

DAFTAR PUSTAKA

- [1] World Health Organization, "Cardiovascular diseases," 31 Juli 2025. [Online]. Available: <https://www.who.int/health-topics/cardiovascular-diseases>
- [2] G. Lippi, F. Sanchis-Gomar, and G. Cervellin, "Global epidemiology of atrial fibrillation: An increasing epidemic and public health challenge," *Int. J. Stroke*, vol. 16, no. 2, pp. 217–221, 2021, doi: 10.1177/1747493019897870.
- [3] R. He *et al.*, "Automatic Detection of QRS Complexes Using Dual Channels Based on U-Net and Bidirectional Long Short-Term Memory," *IEEE J. Biomed. Heal. Informatics*, vol. 25, no. 4, pp. 1052–1061, 2021, doi: 10.1109/JBHI.2020.3018563.
- [4] F. Lin *et al.*, "Artificial-intelligence-based risk prediction and mechanism discovery for atrial fibrillation using heart beat-to-beat intervals," *Med*, vol. 5, no. 5, pp. 414–431.e5, 2024, doi: 10.1016/j.medj.2024.02.006.
- [5] S. Zhang *et al.*, "Hypertensive Disorders in Pregnancy Are Associated With Congenital Heart Defects in Offspring: A Systematic Review and Meta-Analysis," *Front. Cardiovasc. Med.*, vol. 9, 2022, doi: 10.3389/fcvm.2022.842878.
- [6] P. M. Research, "Arrhythmia Market Share, Size, Trends, Industry Analysis Report, By Type (Supraventricular Tachycardias, Ventricular Arrhythmias, Bradyarrhythmias); By Site of Origin Atrial; By Test Equipment; By Region; Segment Forecast, 2022 - 2030," p. 115, 2022, [Online]. Available: <https://www.polarismarketresearch.com/industry-analysis/arrhythmia-market>
- [7] J. Barker *et al.*, "Artificial intelligence for ventricular arrhythmia capability using ambulatory electrocardiograms," *Eur. Hear. J. - Digit. Heal.*, vol. 5, no. 3, pp. 384–388, 2024, doi: 10.1093/ehjdh/ztae004.
- [8] J. Y. Park, K. Lee, N. Park, S. C. You, and J. G. Ko, "Self-Attention LSTM-FCN model for arrhythmia classification and uncertainty assessment," *Artif.*

- Intell. Med.*, vol. 142, 2023, doi: 10.1016/j.artmed.2023.102570.
- [9] R. Feng *et al.*, “Engineering of Generative Artificial Intelligence and Natural Language Processing Models to Accurately Identify Arrhythmia Recurrence,” *Circ. Arrhythmia Electrophysiol.*, vol. 18, no. 1, p. e013023, 2025, doi: 10.1161/CIRCEP.124.013023.
 - [10] S. Chen, H. Wang, H. Zhang, C. Peng, Y. Li, and B. Wang, “A novel method of swin transformer with time-frequency characteristics for ECG-based arrhythmia detection,” *Front. Cardiovasc. Med.*, vol. 11, 2024, doi: 10.3389/fcvm.2024.1401143.
 - [11] G. Silva, P. Silva, G. Moreira, V. Freitas, J. Gertrudes, and E. Luz, “A Systematic Review of ECG Arrhythmia Classification: Adherence to Standards, Fair Evaluation, and Embedded Feasibility,” 2025, [Online]. Available: <http://arxiv.org/abs/2503.07276>
 - [12] E. Coppola, M. Savardi, M. Massussi, M. Adamo, M. Metra, and A. Signoroni, “HuBERT-ECG: a self-supervised foundation model for broad and scalable cardiac applications,” *medRxiv*, p. 2024.11.14.24317328, 2024, [Online]. Available: <https://www.medrxiv.org/content/10.1101/2024.11.14.24317328v1%0Ahttps://www.medrxiv.org/content/10.1101/2024.11.14.24317328v1.abstract>
 - [13] M. T. Liao *et al.*, “Impact of recording length and other arrhythmias on atrial fibrillation detection from wrist photoplethysmogram using smartwatches,” *Sci. Rep.*, vol. 12, no. 1, 2022, doi: 10.1038/s41598-022-09181-1.
 - [14] E. Pasero *et al.*, “Artificial Intelligence ECG Analysis in Patients with Short QT Syndrome to Predict Life-Threatening Arrhythmic Events,” *Sensors (Basel)*, vol. 23, no. 21, 2023, doi: 10.3390/s23218900.
 - [15] S. Tahery, F. H. Akhlaghi, and T. Amirsoleimani, “HeartBERT: A Self-Supervised ECG Embedding Model for Efficient and Effective Medical Signal Analysis,” 2025, [Online]. Available: <https://anonymous.4open.science/r/HeartBert>.
 - [16] S. Thapa, K. Howlader, S. Bhattacharjee, and W. Le, “MoRE: Multi-Modal Contrastive Pre-training with Transformers on X-Rays, ECGs, and

Diagnostic Report,” *Arxiv*, 2024.

- [17] M. Y. Ansari *et al.*, “A survey of transformers and large language models for ECG diagnosis: advances, challenges, and future directions,” *Artif. Intell. Rev.*, vol. 58, no. 9, 2025, doi: 10.1007/s10462-025-11259-x.
- [18] A. Li, Y. Wang, and H. Chen, “AI driven cardiovascular risk prediction using NLP and Large Language Models for personalized medicine in athletes,” *SLAS Technol.*, vol. 32, 2025, doi: 10.1016/j.slant.2025.100286.
- [19] H. Hamil *et al.*, “Design of a secured telehealth system based on multiple biosignals diagnosis and classification for IoT application,” *Expert Syst.*, vol. 39, no. 4, 2022, doi: 10.1111/exsy.12765.
- [20] M. Jiang *et al.*, “HADLN: Hybrid Attention-Based Deep Learning Network for Automated Arrhythmia Classification,” *Front. Physiol.*, vol. 12, 2021, doi: 10.3389/fphys.2021.683025.
- [21] M. Gusev, “AI Cardiologist: Arrhythmia Detection by Transformer-Based Language Model,” *Commun. Comput. Inf. Sci.*, vol. 2436 CCIS, pp. 223–237, 2025, doi: 10.1007/978-3-031-86162-8_16.
- [22] Z. Zhao *et al.*, “Analysis of an adaptive lead weighted ResNet for multiclass classification of 12-lead ECGs,” *Physiol. Meas.*, vol. 43, no. 3, 2022, doi: 10.1088/1361-6579/ac5b4a.
- [23] P. Pabitha, R. Praveen, K. C. J. Chandana, S. Ponlibarnaa, and A. S. Aparnaa, “A Comparative Study of Deep Learning Models for ECG Signal-based User Classification,” 2023. doi: 10.1109/ICoAC59537.2023.10249402.
- [24] H. Mulam, “Electrocardiogram Based Arrhythmia Classification Using Long Short-Term Memory with Luong Attention Mechanism,” *Int. J. Intell. Eng. Syst.*, vol. 17, no. 3, pp. 696–705, 2024, doi: 10.22266/ijies2024.0630.54.
- [25] N. Prasanna Venkatesh, R. Pradeep Kumar, B. Chakravarthy Neelapu, K. Pal, and J. Sivaraman, “Automated atrial arrhythmia classification using 1D-CNN-BiLSTM: A deep network ensemble model,” *Biomed. Signal Process. Control*, vol. 97, 2024, doi: 10.1016/j.bspc.2024.106703.
- [26] S. Hu, “ResNet-TCN: A Joint Model for ECG Heartbeat Classification with

- High Accuracy,” 2023. doi: 10.1109/ICOIN56518.2023.10048913.
- [27] C. J. Zhang, Yuan-Lu, F. Q. Tang, H. P. Cai, Y. F. Qian, and Chao-Wang, “Heart failure classification using deep learning to extract spatiotemporal features from ECG,” *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, 2024, doi: 10.1186/s12911-024-02415-4.
 - [28] S. Yang, “Extracting Pulmonary Nodules and Nodule Characteristics from Radiology Reports of Lung Cancer Screening Patients Using Transformer Models”.
 - [29] P. López-Úbeda, T. Martín-Noguerol, J. Escartín, and A. Luna, “Role of Natural Language Processing in Automatic Detection of Unexpected Findings in Radiology Reports: A Comparative Study of RoBERTa, CNN, and ChatGPT,” *Acad. Radiol.*, vol. 31, no. 12, pp. 4833–4842, 2024, doi: 10.1016/j.acra.2024.07.057.
 - [30] F. Chen, S. M. A. Bokhari, K. Cato, G. Gürsoy, and S. Rossetti, “Examining the Generalizability of Pretrained De-identification Transformer Models on Narrative Nursing Notes,” *Appl. Clin. Inform.*, vol. 15, no. 2, pp. 357–367, 2024, doi: 10.1055/a-2282-4340.
 - [31] S. Khan, M. Naseer, M. Hayat, S. W. Zamir, F. S. Khan, and M. Shah, “Transformers in Vision: A Survey,” *ACM Comput. Surv.*, 2022, doi: 10.1145/3505244.
 - [32] M. Sinnoor and S. K. Janardhan, “Arrhythmia Identification and Classification using Runge Kutta Optimizer-Based Hyperparameter Optimization for Long Short Term Memory,” *J. Inst. Eng. Ser. B*, 2024, doi: 10.1007/s40031-024-01038-7.
 - [33] N. Singh, V. K. Gunjan, F. Shaik, and S. Roy, “Detection of Cardio Vascular abnormalities using gradient descent optimization and CNN,” *Health Technol. (Berl.)*, vol. 14, no. 1, pp. 155–168, 2024, doi: 10.1007/s12553-023-00807-6.
 - [34] R. Anand, S. V. Lakshmi, D. Pandey, and B. K. Pandey, “An enhanced ResNet-50 deep learning model for arrhythmia detection using electrocardiogram biomedical indicators,” *Evol. Syst.*, vol. 15, no. 1, pp. 83–

97, 2024, doi: 10.1007/s12530-023-09559-0.

- [35] H. Serhal, N. Abdallah, J. M. Marion, P. Chauvet, M. Oueidat, and A. Humeau-Heurtier, "Overview on prediction, detection, and classification of atrial fibrillation using wavelets and AI on ECG," 2022. doi: 10.1016/j.compbimed.2021.105168.
- [36] J. Zheng *et al.*, "A High Precision Machine Learning-Enabled System for Predicting Idiopathic Ventricular Arrhythmia Origins," *Front. Cardiovasc. Med.*, vol. 9, 2022, doi: 10.3389/fcvm.2022.809027.
- [37] M. Ramkumar, R. Sarath Kumar, A. Manjunathan, M. Mathankumar, and J. Pauliah, "Auto-encoder and bidirectional long short-term memory based automated arrhythmia classification for ECG signal," *Biomed. Signal Process. Control*, vol. 77, 2022, doi: 10.1016/j.bspc.2022.103826.
- [38] S. Hambarde, A. Paithane, P. Lambhate, A. S. Hambarde, and P. A. Kalyankar, "Smart Arrhythmia Detection Using Single Lead ECG Signal and Hybridized Deep Neural Network Model," *Web Intell.*, vol. 23, no. 2, pp. 155–171, 2025, doi: 10.1177/24056456241297300.
- [39] A. R. Garcia, S. B. Filipe, C. Fernandes, C. Estevão, and G. Ramos, "No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する 共分散構造分析Title."
- [40] A. Kumar, S. A. Kumar, V. Dutt, A. K. Dubey, and V. García-Díaz, "IoT-based ECG monitoring for arrhythmia classification using Coyote Grey Wolf optimization-based deep learning CNN classifier," *Biomed. Signal Process. Control*, vol. 76, 2022, doi: 10.1016/j.bspc.2022.103638.
- [41] V. Kumar, S. Kumar, K. K. Raj, M. H. Assaf, V. Groza, and R. R. Kumar, "ECG Multi Class Classification Using Machine Learning Techniques," 2023. doi: 10.1109/MeMeA57477.2023.10171887.
- [42] L. R. Liu *et al.*, "An Arrhythmia classification approach via deep learning using single-lead ECG without QRS wave detection," *Heliyon*, vol. 10, no. 5, 2024, doi: 10.1016/j.heliyon.2024.e27200.
- [43] S. Saha and S. Barman Mandal, "FPGA implementation of IIR elliptic filters

- for de-noising ECG signal,” *Biomed. Signal Process. Control*, vol. 96, 2024, doi: 10.1016/j.bspc.2024.106544.
- [44] M. Ramkumar, A. Lakshmi, M. Pallikonda Rajasekaran, and A. Manjunathan, “Multiscale Laplacian graph kernel features combined with tree deep convolutional neural network for the detection of ECG arrhythmia,” *Biomed. Signal Process. Control*, vol. 76, 2022, doi: 10.1016/j.bspc.2022.103639.
- [45] K. R. Madhavi, P. Kora, L. V. Reddy, J. Avanija, K. L. S. Soujanya, and P. Telagarapu, “Cardiac arrhythmia detection using dual-tree wavelet transform and convolutional neural network,” *Soft Comput.*, vol. 26, no. 7, pp. 3561–3571, 2022, doi: 10.1007/s00500-021-06653-w.
- [46] D. Tenepalli and T. M. Navamani, “Advancing cardiac diagnostics: high-accuracy arrhythmia classification with the EGOLF-net model,” *Front. Physiol.*, vol. 16, 2025, doi: 10.3389/fphys.2025.1613812.
- [47] “แนวทางเวชปฏิบัติ สำหรับ บุคลากร ู้ ่วยภาวะหัวใจเต้นผิดจังหวะ ชนิด atrial fibrillation (AF) ในประเทศไทย จัดทำโดย • ชมรมช ่วงไฟฟ้าหัวใจ • สมาคมแพทย์ โรคหัวใจแห่งประเทศไทยในพระบรมราชูปถัมภ์.” [Online]. Available: <https://www.news-medical.net/health/Atrial-Fibrillation-%28AF%29.aspx>
- [48] P. Varalakshmi and A. P. Sankaran, “An improved hybrid AI model for prediction of arrhythmia using ECG signals,” *Biomed. Signal Process. Control*, vol. 80, 2023, doi: 10.1016/j.bspc.2022.104248.
- [49] T. Pokaprakarn, R. R. Kitzmiller, J. Randall Moorman, D. E. Lake, A. K. Krishnamurthy, and M. R. Kosorok, “Sequence to Sequence ECG Cardiac Rhythm Classification Using Convolutional Recurrent Neural Networks,” *IEEE J. Biomed. Heal. Informatics*, vol. 26, no. 2, pp. 572–580, 2022, doi: 10.1109/JBHI.2021.3098662.
- [50] A. Manocha, S. K. Sood, and M. Bhatia, “Federated learning-inspired smart ECG classification: an explainable artificial intelligence approach,” *Multimed. Tools Appl.*, vol. 84, no. 19, pp. 21673–21696, 2025, doi: 10.1007/s11042-024-20084-3.

- [51] R. R. Van De Leur *et al.*, “Discovering and Visualizing Disease-Specific Electrocardiogram Features Using Deep Learning: Proof-of-Concept in Phospholamban Gene Mutation Carriers,” *Circ. Arrhythmia Electrophysiol.*, vol. 14, no. 2, p. E009056, 2021, doi: 10.1161/CIRCEP.120.009056.
- [52] H. Halvaei, T. Hygrell, E. Svennberg, V. D. A. Corino, L. Sornmo, and M. Stridh, “Detection of Non-Sustained Supraventricular Tachycardia in Atrial Fibrillation Screening,” *IEEE J. Transl. Eng. Heal. Med.*, vol. 12, pp. 480–487, 2024, doi: 10.1109/JTEHM.2024.3397739.
- [53] L. Krause, “What Is Ventricular Tachycardia? Symptoms, Causes, and More.” [Online]. Available: <https://www.healthline.com/>
- [54] N. Prasanna Venkatesh, R. Pradeep Kumar, B. Chakravarthy Neelapu, K. Pal, and J. Sivaraman, “CatBoost-based improved detection of P-wave changes in sinus rhythm and tachycardia conditions: a lead selection study,” *Phys. Eng. Sci. Med.*, vol. 46, no. 2, pp. 925–944, 2023, doi: 10.1007/s13246-023-01274-z.
- [55] S. Śmigiel, “ECG Classification Using Orthogonal Matching Pursuit and Machine Learning,” *Sensors*, vol. 22, no. 13, 2022, doi: 10.3390/s22134960.
- [56] M. Karri, C. S. R. Annavarapu, and K. K. Pedapenki, “A Real-Time Cardiac Arrhythmia Classification Using Hybrid Combination of Delta Modulation, 1D-CNN and Blended LSTM,” *Neural Process. Lett.*, vol. 55, no. 2, pp. 1499–1526, 2023, doi: 10.1007/s11063-022-10949-9.
- [57] C. Chen, Z. Hua, R. Zhang, G. Liu, and W. Wen, “Automated arrhythmia classification based on a combination network of CNN and LSTM,” *Biomed. Signal Process. Control*, vol. 57, 2020, doi: 10.1016/j.bspc.2019.101819.
- [58] M. H. Mazidi, M. Eshghi, and M. R. Raoufy, “Premature Ventricular Contraction (PVC) Detection System Based on Tunable Q-Factor Wavelet Transform,” *J. Biomed. Phys. Eng.*, vol. 12, no. 1, pp. 61–74, 2022, doi: 10.31661/jbpe.v0i0.1235.
- [59] J. R. Giudicessi *et al.*, “Artificial Intelligence–Enabled Assessment of the Heart Rate Corrected QT Interval Using a Mobile Electrocardiogram Device,” *Circulation*, vol. 143, no. 13, pp. 1274–1286, 2021, doi:

10.1161/CIRCULATIONAHA.120.050231.

- [60] C. Shao, J. Wang, J. Tian, and Y. da Tang, "Coronary Artery Disease: From Mechanism to Clinical Practice," *Adv. Exp. Med. Biol.*, vol. 1177, pp. 1–36, 2020, doi: 10.1007/978-981-15-2517-9_1.
- [61] M. Wasimuddin, K. Elleithy, A. S. Abuzneid, M. Faezipour, and O. Abuzagheh, "Stages-based ECG signal analysis from traditional signal processing to machine learning approaches: A survey," *IEEE Access*, vol. 8, pp. 177782–177803, 2020, doi: 10.1109/ACCESS.2020.3026968.
- [62] M. Martínez-Sellés and M. Marina-Breysse, "Current and Future Use of Artificial Intelligence in Electrocardiography," 2023. doi: 10.3390/jcdd10040175.
- [63] M. Wasimuddin, K. Elleithy, A. Abuzneid, M. Faezipour, and O. Abuzagheh, "Multiclass ecg signal analysis using global average-based 2-d convolutional neural network modeling," *Electron.*, vol. 10, no. 2, pp. 1–29, 2021, doi: 10.3390/electronics10020170.
- [64] P. N. Malleswari, C. R. S. Hanuman, V. R. Kammampati, S. Swathi, and B. E. Raju, "Deep Learning based DWT-Bi-LSTM Classifier for Enhanced Cardiovascular Arrhythmia Classification," *Int. J. Electr. Electron. Res.*, vol. 12, no. 3, pp. 934–939, 2024, doi: 10.37391/IJEER.120325.
- [65] O. Degachi and K. Ouni, "An attention-augmented bidirectional LSTM-based encoder–decoder architecture for electrocardiogram heartbeat classification," *Trans. Inst. Meas. Control*, vol. 47, no. 3, pp. 506–515, 2025, doi: 10.1177/01423312241252459.
- [66] S. Liaqat, K. Dashtipour, A. Zahid, K. Assaleh, K. Arshad, and N. Ramzan, "Detection of atrial fibrillation using a machine learning approach," *Inf.*, vol. 11, no. 12, pp. 1–15, 2020, doi: 10.3390/info11120549.
- [67] L. D. Sharma, J. Rahul, A. Aggarwal, and V. K. Bohat, "An improved cardiac arrhythmia classification using stationary wavelet transform decomposed short duration QRS segment and Bi-LSTM network," *Multidimens. Syst. Signal Process.*, vol. 34, no. 2, pp. 503–520, 2023, doi: 10.1007/s11045-023-00875-x.

- [68] J. Lim, "QRS-Centric Deep Learning for Precision Beat-wise Atrial Fibrillation Detection in ECG Analysis," 2025. doi: 10.1109/ICBEA66055.2025.00009.
- [69] M. Karri and C. S. R. Annavarapu, "A real-time embedded system to detect QRS-complex and arrhythmia classification using LSTM through hybridized features," *Expert Syst. Appl.*, vol. 214, 2023, doi: 10.1016/j.eswa.2022.119221.
- [70] Z. D. Liu, B. Zhou, Y. Li, M. Tang, and F. Miao, "Continuous Blood Pressure Estimation From Electrocardiogram and Photoplethysmogram During Arrhythmias," *Front. Physiol.*, vol. 11, 2020, doi: 10.3389/fphys.2020.575407.
- [71] N. Prasanna Venkatesh, R. Pradeep Kumar, B. Chakravarthy Neelapu, K. Pal, and J. Sivaraman, "Atrial lead system for enhanced P-wave recording: A comparative study on optimal leads using gradient boosting and deep learning algorithms," *Biomed. Signal Process. Control*, vol. 97, 2024, doi: 10.1016/j.bspc.2024.106730.
- [72] S. Hamza and Y. Ben Ayed, "An integration of features for person identification based on the PQRST fragments of ECG signals," *Signal, Image Video Process.*, vol. 16, no. 8, pp. 2037–2043, 2022, doi: 10.1007/s11760-022-02165-8.
- [73] N. Neifar, A. Ben-Hamadou, A. Mdhaftar, M. Jmaiel, and B. Freisleben, "Leveraging Statistical Shape Priors in GAN-Based ECG Synthesis," *IEEE Access*, vol. 12, pp. 36002–36015, 2024, doi: 10.1109/ACCESS.2024.3373724.
- [74] Q. ul ain Mastoi *et al.*, "Machine learning-data mining integrated approach for premature ventricular contraction prediction," *Neural Comput. Appl.*, vol. 33, no. 18, pp. 11703–11719, 2021, doi: 10.1007/s00521-021-05820-2.
- [75] B. Tutuko *et al.*, "DAE-ConvBiLSTM: End-to-end learning single-lead electrocardiogram signal for heart abnormalities detection," *PLoS One*, vol. 17, no. 12 December, 2022, doi: 10.1371/journal.pone.0277932.
- [76] K. Ghanya and K. Reddy Madhavi, "Internet of medical things-based ECG

- monitoring for arrhythmia classification utilizing metaheuristic optimization with ensemble deep learning model,” *Cluster Comput.*, vol. 28, no. 6, 2025, doi: 10.1007/s10586-024-04971-w.
- [77] Z. Wang, K. Wang, X. Chen, Y. Zheng, and X. Wu, “A deep learning approach for inter-patient classification of premature ventricular contraction from electrocardiogram,” *Biomed. Signal Process. Control*, vol. 94, 2024, doi: 10.1016/j.bspc.2024.106265.
- [78] S. EKEN, “Medical Data Analysis for Different Data Types,” *Int. J. Comput. Exp. Sci. Eng.*, vol. 6, no. 3, pp. 138–144, 2020, doi: 10.22399/ijcesen.780174.
- [79] S. Sousa, M. Jantscher, M. Kröll, and R. Kern, “Large Language Models for Electronic Health Record De-Identification in English and German,” *Inf.*, vol. 16, no. 2, 2025, doi: 10.3390/info16020112.
- [80] P. M. Croon, A. F. Pedroso, and R. Khera, “The emerging role of AI in transforming cardiovascular care,” 2025. doi: 10.1080/14796678.2025.2492973.
- [81] Christoph Schröerab, Felix Kruseb, and Jorge Marx Gómezb, “A Systematic Literature Review on Applying CRISP-DM Process Model,” *Procedia Comput. Sci.*, vol. 181, pp. 526–534, 2021.
- [82] S. Allabun, “An Intelligent Learning Approach for Improving ECG Signal Classification and Arrhythmia Analysis,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 15, no. 4, pp. 319–326, 2024, doi: 10.14569/IJACSA.2024.0150433.
- [83] H. A. Huillcen Baca, A. Muñoz Del Carpio Toia, J. A. Sulla Torres, R. Cusirramos Montesinos, L. A. Contreras Salas, and S. C. Correa Herrera, “Detection of Arrhythmias Using Heart Rate Signals from Smartwatches,” *Appl. Sci.*, vol. 14, no. 16, 2024, doi: 10.3390/app14167233.
- [84] E. Kim, J. Kim, J. Park, H. Ko, and Y. Kyung, “TinyML-Based Classification in an ECG Monitoring Embedded System,” *Comput. Mater. Contin.*, vol. 75, no. 1, pp. 1751–1764, 2023, doi: 10.32604/cmc.2023.031663.
- [85] S. Kuila, N. Dhanda, and S. Joardar, “ECG signal classification to detect

- heart arrhythmia using ELM and CNN,” *Multimed. Tools Appl.*, vol. 82, no. 19, pp. 29857–29881, 2023, doi: 10.1007/s11042-022-14233-9.
- [86] X. Tang, Z. Ma, Q. Hu, and W. Tang, “A Real-Time Arrhythmia Heartbeats Classification Algorithm Using Parallel Delta Modulations and Rotated Linear-Kernel Support Vector Machines,” *IEEE Trans. Biomed. Eng.*, vol. 67, no. 4, pp. 978–986, 2020, doi: 10.1109/TBME.2019.2926104.
- [87] O. Yadav, “ResNet-50-CNN and LSTM Based Arrhythmia Detection Model Based on ECG Dataset,” 2023. doi: 10.1007/978-3-031-38281-9_8.
- [88] Z. Yang *et al.*, “A coordinated adaptive multiscale enhanced spatio-temporal fusion network for multi-lead electrocardiogram arrhythmia detection,” *Sci. Rep.*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-71700-z.
- [89] A. Anbarasi and T. Ravi, “Detection and classification of arrhythmia type using hybrid model of LSTM with convolutional neural network,” *Appl. Nanosci.*, vol. 13, no. 5, pp. 3435–3445, 2023, doi: 10.1007/s13204-022-02368-y.
- [90] M. Naz, J. H. Shah, M. A. Khan, M. Sharif, M. Raza, and R. Damaševičius, “From ECG signals to images: a transformation based approach for deep learning,” *PeerJ Comput. Sci.*, vol. 7, pp. 1–18, 2021, doi: 10.7717/PEERJ-CS.386.
- [91] J. P. Allam, S. P. Sahoo, and S. Ari, “Multi-stream Bi-GRU network to extract a comprehensive feature set for ECG signal classification,” *Biomed. Signal Process. Control*, vol. 92, 2024, doi: 10.1016/j.bspc.2024.106097.
- [92] R. M. Ramaiah and K. K. Sriantegowda, “Coronary Heart Disease Classification Using Improved Penguin Emperor Optimization-Based Long Short Term Memory Network,” *IIUM Eng. J.*, vol. 24, no. 2, pp. 67–85, 2023, doi: 10.31436/iiumej.v24i2.2698.
- [93] S. Nithya, M. Mary Shanthi Rani, and V. Sivakumar, “Classification of Cardiovascular Arrhythmia Using Deep Learning Techniques: A Review,” *EAI Endorsed Trans. Pervasive Heal. Technol.*, vol. 10, 2024, doi: 10.4108/eetpht.10.6421.
- [94] A. Zhang, X. Yang, T. Li, M. Dou, and H. Yang, “Classification Method of

- ECG Signals Based on RANet,” *Cardiovasc. Eng. Technol.*, 2024, doi: 10.1007/s13239-024-00730-5.
- [95] M. Shayboun, C. Koch, and D. Kifokeris, “Learning from accidents: machine learning prototype development based on the CRISP-DM business understanding,” *Proc. Jt. CIB W099 W123 Annu. Int. Conf. 2021 Good Heal. Chang. Innov. Improv. wellbeing Constr.*, pp. 43–53, 2021, [Online]. Available: https://www.w099tg592020.com/uploads/1/3/0/5/130510093/cib_proceedings_2021_final.pdf
- [96] R. H. Bemthuis, R. R. Govers, and A. Asadi, “A CRISP-DM-based Methodology for Assessing Agent-based Simulation Models using Process Mining,” *arXiv Prepr. arXiv2404.01114*, 2024, [Online]. Available: <https://arxiv.org/abs/2404.01114> <https://arxiv.org/pdf/2404.01114>
- [97] H. M. Rai, J. Yoo, and S. Dashkevych, “GAN-SkipNet: A Solution for Data Imbalance in Cardiac Arrhythmia Detection Using Electrocardiogram Signals from a Benchmark Dataset,” *Mathematics*, vol. 12, no. 17, 2024, doi: 10.3390/math12172693.
- [98] J. Cai, J. Song, and B. Peng, “Enhancing ECG Heartbeat classification with feature fusion neural networks and dynamic minority-biased batch weighting loss function,” *Physiol. Meas.*, vol. 45, no. 7, 2024, doi: 10.1088/1361-6579/ad5cc0.
- [99] Q. Liu *et al.*, “PSC-Net: Integration of Convolutional Neural Networks and transformers for Physiological Signal Classification,” *Biomed. Signal Process. Control*, vol. 91, 2024, doi: 10.1016/j.bspc.2024.106040.
- [100] Y. Ju, J. L. S. Waugh, S. Singh, C. G. Rusin, A. B. Patel, and P. N. Jain, “A multimodal deep learning tool for detection of junctional ectopic tachycardia in children with congenital heart disease,” *Hear. Rhythm O2*, vol. 5, no. 7, pp. 452–459, 2024, doi: 10.1016/j.hroo.2024.04.014.
- [101] K. Priyadharshini, A. Mathias, R. Santhana Krishnan, N. Kanthimathi, J. Relin Francis Raj, and P. Stella Rose Malar, “A Multi-Resolution Deep Learning Approach for IoT-Integrated Biomedical Signal Processing using

- CNN-LSTM,” 2025. doi: 10.1109/ICTMIM65579.2025.10988087.
- [102] M. Ma, “MST-BiLSTM: An Improved Bi-LSTM Method Based on Multi-Scale Spatio-Temporal Feature Fusion and Attention Mechanism for ECG Recognition,” 2025. doi: 10.1109/FASTA65681.2025.11138627.
- [103] R. F. B. Sabu, “AD-CBM: Attention-Driven CNN-Bi-LSTM Model for ECG-based Arrhythmia Detection and Classification,” 2025. doi: 10.1109/ACCESS65134.2025.11135636.
- [104] J. Rahul and L. D. Sharma, “Automatic cardiac arrhythmia classification based on hybrid 1-D CNN and Bi-LSTM model,” *Biocybern. Biomed. Eng.*, vol. 42, no. 1, pp. 312–324, 2022, doi: 10.1016/j.bbe.2022.02.006.
- [105] R. Gao *et al.*, “Time-distanced gates in long short-term memory networks,” *Med. Image Anal.*, 2020, doi: 10.1016/j.media.2020.101785.
- [106] S. Munawar, G. Angappan, and S. Konda, “Arrhythmia Classification Based on Bi-Directional Long Short-Term Memory and Multi-Task Group Method,” *Int. J. e-Collaboration*, vol. 19, no. 1, 2023, doi: 10.4018/IJeC.315791.
- [107] Y. Meng, L. Lin, Z. Qin, Y. Qu, Y. Qin, and Y. Li, “Biosignal Classification Based on Multi-Feature Multi-Dimensional WaveNet-LSTM Models,” *J. Commun.*, vol. 17, no. 5, pp. 399–404, 2022, doi: 10.12720/jcm.17.5.399-404.
- [108] J. Gutierrez-Ojeda, “ECG Arrhythmia Classification Using Recurrence Plot and ResNet-18,” *Int. J. Comput.*, vol. 22, no. 2, pp. 140–148, 2023, doi: 10.47839/ijc.22.2.3083.
- [109] F. De Marco, F. Ferrucci, M. Risi, and G. Tortora, “Classification of QRS complexes to detect Premature Ventricular Contraction using machine learning techniques,” *PLoS One*, vol. 17, no. 8 August, 2022, doi: 10.1371/journal.pone.0268555.
- [110] A. A. Al-Janabi, S. Al-Janabi, and B. Al-Khateeb, “Healthcare Privacy-Preserving Federated Transfer Learning using CKKS-Based Homomorphic Encryption and PYHFEL Tool,” *Iraqi J. Comput. Sci. Math.*, vol. 5, no. 3, pp. 473–488, 2024, doi: 10.52866/ijcsm.2024.05.03.029.

- [111] K. R. Febeena and C. Kurian, "MAB-Net: an enhanced MobileNet with attention and BiLSTM model for arrhythmia detection using electrocardiogram signals," *Iran J. Comput. Sci.*, 2025, doi: 10.1007/s42044-025-00238-8.
- [112] A. Mukhtar, S. A. Malik, H. Asjad, S. Mufty, M. Tahir, and J. Sheikh, "Hybrid LSTM-Attention Framework for Enhanced Classification of Cardiac Abnormalities from ECG Signals," 2025. doi: 10.1109/ICETECC65365.2025.11070260.
- [113] V. Domazetoski *et al.*, "The influence of atrial flutter in automated detection of atrial arrhythmias - are we ready to go into clinical practice?," *Comput. Methods Programs Biomed.*, vol. 221, 2022, doi: 10.1016/j.cmpb.2022.106901.
- [114] O. O'Donoghue, A. Shtedritski, J. Ginger, R. Abboud, A. E. Ghareeb, and S. G. Rodrigues, "BioPlanner: Automatic Evaluation of LLMs on Protocol Planning in Biology," in *EMNLP 2023 - 2023 Conference on Empirical Methods in Natural Language Processing, Proceedings*, 2023. doi: 10.18653/v1/2023.emnlp-main.162.
- [115] Y. Yang, L. Jin, and Z. Pan, "ECG Arrhythmia Heartbeat Classification Using Deep Learning Networks," 2021. doi: 10.1007/978-3-030-69992-5_14.
- [116] Y. Guan, Y. An, J. Xu, N. Liu, and J. Wang, "HA-ResNet: Residual Neural Network With Hidden Attention for ECG Arrhythmia Detection Using Two-Dimensional Signal," *IEEE/ACM Trans. Comput. Biol. Bioinforma.*, vol. 20, no. 6, pp. 3389–3398, 2023, doi: 10.1109/TCBB.2022.3198998.
- [117] N. K. Sharma, S. Kumar, and N. Kumar, "HGSmark: An efficient ECG watermarking scheme using hunger games search and Bayesian regularization BPNN," *Biomed. Signal Process. Control*, vol. 83, 2023, doi: 10.1016/j.bspc.2023.104633.
- [118] D. Li *et al.*, "Joint extraction of Chinese medical entities and relations based on RoBERTa and single-module global pointer," *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, 2024, doi: 10.1186/s12911-024-02577-1.

- [119] Y. Cheng, W. Zhu, D. Li, and L. Wang, "Multi-label classification of arrhythmia using dynamic graph convolutional network based on encoder-decoder framework," *Biomed. Signal Process. Control*, vol. 95, 2024, doi: 10.1016/j.bspc.2024.106348.
- [120] J. Huang *et al.*, "Research output of artificial intelligence in arrhythmia from 2004 to 2021: a bibliometric analysis," *J. Thorac. Dis.*, vol. 14, no. 5, pp. 1411–1427, 2022, doi: 10.21037/jtd-21-1767.
- [121] A. J. Prakash and M. Atef, "A lightweight deep learning approach for patient-specific electrocardiogram beat classification using local and long-term dependencies," *Eng. Appl. Artif. Intell.*, vol. 152, 2025, doi: 10.1016/j.engappai.2025.110754.
- [122] S. Hu *et al.*, "Semi-Supervised Learning for Low-Cost Personalized Obstructive Sleep Apnea Detection Using Unsupervised Deep Learning and Single-Lead Electrocardiogram," *IEEE J. Biomed. Heal. Informatics*, vol. 27, no. 11, pp. 5281–5292, 2023, doi: 10.1109/JBHI.2023.3304299.
- [123] H. Yan, Y. Liu, L. Jin, and X. Bai, "The development, application, and future of LLM similar to ChatGPT," *J. Image Graph.*, 2023, doi: 10.11834/jig.230536.
- [124] K. Pałczyński, S. Śmigiel, D. Ledziński, and S. Bujnowski, "Study of the Few-Shot Learning for ECG Classification Based on the PTB-XL Dataset," *Sensors*, vol. 22, no. 3, 2022, doi: 10.3390/s22030904.
- [125] R. Doste *et al.*, "Training machine learning models with synthetic data improves the prediction of ventricular origin in outflow tract ventricular arrhythmias," *Front. Physiol.*, vol. 13, 2022, doi: 10.3389/fphys.2022.909372.
- [126] P. López-Úbeda, T. Martín-Noguerol, and A. Luna, "Automatic classification and prioritisation of actionable BI-RADS categories using natural language processing models," *Clin. Radiol.*, vol. 79, no. 1, pp. e1–e7, 2024, doi: 10.1016/j.crad.2023.09.009.
- [127] R. Panchal, S. Tiwari, and S. Agarwal, "Multimodal image fusion on ECG signals for congestive heart failure classification," *Multimed. Tools Appl.*,

2024, doi: 10.1007/s11042-024-19052-8.

- [128] A. Abdullah, S. Nithya, M. M. S. Rani, S. Vijayalakshmi, and B. Balusamy, “Stacked LSTM and Kernel-PCA-based Ensemble Learning for Cardiac Arrhythmia Classification,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 9, pp. 39–48, 2023, doi: 10.14569/IJACSA.2023.0140905.
- [129] A. Sadeghi, F. Hajati, A. Rezaee, M. Sadeghi, A. Argha, and H. Alinejad-Rokny, “3DECG-Net: ECG fusion network for multi-label cardiac arrhythmia detection,” *Comput. Biol. Med.*, vol. 182, 2024, doi: 10.1016/j.combiomed.2024.109126.
- [130] C. Ji, L. Wang, J. Qin, L. Liu, Y. Han, and Z. Wang, “MSGformer: A multi-scale grid transformer network for 12-lead ECG arrhythmia detection,” *Biomed. Signal Process. Control*, vol. 87, 2024, doi: 10.1016/j.bspc.2023.105499.
- [131] R. Nakamoto, B. Flanagan, T. Yamauchi, Y. Dai, K. Takami, and H. Ogata, “Enhancing Automated Scoring of Math Self-Explanation Quality Using LLM-Generated Datasets: A Semi-Supervised Approach,” *Computers*, 2023, doi: 10.3390/computers12110217.
- [132] M. Z. Alam, M. S. Rahman, and M. S. Rahman, “A Random Forest based predictor for medical data classification using feature ranking,” *Informatics Med. Unlocked*, vol. 15, 2019, doi: 10.1016/j.imu.2019.100180.
- [133] W. Zeng, L. Shan, C. Yuan, and S. Du, “Advancing cardiac diagnostics: Exceptional accuracy in abnormal ECG signal classification with cascading deep learning and explainability analysis,” *Appl. Soft Comput.*, vol. 165, 2024, doi: 10.1016/j.asoc.2024.112056.
- [134] S. Kuila, N. Dhanda, and S. Joardar, “ECG signal classification using DEA with LSTM for arrhythmia detection,” *Multimed. Tools Appl.*, vol. 83, no. 15, pp. 45989–46016, 2024, doi: 10.1007/s11042-023-17095-x.
- [135] H. Taniguchi *et al.*, “Explainable artificial intelligence model for diagnosis of atrial fibrillation using holter electrocardiogram waveforms,” *Int. Heart J.*, vol. 62, no. 3, pp. 534–539, 2021, doi: 10.1536/ihj.21-094.
- [136] P. Yang, D. Wang, W. B. Zhao, L. H. Fu, J. L. Du, and H. Su, “Ensemble of

- kernel extreme learning machine based random forest classifiers for automatic heartbeat classification,” *Biomed. Signal Process. Control*, vol. 63, 2021, doi: 10.1016/j.bspc.2020.102138.
- [137] A. Farooq, M. Seyedmahmoudian, and A. Stojcevski, “A Wearable Wireless Sensor System Using Machine Learning Classification to Detect Arrhythmia,” *IEEE Sens. J.*, vol. 21, no. 9, pp. 11109–11116, 2021, doi: 10.1109/JSEN.2021.3062395.
- [138] R. Ranjan, P. Maithili, A. R. Panda, M. K. Mishra, P. K. Mallick, and B. Sahoo, “Comprehensive Comparative Analysis of ECG Arrhythmia Classification,” 2025. doi: 10.1109/ICoICC64033.2025.11052116.
- [139] Y. R. Jin, Z. Y. Li, Y. Y. Tian, X. Y. Wei, and C. L. Liu, “A novel interpretable multilevel wavelet decomposition deep network for actual heartbeat classification,” *Sci. China Technol. Sci.*, vol. 67, no. 6, pp. 1842–1854, 2024, doi: 10.1007/s11431-023-2639-9.
- [140] R. Pashikanti, C. Y. Patil, and S. Amita Anirudhe, “An adaptive Marine Predator Optimization Algorithm (MPOA) integrated Gated Recurrent Neural Network (GRNN) classifier model for arrhythmia detection,” *Biomed. Signal Process. Control*, vol. 94, 2024, doi: 10.1016/j.bspc.2024.106328.
- [141] R. B. Trivedi and S. R. Goyal, “Arrhythmia Detection by Analyzing ECGs Using Autoencoders and LSTM Networks,” 2025. doi: 10.1007/978-981-96-2124-8_21.
- [142] T. Bender *et al.*, “Analysis of a Deep Learning Model for 12-Lead ECG Classification Reveals Learned Features Similar to Diagnostic Criteria,” *IEEE J. Biomed. Heal. Informatics*, vol. 28, no. 4, pp. 1848–1859, 2024, doi: 10.1109/JBHI.2023.3271858.
- [143] Y. Jin *et al.*, “Cardiologist-level interpretable knowledge-fused deep neural network for automatic arrhythmia diagnosis,” *Commun. Med.*, vol. 4, no. 1, 2024, doi: 10.1038/s43856-024-00464-4.
- [144] M. Ramkumar, M. Alagarsamy, A. Balakumar, and S. Pradeep, “Ensemble classifier fostered detection of arrhythmia using ECG data,” *Med. Biol. Eng.*

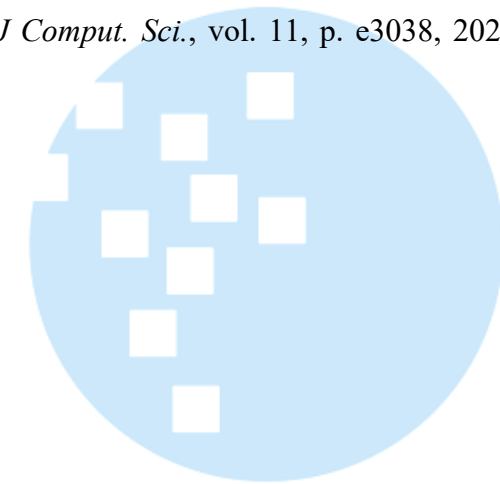
- Comput.*, vol. 61, no. 9, pp. 2453–2466, 2023, doi: 10.1007/s11517-023-02839-6.
- [145] A. Smajić, M. Grandits, and G. F. Ecker, “Using Jupyter Notebooks for re-training machine learning models,” *J. Cheminform.*, vol. 14, no. 1, 2022, doi: 10.1186/s13321-022-00635-2.
- [146] O. Mazumder *et al.*, “Computational Model for Therapy Optimization of Wearable Cardioverter Defibrillator: Shockable Rhythm Detection and Optimal Electrotherapy,” *Front. Physiol.*, vol. 12, 2021, doi: 10.3389/fphys.2021.787180.
- [147] F. J. Wesselius, M. S. van Schie, N. M. S. de Groot, and R. C. Hendriks, “An accurate and efficient method to train classifiers for atrial fibrillation detection in ECGs: Learning by asking better questions,” *Comput. Biol. Med.*, vol. 143, 2022, doi: 10.1016/j.compbiomed.2022.105331.
- [148] K. A. Sharada, K. S. N. Sushma, V. Muthukumaran, T. R. Mahesh, B. Swapna, and S. Roopashree, “High ECG diagnosis rate using novel machine learning techniques with Distributed Arithmetic (DA) based gated recurrent units,” *Microprocess. Microsyst.*, vol. 98, 2023, doi: 10.1016/j.micpro.2023.104796.
- [149] R. K. Hughes *et al.*, “Apical Ischemia Is a Universal Feature of Apical Hypertrophic Cardiomyopathy,” *Circ. Cardiovasc. Imaging*, vol. 16, no. 3, pp. 251–259, 2023, doi: 10.1161/CIRCIMAGING.122.014907.
- [150] A. H. Kashou, A. M. May, and P. A. Noseworthy, “Comparison of two artificial intelligence-augmented ECG approaches: Machine learning and deep learning,” *J. Electrocardiol.*, vol. 79, pp. 75–80, 2023, doi: 10.1016/j.jelectrocard.2023.03.009.
- [151] W. Ji and D. Zhu, “ECG Classification Exercise Health Analysis Algorithm Based on GRU and Convolutional Neural Network,” *IEEE Access*, vol. 12, pp. 59842–59850, 2024, doi: 10.1109/ACCESS.2024.3392965.
- [152] J. Juliano, D. Ajeng, and J. Wiratama, “Enhancing Heart Disease Classification : A Comparative Analysis of SMOTE and Naïve Bayes on Imbalanced Data,” vol. 9, no. September, pp. 2072–2079, 2025.

- [153] T. He, Y. Chen, B. Fang, and J. Chen, "SEVGGNet-LSTM: A Fused Deep Learning Model for ECG Classification," 2024. doi: 10.1007/978-3-031-65126-7_23.
- [154] S. Mian Qaisar, S. I. Khan, K. Srinivasan, and M. Krichen, "Arrhythmia classification using multirate processing metaheuristic optimization and variational mode decomposition," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 1, pp. 26–37, 2023, doi: 10.1016/j.jksuci.2022.05.009.
- [155] K. Yang *et al.*, "ECG-LM: Understanding Electrocardiogram with a Large Language Model," *Heal. Data Sci.*, vol. 5, 2025, doi: 10.34133/hds.0221.
- [156] P. N. Aarotale and A. Rattani, "Deep Learning Models for Arrhythmia Classification Using Stacked Time-frequency Scalogram Images from ECG Signals," 2023. doi: 10.22489/CinC.2023.350.
- [157] T. Tuncer, S. Dogan, P. Pławiak, and U. Rajendra Acharya, "Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ECG signals," *Knowledge-Based Syst.*, vol. 186, 2019, doi: 10.1016/j.knosys.2019.104923.
- [158] V. Krasteva, S. Ménétré, J. P. Didon, and I. Jekova, "Fully convolutional deep neural networks with optimized hyperparameters for detection of shockable and non-shockable rhythms," *Sensors (Switzerland)*, vol. 20, no. 10, 2020, doi: 10.3390/s20102875.
- [159] M. M. Farag, "A Self-Contained STFT CNN for ECG Classification and Arrhythmia Detection at the Edge," *IEEE Access*, vol. 10, pp. 94469–94486, 2022, doi: 10.1109/ACCESS.2022.3204703.
- [160] Y. Han, P. Han, B. Yuan, Z. Zhang, L. Liu, and J. Panneerselvam, "Novel Transformation Deep Learning Model for Electrocardiogram Classification and Arrhythmia Detection using Edge Computing," *J. Grid Comput.*, vol. 22, no. 1, 2024, doi: 10.1007/s10723-023-09717-3.
- [161] T. Habineza, A. H. Ribeiro, D. Gedon, J. A. Behar, A. L. P. Ribeiro, and T. B. Schön, "End-to-end risk prediction of atrial fibrillation from the 12-Lead ECG by deep neural networks," *J. Electrocardiol.*, vol. 81, pp. 193–200, 2023, doi: 10.1016/j.jelectrocard.2023.09.011.

- [162] W. Zhang, Z. Xu, Y. Xiao, and Y. Xue, “Unleashing the power of pseudo-code for binary code similarity analysis,” *Cybersecurity*, 2022, doi: 10.1186/s42400-022-00121-0.
- [163] R. Li, D. Su, S. Shen, S. Lu, Q. Zhang, and S. Zhang, “MVFF-SAT: A classification model for ECG signals integrating multi perspective features,” *Meas. J. Int. Meas. Confed.*, vol. 256, 2025, doi: 10.1016/j.measurement.2025.118149.
- [164] N. Sharma, M. Sharma, and U. Garg, “Predicting Academic Performance of Students Using Machine Learning Models,” *2023 Int. Conf. Artif. Intell. Smart Commun. AISC 2023*, pp. 1058–1063, 2023, doi: 10.1109/AISC56616.2023.10085214.
- [165] J. S. Bosma *et al.*, “The DRAGON benchmark for clinical NLP,” *npj Digit. Med.*, vol. 8, no. 1, 2025, doi: 10.1038/s41746-025-01626-x.
- [166] C. N. Karaeng and D. A. Kristiyanti, “Multimodal Sentiment Analysis Approach Combining Transfer Learning and Generative AI of E-Commerce Product Reviews,” *Proc. - 2025 4th Int. Conf. Electron. Represent. Algorithm Artif. Intell. Creat. Tomorrow's World Today, ICERA 2025*, pp. 215–220, 2025, doi: 10.1109/ICERA66156.2025.11087376.
- [167] Y. Jin *et al.*, “A Novel Interpretable Method Based on Dual-Level Attentional Deep Neural Network for Actual Multilabel Arrhythmia Detection,” *IEEE Trans. Instrum. Meas.*, vol. 71, 2022, doi: 10.1109/TIM.2021.3135330.
- [168] H. Zhao and X. Yin, “Deep VMD-attention network for arrhythmia signal classification based on Hodgkin-Huxley model and multi-objective crayfish optimization algorithm,” *PLoS One*, vol. 20, no. 5 May, 2025, doi: 10.1371/journal.pone.0321484.
- [169] T. Sivaranjani, B. Sasikumar, and G. Sugitha, “Rectified Adam Optimizer and LSTM with Attention Mechanism for ECG-Based Multi-Class Classification of Cardiac Arrhythmia,” *Radioengineering*, vol. 34, no. 2, pp. 195–205, 2025, doi: 10.13164/re.2025.0195.
- [170] H. Yoo, J. Moon, J. H. Kim, and H. J. Joo, “Design and technical validation

- to generate a synthetic 12-lead electrocardiogram dataset to promote artificial intelligence research,” *Heal. Inf. Sci. Syst.*, vol. 11, no. 1, 2023, doi: 10.1007/s13755-023-00241-y.
- [171] W. Yu *et al.*, “RR intervals prediction method for cardiovascular patients optimized LSTM based on ISSA,” *Biomed. Signal Process. Control*, vol. 100, 2025, doi: 10.1016/j.bspc.2024.106904.
- [172] J. Lim, D. Han, M. Pirayesh Shirazi Nejad, and K. H. Chon, “ECG classification via integration of adaptive beat segmentation and relative heart rate with deep learning networks,” *Comput. Biol. Med.*, vol. 181, 2024, doi: 10.1016/j.compbiomed.2024.109062.
- [173] H. Zhang *et al.*, “Cardiac Arrhythmia classification based on 3D recurrence plot analysis and deep learning,” *Front. Physiol.*, vol. 13, 2022, doi: 10.3389/fphys.2022.956320.
- [174] H. Zhang, H. Gu, G. Chen, M. Liu, Z. Wang, and F. Cao, “An atrial fibrillation classification method based on an outlier data filtering strategy and modified residual block of the feature pyramid network,” *Biomed. Signal Process. Control*, vol. 92, 2024, doi: 10.1016/j.bspc.2024.106107.
- [175] S. Ketu and P. K. Mishra, “Empirical Analysis of Machine Learning Algorithms on Imbalance Electrocardiogram Based Arrhythmia Dataset for Heart Disease Detection,” *Arab. J. Sci. Eng.*, vol. 47, no. 2, pp. 1447–1469, 2022, doi: 10.1007/s13369-021-05972-2.
- [176] K. K. Bressemer *et al.*, “medBERT.de: A comprehensive German BERT model for the medical domain,” *Expert Syst. Appl.*, vol. 237, 2024, doi: 10.1016/j.eswa.2023.121598.
- [177] P. Liu, X. Sun, Y. Han, Z. He, W. Zhang, and C. Wu, “Arrhythmia classification of LSTM autoencoder based on time series anomaly detection,” *Biomed. Signal Process. Control*, vol. 71, 2022, doi: 10.1016/j.bspc.2021.103228.
- [178] H. Bleijendaal *et al.*, “Computer versus cardiologist: Is a machine learning algorithm able to outperform an expert in diagnosing a phospholamban p.Arg14del mutation on the electrocardiogram?,” *Hear. Rhythm*, vol. 18, no.

- 1, pp. 79–87, 2021, doi: 10.1016/j.hrthm.2020.08.021.
- [179] M. Y. Ansari *et al.*, “A survey of transformers and large language models for ECG diagnosis: advances, challenges, and future directions,” *Artif. Intell. Rev.*, vol. 58, no. 9, 2025, doi: 10.1007/s10462-025-11259-x.
- [180] W. P. Li, J. H. Chuah, G. J. Tan, C. Liu, and H.-N. Ting, “A progressive attention-based cross-modal fusion network for cardiovascular disease detection using synchronized electrocardiogram and phonocardiogram signals,” *PeerJ Comput. Sci.*, vol. 11, p. e3038, 2025, doi: 10.7717/peerj-cs.3038.



UMN

UNIVERSITAS
MULTIMEDIA
NUSANTARA