

# Multi-Abnormal ECG Signal Classification using Dispersion Entropy and Statistic Feature

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## ABSTRAK

*Elektrokardiogram (EKG) adalah salah satu perangkat medis yang paling banyak digunakan untuk mendiagnosis masalah jantung. Sinyal abnormal EKG mempunyai variasi dan beberapa mirip antara yang satu dengan lainnya. Oleh karena itu, pada penelitian ini diusulkan metode klasifikasi kelainan jantung berdasarkan EKG menggunakan fitur statistik orde satu dan Dispersion Entropy (DisEn) untuk tahap ekstraksi ciri. Sedangkan untuk tahap klasifikasi sinyal EKG multi-abnormal, kami membandingkan metode Support Vector Machine (SVM) dan K-Nearest Neighbor (KNN). Pada penelitian ini diklasifikasikan tujuh kelas EKG, yaitu Normal, Atrial Fibrillation (AFIB), Atrial Flutter (AFL), Atrial Premature Beats (APB), Bigeminy, Left Bundle Branch Block (LBBB), dan Premature Ventricular Contraction (PVC). Dari simulasi ini, sistem dapat mendeteksi sinyal normal dan abnormal dengan akurasi 85,1% menggunakan K-NN. Sementara itu, pada simulasi klasifikasi tujuh kelas sinyal EKG menghasilkan akurasi hingga 75.1%.*

**Kata kunci:** EKG, klasifikasi, Dispersion Entropy, statistik

## ABSTRACT

*Electrocardiogram (ECG) is one of the most widely used medical devices to diagnose heart disease. Abnormal ECG signals have variations and some are similar to another. Therefore, in this study, proposed a method for classifying cardiac abnormalities based on ECG using first-order statistical features and Dispersion Entropy (DisEn) for feature extraction. Meanwhile, for the multi-abnormal ECG signal classification stage, we compared the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) methods. In this study, seven ECG classes were classified, namely Normal, Atrial Fibrillation (AFIB), Atrial Flutter (AFL), Atrial Premature Beats (APB), Bigeminy, Left Bundle Branch Block (LBBB), and Premature Ventricular Contraction (PVC). From this simulation, the system can detect normal and abnormal signals with an accuracy of 85.1% using K-NN. Meanwhile, the classification simulation of seven classes of ECG signals produces an accuracy of up to 75.1%.*

**Keywords:** ECG, classification, Dispersion Entropy, statistics

## 1. INTRODUCTION

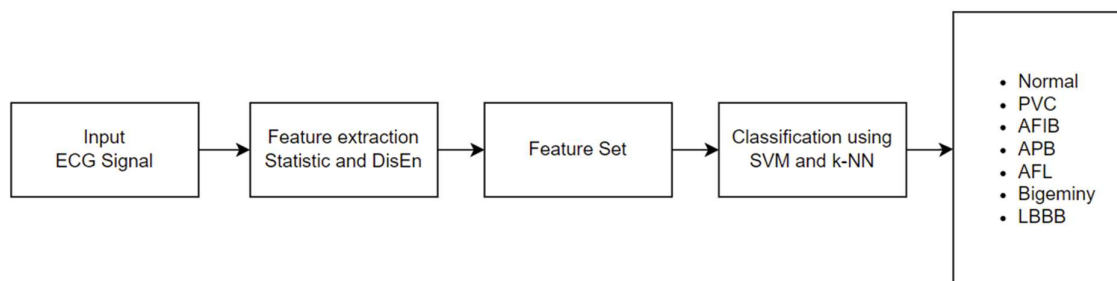
One of the most commonly used procedures for identifying heart disease is the electrocardiogram (ECG) **(Martis et al., 2013) (Kaur and Arora, 2012)**. By applying electrodes on the skin, the ECG monitors the heart's electrical activity over time. This signal is used to diagnose cardiovascular health and can be deciphered by understanding the basics of its four waves: T, U, P, and QRS complex **(Manullang, Simanjuntak, and Ramdani 2019) (Pestana et al., 2020) (Sahoo et al., 2017)**. Our prior work used SVM algorithms as classifiers and built an ECG classification based on ECG signals **(Aulia and Hadiyoso, 2021)**. The results' accuracy, sensitivity, and specificity were 81.1%, 89.8%, and 79.4%, respectively. However, the proposed method has still been refined to aid clinical diagnosis. As a result, we proposed in this paper that we optimize the performance from the previous experiment **(Aulia and Hadiyoso, 2021)** to classify ECG signals into seven categories: Normal, Atrial Fibrillation (AFIB), Atrial Flutter (AFL), Atrial Premature Beats (APB), Bigeminy, Left Bundle Branch Block (LBBB), and Premature Ventricular Contraction (PVC).

Previous studies have attempted to classify heart illness based on the ECG signal, and some of them were extracted in the time domain **(Wei-quan et al., 2016) (Si-yang et al., n.d.) (Natwong et al., 2006) (He et al., 2015) (Candra et al., 2017) (Devi and Audithan, 2017)**. Dispersion Entropy (DisEn), on the other hand, was just launched and performed admirably, showing that it should be explored further, especially in bio-signal cases **(Kafantaris et al., 2019) (Azami and Escudero, 2018)**.

Prior research for identifying ECG data generally used the Support Vector Machine (SVM) technique. The SVM approach was commonly used in previous research to classify ECG data and epileptic ECG signal categorization **(Rizal and Hadiyoso, 2018)**. We achieve a satisfying result from both experiences with a 93.8% and precision of 97.7%, respectively. Another classifier that is mainly used is the K-NN method **(Hassanat et al., 2014)**, because the technique is effortless and highly effective in the field of image processing, machine learning, text analysis, data mining, object recognition, and other fields **(Aulia et al., 2015; Zhang et al., 2017)**. Based on state of the art above, in this study, we use DisEn, which optimizes with the statistic first order (mean, variance, skewness, kurtosis) for the feature extraction. As for the classifier method, we compare the SVM and the K-NN. Five-cross validation was used to divide training and test data in this study. The data originates from a single lead in mat format retrieved from the MIT-BIH Arrhythmia's PhysioNet service.

## 2. MATERIAL AND METHODS

The system overview is presented in Figure 1. The input ECG signal with a duration of 3 seconds will be extracted its essential features using statistical methods (mean, variance, skewness, and kurtosis) and DisEn. Each ECG signal generates 5 features which then become a feature set. The feature set then becomes a predictor in the classification stage. Descriptions of the material and methods used in the findings of this study are presented in the following sub-sections.



**Figure 1. System Overview**

## 2.1 ECG Dataset

The ECG signal database used in this research was recorded with a gain of 200 amplification [adu/mV] at a sampling frequency of 360 Hz. Recording was performed on 45 patients with a minimum age of 23 years for women and 32 years for men with a maximum age limit of 89 years. There were 19 female patients and 26 male patients that were classified into 7 classes, i.e. Normal, Atrial Fibrillation (AFIB), Atrial Flutter (AFL), Atrial Premature Beats (APB), Bigeminy, Left Bundle Branch Block (LBBB), and Premature Ventricular Contraction (PVC). The data comes from one lead in mat format obtained from the MIT-BIH Arrhythmia database from the PhysioNet service (<http://www.physionet.org>). A total of 794 ECG signals with a length of about 3 seconds were simulated in this study.

## 2.2 First Order Statistical Feature Extraction

First-order statistical features that are calculated include mean, variance, skewness, and kurtosis. These features are calculated using the following Equation (1)-(4) (Esmael et al., 2013).

$$\mu = \frac{1}{N} \sum_{i=1}^N s_i \quad (1)$$

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (s_i - \mu)^2 \quad (2)$$

$$sk = \frac{\frac{1}{N} \sum_{i=1}^N (s_i - \mu)^3}{\sigma^3} \quad (3)$$

$$ku = \frac{\frac{1}{N} \sum_{i=1}^N (s_i - \mu)^4}{\sigma^4} \quad (4)$$

with N is the number of sample,  $\mu$  is mean,  $s_i$  is the data,  $\sigma^2$  is variance,  $sk$  is skewness, and  $ku$  is kurtosis.

## 2.3 Feature Extraction Using Dispersion Entropy

Entropy in a signal is an effective measure used for the irregularity and uncertainty of time series. In 1948, Shannon introduced the concept of entropy for the measurement of the amount of regularity of time series which was previously measured using the concept of probability distribution. The system has a maximum entropy if a similar system has a different state otherwise the system has a minimum entropy if a similar system has the same state or the probability value is one (Rostaghi and Azami, 2016) (Richman and Moorman, 2000).

Sample entropy (SE) (**Humeau, 2018; Zaylaa et al., 2015) (Sharma et al., 2015)** and permutation entropy (PE) (**Zanin et al., 2012**) are commonly used entropy in biomedical signals. The disadvantage of SE is that it is not fast enough, especially for long signals, while the drawback of PE is that it does not consider the average value of the amplitude and the difference between the amplitude values (**Redelico et al., 2017**).

Dispersion entropy (DisEn) can overcome the shortcomings that exist in SE and PE. The method used is to convert the data into a new signal. Various signal parameters such as amplitude, frequency, noise power, and bandwidth are processed from randomness to periodic oscillation (**Azami and Escudero, 2018**). The signal processing process includes autoregressive process, MIX process, noise bandwidth increase, and additive noise power enhancement. The new signal obtained is formed into several patterns to calculate the probability of forming the pattern (**Kafantaris et al., 2019**).

The DisEn algorithm includes 4 main steps for a univariate signal of length  $N: x = \{x_1, x_2, \dots, x_N\}$

1. Take a number of linear and nonlinear approaches to map  $x_j (j = 1, 2, \dots, N)$  to class  $c$  from 1 to  $c$ . Normal cumulative distribution function (NCDF) is used to map  $x$  into  $y (y = y_1, y_2, \dots, y_N)$  from 0 to 1. The signal has  $m$  members and each member is an integer from 1 to  $c$ .
2. The number of possible dispersion patterns for each time series  $z_i^{m,c}$  is equal to  $c^m$ . Each embedding vector  $z_i^{m,c}$  has dimensions of length  $m$  template, the delay time  $d$ , and the number of classes  $c$  that represents the number of patterns.  $z_i^{m,c} = \{z_i^c, z_{i+d}^c, \dots, z_{i+(m-1)d}^c\}$ ,  $i = (1, 2, \dots, N - (m-1)d)$  create embedding vector  $z_i^{m,c}$  that is mapped to a dispersion pattern  $\pi_{v_0 v_1 \dots v_{m-1}}$ , where  $z_i^c = v_0$ ,  $z_{i+d}^c = v_1, \dots, z_{i+(m-1)d}^c = v_{m-1}$ .
3. The number of dispersion patterns  $\pi_{v_0 v_1 \dots v_{m-1}}$  is represented as  $p(\pi_{v_0 v_1 \dots v_{m-1}})$  that are assigned to  $z_i^{m,c}$ . For frequency is calculation, the Equation 5 is used for each  $c^m$ .

$$p(\pi_{v_0 v_1 \dots v_{m-1}}) = \frac{\text{Number}\{i | i \leq N - (m-1)d, z_i^{m,c} \text{ has type } \pi_{v_0 v_1 \dots v_{m-1}}\}}{N - (m-1)d} \quad (5)$$

4. DisEn is a method to describe the spread in a data set, according Shannon's definition DisEn is calculated based on Equation 6.

$$\text{DisEn}(\text{signal}, m, c, d) = - \sum_{\pi=1}^{c^m} p(\pi_{v_0 v_1 \dots v_{m-1}}) \cdot \ln(p(\pi_{v_0 v_1 \dots v_{m-1}})) \quad (6)$$

Selection of appropriate parameters is something that must be considered in the DisEn approach. The potential dispersion pattern number ( $c^m$ ) must be smaller than the signal length for signal reliability. When the value of  $c$  does not match, the DisEn method will be sensitive to noise. The selection of the value of  $m$  affects the detection of dynamic changes in the signal.

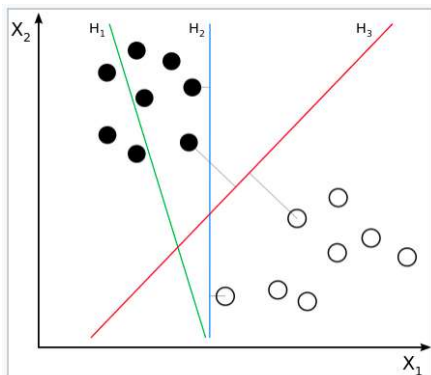
## 2.4 Performance Evaluation

For performance evaluation, there are several performance evaluations which are commonly used, including Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

### 2.4.1 Support Vector Machine

Support Vector Machine (SVM) is one of the methods in supervised learning which is usually used for linear and non-linear classification and regression (**Madan and Gupta, 2014**). SVM has a clearer concept mathematically compared to other classification techniques.

SVM is used to find a hyperplane, which is a function that can be used to separate the best classes by maximizing the distance between classes (**Venkatesan et al., 2018**). As shown in Figure 2, hyperplane 1 (H1) does not separate classes, (H2) separates classes with a small margin, and (H3) performs class separation with a maximum margin.

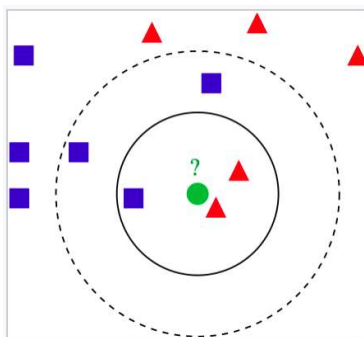


**Figure 2. Finding The Best Hyperplane In SVM**

Two classes are not always perfectly separated, so SVM needs to be reformulated using soft margin techniques. If the soft margin technique is still unable to find the separator in the hyperplane, a kernel is needed to transform the data to a higher dimensional space.

### 2.4.2 K-Nearest Neighbor

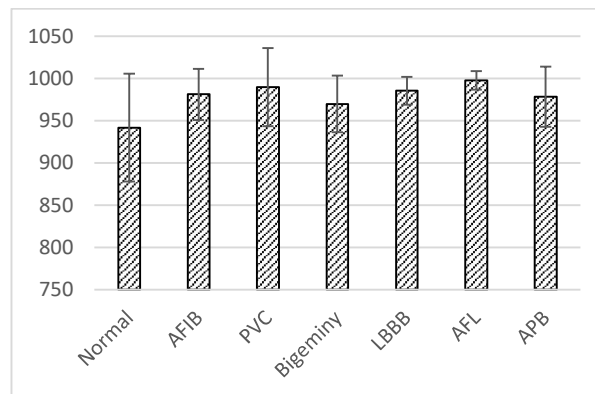
K-Nearest Neighbor (KNN) is an algorithm that is widely used in the world of machine learning for classification. This algorithm classifies data based on similarity or similarity or proximity to other data "neighbors" (**Maniyan and Shivakumar, 2018**). First determining the number of neighbors (K) that will be used for class determination considerations, then calculating the distance from the new data to each data point in the dataset and finally determining the class of the new data with the data reference with the closest distance. The KNN illustration is shown in Figure 3, with a value of  $K = 3$ , the new data will be included in the red class because in a circle with 3 members, there is more red than blue. If the value of  $K = 5$  is used, the new green data will be included in the blue class.



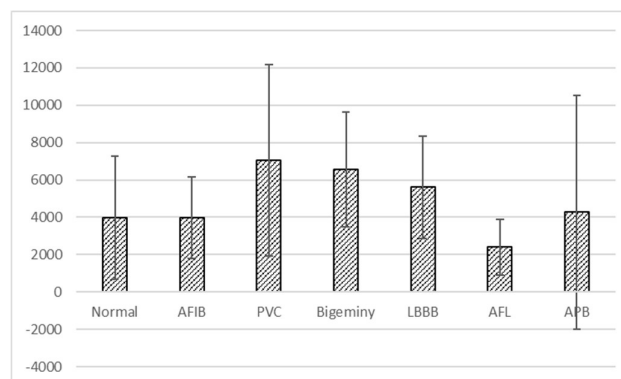
**Figure 3. Classification Using K-NN With  $k=3$**

### 3. RESULTS AND DISCUSSION

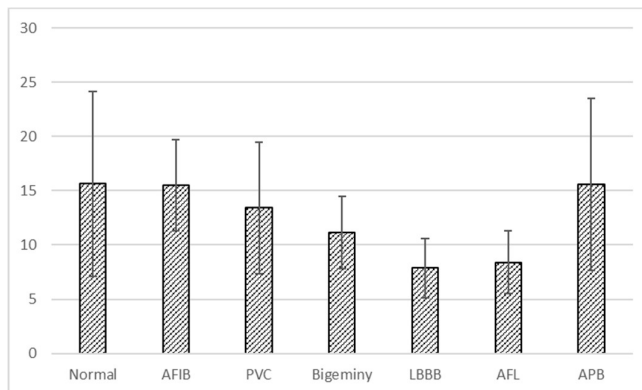
In this section, the results of feature extraction and performance evaluation of proposed methods in the classification of ECG abnormal signals are discussed. The results of the average and standard deviation of the statistical characteristics and DisEn for each ECG signal are presented in Figures 4, 5, 6, 7, and 8. Figure 4 shows the feature mean characteristics of each ECG signal where the ECG signals have a difference of one with each other with overlapping standard deviations. The AFL signal generates the highest mean characteristic compared to others. Figure 5 presents the variance characteristic where this feature tends to generate similar values as indicated by a high standard deviation. The characteristics of kurtosis and skewness as presented in Figures 6 and 7 show the differences between ECG types. However, it has a fairly high standard deviation as the mean feature. Meanwhile, the DisEn feature presented in Figure 8 shows a difference with a low standard deviation. With this result it is thought that all features will be used in the classification simulation so that there is no feature selection scenario as a predictor.



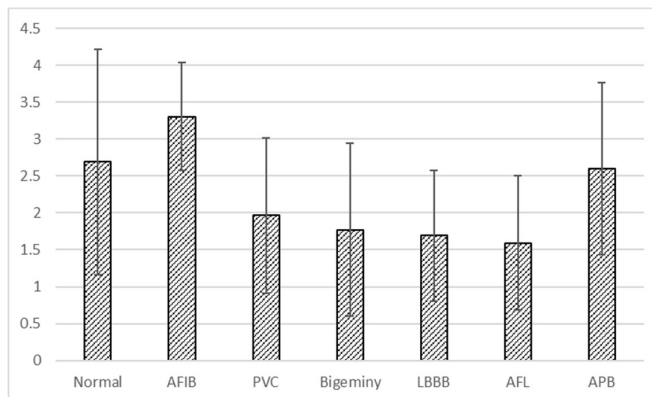
**Figure 4. Feature Mean**



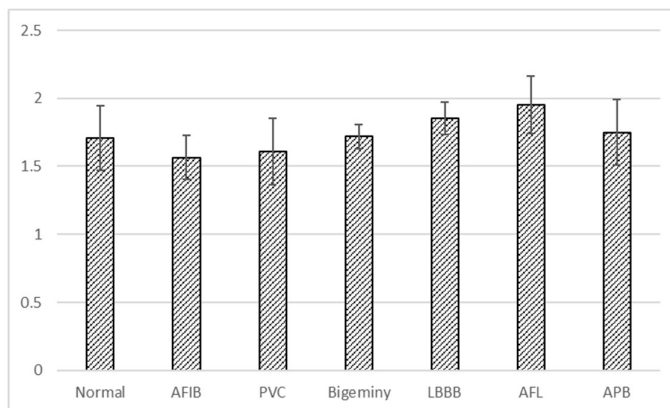
**Figure 5. Feature Variance**



**Figure 6. Feature Kurtosis**



**Figure 7. Feature Skewness**



**Figure 8. Feature DisEn**

The final stage is evaluating the performance of the proposed method using a classifier. At this stage, several classifier methods are used to test the robustness of the proposed method. SVM with kernel variations and K-NN were used in this evaluation. Meanwhile 5-cross validation was employed to share the training and test data. Cross-validation was chosen to avoid overfitting in the case of classification with a relatively small dataset where in this study there were a small number of ECG signal types. Table 1 presents the accuracy of each classifier. Quadratic SVM and K-NN generate the highest accuracy. The highest accuracy produced is 75.1%. Other classification methods also produce similar accuracy (>70%) except for linear SVM. These results indicate that the proposed feature extraction

method is robust. The confusion matrix for the highest accuracy case is presented in Table 2. From Table 2 it can be seen that AFL and APB contribute to generating the highest misclassification. This is because the two types of ECG have similar characteristics, besides that the amount of training data is less than other types.

**Table 1. Classification Accuracy**

Classifier	Accuracy (%)
Linear SVM	59.9
Cubic SVM	72.7
Quadratic SVM	75.1
Gaussian SVM	73.4
K-NN	75.1

**Table 2. The Confusion Matrix Of The Highest Accuracy**

	Predicted Class							Accuracy
	AFIB	AFL	APB	Bigeminy	LBBB	Normal	PVC	
True Class AFIB	116	0	1	0	3	11	4	0.859259
AFL	4	10	0	0	0	6	0	0.5
APB	6	1	35	2	0	18	3	0.538462
Bigeminy	0	0	0	40	6	4	5	0.727273
LBBB	2	1	1	4	83	12	0	0.805825
Normal	12	2	19	5	12	227	6	0.80212
PVC	4	0	9	10	1	24	85	0.639098

**Table 3. Accuracy Normal Vs Abnormal ECG**

Classifier	Accuracy
Linear SVM	76.6
Cubic SVM	81.6
Quadratic SVM	81.4
Gaussian SVM	84.1
K-NN	85.1

Another test scenario that is simulated is the evaluation of the performance of the proposed method in classifying normal and abnormal ECG. Abnormal ECG consists of six types of ECG including PVC, bigeminy, AFL, AFIB, LBBB, and APB. The results of testing this scenario are shown in Table 3. From this simulation, the system is able to detect normal and abnormal signals with an accuracy of 85.1% using K-NN. Meanwhile, SVM yields slightly lower accuracy.

The results of this study yield lower accuracy compared to studies (**Estananto, 2018**) (**Wijayanto et.al., 2022**) (**Aulia and Hadiyoso, 2021**). However, this study presents a system that can classify ECG signals with more signal types. Other studies only present two or three class classifications. Some of the limitations of this study are the small amount of data on some types of ECG. This contributes to lowering the accuracy of the system. Future studies are wide open in the exploration of other feature extraction methods to improve classification accuracy.



#### 4. CONCLUSION

This study presents a classification system of ECG signals into seven classes. The feature extraction method proposed in this study uses the mean, variance kurtosis, skewness, and DisEn. The result of feature extraction shows that the standard deviation overlaps with a relatively small value, so there is no specific feature to be used as a predictor. As a performance test on this classification system, SVM and KNN are used, with 5-cross validation being used to separate the training data from the test data. From the simulations performed, the highest accuracy in the seven-class classification case is 75.1%. Meanwhile, the proposed method can classify normal ECG and abnormal ECG with an accuracy of 85.1%. Limited data makes system accuracy not optimal, as in AFL and APB, this contributes to generating the highest misclassification. For future research, there is an opportunity to explore other feature extraction methods so that accuracy can be improved. Deep learning methods are also thought to generate higher classification accuracy.

#### REFERENCES

- Aulia, S., & Hadiyoso, S. (2021). Abnormal ECG Classification using Empirical Mode Decomposition and Entropy. *Jurnal Rekayasa Elektrika*, 17(3), 191–198. <https://doi.org/10.17529/jre.v17i3.22070>.
- Aulia, S., Hadiyoso, S., & Ramadan, D. N. (2015). Analisis Perbandingan KNN dengan SVM untuk Klasifikasi Penyakit Diabetes Retinopati berdasarkan Citra Eksudat dan Mikroaneurisma. *Elkomika*, 3(1), 75–90.
- Azami, H., & Escudero, J. (2018). Amplitude- and fluctuation-based dispersion entropy. *Entropy*, 20(3), 1–21. <https://doi.org/10.3390/e20030210>.
- Candra, H., Yuwono, M., Chai, R., Nguyen, H. T., & Su, S. (2017). EEG emotion recognition using reduced channel wavelet entropy and average wavelet coefficient features with normal Mutual Information method. 2017 39th *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (pp. 463–466). <https://doi.org/10.1109/EMBC.2017.8036862>.
- Devi, M. C., & Audithan, S. (2017). Diagnosis of Breast Cancer using Wavelet Entropy Features. *International Journal of Electrical and Computer Engineering (IJECE)*, 10(1), 45–51.
- Esmael, B., Fruhwirth, R. K. dan Thonhauser, G. (2013). A Statistical Features Based Approach for Operations Recognition. *Drilling Time Series*, 5, 4545.
- Estananto, N. (2018). Klasifikasi Sinyal Elektrokardiogram Menggunakan Renyi Entropy. *Jurnal Elektro Dan Mesin Terapan*, 4(2), 11–18. <https://doi.org/10.35143/elementer.v4i2.2139>.

- Hassanat, A. B., Abbadi, M. A., & Alhasanat, A. A. (2014). Solving the Problem of the K Parameter in the KNN Classifier Using an Ensemble Learning Approach. *International Journal of Computer Science and Information Security*, 12(8), 33–39. <https://doi.org/10.1007/s00500-005-0503-y>.
- He, H., Tan, Y., & Wang, Y. (2015). Optimal Base Wavelet Selection for ECG Noise Reduction Using a Comprehensive Entropy Criterion. *Entropy*, 17(12), 6093–6109. <https://doi.org/10.3390/e17096093>.
- Humeau-Heurtier, A. (2018). Evaluation of Systems' Irregularity and Complexity: Sample Entropy, Its Derivatives, and Their Applications across Scales and Disciplines. *Entropy*, 20(10), 794. <https://doi.org/10.3390/e20100794>.
- Kafantaris, E., Piper, I., Lo, T.-Y. M., & Escudero, J. (2019). Application of Dispersion Entropy to Healthy and Pathological Heartbeat ECG Segments. *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (pp. 2269–2272). <https://doi.org/10.1109/EMBC.2019.8856554>.
- Kaur, M., & Arora, A. S. (2012). Classification of ECG signals using LDA with factor analysis method as feature reduction technique. *Journal of Medical Engineering & Technology*, 36(8), 411–420. <https://doi.org/10.3109/03091902.2012.702851>.
- Madan, A., & Gupta, D. (2014). Speech Feature Extraction and Classification: A Comparative Review. *International Journal of Computer Applications*, 90(9), 20–25. <http://ijcaonline.com/archives/volume90/number9/15603-4392>.
- Maniyan, P., & Shivakumar, B. L. (2018). Detection of Diseases using Nail Image Processing Based on Multiclass SVM Classifier Method. *Ijesc*, 8(5), 17382–17390.
- Manullang, M. C. T., Simanjuntak, J., & Ramdani, A. L. (2019). Implementation of AD8232 ECG Signal Classification Using Peak Detection Method For Determining RST Point. *Indonesian Journal of Artificial Intelligence and Data Mining*, 2(2), 61. <https://doi.org/10.24014/ijaidm.v2i2.7593>.
- Martis, R. J., Acharya, U. R., & Min, L. C. (2013). ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform. *Biomedical Signal Processing and Control*, 8(5), 437–448. <https://doi.org/10.1016/j.bspc.2013.01.005>.
- Natwong, B., Sooraksa, P., Pintavirooj, C., Bunluechokchai, S., & Ussawawongaraya, W. (2006). Wavelet Entropy Analysis of the High Resolution ECG. *2006 1ST IEEE Conference on Industrial Electronics and Applications*, (pp. 1–4). <https://doi.org/10.1109/ICIEA.2006.257276>.

- Pestana, J., Belo, D., & Gamboa, H. (2020). Detection of Abnormalities in Electrocardiogram (ECG) using Deep Learning. *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies*, (pp. 236–243). <https://doi.org/10.5220/0008967302360243>.
- Redelico, F. O., Traversaro, F., García, M. del C., Silva, W., Rosso, O. A., & Risk, M. (2017). Classification of normal and pre-ictal EEG signals using permutation entropies and a generalized linear model as a classifier. *Entropy*, *19*(2), 1–12. <https://doi.org/10.3390/e19020072>.
- Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology-Heart and Circulatory Physiology*, *278*(6), 2039–2049. <https://doi.org/10.1111/j.1468-0084.1985.mp47002006.x>.
- Rizal, A., & Hadiyoso, S. (2018). Sample Entropy on Multidistance Signal Level Difference for Epileptic EEG Classification. *The Scientific World Journal*, *2018*, 1–6. <https://doi.org/10.1155/2018/8463256>.
- Rostaghi, M., & Azami, H. (2016). Dispersion Entropy: A Measure for Time-Series Analysis. *IEEE Signal Processing Letters*, *23*(5), 610–614. <https://doi.org/10.1109/LSP.2016.2542881>.
- Sahoo, S., Mohanty, M., Behera, S., & Sabut, S. K. (2017). ECG beat classification using empirical mode decomposition and mixture of features. *Journal of Medical Engineering & Technology*, *41*(8), 652–661. <https://doi.org/10.1080/03091902.2017.1394386>.
- Sharma, R., Pachori, R., & Acharya, U. (2015). Application of Entropy Measures on Intrinsic Mode Functions for the Automated Identification of Focal Electroencephalogram Signals. *Entropy*, *17*(2), 669–691. <https://doi.org/10.3390/e17020669>.
- Si-yang, H. U., Kui, D., Wang, Q., Chao-hao, Z., Yong-jie, Y. I., & Chang-rong, Y. (n.d.). A Detection and Analysis System of ECG Signals Based on Wavelet Entropy. *IJSSST*, (pp. 1–6). <https://doi.org/10.5013>.
- Venkatesan, C., Karthigaikumar, P., Paul, A., Satheeskumaran, S., & Kumar, R. (2018). ECG Signal Preprocessing and SVM Classifier-Based Abnormality Detection in Remote Healthcare Applications. *IEEE Access*, *6*, 9767–9773. <https://doi.org/10.1109/ACCESS.2018.2794346>.
- Wei-quan, W., Pan, L. U., Jia-lun, L. I. N., & Jin, Z. (2016). ECG Identification Based on Wavelet Transform. *Joint International Information Technology, Mechanical and Electronic Engineering Conference (JIMEC)*, (pp. 497–501).

- Zanin, M., Zunino, L., Rosso, O. A., & Papo, D. (2012). Permutation Entropy and Its Main Biomedical and Econophysics Applications: A Review. *Entropy*, *14*(8), 1553–1577. <https://doi.org/10.3390/e14081553>.
- Wijayanto, I., Humairani, A., Rizal, A., & Hadiyoso, S. (2022). Klasifikasi Sinyal EKG menggunakan Ciri Statistik dan Parameter Hjorth dengan SVM dan k-NN. *ELKOMIKA: Jurnal Teknik Energi Elektrik, Teknik Telekomunikasi, & Teknik Elektronika*, *10*(1), 132–145.
- Zaylaa, A. J., Harb, A., Khatib, F. I., Nahas, Z., & Karamah, F. N. (2015). Entropy complexity analysis of electroencephalographic signals during pre-ictal, seizure and post-ictal brain events. *2015 International Conference on Advances in Biomedical Engineering (ICABME)*, (pp. 134–137). <https://doi.org/10.1109/ICABME.2015.7323270>.
- Zhang, S., Li, X., Zong, M., Zhu, X., & Cheng, D. (2017). Learning k for kNN Classification. *ACM Transactions on Intelligent Systems and Technology*, *8*(3), 1–19. <https://doi.org/10.1145/2990508>.