ECG ARRHYTHMIA TIME SERIES CLASSIFICATION USING 1D CONVOLUTION - LSTM NEURAL NETWORKS

THESIS

MASTER PROGRAM IN ELECTRICAL ENGINEERING MINOR IN ELECTRONIC CONTROL SYSTEM

Submitted as a partial fulfillment of the requirements for master engineering degree



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BRAWIJAYA UNIVERSITY FACULTY OF ENGINEERING MALANG 2021

THESIS

ECG ARRHYTHMIA TIME SERIES CLASSIFICATION USING 1D CONVOLUTION - LSTM NEURAL NETWORKS

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Presented in front of the examiners Date of the Exam : July, 9th, 2021

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According to the world health organization (WHO), cardiovascular disease (CVD) is the most common cause of death globally, taking an estimated 18 million lives each year, representing 31% of global deaths. Cardiovascular diseases can generally be divided into three groups: electrical (arrhythmia), vascular (vascular disorders), and structural (cardiomyopathies). (Heart Rhythm Society, "Heart diseases and disorders," 2017). In this work, we focused on arrhythmia. (Texas Heart Institute, "Categories of arrhythmias," 2016)

Arrhythmias are abnormal heartbeats caused by changes in the electrical current in the heart. The electrical system that controls the heartbeat is stable and produces two types of beats. Diagnoses of arrhythmias are based on determining which heart rhythms are normal and abnormal; morphology is used to classify electrocardiograms (ECGs) according to their characteristics, which is critical to make the correct diagnosis for the patient.

Typically, arrhythmias are diagnosed by electrocardiography (ECG): measuring the heart's electrical activity. Fig. 1.1 illustrates the ECG waveform with five main waves: P, Q, R, S, and T. The non-invasive and painless nature of the ECG test makes it ideal for collecting large amounts of data, which can be analyzed later. (National Heart Lung and Blood Institute, "Electrocardiogram," 2016).

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Association for the Advancement of Medical Instrumentation (AAMI) divides arrhythmias into five major classes: non-ectopic, ventricular ectopic, supraventricular ectopic, fusion, and unknown. There is a wide variety of types within each class, therefore this study (in the first and second experiments) has selected heartbeats that can be categorized into four different categories, Right bundle branch block (R), Ventricular ectopic (V), Fusion (F), and Normal (N). Moreover, in the third experiment, all AAMI classes are taken. These heartbeats are usually obscured by noise in ECGs, so identifying them is difficult. (American National Standards Institute, "Testing and reporting performance results of cardiac rhythm and

awijaya ST segment measurement algorithms," 2012), wijaya Universitas Brawijaya Universitas Brawijaya

Hospitals are the most common places that provide the equipment for electrocardiograms, and cardiologists perform careful evaluations of the ECGs using their knowledge and experience. The process is time-consuming and error-prone, so an automated approach can assist them in making their decision. It is highly desirable to be able to diagnose an irregular heartbeat accurately and inexpensively because this can help detect early heart problems and prevent further complications. (R. J. Martis, 2014) Increasing global population and pressure on health facilities are driving the demand for an automatic classification system. It is also possible that some cases will require a cardiologist to be dispatched to

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awijava awijaya remote areas or clinics or to remain on-site at all times in hospitals. To reach the best results, the

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classification model must be enhanced for a more in-depth study of classification. Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya There is no surprise that recent literature has focused on this topic, several authors have tested ECG way arrhythmia classification using a variety of methods, including statistical methods, expert systems, and supervised neural networks. Recently, neural networks have been increasingly the subject of practical research (Lippmann, 1987). Pattern recognition and artificial intelligence are areas of study requiring real-time responses, ECG classification involves both areas. awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya ECG beats are classified based on features or time series. Most researchers use features extraction to analyze their models. In this time-based classification model, wavelet transform and neural networks are implemented by the Python language on Google Colab, with R peaks and network nodes as classifiers. awijaya Universitas Brawijay willava UnOther researchers used various kinds of methods for ECG classification such as Combining KNN

and DWT, (Al Qawasmi, A. R., & Dagroug, K, 2010), MLP and VQ Number of beat type 2, (Sumathi, S., & Sanavullah, M. Y.,2009) and SOM with SVD Number of beat type 3, (Privadarshini, B., Ranjan, R. K., & Rajeev A. 2012).

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Figure 1.1 Electrocardiogram signal, waves, and segments

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awijaya awijaya awijaya awijaya awijaya awiiava awijaya awijava awijaya 1.2 Problems Statement awijaya 1) Diagnosing types of arrhythmia can be difficult, therefore an ECG analysis needs to be done by Unive a cardiologist. 2) Since the ECG produces a lot of data, it is time-consuming for a Cardiologist to analyze it. Universitas Brawijaya

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Even if a cardiologist analyzes it, there can still be some lack of accuracy. Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya

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Based on conditions we explained in section 1.1, the problems in ECG arrhythmia classification are :

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repository.ub.ac.id	awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijaya	 4) The majority of research in Arrhythmia classification is based on distinguish the beats, some of which use AAMI categories, and oth this study focused on time series classification for intra-patient follow. Three experiments are conducted to design a model for classifying ty Discrete Wavelet Transform (DWT) and Neural Networks with different Convolution, LSTM, and Dense layers. For model experiments one and two, we take four types of beats from the follow. 	ers that do not. However, AAMI categories. ypes of arrhythmia using types of layers, including MIT-BIH database, which
	awijaya	follows the AAMI standard, and for model experiment three we take all 12	
	awijaya awijaya	Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya	Universitas Brawijaya Universitas Brawijaya
	awijaya	In this study, we will focus on 1,2, and 4 and aim to achieve high accuracy.	
	awijava	II. I. B. D. H. B. H. B. H. B. H. B.	Universitas Brawijaya
		3 Research Objective	Universitas Brawijaya
	awijaya	University (1) Creating an Arrhythmia classification model with high accuracy for for	Universitas Brawijaya
	awijaya awijaya	the MIT-BIH database through pre-processing and building neural n	
	awijaya	the platform using a new library for machine learning published	•
	awijaya	TensorFlow.	niversitas Brawijaya
	awijaya	2) Improving model accuracy by adjusting hyperparameters.	hiversitas Brawijaya
	awijaya	3) Examine the model in all MIT-BIH databases to get excellent class	sification for all heartbeat
	awijaya	types, 12 types of heartbeats.	niversitas Brawijaya
	awijaya	LVDCS. 12 LVDCS OF IICALDCALS.	tify the most appropriate
	awijaya awijaya	4) Comparison of results for the model with other researches to iden classifier.	tify the most appropriate
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Universitas BCHAPTER II itas Brawijaya Universitas Brawijaya Universitas Brawijaya LITERATURE REVIEW Universitas Brawijaya Universitas Brawijaya

The classification of ECG arrhythmias is the subject of several publications; different methods have been used, such as statistical methods, expert systems, and supervised neural networks. Here is a review of a few of these studies.

awijaya For automatic classification of the ECG signal for the diagnosis of heart disease, Vijayavanan argued awiiava that the morphological characteristics of the ECG signal must be used to distinguish between normal and affected (abnormal) arrhythmias. This model was created using a probabilistic neural network (PNN) which captures the feature distributions and classification vectors. With 96.5% accuracy, this method provides accurate detection of arrhythmias in the ECG signal (Vijayavanan et al., 2014).

awi The diagnostic classification of the ECG for 12 lead was done using a combination of two pattern awi recognition methods proposed by Pedrycz et al, cluster analysis and feed-forward backpropagation neural networks. A cluster analysis based on Euclidean distance in parameter space was also applied to the original learning set. The classification accuracy scores ranged from 51.9% to 84.0% when it came to awij classifying 7 classes of ECG abnormalities (Pedrycz et al., 1991).

awijaya The description of the literature includes a review paper by Sanamdikar et al., (2015) that used awijaya modified Wavelet transforms to analyze cardiac arrhythmias and interpret ECG signals, Daubechies Six coefficient wavelet, Pan-Tompkins the algorithm, Hidden Markov models, fuzzy logic methods, neural av network, support vector machine, genetic algorithm, PCA, and SVM methods. We observed that the awii accuracy of other methods was 98%, but the accuracy of wavelet transfer was 100%. awijava

Also, (Silipo and Bortolan 1997), investigated the role of statistical methods and neural network awijava architectures in an automatic ECG analysis procedure that used seven types of beats and 39 features. A neural network classifier produced 91.0%, 94.0%, and 95.0% correct classification for all 7 types, indicating a performance comparable to conventional classifiers. In terms of the neural network architectures, they produced reasonable classification results when trained using unsupervised techniques. In addition, two other characteristics were examined, such as the subjects' age and gender (Silipo and Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Bortolan 1997). Brawijaya

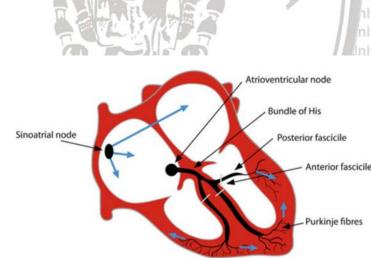
awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya (Salha Samad et al., 2014) used a machine-learning algorithm to classify arrhythmias, which used Nearest

Neighbors, Naive Bayes, and the Decision Tree classifier to achieve an average accuracy of 53%. Universitas Brawijaya

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Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijaya awijaya Universitas Brawijaya Universitas Brawijaya 2.2 Relevant Theories Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Brawijaya 2.2.1 Heart's Anatomy, heartbeat cycle, and the Conduction System Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya There are two main functions of the heart: 1) Pumping blood from the lungs to the tissues of the body; 2) Pumping blood from the tissues back to the lungs. Anatomically, the heart has four chambers composed of cardiac muscles. Right and left atria to function mostly to collect blood, while right and left ventricles work mostly to pump blood around the body (Weinhaus & Kenneth, 2005). Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijava The cardiac muscle (myocardium) forms the walls of the heart. The heart muscle performs mechanical work (=pumping blood). Electrical impulses are transmitted through specialized muscle cells to control the pumping process. ECG waveforms are formed by these impulses, called action potentials. awiiava Electrical impulses are normally generated in the sinoatrial (SA) node, located at the upper part of the right atrium. After propagating down the right atrium with the interatrial pathways, it goes left to the left atrium to the atrioventricular node (AV). The Bundle of His provides access to the left and right ventricles through the left and right bundle branches, which terminate in Purkinje fibers responsible for contracting each ventricle. We should note that not all areas of the heartbeat are at the same speed (beats per minute).

The discussed structure is shown in Figure 2.1



Universitas Brawıjaya Universitas Brawijaya Universitas Brawijaya Figure 2.1 The electrical conduction system of the heart (Gacek and Pedrycz,2012) versitas Brawijava The heart has developed a special cell system for generating electrical impulses to stay on its cardiac

cycle. By releasing these impulses, the heart muscles contract mechanically. It is called the conduction system. Sinus Node (Natural Heart pacemaker) starts every heartbeat with the P-wave. Electrocardiogram wijay waves and segments are shown in figure 1.1. awijaya Universitas Brawijaya

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awijaya • The P-wave is the first electrical event that occurs during a heartbeat or one cardiac cycle when the atria depolarize. Universitas Brawijaya Q-waves are formed during ventricular septal depolarization. The Q-wave is a fast, small, Univ negative wave.va Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya • Use During a cardiac cycle, the R-wave is formed by ventricular depolarization. It is a fast, Univ strong, positive wave with a large amplitude. Versitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya • S-wave is a negative, fast wave. awijaya • The T-wave is the last wave that occurs during a heartbeat. The ventricular repolarization Univ wave creates a positive but gradual response. Versitas Brawijava awijaya awijaya awijaya 2.2.2 Electrocardiogram awijaya

It was Augustus Waller (1887) who developed the first ECG (Addison, 2002). Throughout the world, it is widely used to diagnose diseases of the heart since then. The electrocardiogram records the electrical signals generated as the heart muscle contracts and relaxes. It is the result of the spread of electrical awij activity through the heart cells, causing their voltage to fluctuate. awii

awijaya. An electrocardiogram, a signal-acquisition device, can be used to measure these values with electrodes awi attached to the skin surface. The electrodes can be placed in a variety of ways, and there are different awijav approaches to calculating their position. Derivations allow for potential differences to be obtained in awijay specific directions, resulting in highly correlated measurements that are variable. Each part of the ECG awi represents one stage of the cardiac cycle. (Taspinar, 2018). ECGs are composed on graph paper (Fig. awijay 2.2), on which voltage levels are measured comparing horizontal lines, and time interval is determined based on the vertical lines: two consecutive vertical splits cover 0.04 seconds.

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Vavelet Transform	ⁿ Universitas Brawijaya	Universitas Brawijaya	Universitas Brawijaya
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nurnose of signal	processing is to extract sp	ecific information from	a signal Therefore signals

The purpose of signal processing is to extract specific information from a signal. Therefore, signals are often transformed into different domains to read out the desired information more easily(Gawande and Ladhake, 2015). Wavelet transform (WT) is a remarkable mathematical method that is capable of simultaneously examining the time and frequency aspects of the signal (Haykin, 2009). WT can be divided into three major types, namely continuous (CWT), discrete (DWT), and stationary discrete (SDWT).

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The ECG signal has a non-stationary characteristic whose frequency response differs with time. This is because the heart generates its beats under the influence of physiological factors mediated by the brain, which vary continuously over time. Typically, WT is used to analyze instantaneous and time-varying signals While classical Fourier transform can give a general sense of the signs it represents, its expression is often not intuitive enough. Wavelet transformations can analyze signals at all scales instead of Fourier transforms. Furthermore, the time and frequency domains can be located simultaneously. This is important for the analysis of non-stationary signals. Various low-pass and highpass filters are applied to the time-domain signal in WT, which filter out the high- and low-frequency components of the signal. Whenever some frequency portion of the signal is removed from the signal, this procedure is repeated. The waves are represented by waveforms of real or complex value, which have a definite start and end, as well as a mean value of zero (as shown in figure 2.3). Brawieva Universitas Brawieva

To obtain the WT of a signal, compare the input signal with the extended and shifted releases of the unstretched wavelet, also referred to as the mother wavelet- equation. Equation 2.1 is an example of the mother DWT. In chapter 3, we will discuss what wavelet family we use in our model; wavelets can simultaneously deal with time and frequency, so they are suited to describing events that start and stop, such as non-stationary signals.

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Here a and b are called Dilation (Scale) And Translation (Position) parameters respectively. awijaya awijaya Universitas Br awijaya awijaya awijaya 2.2 awijaya Type of Arrhythmias

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

 $a, b \in \mathbb{R}$

Iniversitas Brawijava versitas Brawijaya (2.1)

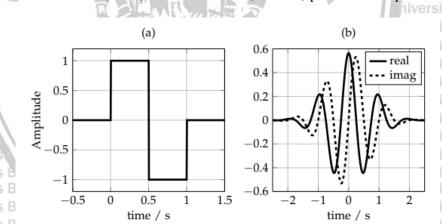


Figure 2.3 Exemplary wavelets, (a) Real valued Haar wavelet and (b) Complex valued

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Since each patient's heart mechanism differs significantly, analyzing an arrhythmia is a difficult task. Wijay There are two types of arrhythmias: sitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya wijaya 1. Rhythmic: consisting of a series of irregular beats raites Brawijaya 2. Morphological: one abnormal beat awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Ilniversitas Brawijava

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awijaya	Uni Table 2.1	The Categories	of heartbeats AAMI	Standard (2012)/ersitas	Brawijaya	Unive	ersitas Brawijaya
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awijaya	Categories		Ν	wijaya	sniversita	V		ersitas Bi p iwijaya
awijaya	Definitions	Nor	mal beat	Atrial	premature	Prematur	e	Fusion of
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awijaya	Universitas	L eft hun	dle block beat	Aberr	ated atrial	contractio	n	normal beat
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awijaya	Universitas	Right hun	dle branch beat		junctional	Ventricula	ar	ersitas Brawijaya
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2.2.3 Discrete Wavelet Transform

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Since the heart produces the ECG under the influence of brain-dependent factors that constantly change, the signal is non-stationary. To characterize them, a simple approach would be to use a time-domain analysis, which would consider factors such as the duration of the QRS complex and the R-R interval. An alternative method is to perform a frequency field analysis using a Fourier transform, which is compatible with small amplitude and duration changes in ECGs of any patient. In reality, the latter is not entirely applicable because an assumption of an evenly distributed frequency in the signal is not accurate: only the constant periodic signal is applicable. We are concerned about the frequency of the signal as well as the specific portion of the signal displaying that frequency when representing the ECG signal.

The DWT employs a wavelet as the basis function instead of a sinusoid as in the Fourier Transform. Wavelets are functions that have a finite duration: their amplitude is set at zero, increases, then decreases. Since wavelets only exist in a specific time interval, they are more localized in time than sinusoids. There are two ways to manipulate the wavelet: by changing its location or by changing its scale (Figure 2.4). Convolutions are highly valuable if the wave is the same shape as the signal at a point. The transform also results in a low value if wave and signal are not well correlated. In the continuous wavelet transform (CWT), this is done continuously, and for the discrete wavelet transform (DWT), it is done in discrete

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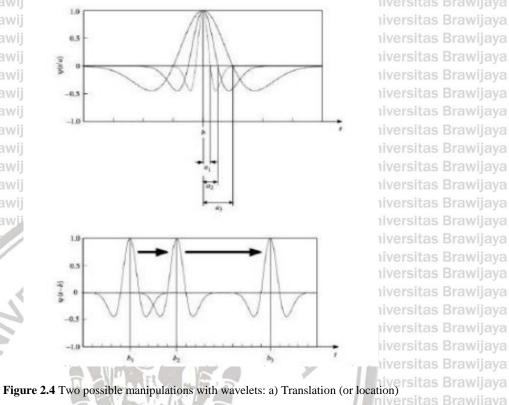
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and b) Scale, (Addison, 2002)

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awijaya. As a result, DWT outputs the signal at different bandwidths, so that at each level of analysis, the output is will a high if there is a strong correlation between the signal at that scale and the wavelet. Many wavelet types exist, and the choice of the right one depends on how similar the shape is to the part of the ECG we want to analyze. (Taspinar, 2018). See figure 2.5.

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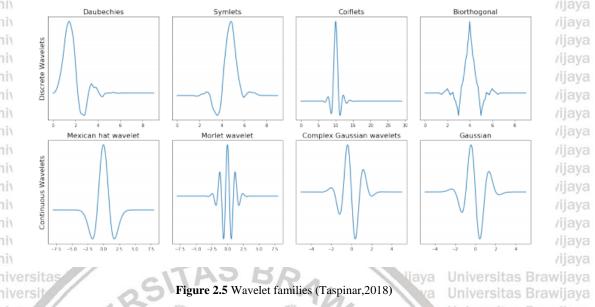
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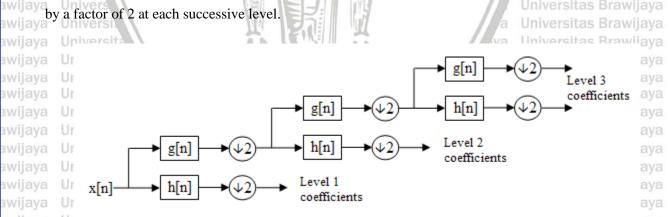
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The DWT is usually implemented as a Filter-Bank (Fig. 2.6), which means it is implemented as a cascade of high-pass and low-pass filters; filter banks are extremely efficient in splitting a signal into awijaya several sub-frequency bands. Two sets of coefficients are returned by the DWT; the approximation coefficients and the detail coefficients. Approximation coefficients correspond to the output of the DWT's low pass filter. A high pass filter of the DCT is used to generate the detail coefficients. The wavelet 3WI transform is applied again on the coefficients of the previous DWT to obtain the wavelet transform of the wild next level, which can be repeated at every level of the system. The original signal is also sampled down

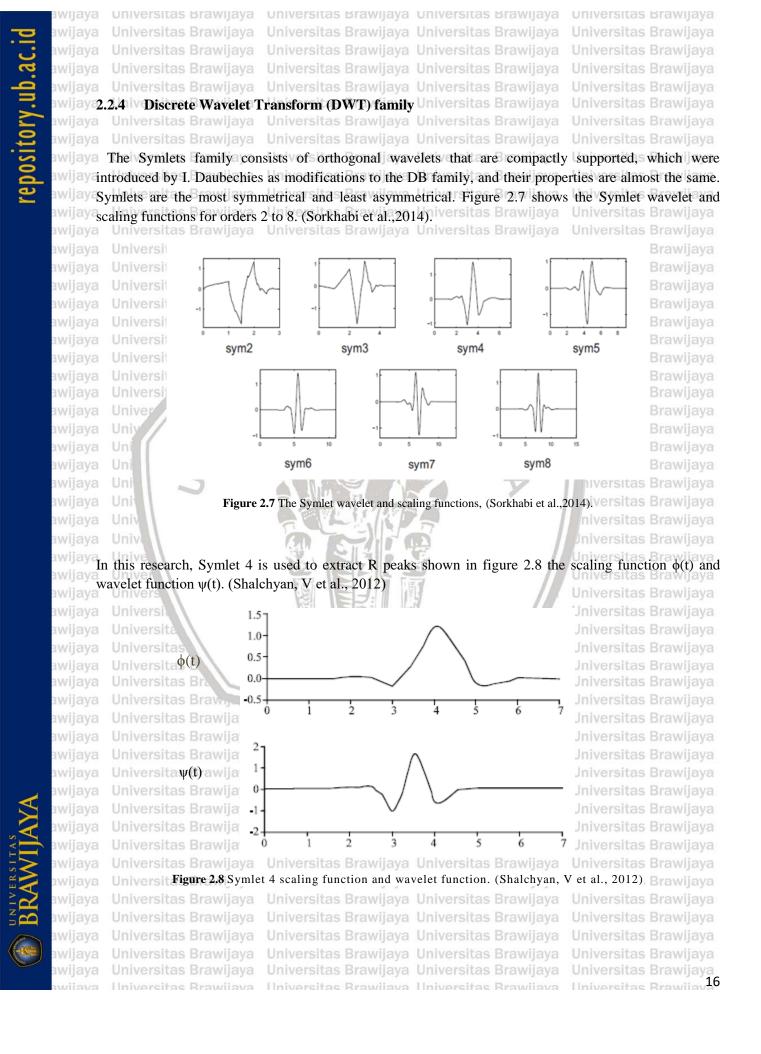


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Figure 2.6 Filter bank; three-level DWT Universitas Brawijaya Universitas Brawijaya

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awijaya 2.2.5 Neural networks

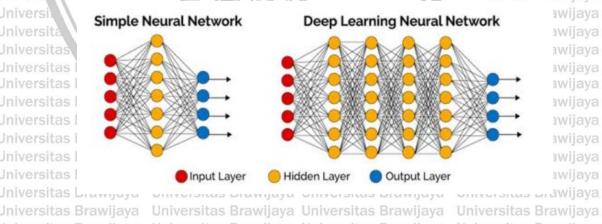
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An artificial neural network is an interconnected set of nodes, similar to the vast networks of neurons in the brain. It consists of a circular knot and an arrow, where each circular node represents an artificial neuron cell and the arrow represents a connection from the output of a neuron cell to another input. Artificial neural networks (ANN) (Gawande and Ladhake, 2015), are generally presented as systems of interconnected "neurons" which are Exchange messages with each other. Communications will a have numerical weights that can be adjusted based on experience, making neural network input adaptive and self-learning. Artificial neural networks (ANNs) are useful in application areas such as pattern recognition, classification, etc. The decision-making process of the ANN is holistic, based on the features of input patterns, and is suitable for the classification of biomedical data. A neural network can awij be characterized by 1) its pattern of connections between the neurons (called its architecture), 2) its algorithm of determining the weights on the connections (called its training, or learning algorithm), and 3) its activation function (Haykin;2009). awijaya

awijaya Traditional machine learning algorithms use only input and output layers, and at most one hidden layer. The use of more than three layers (including input and output) is referred to as deep learning. Figure 2.9 distinguishes between simple NN and deep learning NN, simple neural networks contain only one hidden layer as well as the input and output layers, while deep learning neural networks contain more awijay than one hidden layer. In this case, there are four hidden layers between the input and output layers. awijay

awijaya The main benefit of a Deep Neural Network (DNN) is its ability to recognize more complex features awijay due to the number of hidden layers it contains. This DNN function makes it capable of handling highawijay dimensional large data that has a large number of features. Deep learning networks end with an output layer: a logistic, or softmax, a classifier that assigns a likelihood to a particular outcome or labels WE (Acharya et al., 2016).



Univers Figure 2.9 Compar

	Universitas brawijay	Cl	Uni
i	ison between the simple neura	al r	netwo
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ork (NN) and deep NN; (Acharya et al., 2016)

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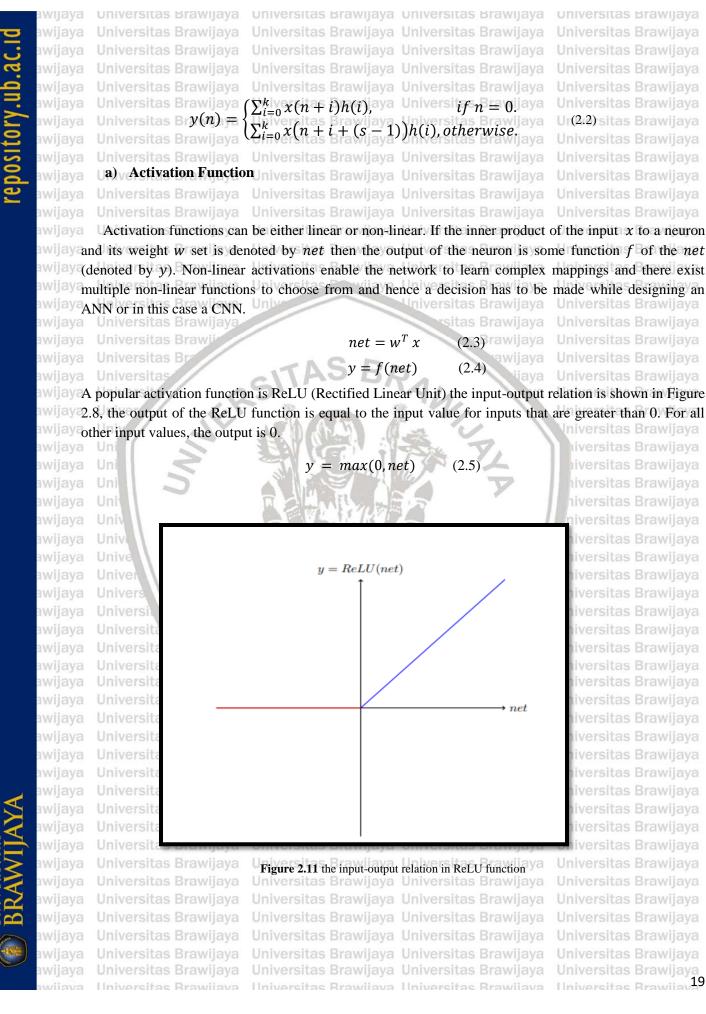
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wijaya	Universitas Brawijaya	Universitas Brawijaya	Universitas Brawijaya	Universitas Brawijaya
wijaya2	2.6 Convolutional Neu	ral Networks (CNNs)	Universitas Brawijaya	Universitas Brawijaya
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wijay An artificial convolutional neural network extracts hierarchical features using the convolution process. wijay Conventionally, CNNs were designed to work with two-dimensional data, which is used for image willay recognition. Fukushima and Miyake proposed the predecessor of Convolutional Neural Networks (CNNs) in 1982 (Fukushima et al., 1982). Machine learning and computer vision processes rely on convolutional neural networks (CNNs). Two-dimensional Convolutional Neural Networks (2D-CNNs are designed to handle multidimensional input and overcome the high number of parameters required in a standard Feedforward Neural Network (FNN), figure 2.10 is a comparison between FNN and CNN. awijay

awijaya Universitas Brawijaya Universitas Pawijaya Universitas Brawijaya Universitas Brawijaya Alternatively, a modified version of Deep Convolutional Neural Networks (1D-CNN) has recently been proposed and has immediately achieved cutting-edge performance levels in a variety of applications, such as personal biomedical data classification and early diagnosis (S. Kiranyaz;2016), structural health monitoring, anomaly detection, and identification in power electronics, and electric motor failure detection (O. Avci;2017).

Because of their low computational complexity, 1D-CNNs are often preferred to their 2D counterparts when treating 1D signals due to some of the following reasons: (1) computational complexity is low; (2) they are especially suitable for real-time and low-cost applications due to their low computation

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awijaya		output layer	000	width	/ersitas	Brawijaya
wijaya	input layer hidden layer 1 hidden	n layer 2			/ersitas	Brawijaya
wijaya	Universita	4.5.11.201	4.1	/ Aya	Universitas	Brawijaya
wijaya	Figure 2.10 Comparison of FN	N versus CNN. In CNN each la	ayer has 3 dimension	ons: depth, heigh	ht, length (visual	recognition)
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iwijaya	Convolutional layers a	re the building blocks of	CNNs. It is co	mposed of a	set of filters	(or kernels)
iwijaya	Universitas Brawijaya	UNIVERSITE	Universitas	Brawijaya	Universitas	Brawijaya
wijaya	hose parameters are learn	ned during training. Type	ically, a single	filter consist	ts of a multi-	dimensional
wijaya _{at}	rray with the same height,	length, and width as the i	input layer.tas	Brawijaya	Universitas	
wijaya	Universitas Brawijaya	Universitas Brawijaya	a Universitas	Brawijaya	Universitas	
wijaya	.2.7 Forward and Bacl	A Propagation in CNN-L	avers	Brawijaya	Universitas	
iwijaya	Universitas Brawijaya	Universitas Brawijaya	a Universitas	Brawijaya	Universitas	
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iwijaya	Let the input to convolution	on laver of length n be	represented by	x and let t	he kernel of	length k be
	epresented by h . Let the keep	5 S.				
wijaya	peration. Then convolution	n between x and h for stri	de s is defined	asrawijaya	Universitas	
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Using dropouts is a way to prevent overfitting, which is a phenomenon in which inputs are memorized instead of learning general traits of the inputs. Neurons that drop out mean that the next layer will receive zero inputs. There can be several neurons in a layer, and whether a neuron drops the output or not is determined by its dropout rate. Newsitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijaya Universitas Function Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya

The loss function describes the deviation of the predicted output from the target output. Categorical problems and multiclass problems refer to classification tasks with more than two labels. The model can estimate the probability of an example belonging to each class label. Therefore, in this study, we will use categorical cross-entropy. It is often desirable to minimize the cross-entropy for the model across the entire training dataset. To calculate this, average cross-entropy is calculated for all training examples.

awijaya awijaya CE: Cross Entropy. C: number of classes

Sj: output vector

Sp: Where Sp is the CNN score for the positive class.

Our objective is to minimize the loss function, ADAM optimizers can be used to reduce the loss

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2.2.8 Long Short Term Memory(LSTM)

awijaya awijaya A Long Short Term Memory network is a special kind of RNN that can learn dependencies over time. Hochreiter & Schmidhuber (1997) introduced them. A long-term dependence problem is avoided with LSTMs. Based on the fact that important events in a time series can be delayed, the LSTM network is well suited for categorizing, processing, and making predictions. During training for neural networks, weights are adjusted proportionally to the partial derivative of the error function in each iteration.

The issue is that the gradient can be vanishingly small in some cases, which effectively prevents the weight from changing. If this happens, the neural network may be prevented from training further. With LSTMs, the vanishing gradient problem that is associated with conventional RNN training can be avoided, The relative sensitivity of the gap length is one advantage of LSTMs over conventional RNNs shown in Fig 2.12. LSTMs generally consist of a cell, an input gate, an output gate, and a forget gate.

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There are three gates in the cell that control how information enters and leaves the cell (Greff's 2017).

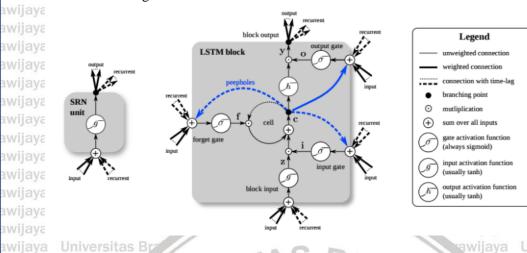


Figure 2.12 comparing a simple recurrent network to an LSTM cell (Greff, 2017)

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2.2.9 Dense neural network

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The dense layer contains a fully connected network of neurons; each is connected to every neuron from awijaya will ave the previous layer, as shown in figure 2.13. Its purpose is to classify the features that have already been wijavæxtracted from the previous layers. It is used at the end of the model.

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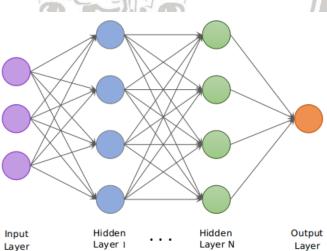


Figure 2.13 Dense Layer architecture Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijava Universitas Brawijava Universitas Brawijava²¹

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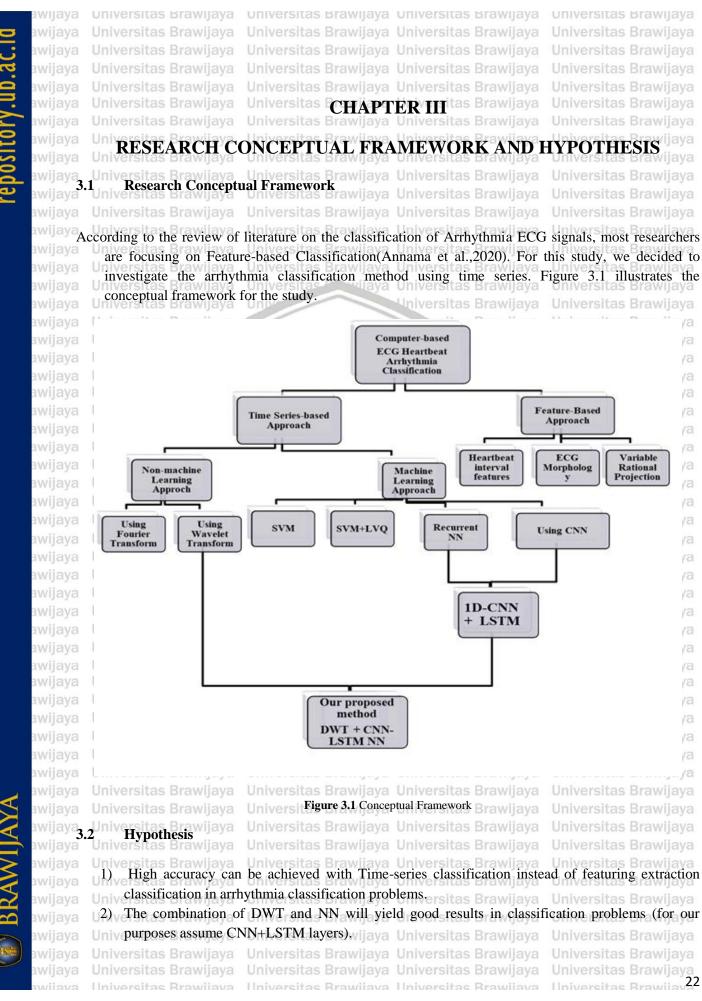
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Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas CHAPTER IVitas Brawijaya Universitas Brawijaya Universitas Brawijaya **RESEARCH METHODS** Universitas Brawijaya Universitas Brawijaya 4.1. Problem Identification

awijaya Taking advantage of the ECG, one of the most cost-effective and accurate methods for diagnosing awij cardiovascular diseases, we can determine the heart's electrical behavior. The ECG is a representation of the heart's electrical activity, which includes the regular and calm contraction of the heart muscles. Various cardiovascular diseases can be diagnosed using an analysis of the ECG waveform. There are five major waves of P, Q, R, S, and T in an ECG. Measurement of the RR-Interval, which is representative of the variety of heartbeats, is one of the most essential parts of the ECG analysis. Through the ECG WE classification, health care costs can be minimized by allowing the appropriate general practitioners to refer only those with serious heart problems to the hospital. Heart disease can also be detected early with awi the aid of ECG classification, shortening hospital waiting lists. An arrhythmia results from a disturbance wild vin the heart's electrical conduction system. People of all ages suffer from arrhythmias. In many cases, wild arrhythmias require constant monitoring and an accurate diagnosis. As a result, we need a non-invasive, accurate, and robust technique. To classify the beats of the MIT-BIH database, we propose the use of discrete wavelet transforms and neural networks.

4.2 Data preparation

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As a basis for the classification of ECG beats, we used the MIT-BIH arrhythmia database. There are 48 ECG records for 48 patients in the MIT Arrhythmia Database available on Physiobank. Each ECG record lasts 30 minutes. The Arrhythmia Laboratory at BIH studied the data between 1975 and 1979. 25 men and 22 women aged 32 to 89 years took part in the study. In-patient records accounted for about 60% of the data. Annotations are included with this dataset along with markings for normal and abnormal 360 Hz is the frequency used in these recordings. Lead II is the lead type that was used to beats. record most of the ECG signals in the MIT-BIH database, figure 4.1 shows the MIT-BIH record 100, figure 4.2 shows the single beat after splitting. A team of cardiologists independently annotated each record. Each annotation corresponds to the peak of the R wave of a single beat so that the beat detection problem has been implicitly solved in this case (Moody and Mark, 2001).

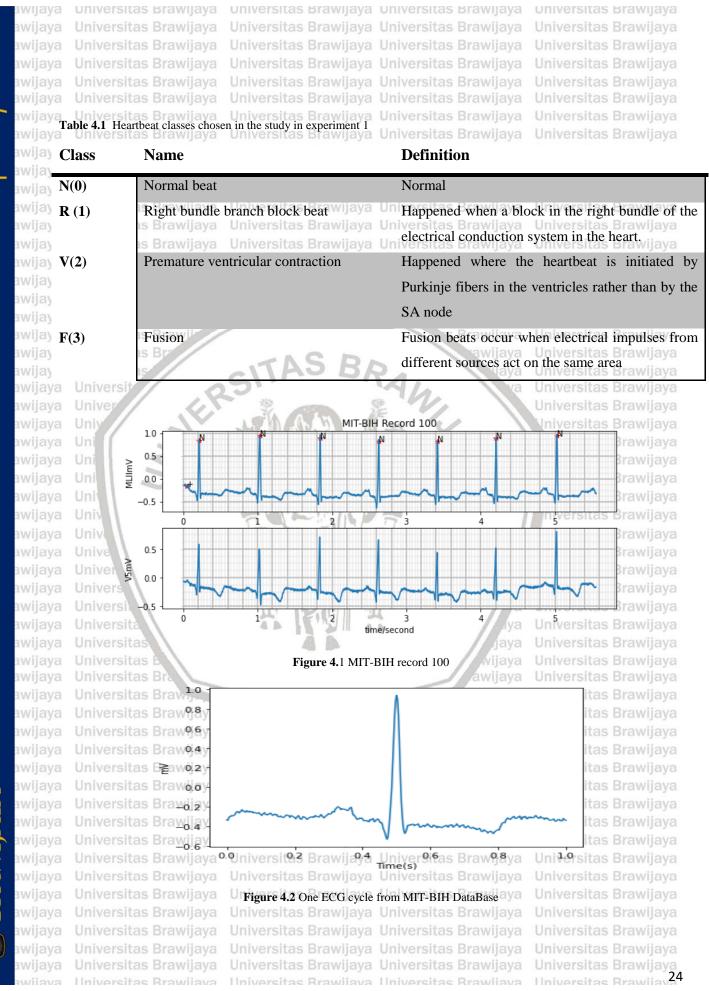
AAMI (2012) recommends standardizing the evaluation of arrhythmia detector algorithms on their performance on five major categories of heartbeats: normal, supraventricular ectopic beats, ventricular ectopic beats, fusion beats, and unclassified beats.

In this research, we used 4 different categories - 'N', 'R',' V', and 'F' - to classify them. Table 2 displays the four arrhythmia classes used in this study in the first and second experiments, and table 1 lists the AAMI classes used in the third experiment.

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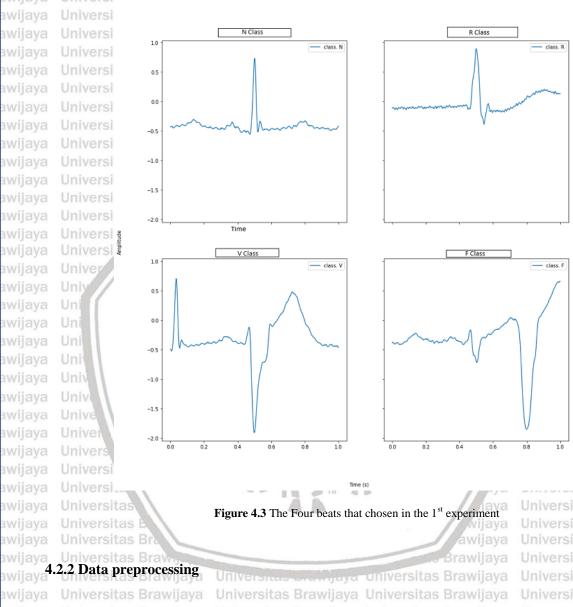
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The N class is more populated than any other: it accounts for 89% of the dataset. Overbalancing can result in inconsistent training and poor quality algorithms. This problem is solved by replicating the data from model 1 and augmenting the data from models 2 and 3. There were two dataset configurations considered, the first involved building the validation set randomly from the dataset, and the second

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involved building the test set. Iniversitas Brawijava Universitas Brawijava Universitas Brawijava During training and validation, the samples are randomly selected for each category in experiments 1, 2, and 3, with different ratios shown in Chapter 5, jaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya

In figure 4.3 the four beats, we choose in experiment 1. Inversities Brawijaya

Universitas Brawijaya Universitas Brawijaya awijaya awijaya awijay 4.3 Design of Proposed Solution ersitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya This research was organized into two stages based on its design: Brawliava Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya First: Data preparation: R detection using the annotation file in the data set, and selecting the window around R to ensure it's the peak we want. The window will be 500 ms to +500 ms around R. Brawieva Second: Wavelet Transform; in this study, DWT coefficients are fed to the deep learning model, we will use the Symlet family from Discrete Wavelet Transform. Versitas Brawijaya Universitas Brawijaya

Figure 4.4 illustrates the Workflow for Exp.1,2, and 3. It will also be used for the Enhancement Model 1. We will start by taking the ECG signal from the MIT-BIH database and choosing one of the four-beat types (in exp.1&2). Using the native Python waveform database (WFDB) package, we will then awi identify the peaks based on the data file annotation. An interval of one second is suggested for taking a window centered on the peak of the R. To convert each pulse of ECG signal into a coefficients matrix, discrete wavelet transforms will be applied. We recommend using the symlet4 family. MinMaxScaler will be used for normalization.

ECG Signal: one single beat

R-detection:annotation file

Select a window around R-peak: 1ms

Discete Wavelet Transform: Symlet 4

Normalization: MinMaxScaler

Proposed clasification model

Classified ECG beat

Figure 4.4 System WorkFlow. Source: by Researcher

awijaya awijaya awijaya awijaya awijaya awijaya awijava awijaya awijaya awijaya awijaya awijava awijaya awijaya Universitas Brawijaya awijaya awijaya In this study, we proposed to apply two 1D convolution layers and an LSTM layer, and then two dense experiments use this architecture with various hyperparameters and samples of data.

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layers would be applied to the outputs. The proposed model is shown in figure 4.5. Note that the three

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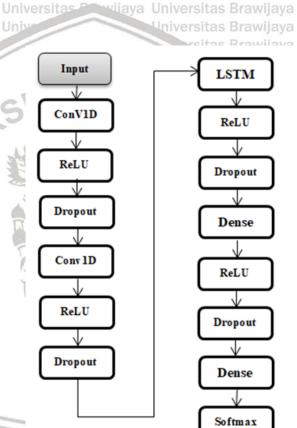
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In Figure 4.5, we see the input from the previous stage which is normalized coefficients of DWT feed to the first layer from the 1D CNN had 32 filters, and the second one had 64 filters, kernel size 5, and an LSTM layer with 256 units (neuron). These three layers used the ReLU as the activation function. We awijay provide convergence stability to the model by using 64 filters in the second layer of 1D CNN. In this study, Rectified Linear Unit is used as the activation function. It was used to decide the output by mapping it to some values, like 1 and 0, based on the function of the model. Fully connected layers awijay consist of two dense layers, the first dense layer with 64 units and ReLU activation function, and the awijay second dense layer with 4 units and Softmax activation layer, which predicts output class probabilities. As awijay you will see in Chapter 5, the dropout layers and learning rate as well as other hyperparameters will differ awijay

between experiments. awijay awijaya Universitas Brawijaya awijaya Universitas Brawl awijaya awijaya NER awijaya awijaya

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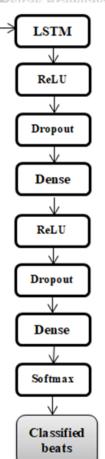


Figure 4.5 The Architecture Of The Proposed Networks

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awijaya	.4 Implementation ijaya Universitas Brawijaya Universitas Brawijaya	Universitas Brawijaya
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awijaya	Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya	Universitas Brawijaya
awijaya	Ve used Keras and Tensor Flow for Python 3.7 to implement the proposed mod	el to train it for 50 epochs
awijayao	n Google Colaboratory. The Softmax output is the loss function from c	ross-entropy loss. Adam
awijaya <mark>o</mark>	ptimizer with a learning rate of 0.0001 in Exp.1 and a learning rate of 0.001 in	Exp.2 and 3, that decays
	xponentially by a factor of -0.001 are used in this model. Versitas Brawijaya	-
awijaya	Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya	
awijaya	Ua) We Google Colab is a free cloud-based Jupyter notebook environment. Y	ou can write and execute
wijaya	Univecode in Python on Colab, create/load from/to Google Drive, import/	
awijaya	Univeyour Google Drive, and integrate Python, TensorFlow, Keras, Op	
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awijaya		tata tati tati ana ing
awijaya	can use Google hardware regardless of the power of your machine, you	A REPORT OF A R
awijaya	b) TensorFlow is an open-source platform for building and deploying M	1L models, with a special
awijaya	focus on deep learning.	Universitas Brawijava
awijaya	c) Keros is an ML (machine learning) API (Application Programming In	terface) written in Python
awijaya	University and running on TensorFlow. It provides essential abstractions and build	ing blocks for developing
awijaya	machine learning solutions.	Universitas Brawijaya
wijava		niversitas Brawijaya
wijava4	.5 Evaluate the performance of classification	niversitas Brawijaya
awijaya		niversitas Brawijava
awijaya	To evaluate the performance of classification we used many parameters in	
awijaya	and F-score.	niversitas Brawijaya
awijaya	1. The precision of a test represents the fraction of positive results among al	l false-positive results
awijaya	plus true-positive results.	Universitas Brawijaya
awijaya	University $precision = \frac{tp}{tp+fp}$ (4.1)	Universitas Brawijaya
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	2. Recall is the percentage of true positives over a total number of true positives	tives plus false negatives).
awijaya		SILLO SILLO SILLIGIO
awijaya	Universitas $recall = \frac{tp}{tp+fn}$ (4.2) Jaya	Universitas Brawijaya
awijaya awijaya	Universitas B Universitas Braudi (4.2) _i jaya	Universitas Brawijaya
awijaya		
awijaya	If the Precision and Recall are both equal to <i>I</i> then we said that the classif	fier is perfect.
awijaya	3. The F1-score measures the accuracy of the model on a dataset. A great	model mean F-score=1.
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	$F1 = \frac{tp}{1 + 1 + 1} $ (4.3)	TIMVEISITAS BRAWNAVA
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examine the results of each of them, the three parts are data set preparation, discrete wavelet transforms coefficients, and then the classification results. In the following sections, we will show the results for the three experiments and the three stages of each one.

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		ole (Stage one)		

According to the dataset, the N class comprises 89% of the whole dataset. Due to this overbalancing, poor-quality algorithms can result from the training process. The problem is solved by duplicating the data and doing an up-sample (as we did in Experiment one) or augment the data(as we did in Experiments two and three) to overcome this problem.

Here are two dataset configurations we have considered. Firstly, we created the test set, followed by the validation set, which was randomly selected from the dataset.

Table 5.1 shows that each category is randomly sampled 2000 times for training and validation (90:10%, respectively). Within class F, there are only 1784 samples, so it is randomly repeated to produce 2000 samples. The frequency distribution for the various labels before and after upsampling is shown in Figures 5.1 and 5.2.

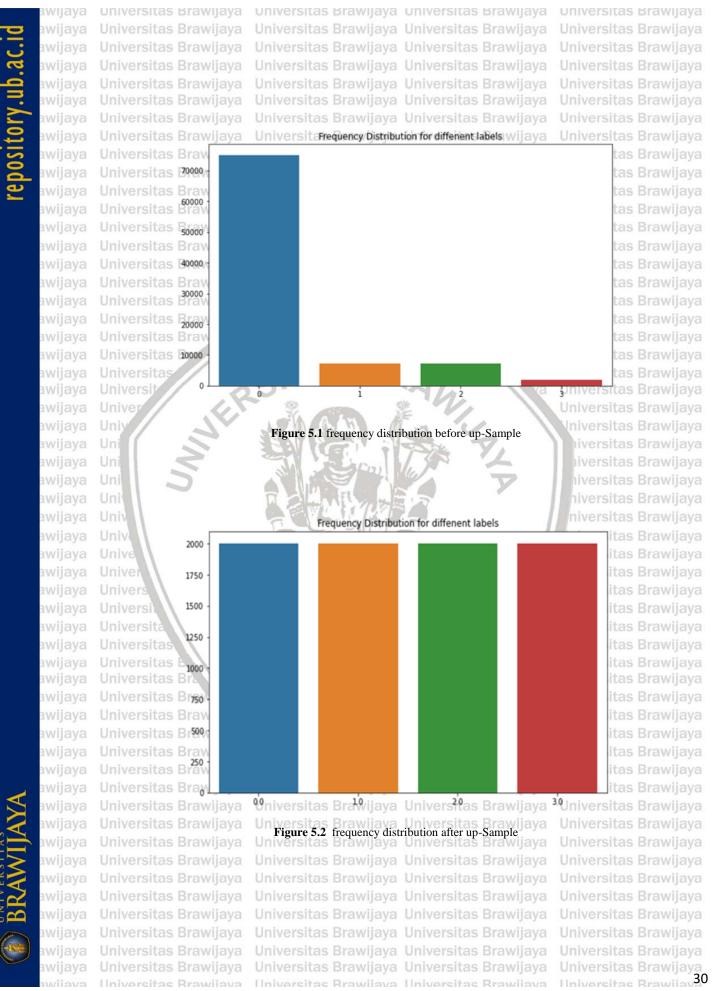
Figures 5.1 and 5.

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Table 5.1 Traning and Validation Dataset used in the experiment (1)

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vijaya	Universitas Brawijaya	Universitas Br	awijaya	Universita	s Brawijaya	Universitas Brawi	jaya
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awijaya The original signal which beats here is multiplied along the x-axis with wavelets so we start from Lower(4) coefficient when the wavelet is compressed capturing details in the high-frequency range, and Higher(0) coefficient when the wavelet is expanded capturing details in the low-frequency range. These coefficients are fed to our Deep Learning model, and help the model to predict the beat class with better Universitas Brawijaya Universitas Brawijaya

accuracy. awijaya awilava awijaya awijaya Univ awijaya awijaya awijaya awijaya awijaya awijava awijaya awijaya awijaya

Universitas Powijaya Universitas Brawijaya Universitas Brawijaya DWT sample for every category class. N class. R Level m Time Time class. F class. V Time Time Figure 5.3 The Scalogram For Discrete Wavelet Coefficients for experiment 1

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Universitas Brawijaya Universitas Brawijaya awijaya awijaya awijaya 5.1.3 The evaluation of the classifier in Exp.1 (stage three) that Brawlaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya U Our goal is to show the results of evaluating the proposed classifier in section 4.3, applying it to the awijava dataset for experiment 1, and showing the results on both training and testing datasets for each experiment awijayarespectivelitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya A. Training Set Results: In Section 4.3, the arrhythmia classifier was evaluated on 8000 heartbeats awijaya awijaya (2000 for each class). Figure 5.4, which shows the confusion matrix for the applied classifier, awijaya indicates that the model can classify and distinguish between different classes with an overall awijaya accuracy of 99%. The Classification Report for the training data is shown below, as shown in awijaya Figure 5.5. The performance is excellent, F1 score and recall are almost 1.0 Versitas Brawlaya awijaya awijaya Brawijaya awijaya awijaya -1750 rsitas Brawijava awijaya awijaya awijaya awijaya awijaya awijaya awijaya awijava awijaya ò ż ż п awijaya Predicted awijaya awijava awijaya Figure 5.4 The Confusion Matrix For Applying The Model On The Training Set awijaya recall f1-score precision support awijaya 0 0.99 0.98 0.98 2000 awijaya 1 1.00 1.00 1.00 2000 awijaya 2 0.98 0.98 2000 0.99 awijaya 3 0.98 0.98 0.98 2000 awijaya awijaya 0.99 8000 accuracy 0.99 0.99 0.99 8000 macro avg weighted avg 0.99 0.99 0.99 8000

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Figure 5.5 The Classification Report On The Training Data

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Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya B. Testing Set Results: When we evaluated the arrhythmia classifier in Section 4.3 on 18236 heartbeats, we got 97% accuracy. Based on Figure 5.6, it appears that the model provides accurate predictions and classifies four different classes when applied to the testing set. The Classification Report in Figure 5.7 shows that the testing data perform well. The F1score and Recall numbers are very close to 1, which is their optimal number. Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya awijaya awijaya niv awijaya awijaya Universitas Brawijay awijaya Universitas Braw awijaya awijaya

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Figure 5.6 The Confusion Matrix For Applying The Model On The Testing Set (exp.1)

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s		precision	recall	f1-score	support	
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sitas	1	0.98	0.99	0.99	1422	
sitas B	2	0.86	0.98	0.91	1461	
sitas B	3	0.65	0.94	0.77	363	
sitas B						
sitas B	accuracy			0.97	18236	
sitas B	macro avg	0.87	0.97	0.91	18236	
sitas B	weighted avg	0.98	0.97	0.98	18236	
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Universitas Brawijay Figure 5.7 The Classification Report On The Testing Data (exp.1) Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya

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Universitas Brawijaya Universitas Brawijaya awijaya awijay 5.2 Expermint Two Results Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya In this experiment, we tested our model on four beats from the MIT-BIH database as experiment one but we made a little change in the heartbeats types, we used S instead of R (see table 2.1). Also, we made enhancements to the model we changed hyperparameters, and the data was augmented in this experiment. in the following results for the three stages at experiment 2. Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya wijay 5.2.1 The Data Augmentation (Stage one) rawijaya Universitas Brawijaya Universitas Brawijaya awijava Universitas Brawijava Universitas Brawijava Universitas Brawijava Universitas Brawijava To enhance Exp.1, we use data augmentation, we take one sample of ECG waveform and augment it. awi Figure 5.8 shows the data used in exp.2. Note that in the enhancement model we took 10000 samples per category, with the categories 0: N, 1: S, 2: V, 3: F', we replace R with S only, as 20%:10% for testing and validation data respectively. vijaya awijaya Frequency Distribution for the selected labels awijaya Brawijaya awijaya 75011.0 70000 Brawijaya Brawijaya 60000 Brawijaya 50000 Brawijaya awijaya Brawijaya awijaya 40000 Brawijaya Brawijaya 30000 Brawijaya awijaya Brawijaya 20000 Brawijava 10000 7255.0 7129.0 Brawijaya 1784.0 ٥ i 2 wijaya ά Universitas Brawijava Figure 5.8 The frequency distribution for the data for the enhancement model ersitas Brawijava awiiava awijava av 5.2.2 The Discrete Wavelet Transform coefficients (stage 2) tas Brawijava awijaya awijaya The Scalogram For Discrete Wavelet Coefficients in Figure 5.9 shows the detailed coefficients in awijaya experiment 1, The original signal which beats here is multiplied along the x-axis with wavelets so we start from Lower(4) coefficient when the wavelet is compressed capturing details in the high-frequency range, and Higher(0) coefficient when the wavelet is expanded capturing details in the low-frequency range. These coefficients are fed to our Deep Learning model, and help the model to predict the beat class with better accuracy.

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Figure 5.9 The Scalogram For Discrete Wavelet Coefficients for experiment 2 CISITAS Brawlaya

5.2.3 The evaluation of the classifier in Exp.2 (stage three) Universitas Brawijaya Universitas Brawijaya

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awijaya Universitas Brawijaya Here we discusses the results of evaluating the proposed classifier in section 4.3, applying it to the dataset used in experiment 2, and showing the results from both training and testing datasets for each experiment. niversitas Brawijaya niversitas Brawijaya Universitas Brawij

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Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya A. Training Set Results: The arrhythmia classifier in Section 4.3 was evaluated using 72943 heartbeats (10000 from each class). Figure 5.10, which shows the confusion matrix for the applied classifier, can make accurate classifications and determine between the different classes to an overall accuracy of 99%. The Classification Report on the Training Data is shown in Figure 5.11. The performance is Universitas Brawijaya Universitas Brawijaya excellent, the F1 score and Recall are almost 1. Universitas Brawijava Confusion matrix awijaya awijaya

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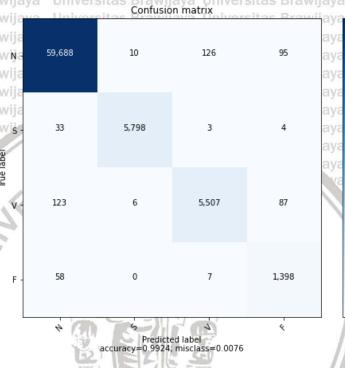
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Figure 5.10 The Confusion Matrix For Applying The Model On The Training Data (exp.2)

Figure 5.10 shows that for example, the predicted N class are 59688 beats are true classified, 33 was classified as S class, 123 beats as V class, and finally, 58 beats were classified as F class.

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ijaya	Universitas	Brawij	0	1.00	1.00	1.00	59919	niversitas	Brawijay
ijaya	Universitas	Brawij	1	1.00	0.99	1.00	5838	niversitas	Brawijay
ijaya	Universitas	Brawij	2	0.98	0.96	0.97	5723	niversitas	Brawijay
ijaya	Universitas	Brawij	3	0.88	0.96	0.92	1463	niversitas	Brawijay
ijaya	Universitas	Brawij						niversitas	Brawijay
ijaya	Universitas	Brawij	accuracy			0.99	72943	niversitas	Brawijay
ijaya	Universitas	Brawij	macro avg	0.96	0.98	0.97	72943	niversitas	Brawijay
ijaya	Universitas	Brawij	weighted avg	0.99	0.99	0.99	72943	a luca va lita a	Brawijay
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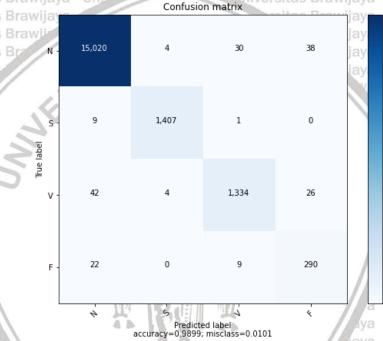
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Universitas Brawijaya awijaya B. Testing Set Results: A "98.99% accuracy" result was observed when the arrhythmia classifier of Section 4.3 was used to analyze 18236 heartbeats. According to the confusion matrix in Figure 5.12, the model gives accurate results and classifies four classes when applied to the testing set. Furthermore, the Classification Report in figure 5.13 shows that the performance of the testing data is excellent. Both F1score and Recall are close to 1, which is an ideal number for them. By changing the hyperparameters and the samples that were already taken, we did a clear enhancement in Experiment1. awijaya Figure 5.12 shows that for example, the predicted S class are 1407 beats are true classified, 4 was awijaya

classified as N class, 4 beats as V class, and finally, 0 beats were classified as F class.

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Figure 5.12 The Confusion Matrix For Applying The Model On The Testing Set (exp.2)

	precision	recall	f1-score	support
0	1.00	1.00	1.00	15092
1	0.99	0.99	0.99	1417
2	0.97	0.95	0.96	1406
3	0.82	0.90	0.86	321
accuracy			0.99	18236
macro avg	0.94	0.96	0.95	18236
eighted avg	0.99	0.99	0.99	18236

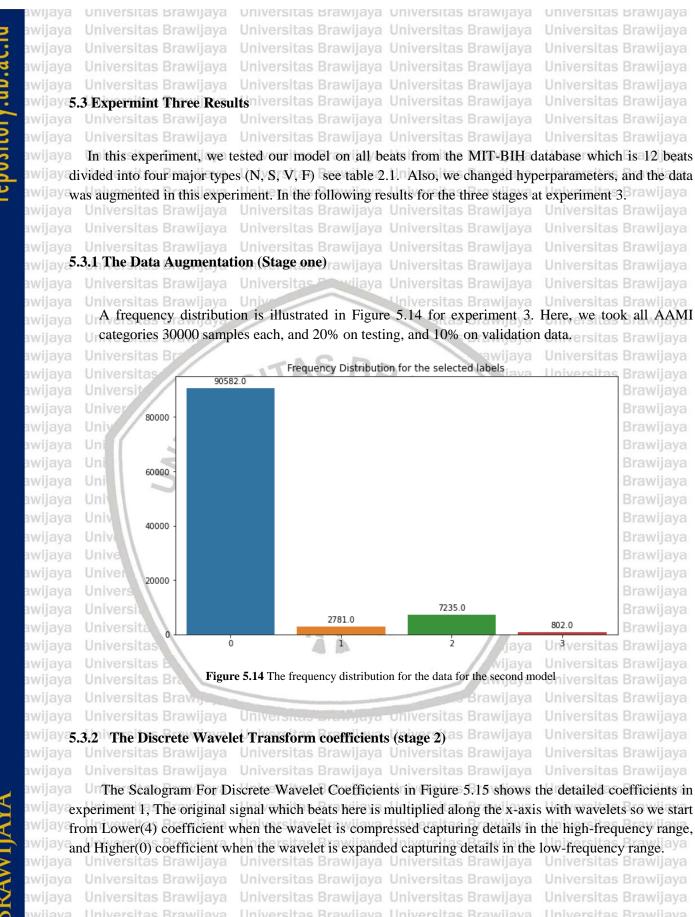
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Figure 5.13 The Classification Report On The Testing Data (exp.2)

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The purpose of this section is to discuss the results of the evaluation of the proposed classifier, applying it to the dataset for experiment 3, and showing the results on both training and testing datasets for the awijaya Universitas Brawijaya A. Training Set Results: Using the arrhythmia classifier in Section 4.3, 81000 heartbeats were Univer evaluated (30000 from each class). On the confusion matrix found in Figure 5.16, the model can classify and distinguish between the different classes with

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<u> </u>	awijaya	Universitas Brav	vijaya Univ	ersitas Brawij	aya Universi	tas Brawijay	a Univ	ersitas Brawija	ya
.	awijaya	Univer 98.2% acc	uracy in the	testing set. Fig	are 5.17 show	s the classifica	tion rep	ort on training da	ata,
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e.	awijaya	classified as S	class, 45 bea	ts as N class, ar	id finally, 10 b	eats were class	sified as	F class. ersitas Brawija	va
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÷2	awijaya	Universitas Brav	Figure 5.1	7 The Classificatio	n Report On The	Training Data (ex	p.3) ^{Univ}	ersitas Brawija	/a
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B. Testing Set Results: Using 20280 heartbeats, we tested the arrhythmia classifier described in Section 4.3. We achieved 97.7% accuracy. When the model is applied to the testing set, the confusion matrix in Figure 5.18 appears to give accurate predictions and classify four different classes. Also, in figure 5.19, we see a very good performance from the testing data. Both versitas Brawijaya F1score and Recall are close to 1, which is an ideal number for them.

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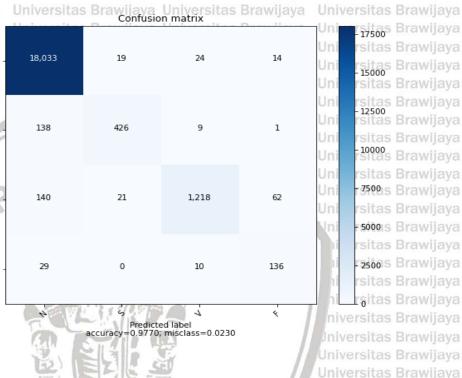


Figure 5.18 The Confusion Matrix For Applying The Model On The Testing Set (exp. 3)

Figure 5.18 shows that for example, the predicted N class are 18033 beats are true classified, 138 was classified as S class, 140 beats as V class, and finally, 29 beats were classified as F class.

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Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijay **5.4 Summary** Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya To classify arrhythmia beats for the MIT-BIH database, we implemented one classifier model and awijaya tested it three times, changing the hyperparameters and data amount, as well as the beat categories. We wijay test three experiments: aya Universitas Brawijaya Universitas Brawijaya awijaya 1) Experiment One: Classified 4 beat types (Normal only, R, V only, F), Universitas Brawijaya Universitas Brawijaya 2) Experiment Two: Improvement for experiment number 1 (Nonly, S, V only, F) 3) Experiment Three: Classified 12 beat types into four major AMMI categories (N, S, V, F) awi In the first model, we get 97% without overfitting, we do not do data augmentation but just upsample, awi and we use the discrete wavelet transform in all experiments. (Alqaisi, Y. Muslim, M. Rahmadwati, 2021). Furthermore, we get 99% without overfitting in enhancement experiment 1 by doing data augmentation and raising the number of samples, while making minor changes to the hyperparameters. In the third analysis, we obtain 97.7% without overfitting from all data and all types of beats as AAMI

standards. Here is a comparison between the three experiments and the hyperparameters used in Table

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awijay Table 5.2 The hyperparameters used in the three experiments

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Universitas Brawijaya Universitas Brawijaya awijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya awijaya Table 5.3 displays a comparison between our work and others, although we employ a time-series method, awijay not a feature extraction one. Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya We mean by feature extraction in ECG, extract the segments and intervals between points such as RR interval, the amplitude of P, R, and T wave, also QRS offset. And that happened by many methods such as machine learning and non-machine learning, statistical, wavelet transforms, etc. In another hand, this wijay research used annotation files to detect R peaks. Java Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya The table has shown that our proposed model (CNN+LSTM+DWT) achieve high accuracy in the three awijavæxperiments as Brawijava Universitas Brawijava Universitas Brawijava Universitas Brawijava Universitas Pa awiiava
 Table 5.3 Another works on the topic of arrhythmia

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awijaya Work Approach Average Accuracy (%) awijaya This work: 1st EXP./2^{ed} /3rd **CNN-LSTM +DWT** 97/99/97.7 awijaya awijaya 93.4 M. Kachuee (2018) DR-CNN awijaya 93.8 Martis (2013) DWT + SVMawijaya Acharya (2017) Augmentation + CNN 93.5 awijaya 94.6 Li (2016) DWT + RFawijaya 94 Yeh et al., (2012) Clustering awijaya 90 Morlet Wavelet+ Lin et al., (2008) AWN awijaya Korurek and Nizam (2008) ACO-based Cluster, kNN 94 awijaya

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6.1 Conclusions	Universitas Brawijaya	Universitas Brawijaya	Universitas Brawijaya
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Three experiments were con	nuclea in this study. In t	ne msi experiment, we se	iccicu iour deals fioni the

Three experiments were conducted in this study. In the first experiment, we selected four beats from the MIT-BIH database and classified them using a time series model based on deep learning (1D-CNN+LSTM), and DWT to prepare the data for analysis. There was a 97% accuracy rate. With the second experiment we improved output to 99% after changing hyperparameters and with the third experiment, we applied the proposed model to all MIT-BIH databases (12 beat types) for Arrhythmia following the AAMI standard and achieved an accuracy.

According to our problem statements the results of our research shows the following:

The model solved the difficulties of diagnosing types of arrhythmia and the needing for analysis by a cardiologist. by showing that no need for a cardiologist to analyze the ECG data and diagnosing types of arrhythmia, we can do that using the model of classification.

The model solved the time-consuming by a Cardiologist to analyze data. by computerized classification that offers a very high speed in deal with ECG data. The program takes **26.761**s to **36.234s** in the prediction of the classes.

The model solved the problem of lack of accuracy, the model achieved very high accuracy in the three experiments from (97-99)%.

The research is focused on Time-series Classification following AAMI categories which added value to this field. Because The majority of research in Arrhythmia classification is based on features classification to classify the beats, some of which use (AAMI) categories, and others that do not.

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In our study, Deep Learning and Discrete Wavelet Transform combine to achieve high classification accuracy. Using the proposed model (1D-Convolution, LSTM, and Dense) we improved the Time series classification approach to achieve high classification accuracy, as well as to announce that the proposed model is reliable in classification tasks with time-series data.

By doing this, we reduced the time taken by cardiologists to detect arrhythmia, helped non-specialist health workers distinguish between the different types of arrhythmia heartbeats, and detected them faster.

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awijaya awijaya awijaya wijay 6.2 Suggestions rawijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Therefore, based on our study, it is possible to increase the third experiment to 99% or 100%

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accuracy. Additionally, researchers might find it interesting to test this proposed model on another data set. The Time series approach can also be used to experiment with other classifiers due to the lack of awijaya esearch in this area wijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya Universitas Brawijaya In summary, we achieved our goals when designing an arrhythmia classification model. The model was wijay also applied to part of the samples and the whole dataset. iversitas Brawijaya Universitas Brawijaya awijaya Universitas Brawijaya Universitas Parwijaya Universitas Brawijaya Universitas Brawijaya This method uses a time series instead of a feature extraction method, and it has proven to be reliable,

will av reducing the time needed for the health workers to classify the arrhythmia beats. Universitias Brawijava awiiava Deep learning demonstrates a very good ability to predict and classify problems. Furthermore, we encourage the researcher to test more ML algorithms. NURI

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