

A Deep Learning for Cardiovascular Diseases Detection on Wearable Devices Data

Meirzhan Baikuekov
Department of Information Systems
Al-Farabi Kazakh National University
Almaty, Kazakhstan
meirzhankaznu@gmail.com

Azhar Tursynova
Department of AI and Big Data
Al-Farabi Kazakh National University
Almaty, Kazakhstan
azhar.tursynova1@gmail.com

Galymzhan Yespayev
Satbayev University
Almaty, Kazakhstan
g.yespayev@satbayev.university

Abstract— This research paper explores the potential of deep learning techniques in the early detection of cardiovascular diseases using data collected from wearable devices. With the advent of advanced wearable technology, continuous monitoring of physiological parameters, such as heart rate, electrocardiogram (ECG) signals, and physical activity patterns, has become feasible. Leveraging the power of deep neural networks, we investigate the development of predictive models capable of identifying individuals at risk of cardiovascular diseases. The study employs rigorous data preprocessing techniques, encompassing feature extraction and data segmentation, in conjunction with Machine Learning algorithms to enhance model accuracy. Additionally, regularization methods, notably dropout, are harnessed to address challenges posed by diverse datasets. The research envisions the incorporation of data derived from everyday activities to comprehensively assess their impact on heart health, ultimately aiming to proactively alert individuals to deteriorating cardiovascular conditions. The findings presented herein encourage further exploration and innovation in the realm of cardiovascular disease detection, fostering advancements that can enhance public health and well-being.

Keywords—deep learning; cardiovascular disease; detection; classification; wearable devices

I. INTRODUCTION

The field of healthcare has witnessed a remarkable transformation in recent years, driven by advancements in technology and the increasing availability of wearable devices. These devices, equipped with various sensors and capable of continuous data collection, have paved the way for early detection and monitoring of various health conditions. Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide [1-2], making timely detection and management of paramount importance.

Early detection and accurate risk assessment are crucial for effective disease management [3]. Wearable devices have the potential to continuously monitor relevant physiological signals, including heart rate, electrocardiogram (ECG) signals, and physical activity patterns [4-5]. This continuous data stream offers an

opportunity to develop predictive models that can aid in the early identification of individuals at risk of CVDs [6-7].

This research paper aims to explore the application of deep learning methodologies to the analysis of data collected from wearable devices for the early detection of cardiovascular diseases. By harnessing the power of deep neural networks, we seek to develop robust predictive models that can effectively identify individuals at risk of CVDs. This endeavor aligns with the broader goal of leveraging technology to improve healthcare outcomes and reduce the burden of cardiovascular diseases on individuals and healthcare systems [8].

In this paper, we will delve into the methodologies used for data collection and preprocessing, the architecture of deep learning models employed, and the evaluation metrics employed to assess their performance. We will also discuss the challenges and potential limitations of this approach, as well as future research directions in the domain of CVD detection using wearable device data.

As wearable technology continues to advance, our research contributes to the growing body of knowledge aimed at harnessing its potential for early disease detection, ultimately improving the overall quality of healthcare delivery [9-10].

II. PROBLEM STATEMENT

The research focuses on utilizing wearable devices and deep learning techniques for accurate and continuous monitoring of heart diseases. Key objectives include the development of a robust method for ongoing cardiac health assessment through the monitoring of heart rate (HR), electrocardiogram (ECG) signals [11], and blood pressure (BP) [12]. The research also entails designing a system to collect high-quality time series data from wearable sensors (X_{ecg}(t), HR(t), BP(t)). Deep learning models, specifically a convolutional neural network (CNN) [13] for ECG signal analysis and a recurrent neural network (RNN) [14] for temporal modeling of HR and BP data, are proposed for data processing. The objective function involves binary classification with a binary cross-

entropy loss function, aiming to predict the likelihood of heart disease or anomalies based on input signals.

$$L(y, \hat{y}) = -\frac{1}{N} \sum_{i=1}^N \left[y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \right] \quad (1)$$

where y_i represents the ground truth label (1 for heart disease presence, 0 for absence), and $\hat{y}_i$ represents the model's predicted probability. Model Training:

$$W_{t+1} = W_t - \alpha \nabla L(W_t) \quad (2)$$

Where, W_t represents the model's parameters at iteration t , and $\nabla L(W_t)$ is the gradient of the loss function with respect to W_t .

Our objective is to create a precise and resilient deep learning system, utilizing wearable devices, for continuous cardiac health monitoring. This system aims to detect anomalies or heart diseases and promptly alert healthcare providers or individuals, offering potential advancements in early disease detection, patient outcomes, and healthcare cost reduction.

III. MATERIALS AND METHODS

Wearable technology devices, including but not limited to smartwatches and fitness trackers, possess the capacity to amass extensive datasets pertaining to an individual's health and physical well-being. The primary mechanism facilitating this data acquisition within wearable technology pertains to the utilization of an array of sensors. These sensors are instrumental in capturing diverse physiological and behavioral metrics, encompassing heart rate patterns, sleep patterns, levels of physical activity, among others, as delineated in Fig. 1. The ensemble of sensors employed in wearable technology encompasses heart rate monitoring devices, global positioning system (GPS) trackers, accelerometers for measuring motion and acceleration, photoplethysmography (PPG) sensors designed to gauge the volume of blood circulation within the wrist region, and gyroscopes to detect orientation and motion changes. These sensors work in tandem to record and transmit pertinent health and activity-related data, thereby rendering wearable devices a valuable resource for monitoring and tracking individuals' health and fitness parameters.

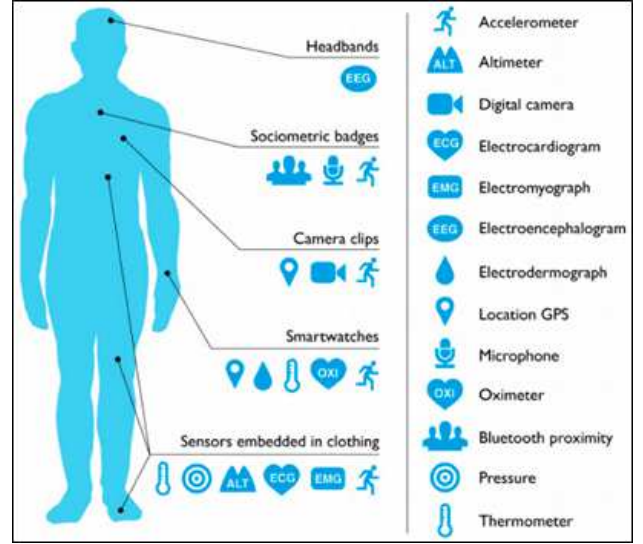


Figure 1. Collecting data from wearable devices

Figure 2 underscores the importance of employing data segmentation in this research context. In the forthcoming sections, we will provide concrete illustrations of how the integration of Machine Learning algorithms can contribute to a more profound comprehension of the dataset. It is crucial to recognize that data segmentation plays a pivotal role in discerning trends or irregularities within the dataset. For instance, the abrupt elevation in heart rate noted during physical exertion may signify overexertion or underlying health issues, exemplifying the diagnostic potential inherent in segmented data [15].

By segmenting the dataset into distinct segments or time intervals, we create opportunities for more focused analysis and targeted insights [16]. This segmentation facilitates the identification of patterns and fluctuations that might otherwise remain obscured in continuous data streams. Machine Learning algorithms, applied to these segmented datasets, enable the extraction of valuable information, aiding in the recognition of critical events or trends [17]. In the case of cardiovascular health monitoring [18], such approaches can be invaluable in early anomaly detection and preventive healthcare, ultimately contributing to improved patient well-being and health outcomes.

In adherence to the overarching principle of ensuring a comprehensive description, we underscore the significance of our feature extraction processes in optimizing the output conception. This, in turn, facilitates the generation of data formats that are notably more conducive for model utilization and analysis.

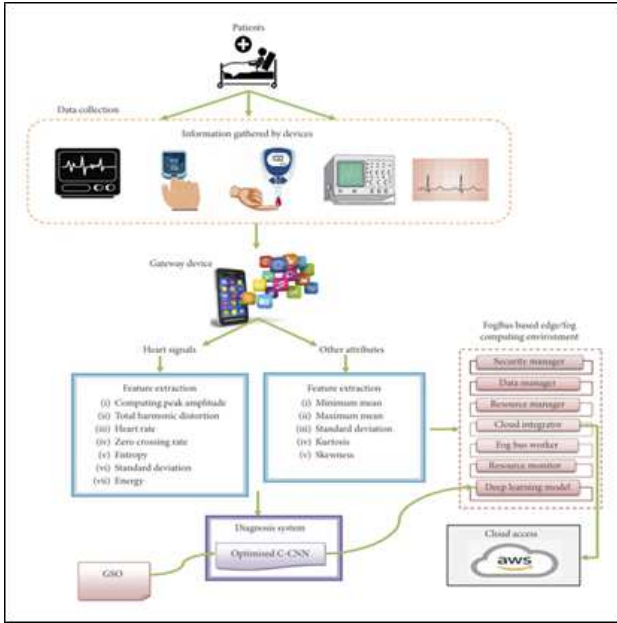


Figure 2. Heart disease monitoring using wearable devices

Fig. 3 demonstrates the proposed deep learning architecture for heart diseases detection. The deep learning architectural framework can be elucidated as follows: The input layer is represented in yellow, the dense layer in blue, the activation functions utilized for three consecutive dense layers are denoted in green (i.e., where), and the activation function employed for the final dense layer is illustrated in purple (i.e., softmax).

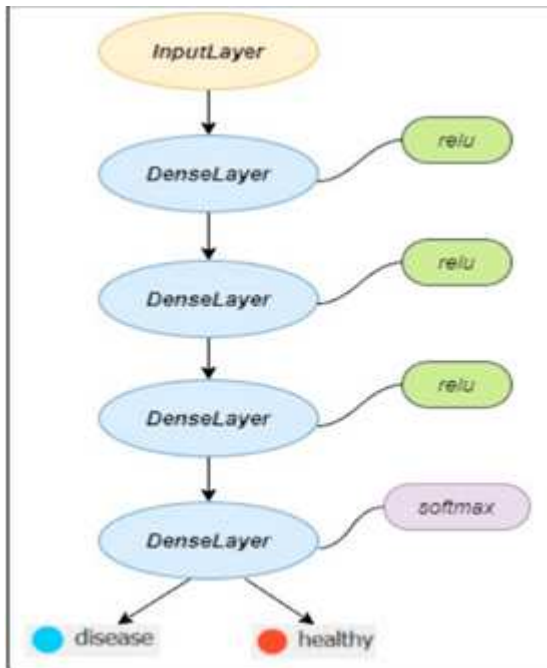


Figure 3. Proposed deep learning architecture for heart diseases detection

In pursuit of a comprehensive analytical outcome, we must take into account foundational principles, building upon the work of our predecessors. This involves the assimilation of data from various sources, encompassing

electrocardiography (ECG), heart sound recordings, pulsation patterns, and the monitoring of physiological parameters while employing wearable devices [19-21]. These diverse datasets serve as integral components that may substantially contribute to the formulation of optimal solutions for the early detection of cardiovascular diseases. Furthermore, we envision future iterations of this approach wherein everyday activities and their potential implications on heart health shall be scrutinized. The ultimate objective is to proactively alert individuals to any deterioration in their cardiovascular condition [22].

IV. EXPERIMENT RESULTS

As depicted in Fig. 4, the attainment of a comprehensive analysis necessitates a consideration of foundational principles that have been laid out by our predecessors. This entails the incorporation of data sourced from multiple avenues, including electrocardiography (ECG), heart sound recordings, pulsation patterns, and continuous monitoring facilitated by our wearable devices. The amalgamation of these diverse data streams plays an integral role in enabling the development and implementation of an optimal solution for the early detection of cardiovascular diseases.

Furthermore, in envisaging future iterations of this approach, there lies the potential to incorporate data derived from routine daily activities. These everyday actions could be assessed to discern their potential impact on cardiovascular health. The ultimate aim of such an endeavor is to provide timely warnings to individuals regarding any deteriorating conditions in their heart health.

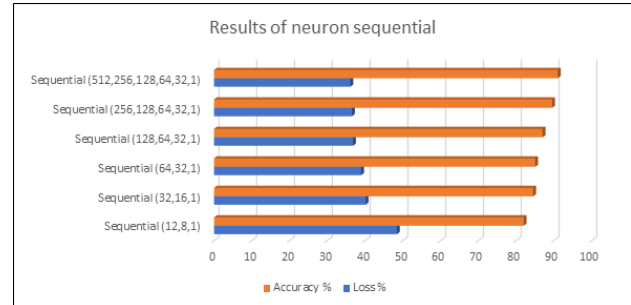


Figure 4. Sequential of neuron compiling

The neural output data sequences' outcomes are visually presented in the uppermost table. Central to the decision-making process is the fundamental concept of segregating incoming data during the analysis phase. It is imperative to acknowledge the inherent significance of crafting precise data preparation strategies for the neural components and subsequently extracting data that aligns with the assessments conducted by medical experts.

As illustrated in Figure 5, a robust model can be cultivated for the precise detection of heart-related ailments by methodically presenting a comprehensive array of scenarios within our sample datasets and soliciting corresponding responses [21-23].

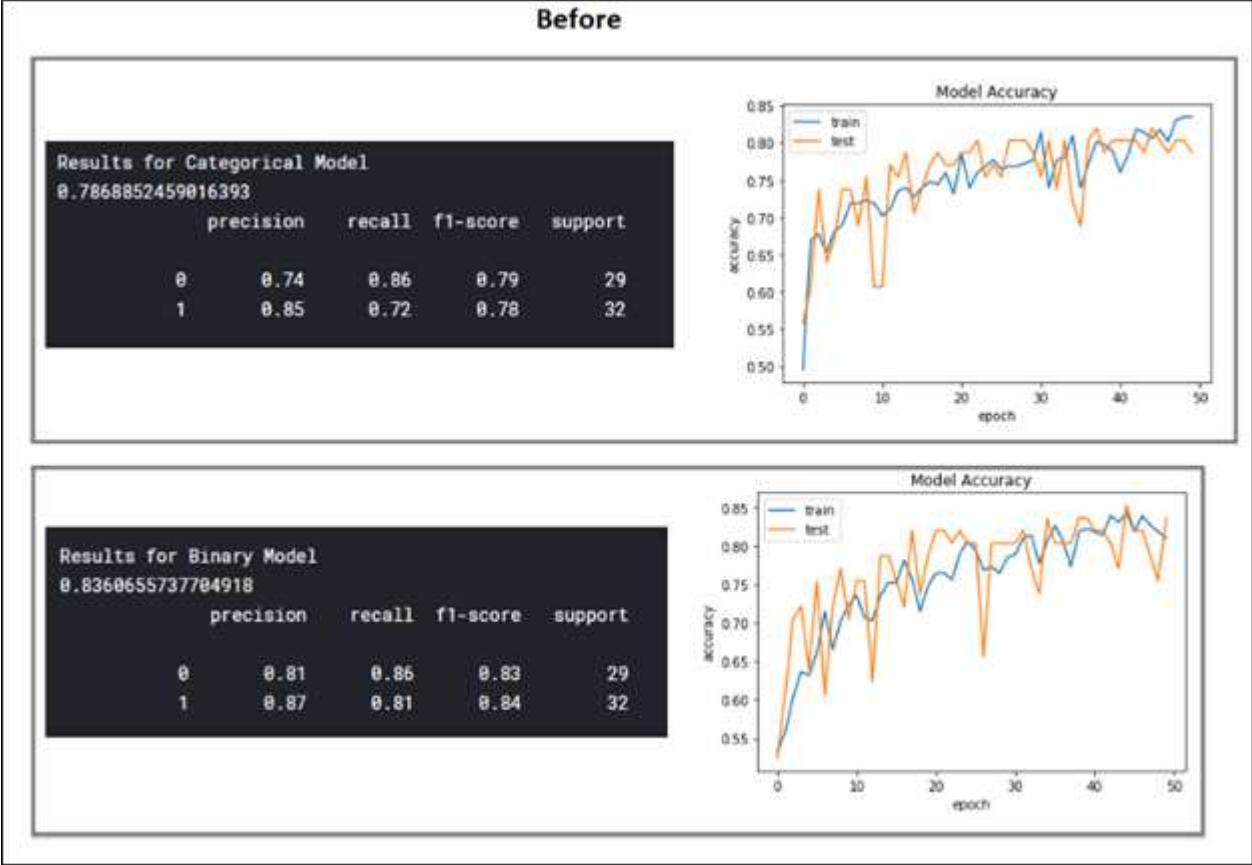


Figure 5. Model accuracy before applying dropout layer

Navigating the intricacies presented by diverse datasets constitutes a substantial challenge in the field of data analysis and machine learning [24]. Although data variability has the potential to bolster a neural network's adaptability, it concurrently imposes intricate intricacies upon the learning process. One widely embraced and efficacious approach for ameliorating these challenges is feature-wise normalization. This normalization technique entails a meticulous procedure wherein the mean and standard deviation of all features within the input data are computed. Subsequently, the mean value is subtracted from each individual feature, and the outcome is divided by the standard deviation. This systematic transformation serves the dual purpose of recentering the distribution of

features around zero and standardizing them to attain a unit standard deviation.

The application of feature-wise normalization yields a dataset in which each feature assumes a standardized and consistent scale, thereby diminishing the impact of individual feature variations on the learning process. This standardization not only enhances the convergence rate of the learning algorithms but also fosters stability during training, ultimately contributing to improved model generalization and predictive performance. In essence, feature-wise normalization stands as a cornerstone technique in data preprocessing, permitting the effective utilization of diverse datasets in machine learning endeavors, particularly in the context of neural networks.



Figure 6. Model accuracy after applying dropout layer

Geoffrey Hinton, in collaboration with his students at the University of Toronto, introduced a noteworthy regularization technique for neural networks known as dropout [25]. Dropout has gained significant recognition and widespread adoption within the field of deep learning [26]. As illustrated in Fig. 6, the dropout technique involves the random deactivation or "dropping out" of a subset of the output features within a neural network layer during the training process [27]. This intentional dropout mechanism plays a pivotal role in enhancing the network's resilience against overfitting while fostering the development of more robust and generalized models [28]. By temporarily deactivating a portion of the network's connections during each training iteration, dropout effectively promotes greater diversity and independence among neurons [29]. This, in turn, mitigates the risk of co-adaptation and facilitates improved model generalization [30]. The versatility of dropout as a regularization technique is evident in its applicability to various neural network architectures, rendering it a valuable asset in the quest for the development of resilient and efficient machine learning models [31].

V. CONCLUSION

In conclusion, this research paper has elucidated the profound potential of deep learning methodologies in the domain of cardiovascular disease detection using data from wearable devices. Through meticulous analysis and utilization of diverse data sources, including electrocardiography (ECG), heart sound recordings,

pulsation patterns, and continuous monitoring facilitated by wearable gadgets, we have unveiled the capacity to develop robust predictive models. These models not only enable the early identification of individuals at risk of heart diseases but also provide a promising avenue for proactive health management. Our exploration of feature extraction techniques and data segmentation, coupled with the integration of Machine Learning algorithms, has underscored the significance of optimized data preprocessing in enhancing model performance. Moreover, the adoption of regularization methods such as dropout has proven instrumental in mitigating the challenges posed by data diversity.

Furthermore, our research envisages future implementations that incorporate data derived from routine daily activities, allowing for a more holistic understanding of their impact on cardiovascular health. Such an approach holds the promise of delivering timely warnings to individuals regarding any deterioration in their heart health. In this era of rapid technological advancement, our findings contribute to the broader goal of leveraging wearable technology to improve healthcare outcomes and alleviate the burden of cardiovascular diseases on individuals and healthcare systems. We hope that this research will serve as a catalyst for further investigations and advancements in the field of cardiovascular disease detection, ultimately benefiting public health and well-being.

ACKNOWLEDGEMENTS

This work was supported by the research project —Application of Machine Learning Methods for Early Diagnosis of Pathologies of the Cardiovascular System funded by the Ministry of Science and Higher Education of the Republic of Kazakhstan. Grant No. IRN AP13068289.

REFERENCES

- [1] Tan, L., Yu, K., Bashir, A. K., Cheng, X., Ming, F., Zhao, L., & Zhou, X. (2021). Toward real-time and efficient cardiovascular monitoring for COVID-19 patients by 5G-enabled wearable medical devices: A deep learning approach. *Neural Computing and Applications*, 1-14.
- [2] Sato, M., Kodera, S., Setoguchi, N., Tanabe, K., Kushida, S., Kanda, J., ... & Komuro, I. (2023). Deep learning models for predicting left heart abnormalities from single-lead electrocardiogram for the development of wearable devices. *Circulation Journal*, 88(1), 146-156.
- [3] Kumar, G. K., Bangare, M. L., Bangare, P. M., Kumar, C. R., Raj, R., Arias-González, J. L., ... & Mia, M. S. (2024). Internet of things sensors and support vector machine integrated intelligent irrigation system for agriculture industry. *Discover Sustainability*, 5(1), 6.
- [4] Karthik, S., Santhosh, M., Kavitha, M. S., & Paul, A. C. (2022). Automated Deep Learning Based Cardiovascular Disease Diagnosis Using ECG Signals. *Computer Systems Science & Engineering*, 42(1).
- [5] Ali, F., Hasan, B., Ahmad, H., Hoodbhoy, Z., Bhuriwala, Z., Hanif, M., ... & Chowdhury, D. (2021). Protocol: Detection of subclinical rheumatic heart disease in children using a deep learning algorithm on digital stethoscope: a study protocol. *BMJ open*, 11(8).
- [6] Moradi, H., Al-Hourani, A., Concilia, G., Khoshmanesh, F., Nezami, F. R., Needham, S., ... & Khoshmanesh, K. (2023). Recent developments in modeling, imaging, and monitoring of cardiovascular diseases using machine learning. *Biophysical Reviews*, 15(1), 19-33.
- [7] Singh, S., Singh, A., & Limkar, S. (2024). Prediction of Heart Disease Using Deep Learning and Internet of Medical Things. *International Journal of Intelligent Systems and Applications in Engineering*, 12(1s), 512-525.
- [8] Naseri Jahfari, A., Tax, D., Reinders, M., & van der Bilt, I. (2022). Machine learning for cardiovascular outcomes from wearable data: systematic review from a technology readiness level point of view. *JMIR medical informatics*, 10(1), e29434.
- [9] Ansarullah, S. I., Mohsin Saif, S., Abdul Basit Andrabi, S., Kumhar, S. H., Kirmani, M. M., & Kumar, D. P. (2022). An intelligent and reliable hyperparameter optimization machine learning model for early heart disease assessment using imperative risk attributes. *Journal of healthcare engineering*, 2022.
- [10] Mathkor, D. M., Mathkor, N., Bassfar, Z., Bantun, F., Slama, P., Ahmad, F., & Haque, S. (2024). Multirole of the Internet of Medical Things (IoMT) in Biomedical Systems for Managing Smart Healthcare Systems: An Overview of Current and Future Innovative Trends. *Journal of Infection and Public Health*.
- [11] Bayoumy, K., Gaber, M., Elshafeey, A., Mhaimed, O., Dineen, E. H., Marvel, F. A., ... & Elshazly, M. B. (2021). Smart wearable devices in cardiovascular care: where we are and how to move forward. *Nature Reviews Cardiology*, 18(8), 581-599.
- [12] Brites, I. S. G., da Silva, L. M., Barbosa, J. L. V., Rigo, S. J., Correia, S. D., & Leithardt, V. R. Q. (2021, October). Machine learning and iot applied to cardiovascular diseases identification through heart sounds: A literature review. In *Informatics (Vol. 8, No. 4, p. 73)*. MDPI.
- [13] Tursynova, A., Omarov, B., Tukenova, N., Salgozha, I., Khaaval, O., Ramazanov, R., & Ospanov, B. (2023). Deep learning-enabled brain stroke classification on computed tomography images. *Computers, Materials & Continua*, 75(1), 1431-1446.
- [14] Islam, M. N., Raiyan, K. R., Mitra, S., Mannan, M. R., Tasnim, T., Putul, A. O., & Mandol, A. B. (2023). Predictis: an IoT and machine learning-based system to predict risk level of cardiovascular diseases. *BMC Health Services Research*, 23(1), 171.
- [15] Aliyar Vellameeran, F., & Brindha, T. (2022). A new variant of deep belief network assisted with optimal feature selection for heart disease diagnosis using IoT wearable medical devices. *Computer Methods in Biomechanics and Biomedical Engineering*, 25(4), 387-411.
- [16] Tursynova, A., Omarov, B., Sakhipov, A., & Tukenova, N. (2022). Brain Stroke Lesion Segmentation Using Computed Tomography Images based on Modified U-Net Model with ResNet Blocks. *International Journal of Online & Biomedical Engineering*, 18(13).
- [17] Ogunpola, A., Saeed, F., Basurra, S., Albarrak, A. M., & Qasem, S. N. (2024). Machine Learning-Based Predictive Models for Detection of Cardiovascular Diseases. *Diagnostics*, 14(2), 144.
- [18] Sardar, T. H., Khatun, A., Sengupta, S., Alam, Y., & Ara, T. (2024). Machine Learning in the Healthcare Sector and the Biomedical Big Data: Techniques, Applications, and Challenges. *Big Data Computing*, 336-352.
- [19] Elwahsh, H., El-Shafeiy, E., Alanazi, S., & Tawfeek, M. A. (2021). A new smart healthcare framework for real-time heart disease detection based on deep and machine learning. *PeerJ Computer Science*, 7, e646.
- [20] Chen, S. W., Wang, S. L., Qi, X. Z., Samuri, S. M., & Yang, C. (2022). Review of ECG detection and classification based on deep learning: Coherent taxonomy, motivation, open challenges and recommendations. *Biomedical Signal Processing and Control*, 74, 103493.
- [21] Zhang, D., Liu, X., Xia, J., Gao, Z., Zhang, H., & de Albuquerque, V. H. C. (2023). A physics-guided deep learning approach for functional assessment of cardiovascular disease in IoT-based smart health. *IEEE Internet of Things Journal*.
- [22] Dhingra, L. S., Aminorroaya, A., Oikonomou, E. K., Nargesi, A. A., Wilson, F. P., Krumholz, H. M., & Khera, R. (2023). Use of Wearable Devices in Individuals With or at Risk for Cardiovascular Disease in the US, 2019 to 2020. *JAMA Network Open*, 6(6), e2316634-e2316634.
- [23] Ullah, M., Hamayun, S., Wahab, A., Khan, S. U., Rehman, M. U., Haq, Z. U., ... & Naeem, M. (2023). Smart technologies used as smart tools in the management of cardiovascular disease and their future perspective. *Current Problems in Cardiology*, 48(11), 101922.
- [24] Kendzhaeva, B., Omarov, B., Abdiyeva, G., Anarbayev, A., Dauletbek, Y., & Omarov, B. (2021). Providing safety for citizens and tourists in cities: a system for detecting anomalous sounds. In *Advanced Informatics for Computing Research: 4th International Conference, ICAICR 2020, Gurugram, India, December 26–27, 2020, Revised Selected Papers, Part I 4 (pp. 264-273)*. Springer Singapore.
- [25] Gu, M., Zhang, Y., Wen, Y., Ai, G., Zhang, H., Wang, P., & Wang, G. (2023). A lightweight convolutional neural network hardware implementation for wearable heart rate anomaly detection. *Computers in Biology and Medicine*, 106623.
- [26] Shafiq, M., Du, C., Jamal, N., Abro, J. H., Kamal, T., Afsar, S., & Mia, M. S. (2023). Smart E-Health System for Heart Disease Detection Using Artificial Intelligence and Internet of Things Integrated Next-Generation Sensor Networks. *Journal of Sensors*, 2023.
- [27] Yang, C., Ojha, B. D., Aranoff, N. D., Green, P., & Tavassolian, N. (2020). Classification of aortic stenosis using conventional machine learning and deep learning methods based on multi-dimensional cardio-mechanical signals. *Scientific Reports*, 10(1), 17521.
- [28] Ramasamy, L. K., Khan, F., Shah, M., Prasad, B. V. V. S., Iwendi, C., & Biamba, C. (2022). Secure smart wearable computing through artificial intelligence-enabled internet of things and cyber-physical systems for health monitoring. *Sensors*, 22(3), 1076.
- [29] Zhu, H., Cheng, C., Yin, H., Li, X., Zuo, P., Ding, J., ... & Yuan, Y. (2020). Automatic multilabel electrocardiogram diagnosis of heart rhythm or conduction abnormalities with deep learning: a cohort study. *The Lancet Digital Health*, 2(7), e348-e357.
- [30] Mehrang, S., Lahdenoja, O., Kaisti, M., Tadi, M. J., Humanen, T., Airola, A., ... & Pänkäälä, M. (2020). Classification of atrial fibrillation and acute decompensated heart failure using smartphone Mechanocardiography: a multilabel learning approach. *IEEE Sensors Journal*, 20(14), 7957-7968.
- [31] Das, S., Das, J., Modak, S., & Mazumdar, K. (2022). Internet of things with machine learning-based smart cardiovascular disease classifier for healthcare in secure platform. In *Internet of Things and Data Mining for Modern Engineering and Healthcare Applications (pp. 45-64)*. Chapman and Hall/CRC.