentrates on generating synthetic samples for ECG signals [19]. They illustrated that the proposed model with a Generative Adversarial Network improves the classification accuracy compared to the ResNet34-LSTM3 model.

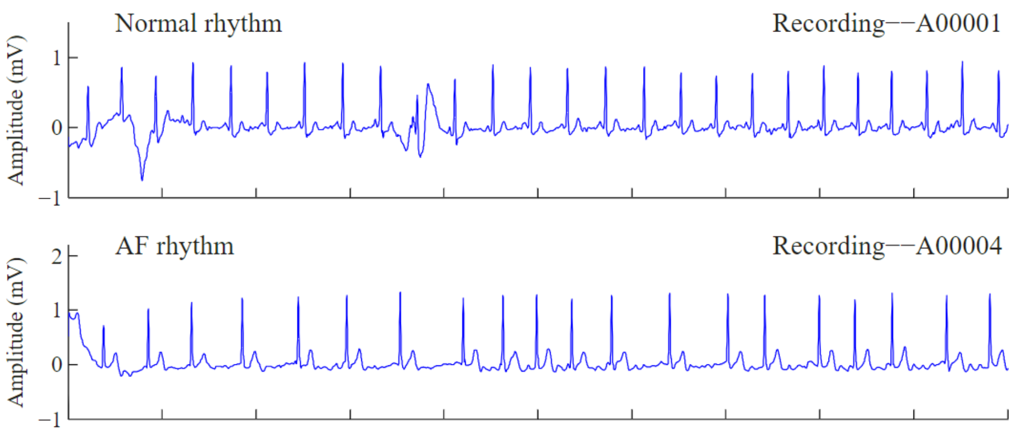

Figure 1. (top) Normal Sinus Rhythm and (bottom) Atrial Fibrillation ECG recordings [22].

3. Background

3.1 ECG and Atrial Fibrillation

Electrocardiography (ECG) is a technique that records the electrical activity of the heart by detecting and amplifying the small electrical impulses generated by cardiac muscle depolarization and repolarization. This process is depicted as waves and intervals on the ECG tracing, including the P-wave, QRS complex, and T-wave, each representing specific electrical events in the cardiac cycle. By carefully interpreting these waveform characteristics, clinicians can assess rhythm regularity, identify conduction abnormalities, and recognize signs of ischemia or infarction. This diagnostic tool is commonly used for its rapidity, simplicity, and cost-effectiveness, making it indispensable even in resource-constrained settings. ECG plays a crucial role in diagnosing various cardiac and systemic conditions with its ability to provide insights into the physiological and structural status of the heart. Typically, ECG recordings are made for a few seconds to get a quick idea of the heart's rhythm. Holter ECG monitoring detects arrhythmic conditions that cannot be captured during a standard ECG. Continuously recording heart activity over an extended period, such as 24 hours, provides crucial information for diagnosing and managing heart conditions.

Atrial fibrillation is a commonly encountered arrhythmia that can lead to stroke, embolism, or even death when diagnosed late. The most used method for timely detection of this severe condition is the examination of ECG records. In ECG recordings, three specific signs of atrial fibrillation are mainly considered: the absence of the P wave, irregular RR intervals, and fibrillation on the baseline.

Figure 1 illustrates examples of ECG recordings of normal sinus rhythm and atrial fibrillation. As can be observed from the upper graph, P waves, QRS complexes, and T waves can be easily identified for each beat. The distance between R peaks is regular. However, in the second graph, beats are observed in irregular time instants. Furthermore, P peaks are absent, and a quivering isoelectric line is shown at the TQ interval.

3.2 Autoencoders and Anomaly Detection

Autoencoders (AEs) are a type of neural network extensively researched in deep learning. They are mainly used for unsupervised learning tasks such as dimensionality reduction, data compression, and feature extraction. The basic idea of an autoencoder is to learn a compressed representation of input data, encode it into a lower-dimensional latent space, and then decode it back to its original form [13]. The autoencoder's working process involves using two networks: an encoder and a decoder. The encoder takes the input data and creates a compressed representation, then fed to the decoder. The decoder then reconstructs the original input data from the compressed representation.

This study used an autoencoder in anomaly detection mode. NSR ECG signals constructs the normal class where AF signals were treated as abnormal beats. Thus, the autoencoder was trained with only NSR signals as represented in Figure 2. In the testing phase, both NSR and AF signals are applied to the autoencoder, and the reconstruction error is calculated, as seen in Figure 2. This approach allowed for the evaluation of how well the autoencoder could reconstruct both NSR and AF signals, providing insights into its performance in distinguishing between the two rhythm types. If the error is less than the given threshold value, it is labeled as NSR; if it is greater than the given threshold value, it is labeled AF.

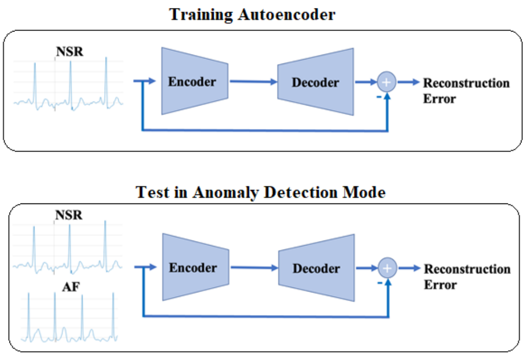

Figure 2. Training and testing autoencoder for the classification of NSR and AF heart rhythms in anomaly detection mode.

The critical issue in anomaly detection is to select the threshold. In this study, the following steps are applied to obtain an acceptable threshold value that leads to successful detection:

1. Calculate reconstruction loss on normal data using the model.
2. Calculate reconstruction loss on anomalous data using the model.
3. Generate a range of threshold values between the minimum and maximum reconstruction loss values observed in the normal data.
   - Iterate over different threshold values to find the best F1 score. For each threshold value, compute the precision, recall, and F1 scores.
   - Update the best F1 score and corresponding threshold if the current F1 score exceeds the previous one.
4. Return the best threshold and corresponding F1 score as the optimal threshold.

The identified optimal threshold is applied to the mixed test data, consisting of normal and atrial fibrillation samples. The performance of the selected threshold is evaluated based on various metrics, such as Precision, Recall, and F1 score, to assess the effectiveness of the anomaly detection system.

3.3 Wavelet Transform

The Continuous Wavelet Transform (CWT) operates by sliding a scaled wavelet function along the time axis of a signal, adjusting its magnitude through scaling and its position through translation [24]. Functions meeting specific mathematical criteria can be named wavelets, with common examples including Gaussian, Mexican Hat (the second derivative of a Gaussian), Haar, and Morlet functions [24]. In mathematical terms, convolving a signal x(t) with a wavelet function ψ(t), yields the wavelet transform of x(t). Using two parameters, translation b and dilation a, the Continuous Wavelet Transform (CWT) is defined as:

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt \qquad (1)$$

Here, '*' denotes the complex conjugate of the wavelet function. Parameter b indicates location in time axis, while a signifies the scale of the wavelet. The scaled and translated wavelet is defined as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a}\right) \qquad (2)$$

The closer the wavelet matches the characteristics of the signal, the more detailed information can be extracted from the signal. The Discrete Wavelet Transform (DWT) applies an orthogonal wavelet basis to a continuous signal in discrete steps. It employs discrete values of parameters a and b moving in each b position with discrete steps proportional to a, establishing a connection between a and b. This relationship is encapsulated in a wavelet form expressed as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a_0^m}} \psi \left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \qquad (3)$$

The most typical values of dilation and translation steps are $a_0 = 2$ and $b_0 = 1$, that is called as dyadic grid. The dyadic wavelet equation can be mathematically expressed as

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$$\psi_{m,n}(t) = \frac{1}{\sqrt{2^m}}\psi\left(\frac{t-2^m}{2^m}\right) \quad (4)$$

where the scale index is m. The scaling function is denoted by

$$\phi_{m,n}(t) = \frac{1}{\sqrt{2^m}}\phi\left(\frac{t-n}{2^m}\right) \quad (5)$$

Here, $\phi_{m,n}(t)$ represents the scaling function derived from the shift value n on the time axis for the m^{th} index of the scaling function. As a result of the convolution of the scaling function and the signal yields $S_{m,n}$, the approximation coefficient.

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\phi_{m,n}(t)dt \quad (6)$$

If the input signal is finite and bounded by certain integers it can be obtained as

$$S_{m+1,n} = \frac{1}{\sqrt{2}}\sum_k c_{k-2n}S_{m,k} \quad (7)$$

The c_k are the scaling coefficients. Multiplying c_k by $1/\sqrt{2}$ yields the high-pass filter vector [24]. Similarly, utilizing the approximation coefficients in terms of b_k, detail coefficients can be computed.

$$T_{m+1,n} = \frac{1}{\sqrt{2}}\sum_k b_{k-2n}S_{m,k} \quad (8)$$

Here, b_k represents the reconfigured scaling coefficients of c_k. Multiplying b_k by $1/\sqrt{2}$ yields the low-pass filter vector. The reconstruction low-pass and high-pass filter coefficients wavelets are obtained by time-reversal of analysis filter coefficients. The following steps are followed to calculate the wavelet coefficients [24]:

1. Take a signal S with length N, assume that $S_{0,k} = x_k$
2. Select a discrete wavelet suitable for signal S.
3. Use the high-pass and low-pass filter coefficients of the selected wavelet.
4. Convolve signal S with the low-pass filter coefficients obtained from the corresponding wavelet, essentially containing a sequence of $(1/\sqrt{2})c_k$ values.
5. Apply the same process as in step 4 with the high-pass filter coefficients, essentially containing a sequence of $(1/\sqrt{2})b_k$ values.
6. Down-sample the results of the high-pass and low-pass filtering by selecting every (2n+1)th value along the length of the vector.
7. Obtain detail coefficients after high-pass filtering and down-sampling.
8. Obtain approximation coefficients after low-pass filtering and down-sampling and repeat the algorithm from step 1 using the result of this step.

This process achieves the atomic decomposition of the signal through filtering, as depicted schematically in Figure 3.

Table 1. Description of the databases.

Data	*Subject*	*Lead*	*Duration of recordings*	*Sampling frequency*
NSRDB	18	2	24 hours	128 Hz
AFDB	25	2	10 hours	250 Hz
AFPC	771	1	10-60 seconds	300 Hz

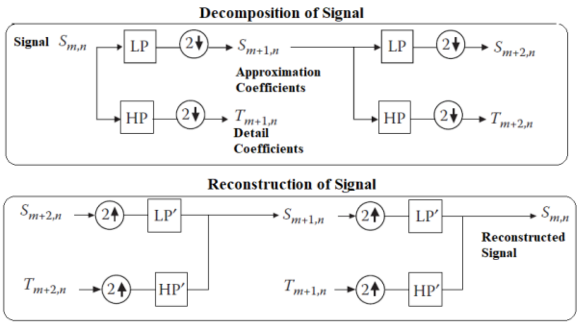

Figure 3. Two-level signal decomposition and reconstruction using wavelet coefficients [24].

4. Materials and Methods

4.1. Dataset

Autoencoder studies were carried out using publicly available ECG databases. NSR data "MIT-BIH Sinus Rhythm Database" (NSRDB) [20] and Atrial Fibrillation data "MIT-BIH Atrial Fibrillation Database (AFDB)" [21], "The PhysioNet/Computing in Cardiology Challenge 2017" (AFPC) [22] taken from databases. The features of the entire database are listed in Table 1.

Table 1 shows that NSRDB includes 24-hour data from 18 healthy individuals. The AFDB database recordings were obtained with ECG recorders with a frequency bandwidth of approximately 0.1 Hz to 40 Hz with a sampling frequency of 250Hz [21]. AFDB consist of records that obtained from 25 different patients. Each records have 10 hours duration and labelled as AF and other type of rhythms. The single-channel ECG recordings from AFDB was used in the competition held by Physionet in 2017. Only the AF labelled beats of the Physionet competition data was included in this study. The locations and beat labels of the QRS complexes of ECG signals in the NSRDB and AFDB databases are available. AFPC recordings were taken with the AliveCor device, and the sampling frequency is 300Hz [22]. The AFPC training set includes 8528 records which have the time duration from 10 to 60 seconds. These records labelled as normal, AF, noisy and other rhythms. AF signals in the AFPC database were separated with the Pan Tompkins algorithm and labeled by expert authors of this study. The sampling frequency was converted to 250 Hz for data at different sampling frequencies, thus same window length can be used for experiments. Before the data was applied to the autoencoder, signal is divided into 256 samples windows as illustrated in Figure 4.

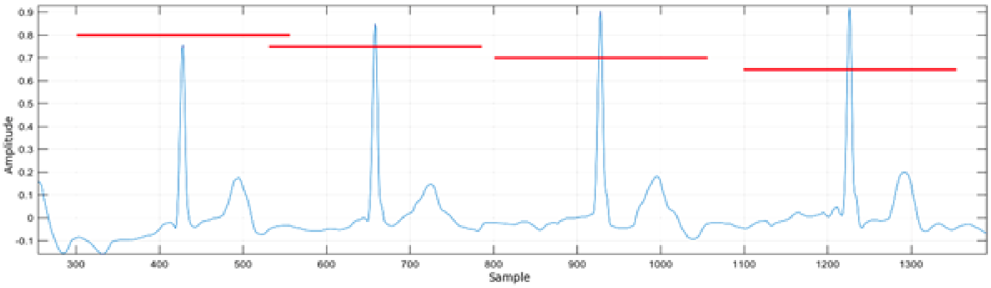

Figure 4. Illustration of ECG Signal Windowing, red lines represent signal windows.

The located R peaks are aligned in the middle of each window. In Figure 4, each red line shows the interval of a signal window. The number of data windows resulting from the process is listed in Table 2.

Table 2. Number of Data Windows Used in Training and Testing

Data	*NSRDB*	*AFDB*	*AFPC*
Number of frames used for training	800,000	-	-
Number of frames used testing (Test 1)	395,455	395,455	-
Number of frames used testing (Test 2)	32,010	-	32,010

4.1 Wavelet Based Convolutional Autoencoder Design

A Wavelet-based Convolutional AutoEncoder (WCAE) structure, that was proposed in our previous study [16], was employed in anomaly detection mode in this study. In the literature, wavelet transform is commonly employed as a preprocessing method, where wavelet coefficients or signals filtered by wavelet filters are used as inputs to deep learning architectures for training. In our proposed approach, a wavelet layer is integrated as a layer into a convolutional autoencoder structure. The custom-designed EncoderMiniBlock and DecoderMiniBlock are optimized during training to effectively model the signal. When considering the feature space, the likelihood of overfitting increases with the complexity of the model during training. In this study, a simple architecture was preferred to avoid overfitting and simultaneously reduce computational complexity. The proposed model is given in Figure 5.

The best model was discovered through experimenting with different models, changing architectures, layer counts, and other configurations. We found that the proposed model performed the best after trying various options. As seen in Figure 5, three EncoderMiniBlocks containing 128, 64 and 32-dimensional filters are used in the encoder. Similarly, in the decoding section, 32, 64, 128 dimensional decoding MiniBlocks are included. The last layer contains a single-unit Fully Connected Layer (Dense layer) and Rectified Linear Unit (ReLu). Within the EncoderMiniBlock, there are convolutional layer or 1D convolution layer, Discrete Wavelet Transform (ADD) layer, batch normalization layer and dropout layer, respectively. WaveTF library was used for wavelet function implementation [23].

WaveTF is a TensorFlow library that implements 1D and 2D wavelet transforms and exposes them as Keras layers, so they can be easily added to machine learning workflows. The library implements the most used Haar and DB2 wavelet kernels. To handle boundary effects, anti-symmetric reflection filling is applied, which broadens the signal while preserving its first-order finite difference at the boundary. WaveTF transparently supports both 32- and 64-bit floating point at runtime.

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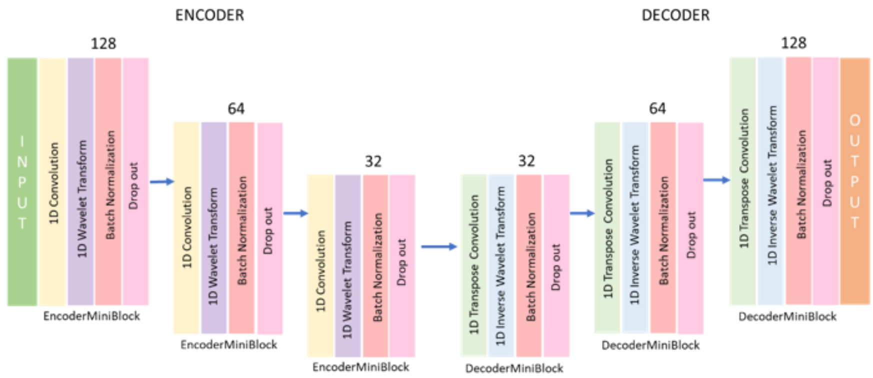

Figure 5. Proposed Wavelet-Based Convolutional Autoencoder Model

Table 3. Reconstruction low pass filter coefficients of the wavelet functions used in this study

	DB 2	DB3	DB 4	SYM 4	COIF 2	BIOR 3.5
$g_0[0]$	0.48296	0.03223	-0.230378	0.032223	0.016387	0.0
$g_0[1]$	0.836516	0.08544	0.714847	-0.012604	-0.041465	0.0
$g_0[2]$	0.2241439	-0.13501	0.630881	-0.099219	-0.067373	0.0
$g_0[3]$	-0.1294095	-0.45988	-0.027984	0.2978578	0.3861101	0.0
$g_0[4]$		0.80689	0.187035	0.8037388	0.8127236	0.1767767
$g_0[5]$		-0.33267	0.0308414	0.4976187	0.417005	0.5303301
$g_0[6]$			-0.0328830	-0.029636	-0.0764886	0.5303301
$g_0[7]$			-0.010597	-0.075766	-0.0594344	0.1767767
$g_0[8]$					0.02368017	0.0
$g_0[9]$					0.00561144	0.0
$g_0[10]$					-0.0018232	0.0
$g_0[11]$					-0.0007206	0.0

If wavelet transformation is active in the EncoderMiniBlock, the transformation function is defined for the selected wavelet. In the original version of the library, only Haar and Daubhecies 2 wavelets are defined. However, we observed from our studies and from the literature reviews that when the signal shape resembles the analyzed signal the wavelet transform analysis extracts more meaningful information from the signal. Thus in this study, wavelets, which were successfully used in ECG classification and AF detection in literature, were also adapted to the library. The DecoderMiniBlock contains a 1D transpose convolution layer, Inverse Wavelet Transform (IDWT) layer, batch normalization layer and dropout layer, respectively. In this study, autoencoder experiments were conducted with Haar and DB2 wavelets as well as wavelets that generally give successful results in biomedical signal classification. By entering low-pass reconstruction filter coefficients, new wavelets can be implemented in WaveTF library. The wavelet coefficients used are listed in Table 3.

5. Results and Discussions

This study aims to train the wavelet-based convolutional autoencoder with a single class of data, optimize it according to this signal, and obtain an efficient system separating the signal type from others in the testing phase. Model in Figure 5 was trained with NSR data from the NSRDB database. At the end of the training, the tests were performed with data from the NSRDB database, which the model did not see in training, and data taken from two different databases, AFDB and AFPC. Experiments were conducted in the TensorFlow 2 environment in Python 3 of Google Colaboratory. If there is no improvement in the validation error for ten epochs, early stopping is applied to prevent overfitting. Adagrad optimization algorithm was used with 128-dimensional batches. The initial learning rate was chosen as 10-3. The training is set to continue for a maximum of 50 epochs. In Test 1, 395,455 entries from the NSRDB database and 395,455 from the AFDB database were used.

In Test 2, 32,010 entries from the NSRDB database and 32,010 from the AFPC database were used. The model was trained with 800,000 NSR entries from the NSRDB database for both tests. The data is divided into separate sets for training and testing purposes. During the training phase, the model learns to reconstruct the input data without exposure to the data of the patients in the test set. This ensures that the test set consists of unseen examples, allowing for a rigorous evaluation of the model's generalization performance. Therefore, when training an autoencoder, the test data remains entirely independent, ensuring an unbiased assessment of the model's ability to reconstruct unseen instances.

5.1 Experiment 1: Effect of Wavelet Family on Performance

This experiment assesses how different wavelet families impact the performance of convolutional autoencoder models in anomaly detection tasks using ECG signals. By training multiple models with various wavelet families (e.g., Daubechies, Symlet, Coiflet), the study aims to identify the optimal wavelet family that enhances the model's ability to extract relevant features and accurately detect anomalies.

The WCAE Model (Figure 5) structure was established without a wavelet layer and also with the various wavelets. The system was optimized, and the loss function MAE, which gave the best results, was selected. The results of the experiments are listed in Table 4. In Figure 6 (a) and (b), separate performance graphs for both experiments are given according to wavelet type.

Table 4. Experiment 1 Results: Analysis and Findings.

Wavelet		*Accuracy* %	*Precision* %	*Recall* %	*F1* %
No Wavelet	Test 1	57.09	78.62	55.02	64.74
	Test 2	50.14	99.37	50.07	66.58
Haar	Test 1	91.44	94.61	87.92	91.14
	Test 2	94.03	99.98	88.09	93.66
Db2	Test 1	91.79	94.41	88.88	91.56
	Test 2	93.94	99.96	87.92	93.55
Db3	Test 1	92.21	98.48	85.77	91.69
	Test 2	94.23	99.99	88.46	93.88
Db4	Test 1	84.23	85.32	82.77	84.02
	Test 2	91.44	100.00	82.89	90.64
Sym4	Test 1	92.96	94.95	90.77	92.81
	Test 2	95.44	99.99	90.90	95.23
Coif2	Test 1	76.70	72.87	85.22	78.56
	Test 2	92.68	99.96	85.39	92.10
Bior3.5	Test 1	86.98	87.89	85.85	86.86
	Test 2	93.02	99.99	86.05	92.50

When Table 4 and Figure 6 are examined, it is observed that the addition of a wavelet layer improves the classification performance noticeably. Among all wavelet families, Symlet 4 produced the best accuracy, and all the scores are balanced for this wavelet. In Test 2, all wavelets achieved better results compared to Test 1. The downloaded site provided the labels of the AFDB database used in Test 1. However, upon visual inspection by the experts, it was determined that the labeling was done in blocks, and some AF beats had more normal sinus rhythm characteristics than AF. Our cardiologist authors relabeled all the beats in AFPC dataset, and all the beats used in Test 2 were correctly identified. This may explain the difference between the classification performance. Symlet 4 wavelet is evenly ahead in all performance scores for both sets.

5.2 Experiment 2: Effect of Input Window Size on Performance

This experiment focuses on the influence of input window size variations on the performance of anomaly detection models trained on ECG signals. By varying the window size and evaluating model performance metrics, the experiment aims to determine the optimal window size for effectively capturing temporal dependencies and detecting anomalies in ECG data. The Sym4 wavelet and AFPC database were used in the tests. The results are given in Table 5 and Figure 7. The highest success was achieved for length 256.

Table 5. The effect of different window size on the performance metrics

Window Size	*Accuracy* %	*Precision* %	*Recall* %	*F1* %
256	**95.44**	**99.99**	90.9	**95.23**
512	92.35	91.44	**93.13**	92.28
1024	90.36	96.36	86.03	90.90

5.3 Discussion

This study proposes a new custom-designed autoencoder model for detecting atrial fibrillation. The integration of the wavelet layer into autoencoder architecture is investigated, and the network's performance is tested under different conditions. In an unbalanced dataset, even good accuracies are obtained with most of the deep learning algorithms, and either the precision or recall values will be lower according to the type of data insufficiency. When the number of data given in Table 2 is considered, the data is unbalanced in favor of NSR beats in our study, as in real-world cases. The proposed model consists of 514,113 trainable parameters. While practical guidelines often recommend having at least ten times the number of samples as trainable parameters,

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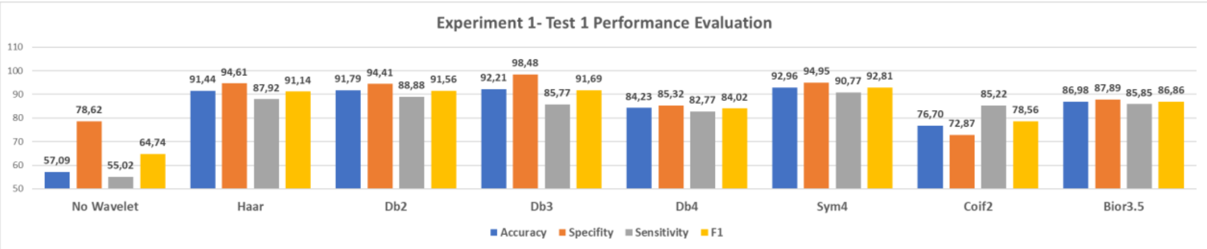
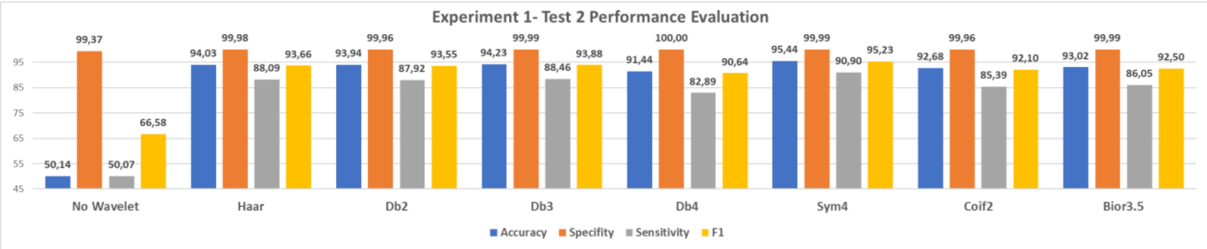
which would amount to roughly 5 million samples, the common QRS pattern in ECG data allowed for sufficient training with 800,000 NSR entries from the NSRDB database.

Another contribution of this study is integrating the wavelet layer into the autoencoder model. Although wavelet analysis is extensively used for noise reduction and compression tasks, the wavelet-based autoencoder is a new approach to arrhythmia detection.



(a)



(b)

Figure 6. Mother Wavelet Performance Comparison of WCAE (a) Test 1 results with AFDB dataset (b) Test 2 results with AFPC dataset.

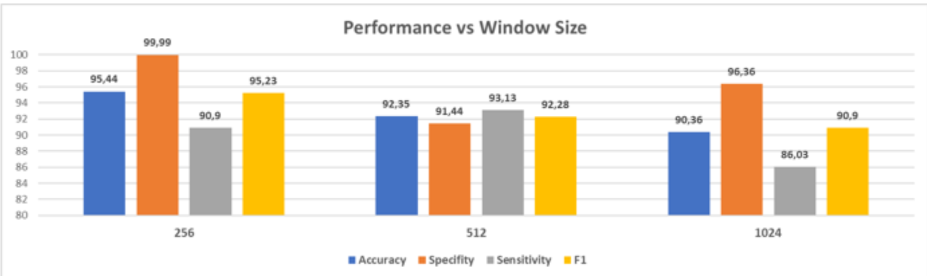


Figure 7. Impact of Window Size on Performance Metrics

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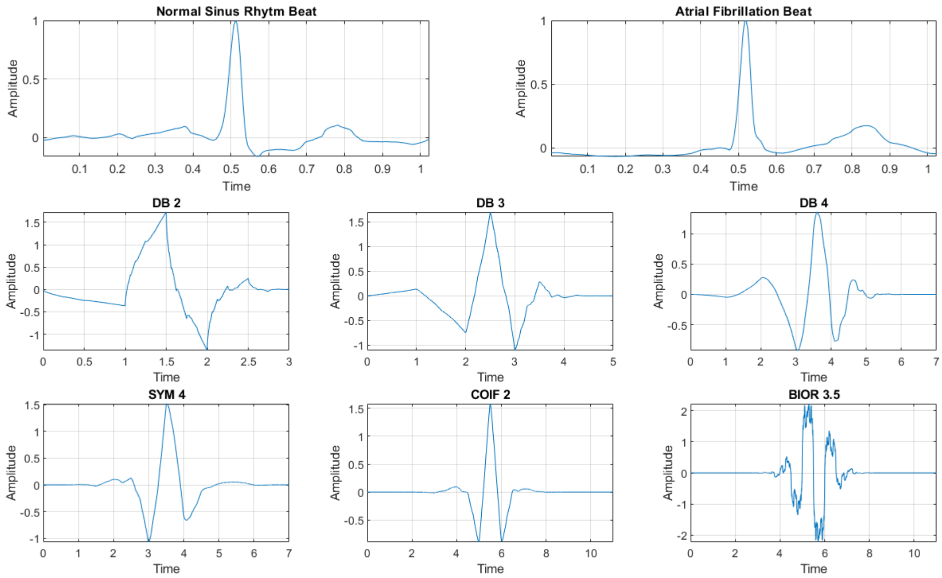

Figure 8. Samples of NSR and AF beats compared to mother wavelet morphology.

In experiment 1, different wavelet families are tested. We observed that with the addition of wavelet layer, a notable enhancement in the detection performance was obtained. Furthermore, it is observed that the Symlet 4 wavelet produces the best results. The results validate our intuition that the wave closely resembling the analyzed normal sinus rhythm waveform will be deemed successful. In Figure 8, the graph of normal sinus rhythm and atrial fibrillation beat samples are introduced to compare with the mother wavelets used in this paper. As can be observed from the figure, the Symlet 4 wavelet is the most similar wavelet morphologically. During the model design phase, the impact of altering the structures by varying the number and positions of the layers were conducted. Our findings revealed that the proposed model, as depicted in Fig. 5, outperforms the other models tested, thus other models were not included in the paper.

As another experiment, the input window size of the system is changed for the proposed model with Sym4 wavelet. The window size 256 is observed to perform better in accuracy, precision, and F1 scores. The AF detection performance of the state-of-the-art machine learning models in the literature is also considered. In [8], a feedforward neural network is trained and tested with PhysioNet Computing in Cardiology Challenge 2017, MIT-BIH arrhythmia, and 84% accuracy is obtained. Cheng et al. [9] classified 10s duration ECG signals into two classes, AF and non-AF, using a one-dimensional convolutional neural network and considering the effect of compression. According to the compression ratio, the accuracies vary from 91.63% to 98.40%. In [10], a pre-trained model, EfficientNet, is used for spectrogram images of ECG signals. The best accuracy is obtained as 97.3% with an F1 score of 88.24% for 9 to 61 seconds samples from PhysioNet Computing in Cardiology Challenge 2017. An LSTM model is trained with RR interval signals from the MIT-BIH Atrial Fibrillation Database and achieved 98.51% accuracy [11]. Unlike our study, only RR interval irregularities are considered, and data blocks of 100 RR intervals are needed for testing. The final accuracy of the model is 98.51%. Rasmussen et al. [12] consider semi supervised learning with the Variational Autoencoder model. They used 10-second samples from the MIT-BIH

Atrial Fibrillation Database, and encoded data is classified with a fully connected model. 111,894 segments and 12,434 segments were used for training and testing, respectively. The testing accuracy varies between 94% and 98.8% for different amounts of labeled data proportion. Among the literature studies, the most significant data size collected from different datasets is considered in our study. A promising accuracy values and F1 scores were achieved with a short window of approximately 1 second. Our manuscript introduces a novel wavelet-based convolutional autoencoder for detecting AF beats, where the integration of a wavelet layer significantly enhances anomaly detection performance. This approach leverages the inherent ability of wavelets to capture both time and frequency information, providing a more robust feature representation compared to traditional convolutional autoencoders. As a result, our model outperforms state-of-the-art methods by improving detection accuracy and reducing false positives in AF beat identification.

The computational complexity of our proposed model was rigorously assessed, taking into account both its resource demands and its effectiveness in real-time applications. Comprising 514,113 trainable parameters and 384 fixed wavelet transform parameters, the model operates with an average of 17.1 GB of system memory, 17.4 GB of GPU memory, and 27 GB of disk space during training. Extensive measurements of processing times for both training and testing reveal that our model achieves a computational complexity of approximately O(n), with processing times scaling linearly with data size. This linear scalability, as detailed in Table 6, underscores the model's efficiency and suitability for real-world deployment.

Table 6. Train and test processing times

Experiment	*Processing Time (Seconds)*
Train	4097
Test 1	267
Test 2	92

To experimentally determine the processing complexity, processing time was measured for different data sizes. When the data size increases 10 times, the processing time also increases approximately 10 times. This means that the processing complexity is approximately O(n).

6. Conclusions

In this study, we developed a robust autoencoder structure based on wavelets, which proved highly effective even for a short window of approximately 1 seconds. We conducted various tests using different basic wavelets and analyzed key performance metrics such as accuracy, sensitivity, precision, and F1 score. These evaluations helped us to compare the effectiveness of different wavelets. We also examined factors like input length and loss function across various models. Among the tested methodologies, the Sym4 wavelet emerged as the most promising and successful.

The wavelet layer is shown to improve the performance of the autoencoder structure in anomaly detection mode. Thus, the proposed model can be employed in different signal-processing applications, even for unbalanced datasets. The selection of wavelets plays an essential role in the network performance.

The proposed model can be used to detect abnormal heart rhythms in Holter recordings or within wearable health monitoring systems. Once the system is trained and optimized with data collected from the new system, its short testing time will enable near real-time applications. However, there are two main limitations to the study. In this study, the selection of the wavelet family was heuristic which directly determines the system performance. We are planning to propose a signal-specific wavelet construction procedure to improve the classification performance. Furthermore, the deep learning techniques, especially the autoencoder is characterized by a sophisticated architecture, leading to significant computational demands. Future research also includes efforts to reduce the process complexity.

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Author's Contributions

Öykü Eravcı: Design, data collection and processing, analysis, literature review, writing.

Nalan Özkurt: Conception, design, interpretation, supervision, writing, critical review

Özlem Memiş: Data collection, analysis and interpretation, writing.

Evrim Şimşek: Conception, design, interpretation, supervision, critical review

Ethics

There are no ethical issues for the publication of this manuscript.

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