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RESEARCH ARTICLE

Implementation of Discrete Wavelet Transform and Xception for ECG Image Classification of Arrhythmic Heart Disease Patients

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Abstract: The electrocardiogram (ECG) is one of the most important methods in the process of diagnosing heart disease. Visualizes the voltage and time relationship of the electrical activity of the heart. Cardiovascular or heart disease can be classified into several types, one of which is arrhythmia, a condition that involves changes in heartbeat rhythm, either too fast or too slow at rest. This study aims to develop a cardiac arrhythmia classification model using Deep Wavelet Transform (DWT) and Xception. It was evaluated on 2,200 spectrogram samples from the MIT-BIH dataset, containing normal and arrhythmia classes. The process compared epochs 30, 50, and 100 with learning rates of 0.001 and 0.0001 using cross-validation. Data were converted into spectrogram images for classification with Xception. The highest accuracy, 99.79%, was achieved at epoch 100 with a 0.0001 learning rate. Then, the highest precision occurs when the epoch is 50 with a learning rate of 0.001 and 0.0001, which is 100%. Lastly, Xception performed very well in the ECG image classification. This advantage demonstrates the ability of the model to recognize complex patterns in ECG data more effectively, increasing the reliability of arrhythmia detection. In addition, using DWT as a feature extraction technique allows better signal processing, which contributes to optimal results.

Keywords: arrhythmia, discrete wavelet transformation (DWT), electrocardiogram (ECG), MIT-BIH, xception

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1 Introduction

Heart disease is one of the leading causes of death in the world. Based on statistical data from 2019 from the World Health Organization (WHO), there were 17.9 million people, or 32% of all deaths in the world, caused by heart disease [1]. ECG technology in Indonesia can be justified by several factors, including limited access to modern hospital equipment, especially in remote areas, which hinders the timely diagnosis of arrhythmias. The high cost of investing in health technology often hinders small hospitals and clinics from upgrading their equipment. In addition, the lack of training of medical personnel in using ECG technology reduces the device's effectiveness. The limitations of general health infrastructure, including health data and information management systems, also contribute to this backwardness, affecting the quality of health services throughout the country [1]. One type of heart disease is Arrhythmia. Patients with arrhythmia experience a heart condition that beats too fast or even too slow in resting conditions [2, 3]. Electrocardiography (ECG) is a vital method for monitoring heart activity, providing insights into the heart's electrical functioning. It visualizes the relationship between voltage and time, allowing healthcare professionals to detect abnormalities in real time [4, 5]. The ECG waveform represents the electrical impulses that trigger each heartbeat, making it an invaluable tool in diagnosing various cardiac conditions. However, despite its widespread use, the current technological landscape for ECG analysis, particularly in Indonesia, is lagging behind global advancements. This gap in technology emphasizes the necessity for improved methods to enhance the diagnostic capabilities of ECG systems and facilitate earlier intervention for patients at risk [6].

The development of ECG technology at this time, especially in hospitals in Indonesia, is still lagging behind the development of existing technology. The proposed solution aims to enhance the efficiency of ECG technology in detecting heart disease by utilizing automatic ECG image processing and classification, which can facilitate early diagnosis. Traditional methods of ECG interpretation often rely on manual analysis, a process that can be time-consuming and prone to human error. Consequently, there is a growing need for automated systems that can analyze ECG data efficiently and accurately [7]. Recent advancements in machine learning and signal processing offer promising solutions to these challenges [7].

The method proposed in this research is the Discrete Wavelet Transform (DWT) signal extraction method using the mother wavelet db10 level 3 and image classification using the Convolution Neural Network (CNN) method with Xception architecture to produce automatic detection. The update given in this research is the combination of the DWT extraction method and CNN classification with Xception architecture on the spectrogram image of the ECG signal [7, 8]. Spectrograms were chosen because they provide a visual representation of changes in frequency and amplitude of the ECG signal over time, which facilitates pattern analysis, by using spectrograms, arrhythmia characteristics that may not be visible in the original signal can be more clearly identified, increasing detection accuracy Spectrograms were chosen because they provide a visual representation of changes in frequency and amplitude of the ECG signal over time, which facilitates pattern analysis, by using spectrograms, arrhythmia characteristics that may not be visible in the original signal can be more clearly identified, increasing detection accuracy [9].

Reference [8] introduces a new method for ECG classification that uses DWT with deep techniques. It emphasizes pre-processing signals for feature extraction before applying them to deep learning models. This study main innovation is the use of a specific combination of DWT and a unique deep learning model, making it an innovative approach in ECG analysis, [8] used DWT for extraction and obtained an accuracy of 95.4%, Although effective in decomposing signals for frequency analysis, DWT often yields limited information about temporal features that are important for arrhythmia detection. This can lead to loss of crucial details in signal variations, thus reducing classification accuracy.

Other studies using DWT in detecting Arrhythmia also produced an excellent accuracy of 96.50%, investigating ECG classification using DWT for feature extraction. Still, the focus was on comparing different machine learning techniques, such as SVM and Random Forest. This approach provides a broader perspective on the effectiveness of various methods in ECG classification [10]. This study [11] does not offer a new method but provides a larger context on how DWT and machine learning techniques have been applied in previous research. Although all three references use DWT, they have different focuses: [8] emphasizes specific methods, [10] compares techniques, and [11] provides a comprehensive review of developments in the field of ECG classification. CNN classification method with Xception architecture also produces good image classification performance. Xception architecture has been used in the classification of scenery images, resulting in an accuracy of 91.20% [12]. The Xception architecture, known for its depth-wise separable convolutions, has demonstrated superior performance in various image classification tasks. By leveraging this robust architecture in conjunction with DWT for feature extraction, this research aims to develop a strong system for classifying ECG spectrogram images. This innovative approach not only aims to improve classification accuracy but also to facilitate faster and more reliable diagnoses of arrhythmias, ultimately enhancing patient care [12, 13], but this architecture has not been used in the classification of ECG spectrogram images.

The main contributions of this research can be summarized as follows:

1. Evaluating the performance of combining the Discrete Wavelet Transform (DWT) extraction method and Convolution Neural Network (CNN) classification with the Xception architecture in classifying standard and Arrhythmia ECG images.
2. Analyzing the Xception model with different epochs and learning rates on arrhythmia and standard ECG image data.
3. Application of (DWT) and classification (CNN) methods with Xception architecture to improve efficiency in reading ECG recording results.

2 Related Work

This study [13] focused on an efficient system for classifying ECG cardiac arrhythmias. Discrete Wavelet Transform (DWT) was used for the ECG signal preprocessing mechanism, Independent Component Analysis (ICA) was used for dimension reduction and Feature Extraction process of the ECG signal, and a Multi-Layer Perceptron (MLP) neural network was used to perform the classification task. As a result of classification, results have been obtained on categorizing Normal Beats under the Non-Ectopic Beats class, Atrial Premature Beats under the Supra-Ventricular Ectopic Beats class, and Ventricular Escaped Beats under the Ventricular Ectopic Beats class based on the standardization given by ANSI/AAMI EC57: 1998. For ECG signal acquisition, the MIT-BIH fishnet arrhythmia database was used in this study, in addition to being used for the training process and testing process of the MLP-NN-based classifier. The results obtained from the simulation indicate that the classification accuracy of the proposed algorithm is 96.50%. In this paper [14], a universal ECG signal arrhythmia classification system is proposed. The proposed system is based on the use of wavelet transform in its two known forms, namely, discrete wavelet transforms (DWT) and wavelet packet transform (WPT), or a combination of both. The research reported here aims to find a universal classification system in the sense that it provides the capability for simultaneous classification of all known types of cardiac arrhythmias. Three algorithms based on the wavelet transform were tested for different wavelet levels, wavelet functions, training and testing ratios, and elapsed times. The algorithms used were then compared according to the elapsed time required for their processing across loops of eight different arrhythmia classes. The results obtained showed that the WPT algorithm was the most superior method among the other methods. The DWT method can also be categorized as a good method after the use of the WPT method.

In [15], the authors discuss a real-time ECG classification system based on DWT and Support Vector Machine (SVM) methods. An SVM machine learning algorithm has been used to classify ECG signals. This DWT and SVM method has implemented a hardware system that includes extracting ECG signals, feature extraction, and classification on an Xilinx ZYNQ SoC. The DWT method in this research serves as a system power saver. The accuracy result of the system classification is 98.7%, and the classification time of each heartbeat is 280 ps with an on-chip power of 2.059 W, which meets the requirements of real-time systems. SVM, although known for its ability to separate data with optimal margins, often struggles with large and complex datasets, which can result in long training times and overfitting. In addition, SVM requires good feature selection and careful parameter tuning, which can be challenging in practical applications. This research gap indicates the need for a more effective and efficient approach to ECG signal classification. This paper will address this by proposing a new model that can integrate the strengths of various processing and machine learning techniques to improve classification accuracy and speed [15]. This study [16] describes a modified approach to detect cardiac abnormalities and QRS complexes using machine learning and support vector machine (SVM) classifiers. The suggested technique surpassed the prevailing approaches in terms of sensitivity and specificity, with a detection error rate of 0.45 percent for cardiac irregularities. Moreover, the vector machine classifier validated the superiority of the proposed method by accurately categorizing four types of ECG beats: standard, LBBB, RBBB, and paced beats. The technique has 96.67% accuracy in MLP-BP and 98.39% accuracy in the vector machine classifier support. The results imply that SVM classifiers can play an essential role in the analysis of cardiac abnormalities. Furthermore, SVM classifiers also categorize ECG beats using DWT characteristics collected from ECG signals.

This study [17] Deep learning (DL) has been applied to automatically classify heart abnormalities using ECG signals, although its use in real-world medical practices remains limited. A systematic review has been conducted to explore the ECG database, preprocessing methods, DL approaches, evaluation frameworks, performance metrics, and code accessibility, aiming to uncover trends, challenges, and opportunities in DL-based ECG arrhythmia classification. Specifically, 368 studies that met the eligibility criteria were included. Of these, 223 studies (61%) utilized the MIT-BIH Arrhythmia Database to develop DL models. Additionally, 138 studies (38%) focused on removing noise or artifacts from ECG signals, while 102 studies (28%) used data augmentation to enhance the representation of minority arrhythmia types. Convolutional neural networks emerged as the most frequently used model, appearing in 58.7% (216) of the reviewed studies, with an increasing trend of integrating multiple DL architectures in recent years. A total of 319 studies (86.7%) and 38 studies (10.3%) explicitly stated their evaluation paradigms, distinguishing between intra- and inter-patient paradigms, with notable performance decline noted in the inter-patient evaluations. Compared to the overall accuracy rates, the average F1 score, sensitivity, and precision were significantly lower in the studies examined. For implementing DL-based ECG classification in practical clinical settings, opportunities for future research include utilizing a variety of ECG databases, developing advanced noise reduction and data augmentation techniques, incorporating innovative DL models, and conducting more in-depth investigations into the inter-patient paradigm. [18] has highlighted cardiac arrhythmias as one of the leading causes of global mortality, which occur due to disruptions in the electrical signals that coordinate the heartbeat. This study suggests that factors such as poor sleep, a high-fat diet, and lack of exercise may increase the risk of arrhythmias. Based on the structure of the Heart's electrical system, there are four main functional pathways, namely the SA node, AV node, bundle branch, and Purkinje fibers, whose roles can be analyzed through electrocardiogram (ECG) signal readings. This study uses a dataset of 10,000 ECG images from ATM's Physio Bank that are grouped into four classes: abnormal SA+AV nodes, abnormal bundle branches, abnormal Purkinje fibers, and normal conditions. This study aims to compare the performance of two Convolutional Neural Network (CNN)-based transfer learning models, namely MobileNetV2 and Xception, in detecting cardiac Arrhythmia. The results showed that the MobileNetV2 model produced an accuracy of 98.58%, higher than Xception, which achieved an accuracy of 94.51%. Xception is better suited than MobileNetV2 and AlexNet in image classification due to its more profound architecture and use of depthwise separable convolutions, allowing the model to capture more complex and diverse features. This contributes to its higher accuracy, reaching 98.58% compared to MobileNetV2 and 89.03% for AlexNet. Furthermore, despite Xception being deeper, it remains efficient in its use of parameters, making it an ideal choice for applications on resource-constrained devices. Its better generalization ability on diverse datasets demonstrates Xception's effectiveness in handling high variance in image classification. With this combination of advantages, Xception proves to be a more appropriate choice for classification tasks that require high accuracy and efficiency.

This study [19] proposes a stress classification method based on multi-dimensional feature fusion of LSTM and Xception using ECG. This is because previous research on stress classification based on ECG only uses one-dimensional feature data, making it challenging to analyze the data more closely and comprehensively due to a bias towards certain aspects. The experimental results showed that the application of multi-dimensional feature fusion of the weighted average method using ECG data with outlier signals removed resulted in a stress classification of 99.51%, an improvement of 1.25% from the previous study which only used one-dimensional feature data of ECG, thus highlighting the excellent performance of the proposed stress classification method using ECG based on multi-dimensional feature fusion of LSTM and Xception. This paper [20] proposes Xception-based transfer learning and analyzes the performance of the model by comparing it with the Inception-V3 model. The Xception model has advantages in processing image classification, but it has not been used for scene image classification. Experimental results on the Intel Image Classification Challenge dataset showed that the use of Xception obtained an accuracy of 91.20% compared to the training accuracy of 1.12%. The authors found that Xception-based transfer learning significantly outperforms other methods, such as Inception-V3, which is well demonstrated by the experimental results on the Intel Image Classification Challenge dataset. In addition, Xception has shown greater robustness and ability to generalize with fewer overfitting issues. Several related studies above support the use of DWT and Xception in this study for several strong reasons. First, DWT is very effective in capturing frequency information from ECG signals, allowing the identification of essential features that other methods may miss. DWT's ability to analyze signals at multiple scales contributes to more accurate arrhythmia detection. In addition, DWT converts ECG signals into image representations (spectrograms), which facilitate visual analysis and allow deep learning models to utilize image classification techniques. On the other hand, the Xception architecture, which relies on depth-wise separable convolutions, has been shown to provide superior performance in various image classification tasks. Combining these two methods creates a synergy between efficient feature extraction and accurate classification. By using DWT to prepare data before processing it with Xception, this system is expected to produce faster and more accurate diagnoses in detecting arrhythmias, significantly improving patient care.

3 Research Method

Figure 1 shows the flowchart of the research conducted. The study utilized a dataset divided into two classes: Arrhythmia and Normal. The Arrhythmia class comprises 11 patient data points, while the Normal class contains 22 patient data points. Training and testing data are carried out in parallel, with the training and testing data separated in advance, with 70% of the data allocated for training and the remaining 30% for testing. The applications used to analyze the data are MATLAB R2022a and Kaggle. MATLAB is used to preprocess and extract data because of its detailed coefficients and results. Kaggle processes overlapping windows, converts ECG signals into spectrograms, and classifies them using Xception. Kaggle is used because it has a fast accelerator to run data codes.

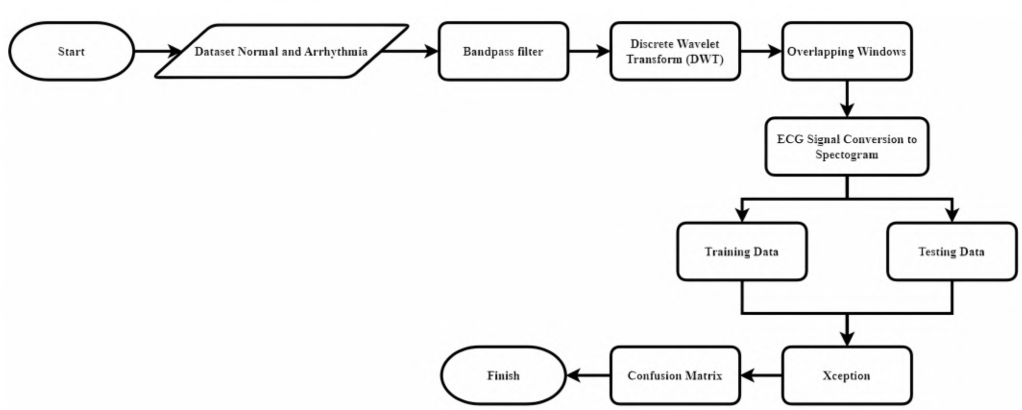

Figure 1: Research flow.

3.1 Data Collection

Figure 2 shows a view of the signal data taken from the MIT-BIH Arrhythmia Database. The data comes from Beth Israel Hospital, located in Boston, USA. This data contains 48 half-hour ECG recordings taken from 47 patients [21]. Of the 48 recordings, 22 were used for normal data and 11 for arrhythmia data. Arrhythmia patient recordings were taken as long as 2 minutes/patient, while normal patient recordings were taken as long as 1 minute/patient. This is because there is more normal patient data than arrhythmia patient data. The impact of data duration, such as the comparison between 2 minutes and 1 minute, is significant in ECG signal analysis. Longer durations, such as 2 minutes, provide more information and context, allowing the model to capture wider variations in the signal, including temporal changes that may not be visible in shorter durations. This improves classification accuracy, as the model has a better chance to learn from consistent, relevant features. In arrhythmia detection, longer durations are critical for identifying transient episodes that may be missed in short measurements. However, it should be noted that while longer durations can improve performance, they also increase the risk of overfitting if the model is not tuned correctly. In addition, more extended data requires more time to process, which can be a constraint in real-time applications. Thus, the choice of data duration should consider the balance between sufficient information and processing efficiency.

The parameters in this study were selected based on several important considerations. First, striking a balance between model complexity and performance was crucial; too many parameters can lead to overfitting, while too few can limit the model's ability to learn from the data. Additionally, the size and complexity of the dataset influenced this decision, as a larger dataset allowed for more parameters to be applied without a significant risk of overfitting. The results of preliminary trials or previous experiments were also important references; if previous studies showed that a certain number of parameters yielded optimal results, this became the basis for parameter selection. Furthermore, adhering to established standards in this research field also helped ensure that the approach used was acceptable to the scientific community. Finally, the study's specific objectives also influenced the number of parameters chosen, thereby supporting the achievement of the desired results.

3.2 Bandpass Filter

Butterworth Bandpass filters are often used to remove noise or interference from signals. This filter produces an even frequency response throughout the desired frequency range by allowing signals with frequencies within the range and dampening signals outside the range. Applying the Butterworth Bandpass filter to a signal aims to improve the signal quality by removing the noise contained in the signal [22]. Figure 3 shows the Bandpass filter, which consists of a high-pass filter and a low-pass filter. When the input frequency falls within a specific frequency range, or "spread," which is between the upper and lower cut-off frequencies, it produces a fixed output. The calculation to determine the upper and lower limits is determined in Eq. (1) where f_N is the Nyquist Frequency and f_S is the Sampling Frequency.

$$f_N = \frac{1}{2} \times f_S \tag{1}$$

The Nyquist Frequency is the center value taken from a sampling frequency of 360 Hz.

Figure 2: ECG raw signal.

$$f_c\text{Lower} = 18 \times f_N \tag{2}$$

f_c Lower is the cut-off frequency that has a low value.

$$f_c\text{Higher} = 90 \times f_N \tag{3}$$

f_c The higher the cut-off frequency, the higher the value.

This process was performed on MATLAB R2022a software using Normal and Arrhythmia signal datasets with **.mat* file format.

3.3 Feature Extraction: Discrete Wavelet Transform (DWT)

Wavelets are rapid oscillatory functions that rapidly diminish over time or space and have an average value of zero [23]. Wavelets have two important concepts: scale and shift. Wavelet ECG segment coefficients $c_{j,k}$, and the scaling function $\phi_{j,k}(t)$.

$$\phi_{j,k}(t) = 2^{j/2}\,\phi(2^j t - k) \tag{4}$$

$\phi_{(j,k)}$ shows the mother scaling function, which illustrates the scaling function. Dilatation parameter j. The scale parameter controls the scale of the wave, and the translation parameter k controls the position of the wave along the time axis [24].

$$a_{j,k} = \sum_l h(l - 2k)\,a_{j-1,m} \tag{5}$$

$$d_{j,k} = \sum_l g(l - 2k)\,a_{j-1,m} \tag{6}$$

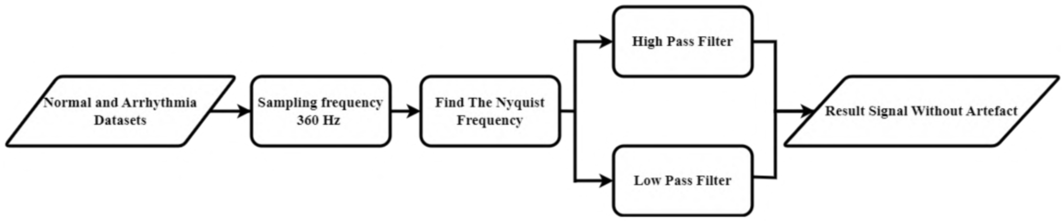

Figure 3: Bandpass filter flowchart.

The above equation shows the decomposition of the DWT using multiregional analysis. $a_{j,k}$ represents the low-frequency component and $d_{j,k}$ represents the high-frequency component. l is the number of levels selected in the scaling process. $h(l)$ and $g(l)$ denote the low and high filters, respectively. Here, m is used in the scaling function as a translation of the scale j [25]. ψ represents the mother wavelet function, and its conjugate version is defined by [26].

After obtaining the preprocessed signal, it is segmented into several sub-bands, divided into three levels, to analyze the resulting signal estimates. Next, the parent wavelet db10 is applied to extract the main frequency characteristics of the ECG signal, providing information about the relevant spectral components. Using the Daubechies 10 (db10) wavelet at level 3 in ECG signal analysis is very beneficial. Db10 effectively captures detail and frequency information, essential for accurate feature extraction. Level 3 strikes a balance between complexity and analysis capability, being deep enough to capture variations without producing excessive noise. In addition, db10 helps reduce noise and improve data quality, making the classification model more accurate. With a good representation in the time and frequency domains and support from previous studies, level 3 db10 is a good choice for the detection of arrhythmias [27]. Figure 4 illustrates the stage of the feature extraction process using the DWT method, which uses MATLAB R2022a software as the processing container.

3.4 Overlapping Windows

Windowing is a data processing technique that is used to cut a dataset into several small parts called windows or frames [28]. Overlapping windows is a technique that works by cutting out the original data and having parts that overlap with each other. Figure 5 illustrates the process of overlapping the window on the ECG signal. The overlapping

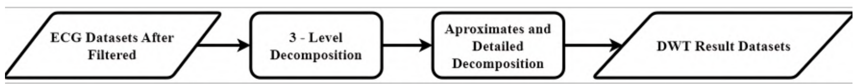

Figure 4: Feature extraction flowchart.

process provides information on the previous windowing signal and can help increase the variation in the dataset.

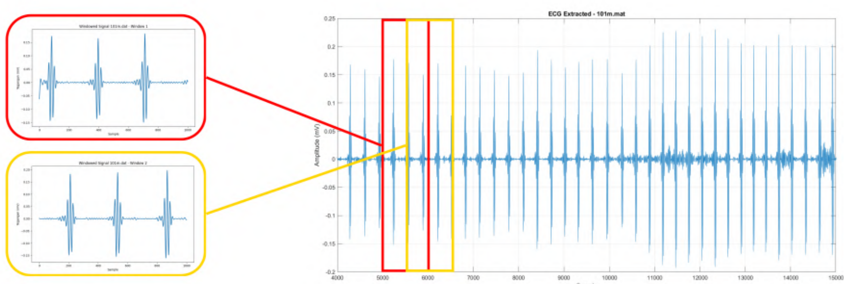

Figure 5: Overlapping windows.

Based on Figure 5, the use of overlapping window parameters allows the model to capture subtle transitions in the signal, increasing sensitivity to significant changes. Overlapping windows also help mitigate the effects of boundaries that can affect the analysis results. With db10's ability to reduce noise and improve data quality, as well as support from previous studies, db10 level 3 is the right choice for detecting arrhythmias.

3.5 ECG Signal Conversion to Spectrogram

Figure 6 represents the process of converting ECG signal data into spectrograms using the Matplotlib module. In the spectrogram visualization, the image dimensions are set at 10×6 inches, with an 'inferno' color scheme that depicts the variation in amplitude of cardiac activity in each channel.

Figure 6: The process of converting an ECG signal into a spectrogram is illustrated through two stages of visualization. On the left, we see the ECG signal in the time domain, where the x-axis represents time in seconds and the y-axis shows the signal amplitude. This

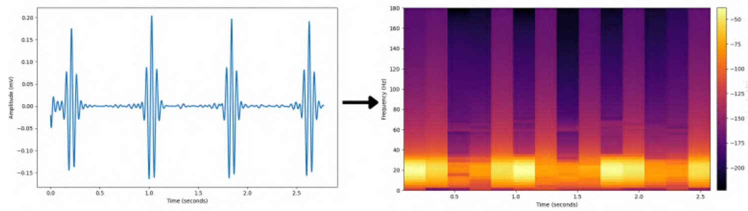

Figure 6: Convert ECG signal into spectrogram.

signal indicates the heart's identifiable electrical activity. On the right, the same signal is converted into a spectrogram, where the x-axis still shows time, while the y-axis shows frequency. The color intensity shows the energy density of the frequency at a given time, with lighter colors indicating higher amplitudes. This process enables a more in-depth analysis of the frequency components of the ECG signal, facilitating the detection of patterns and cardiac arrhythmias that may not be visible in the time domain.

Table 1 shows the number of data samples that will be used as datasets in the classification process. This dataset comprises a spectrogram image derived from an ECG signal, stored in a *.*png* file format.

Table 1: Data sample

Data Name	**Data Type**	**Description**
train data	normal	770 sample
	arrhythmia	770 sample
test data	normal	330 sample
	arrhythmia	330 sample
total	normal	1100 sample
	arrhythmia	1100 sample

3.6 Classification using Xception

A Convolutional Neural Network (CNN) is a type of artificial neural network architecture designed to handle image and visual processing tasks [29, 30]. Xception is one of the CNN architectures based on the inception module, which improves CNN performance by utilizing a linear stack of depth-separable convolutional layers with residual connections to reduce time and space complexity. Xception separates channel-wise and space-wise feature learning. Residual connections are used to solve the problem of missing gradients and representational bottlenecks by creating shortcuts in the sequential network [20]. Figure 7 illustrates the stages of the classification process using the Xception architecture, which is carried out on the Kaggle Web page.

Table 2 shows the parameters and specifications used in the classification process using the exception architecture. These parameters aim to improve accuracy, prevent overfitting, and determine the best classification specifications. The selection of hyperparameters in a machine learning model is critical to achieving optimal performance. Batch size, for example, affects training speed and generalization ability; smaller batch sizes improve gen-

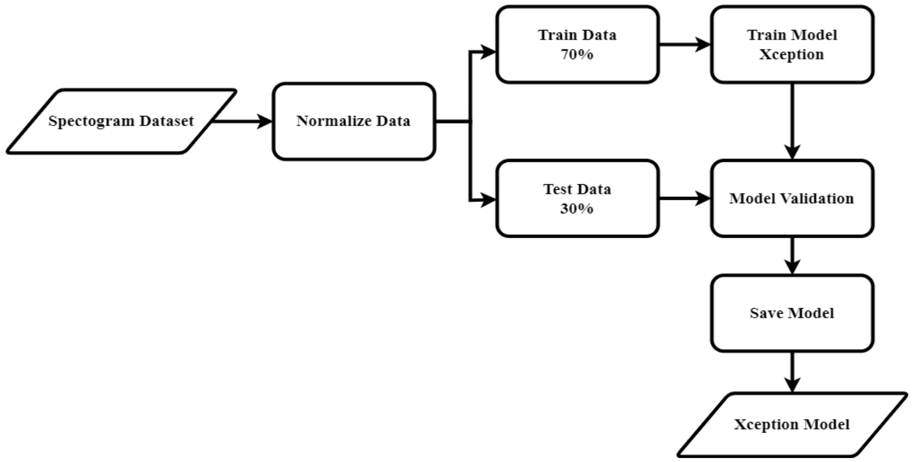

Figure 7: Xception classification flowchart.

eralization, while larger batch sizes speed up the process but risk overfitting. The Adam optimizer is advantageous because it adjusts the learning rate for each parameter, allowing rapid adaptation to data variability. Additionally, anti-overfitting methods, such as regularization and dropout, help prevent the model from overfitting the training data, thereby improving accuracy and generalization ability in ECG signal analysis. In addition, anti-overfitting methods, such as regularization and dropout, help prevent the model from overfitting the training data. In terms of data set splitting, the data is often randomly split in a 70:30 ratio, where 70% is used for training and 30% for testing. It is essential to group this data to maintain class balance, so that the model can learn effectively from each existing class, improving accuracy and generalization ability in ECG signal analysis.

Table 2: Hyperparameter training model

Parameters	**Specification**
Epoch	30, 50, 100
Learning rate	0.001, 0.0001
Optimizer	Adam
Batch Size	32

3.7 Confusion Matrix

The Confusion Matrix is a table that summarizes the performance of a machine learning classification model. There are four main parameters used to calculate the confusion matrix, namely:

1. The actual value is positive, and the electrocardiogram classification model considers it as the number of positives (True Positive = TP).
2. The actual value is negative, and the electrocardiogram classification model classifies it as negative (False Negative = FN).

3. The actual value is negative, and the electrocardiogram classification model classifies it as a negative number (False Positive = FP).
4. The actual value is negative, and the electrocardiogram classification model categorizes it as a true negative (TN).

The four parameters in the confusion matrix are calculated using the following equation:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{7}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{8}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

4 Results and Discussion

4.1 The Result of Xception with Epoch 30 and Learning Rate 0.001

Figure 8 is a graph of the relationship between epoch and accuracy, which shows training accuracy of 97.34% and validation accuracy of 70.65%. The training accuracy is 26.43% greater than the validation accuracy. Figure 9 shows the epoch and loss relationship graph. The training loss has a value of 0.007, while the validation loss is 0.51.

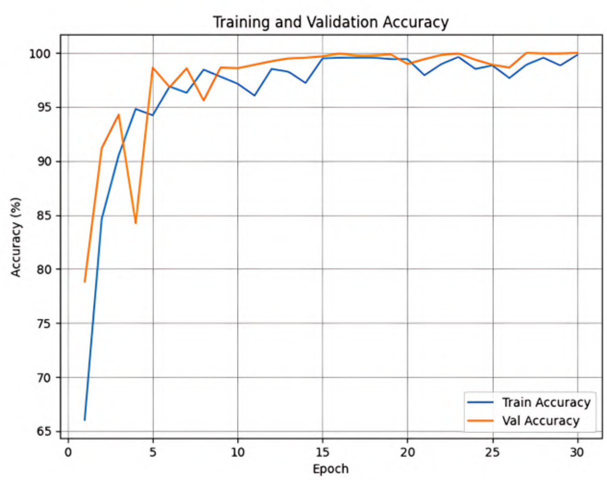

Figure 8: Xception with epoch 30 and learning rate 0.001 training and validation accuracy.

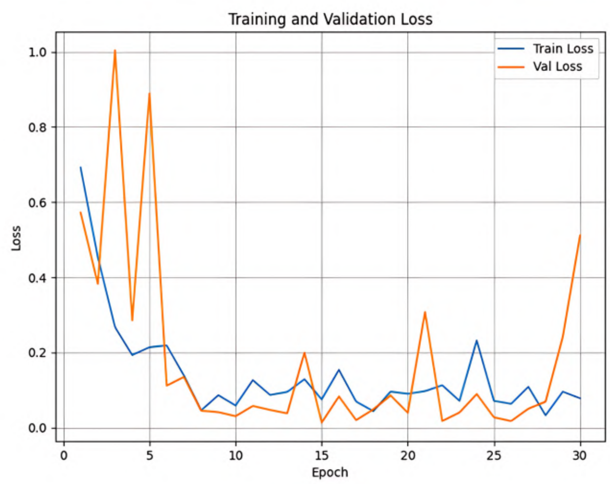

Figure 9: Xception with epoch 30 and learning rate 0.001 training and validation loss.

4.2 The Result of Xception with Epoch 100 and Learning Rate 0.0001

Figure 10 illustrates the relationship between epoch and accuracy, showing a training accuracy of 99.94% and a validation accuracy of 100%. Figure 11 shows the epoch and loss relationship graph. Training loss has a loss value of 0.002, while validation loss is 0.0004.

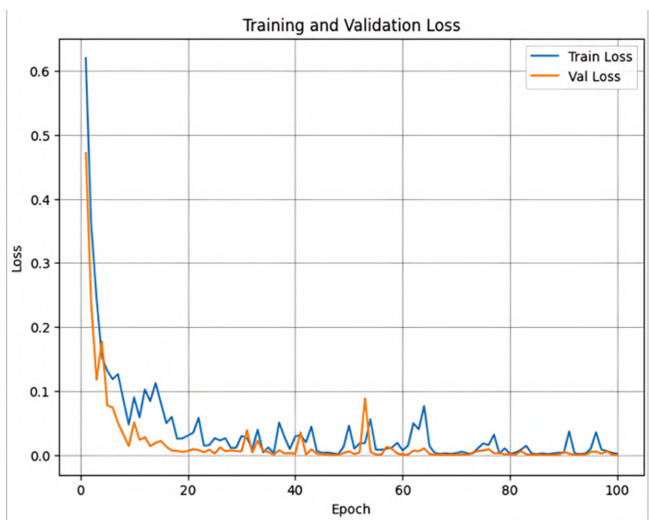

Figure 10: Xception with epoch 100 and learning rate 0.0001 training and validation accuracy.

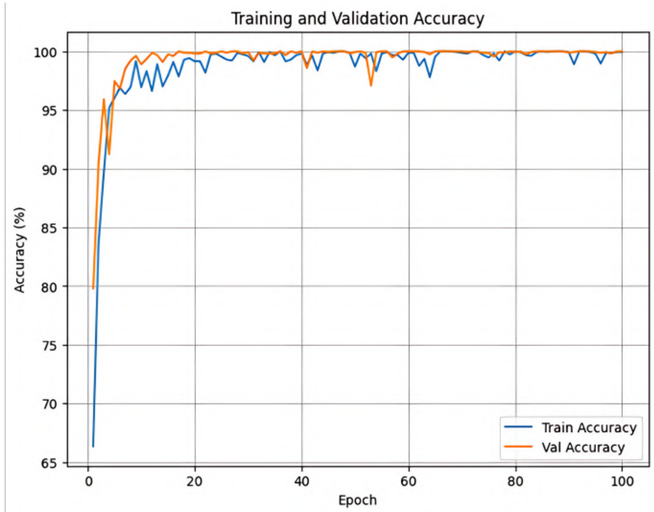

Figure 11: Xception with epoch 100 and learning rate 0.0001 training and validation loss.

4.3 The Result of the Confusion Matrix

A confusion matrix is a table that evaluates the performance of a machine-learning classification model [31]. In the confusion matrix, the X-axis shows the predicted labels, while the Y-axis shows the actual labels. A positive value (1) indicates the Normal class, and a negative value (0) suggests the arrhythmia class.

Figure 12 is the confusion matrix of the exception model with 30 epochs and a learning rate of 0.001, which shows that the correct prediction in the regular class (1) is 322 images, and eight images are wrong. The accurate prediction results in the arrhythmia class (0) were 144, and incorrect in as many as 186 images. Figure 13 is the confusion matrix on the exception model with epoch 100 and learning rate 0.0001, which shows the correct prediction on the regular class (1) with as many as 329 images, and as few as one image is wrong. The accurate prediction results in the arrhythmia class (0) were 329, and 1 image was incorrect.

Table 3 compares the performance values of the exception architecture. The highest accuracy is achieved at epoch 100 with a learning rate of 0.0001, reaching 99.79%. The highest precision is attained at epoch 50 with a learning rate of 0.001 and 0.0001, both achieving 100%. The highest sensitivity is at epoch 100 with a learning rate of 0.0001, which is 99.70%. The highest F1 score is also at epoch 100 with a learning rate of 0.0001, which is 99.70%.

Table 4 compares various studies related to this research, each using different models and techniques.

Based on Table 4, in the study [5], CNN and AlexNet methods were used to analyze ECG signals. This study focused on classifying high-risk heart rates using a dataset of various heart signals. Although it achieved an accuracy of 89.03%, limitations in the dataset and the smaller number of classes compared to this study may affect the generalization results. The study [9] proposed a method that analyzes the time-frequency features of ECG signals by converting 1D signals into 2D images (scalograms) before being used as input for

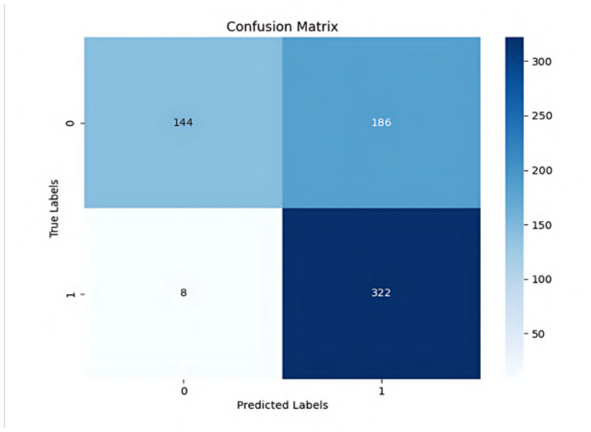

Figure 12: Confusion matrix of proposed model Xception with epoch of 30 and learning rate of 0.001.

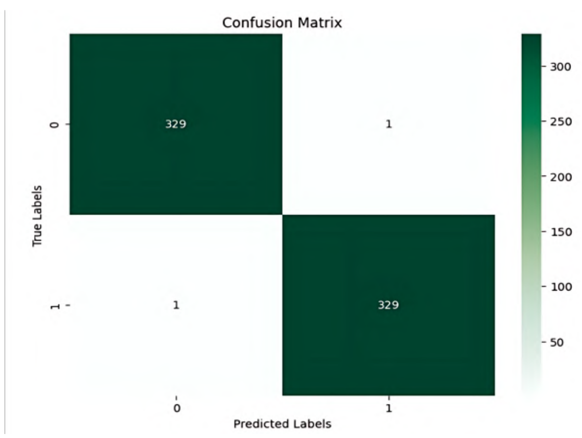

Figure 13: Confusion matrix of proposed model Xception with epoch of 100 and learning rate of 0.0001.

Table 3: Hyperparameter training model

Epoch	Learning Rate	Accuracy	Precision	Recall	F1-score
30	0.001	70.61%	63.39%	97.58%	76.85%
	0.0001	99.39%	99.39%	99.39%	99.39%
50	0.001	98.48%	100%	96.97%	98.39%
	0.0001	99.39%	100%	98.79%	99.39%
100	0.001	99.09%	99.39%	98.79%	99.09%
	0.0001	99.70%	99.70%	99.70%	99.70%

Table 4: Benchmarking

Authors	Features	Accuracy
M. Zubair, et. al. [5]	CNN, AlexNet	89.03% from CNN
R. Pathak and Y. Singh [9]	2D deep neural network model, AlexNet	98.7% from 2D- deep neural network
Our proposed	DWT, Xception	99.79% from DWT and Xception

a deep neural network model. Using AlexNet, this study achieved an accuracy of 98.7%. However, this method also has limitations related to the complexity of the dataset used, which may not be equivalent to the challenges faced in this study. Our proposed method is superior to 89.03% and 98.7% accuracy, successfully obtained by 99.79%. DWT reduces noise and improves the quality of ECG signals, resulting in a more stable and informative representation. In addition, the Xception architecture, which is more sophisticated than traditional CNN, can capture complex features in ECG data, improving classification capabilities. This method also maintains class balance in the dataset, which is essential to prevent bias towards the dominant class.

5 Discussion

This study implements DWT and Xception architecture for ECG image classification in patients with arrhythmic heart disease, which is very relevant considering the high mortality rate from heart disease, where Arrhythmia is one of the leading causes. The method used in this study, namely the combination of DWT and CNN with the Xception architecture, showed excellent results, with the highest accuracy reaching 99.79% at epoch 100 and a learning rate of 0.0001. The use of bandpass filters to remove noise from the original signal also strengthens the quality of the data used for analysis, producing a more stable representation and providing ECG signals. Compared to other studies, such as those conducted by [13, 15], which also used DWT for ECG classification, the results of this study showed better performance in terms of accuracy, so it is stated that the combination of DWT and Xception can be a more effective approach in detecting arrhythmias. The findings suggest that the combination of DWT and Xception is a more effective approach for arrhythmia detection. High accuracy has essential implications for the medical field, as it indicates potential for integration into automated detection systems, facilitating quicker and more accurate diagnoses by clinicians, ultimately improving treatment outcomes. The results of this study have important implications in the medical field because, with the high accuracy achieved, this method has the potential to be used in automated detection systems that can help doctors diagnose arrhythmias faster and more accurately, which in turn can improve treatment and clinical outcomes for patients.

Although the results obtained are auspicious, this study also faces several challenges, such as the need to test this method on larger and more diverse datasets to ensure the generalizability of the results. Therefore, further research can focus on the development of more efficient algorithms and testing in real clinical environments to assess their performance in daily practice. This study makes a significant contribution to the field of ECG classification and can serve as a basis for further research in the development of cardiac diagnostic technologies. The comparison with previous studies explains that, in [5], using CNN and AlexNet methods, the signal has information about heart performance. CNN is used to classify high-risk heart rates, thus obtaining an accuracy of 89.03%. In this study [32], the proposed method used in this research analyzes the time-frequency features of an ECG signal by first converting the 1D ECG signals to the 2D Scalogram images, and subsequently, the 2D images are used as an input to the 2D deep neural network model, AlexNet. In this work, we have identified the best-fit parameters for the AlexNet model that could successfully predict common heart diseases with an accuracy of 98.7%. Based on several comparisons in previous studies, the accuracy of the DWT and Xception architecture method in predicting ECG image classification of arrhythmic heart disease patients is very high, at 99.79%. This shows that this study is excellent compared to previous studies because the accuracy level is very high.

6 Conclusion

In the effort to advance ECG classification using the exception architecture model with ECG signal data processed into spectrogram images, our proposed method has provided good results with an accuracy of 99%. The technique was designed by including the filtering process using a bandpass filter, extraction using DWT, and changing the ECG signal into a spectrogram image, which can provide good accuracy in the classification process for people with Normal and Arrhythmic heart disease. The hope is that the combination of these methods can help speed up the detection process of arrhythmic heart disease. Future work in this study can be done to develop ECG image classification further using DWT and Xception architecture. In addition, it is essential to use larger and more diverse datasets and conduct testing in real clinical environments to assess system performance. In addition, model optimization through fine-tuning and the application of more sophisticated deep learning methods, such as RNN or LSTM, can improve accuracy. Integration of the classification system into clinical applications and the combination of ECG data with other medical information will also provide a better understanding of the patient's heart health. These steps are expected to improve the diagnosis and treatment of cardiac arrhythmias significantly. Future work should focus on validating the method on larger and more diverse datasets to ensure generalizability. Additionally, further exploration of the specific contributions of bandpass filtering and DWT in improving accuracy could provide valuable insights. Overall, this study significantly contributes to ECG classification and lays the groundwork for further advancements in cardiac diagnostic technologies. When compared to previous works, such as those employing CNN and AlexNet, which reported accuracies of 89.03% and 98.7%, respectively, the DWT and Xception method stands out for its exceptional accuracy of 99.79%, highlighting its effectiveness in predicting arrhythmic heart disease. Relevant limitations are the size of the dataset used; if the dataset is limited, this can affect the model's generalization and classification accuracy. In addition, variations in the ECG signal, such as noise or artifacts introduced during data acquisition, can affect the quality of feature extraction. Using complex architectures such as Xception can also lead to long training times and high computational requirements, which may not be practical in real clinical applications. Other limitations include validation that may not include a wide range of datasets, so the results do not fully reflect the model's performance in the real world. Finally, this study may not have considered other clinical factors affecting arrhythmia detection, such as the patient's health condition. Mentioning these limitations will provide the reader with a better understanding of the study's context and areas for future attention.

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