# Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis


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***Abstract*— This research presents an innovative method for analyzing heart sounds by integrating machine learning models into an accessible web application created with the Django framework. In order to identify and diagnose various heart illnesses early on, The main objective is to establish a trustworthy and efficient system for classifying cardiac sounds from audio recordings. The system provides thorough medical information, including linked illnesses, their causes, preventative measures, etc., after analyzing and classifying heart sound recordings into several groups. The Django framework is a powerful backend solution that ensures secure data management and smooth user interaction. The ability of the system to store and retrieve historical data from a centralized database makes it a valuable tool for clinicians to monitor and assess heart health. By combining machine learning with a scalable internet application, the initiative aims to encourage the broader usage of automated heart sound analysis, which will ultimately improve patient outcomes and medical procedures.**



***Keywords— Accuracy, comparison, RNN, LSTM, GRU, Web integration, Django.***


## I. Introduction

New applications in the healthcare sector have been made possible by developments in machine learning and artificial intelligence. A vital aspect essential for the early identification and diagnosis of cardiovascular diseases is the analysis of heart sounds. This article introduces a clever approach that uses recurrent neural networks (RNN) to effectively classify recordings of heart sounds. When included into a web-based platform developed using the Django framework, the system provides a practical and easy-to-use method for analyzing heart sounds. The proposed method not only automates the classification process but also provides extensive medical insights, including linked diseases, causes, and preventive actions. The goal of combining state-of-the-art technology with clinical applications is to increase diagnostic precision and optimize productivity in medical settings.

### *A. Objectives*

The primary aim of this project is to develop a reliable and efficient classification system utilizing machine learning techniques for the analysis of heart sounds. The specific objectives are as follows:

*Automated Classification:* To aid in the early identification of cardiac disorders, classify heart sound recordings into different groups using machine learning algorithms.

*User-Friendly Web Application:* Use the Django framework to build an interactive, scalable web platform that ensures accessibility and smooth user interaction.

*Medical Advice and Insights:* Provide thorough medical advice that covers associated ailments, potential causes, and preventative measures to assist medical professionals in making judgments.

*Data Management and Storage:* To enable continuous patient monitoring, establish a centralized database to securely store and retrieve previous cardiac sound recordings.

*Clinical Utility and Integration:* To assist medical professionals in more accurately diagnosing and treating cardiovascular illnesses, make the system simpler to utilize in clinical settings.

The program aims to help with the early detection and prevention of heart problems in order to enhance patient outcomes and healthcare practices.

### *B. Literature Review*

Deep learning algorithms have shown enhanced effectiveness in analyzing intricate cardiac sound patterns, surpassing the results obtained from traditional machine learning methods such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). Additionally, research has focused on explainability techniques to ensure that model predictions are understandable, thereby assisting healthcare professionals in their decision-making processes. This effort aims to build on these findings by developing a scalable and efficient heart sound analysis system that links research with practical clinical application.

**TABLE I. INFERENCES FROM LITERATURE REVIEW**

| S. No | Source | Methodology | Inference |
|---|---|---|---|
| 1. | Ren Z. et al. [1] | This research offers an extensive examination of deep learning methods applied to the analysis of cardiac sounds. | Highlights gaps in real-time applications and suggests future research directions in automated analysis. |
| 2. | Mohan S. et al. [2] | The research combines multiple machine learning models to predict heart disease effect | Demonstrates potential with improved accuracy but lacks validation on robust real-world datasets. |
| 3. | Alrabie S. et al. [3] | The study introduces a multiclass dataset and applies CNN for cardio vascular disease detection. | Introduces a multiclass dataset, effective for disease detection but with limited data for certain diseases. |
| 4. | Hamza M. F. A. B. et al. [4] | This survey provides an overview of deep learning and machine learning techniques utilized for the analysis of cardiac sounds. | Surveys techniques, challenges, and advancements but lacks specific deep model implementations. |
| 5. | Qiao L. et al. [5] | This technique uses a dynamic mask encoder in conjunction with time-compressed and frequency-expanded TDNN to identify irregularities in cardiac sounds. | Combines embeddings and time- frequency features for high accuracy but requires preprocessing steps. |
| 6. | Fernando T. et al. [6] | The research employs bidirectional LSTMs with an attention mechanism for segmenting heart sounds. | Improves segmentation accuracy, leveraging attention mechanisms, but is computationally expensive. |
| 7. | Zhang H. et al. [7] | A decision fusion network combining multiple features and decision-making processes is used for detection. | Combines multiple features for robust detection, requiring high computational resources. |
| 8. | Susic D. et al. [8] | The study introduces PCGmix, a novel data augmentation technique, to improve heart sound classification. | Boosts accuracy and generalization but may not cover all real-world scenarios. |
| 9. | Katarya R. et al. [9] | This survey examines different machine learning techniques aimed at the early prediction of heart disease. | Offers an assessment of machine learning; however, it does not include experimental validation tailored to heart sounds. |
| 10. | Chen J. et al. [10] | Ensemble learning methods are employed by combining multiple classifiers for heart sound classification. | Achieves high accuracy by combining classifiers but can be computationally intensive. |
| 11. | S. V. R. et al. [11] | The research employs wavelet packet transform for the extraction of features and utilizes machine learning techniques for classification purposes. | Combines signal processing with ML for improved detection but needs more real-world validation. |
| 12. | Lee J. et al. [12] | The research applies deep learning techniques frequency-time domain features for heart murmur detection. | Effective at murmur detection but tested on a limited dataset. |
| 13. | Habijan M. et al. [13] | Deep learning models are utilized for accurate heart sound classification. | Achieves high accuracy but faces data imbalance challenges. |
| 14. | Roy T. S. et al. [14] | The study uses a CNN-based residual network to predict valvular heart disease. | Improves prediction for valvular diseases but requires large datasets for training. |
| 15. | Banerjee M. et al. [15] | A 2D convolutional neural network is applied for multi- class classification of heart sounds. | Allows high-accuracy multi-class classification but may not generalize across populations. |
| 16. | Qiao P. et al. [16] | Wavelet analysis is combined with random forest algorithms to diagnose adolescent heart sounds. | Targets adolescent heart sound diagnosis, with limited generalization to other age groups. |
| 17. | Bao X. et al. [17] | The study compares time-frequency distribution techniques for enhancing CNN's ability to classify cardiac sounds. | Optimizes CNNs for heart sounds but explores limited TFD techniques. |
| 18. | Grooby E. et al. [18] | Signal quality assessment methods are combined withmachine learning to estimate heart and lung rates in neonates. | Focuses on neonatal sound quality for telehealth, limited to specific applications. |
| 19. | Tsai K.-H. et al. [19] | A self-supervised model is utilized to separate lung and heart sounds using a deep autoencoder that is periodic-coded. | Innovative unsupervised separation model but computationally expensive. |

## II. Reasearch Methodology

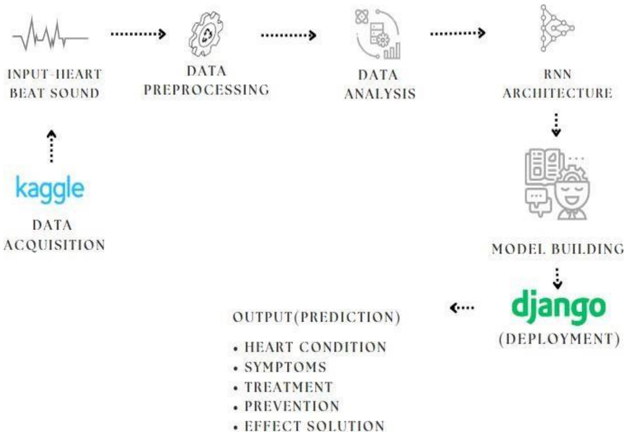


*Fig.1 Architecture Diagram of the Approach*

This architecture diagram shows the entire process of machine learning-based heart sound analysis, from data collection to deployment. First, heartbeat sound data is gathered, either from publicly accessible datasets like Kaggle or from medical equipment. To remove noise, normalize signals, segment audio, and extract crucial parameters like frequency or Mel-Frequency Cepstral Coefficients (MFCCs), the raw data is first preprocessed. After that, any data imbalances are addressed and patterns are found using exploratory data analysis. The system's central component is an RNN (Recurrent Neural Network) architecture, which has been shown to perform more accurately for this particular application than Long Short-Term Memory (LSTM) and Gated Recurrent Unit (G RU) architectures. To efficiently classify heart sounds and forecast possible cardiac problems, the RNN is trained on preprocessed data. The model produces outputs including cardiac disease forecasts, preventive actions, suggested precautions, and customized remedies for situations that have been recognized after training is finished. After the training phase, the model is integrated into a Django web application, allowing users to upload heart sound recordings, receive real-time predictions, and obtain actionable insights through a user-friendly interface. This thorough process leverages machine learning to support the early detection and diagnosis of cardiac conditions.

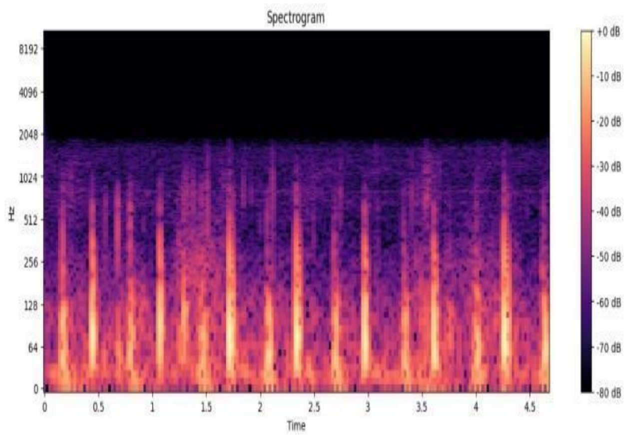


*Fig. 2 Spectrogram Graph For Feature Extraction*

The spectrogram illustrates the time-frequency distribution of heart sound data, with frequency (measured in Hertz) represented on the y-axis and time (in seconds) on the x-axis. Brighter sections imply that the majority of energy is focused below 512 Hz. Brighter regions are associated with particular heartbeats or occurrences, and the color intensity represents energy levels. The algorithm finds patterns for precise heart sound categorization with the help of this visualization, which facilitates feature extraction

## III. Experiemental Result Analysis

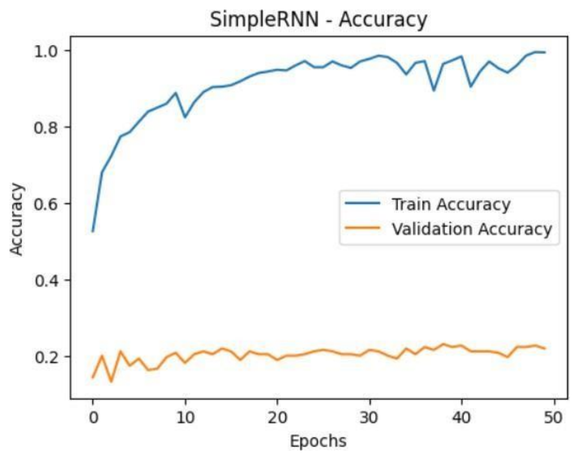


*Fig.3 Sub Plot of Simple RNN-Accuracy*

This graph illustrates the SimpleRNN model's robust learning ability. The model shows a steady and significant improvement in training accuracy as training goes on, eventually performing almost flawlessly on the training set. This demonstrates how well the model can identify and understand the patterns in the training dataset.

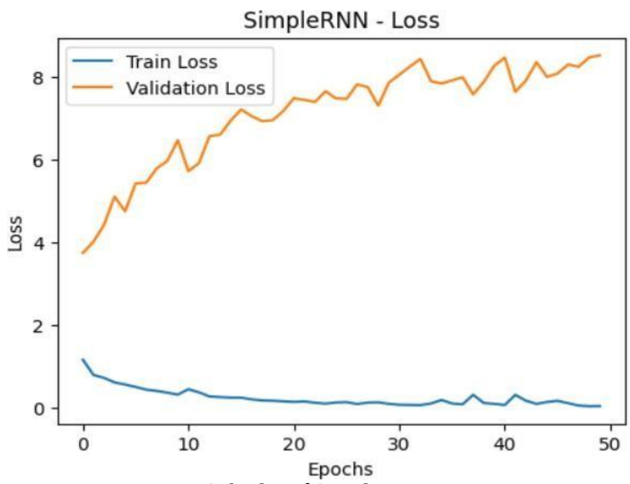


Fig.4 Sub Plot of SimpleRNN-Loss

This figure demonstrates that training loss is effectively reduced by the SimpleRNN model. The consistent and noticeable reduction in training loss with the ages shows how well the model can learn and match the training data. This illustrates the models performance and Capacity to improve prediction accuracy on the training set.

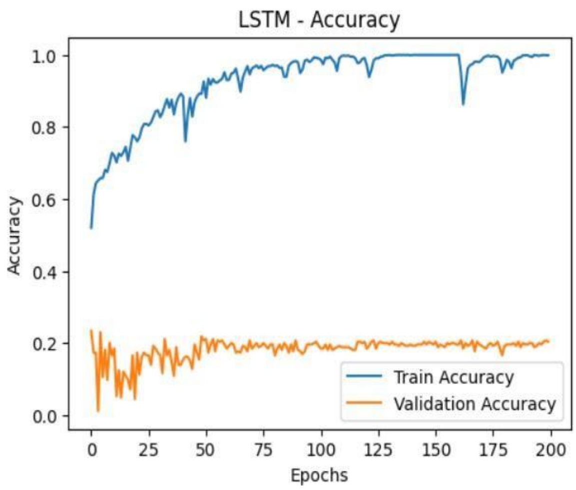


*Fig.5 Sub Plot of LSTM-Accuracy*

This graph illustrates the LSTM model's remarkable learning efficiency. The incredibly high accuracy the model achieves on the training data in a short amount of training epochs demonstrates its amazing capacity to quickly identify and understand complex patterns. This ability to learn quickly demonstrates how effectively LSTM models can process intricate sequential input.

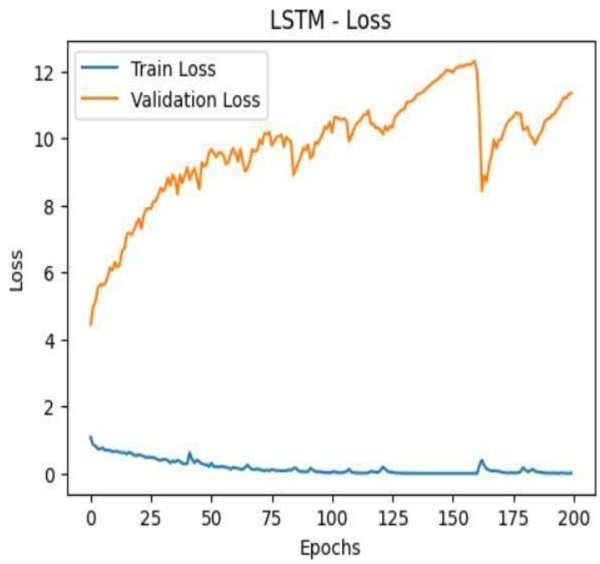


*Fig.6 Sub Plot of LSTM-Loss*

This graph showcases the remarkable capability of the LSTM model to enhance its performance on the training set. The consistent and efficient decrease in training loss indicates the model's proficiency in learning and adjusting to the intricacies of the training dataset. The model's effective training loss optimization demonstrates its capacity to produce precise predictions.

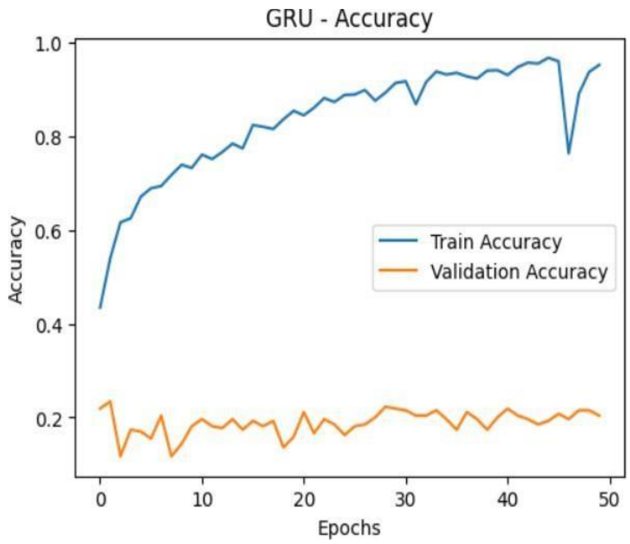


*Fig.7 Sub Plot of GRU-Accuracy*

This graph shows how well the GRU model learned from the training data. The model performs well and shows a discernible and consistent improvement in training accuracy. Its ability to identify and assimilate patterns in the training dataset is demonstrated by this.

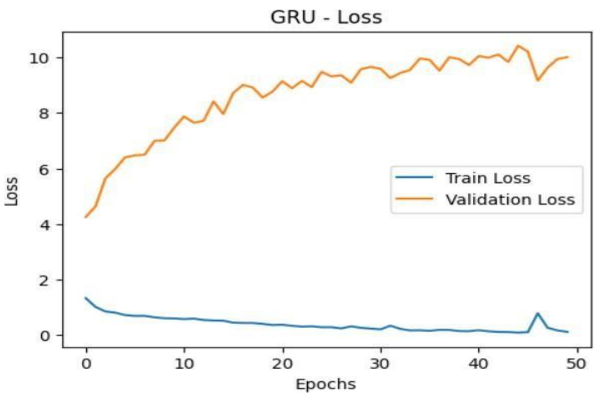


*Fig.8 Sub Plot of GRU-Loss*

Given that the validation loss thus declines in the early epochs, the model exhibits strong initial generalization ability. This indicates that both the hyperparameters and the model architecture are fundamentally effective and capable of retrieving relevant information from the data.

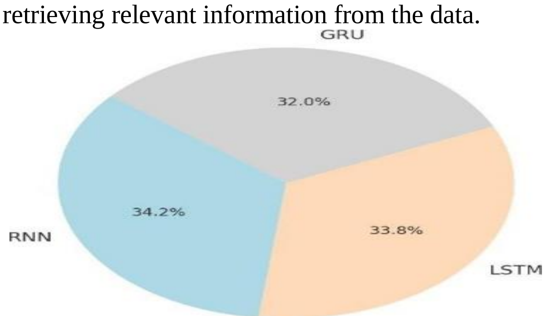


*Fig.9 Pie Chart of the Comparison*

All things considered, the downward trend in losses, particularly during the first phase, is encouraging and shows that the model may function effectively with the right modifications.

The percentage of real positive cases that each model accurately identified is shown in this pie chart. 94% of the true positive cases are successfully identified by the RNN model, which has a 94% recall. With a 93% recall, the LSTM model comes in second, and the GRU model has an 88% recall. This suggests that RNN outperforms both LSTM and GRU in detecting positive cases from the dataset. In terms of accuracy, recall, and precision, RNN routinely beats LSTM and GRU, according to these comparison criteria, which makes it a good model for heart sound analysis.

*TABLE II. Accuracy Analysis of the Algorithms*

| **Classifier** | **Accuracy** |
| --- | --- |
| RNN | 94. 0 |
| LSTM | 93. 0 |
| GRU | 88. 0 |

## IV. CONCLUSION

In this study, we used the Librosa package to evaluate the LSTM and RNN architectures for heartbeat sound analysis. RNN was chosen for our implementation because of its increased efficiency. The model illustrated deep learning's potential in biomedical signal processing by successfully classifying different pulse types based on extracted acoustic parameters. The smooth interface that allowed users to upload audio files and get real-time predictions thanks to integration with Django highlighted the usefulness of this study in clinical settings. Even with the effectiveness of the suggested system, there is still room for improvement in areas like imbalance in the data, processing in real time, and interpretability of the model. Studies in the future might concentrate on adding real-time monitoring capabilities, diversifying datasets, and integrating explainable AI approaches. All things considered, this effort advances automated heart sound analysis, opening the door to more effective, precise, and easily available cardiac diagnosis tools. The integration of machine learning in healthcare holds significant promise for improving clinical workflows and patient outcomes.

## V. DISCUSSION

RNN, LSTM, and GRU were among the deep learning architectures that were compared in order to determine which was best suited for this task. Although LSTM and GRU are well- known for managing long-term dependencies, RNN demonstrated superior accuracy at a lower computational cost. The findings show that because deep learning-based methods can recognize intricate patterns, they perform noticeably better in heartbeat classification than conventional machine learning techniques. Additionally, a user-friendly online interface made possible by the Django connection allowed for real-time forecasts and smooth audio file submissions. This valuable application enhances access to advanced cardiac testing, potentially serving as a significant tool for the early identification of heart disease. Notwithstanding its achievements, the system's functionality could be enhanced even more by investigating cutting-edge architectures such as transformer-based models, optimizing hyperparameters, and adding more varied datasets.

## VI. .FUTURE ENHANCEMENTS

*Model Optimization:* Through the exploration of intricate architectures such as hybrid models, which integrate Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs), the machine learning models (including RNN, LSTM, and GRU) can be enhanced to boost accuracy and minimize both false positives and false negatives in the classification of heart sounds.

*Real- Time Analysis:* Put in place real-time heart sound recording and analysis so that users can record and get prompt heart health feedback. This would improve the system's usefulness in clinical settings and user experience.

*Extend Dataset:* To increase the model's generalizability, incorporate a larger and more diversified collection of heart sound recordings, such as those from individuals with a range of medical problems, age groups, and ethnicities.

*Multi-Modal Integration:* For a more thorough diagnosis, combine information from additional diagnostic instruments, such as X-rays or ECGs. This may provide a more comprehensive understanding of the patient's heart condition and enhance the accuracy of predictions.

*User Personalization:* Include tools that allow users to customize the app according to their medical history. For example, make recommendations for particular cardiac diseases or offer insights based on historical health patterns.

*Integration of Mobile Applications***:** Create a smartphone app that will make it simple for people to capture heart sounds and get immediate analysis, increasing accessibility.

*Explainable AI:* Include explainability elements that assist users in comprehending the rationale behind particular classifications or forecasts. Particularly in clinical contexts, this could contribute to the development of systemic trust

.

*Long-Term Monitoring and Alerts:* Provide patients with chronic illnesses with long-term cardiac sound monitoring. When abnormalities are found, alert medical experts, enabling improved continuing treatment.

*Global Language Support:* Add multilingual support to accommodate users from around the world, extending the tool's reach and making it usable for non-native English speakers.

REFERENCES


[1] Z. Ren, Y. Chang, T. T. Nguyen, Y. Tan, K. Qian and B. W. Schuller, "A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era," in IEEE Computational Intelligence Magazine, vol. 19, no. 3, pp. 42-57, Aug. 2024, doi: 10.1109/MCI.2024.3401309.

[2] S. Mohan, C. Thirumalai and G. Srivastava, "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques," in IEEE Access, vol. 7, pp. 81542-81554, 2019, doi: 10.1109/ACCESS.2019.2923707.

[3] S. Alrabie and A. Barnawi, "HeartWave: A Multiclass Dataset of Heart Sounds for Cardiovascular Diseases Detection," in IEEE Access, vol. 11, pp. 118722-118736, 2023, doi: 10.1109/ACCESS.2023.3325749.

[4] M. F. A. B. Hamza and N. N. A. Sjarif, "A Comprehensive Overview of Heart Sound Analysis Using Machine Learning Methods," in IEEE Access, vol. 12, pp. 117203-117217, 2024, doi: 10.1109/ACCESS.2024.3432309.

[5] L. Qiao, Y. Gao, B. Xiao, X. Bi, W. Li and X. Gao, "HS-Vectors: Heart Sound Embeddings for Abnormal Heart Sound Detection Based on Time-Compressed and Frequency- Expanded TDNN With Dynamic Mask Encoder," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 3,pp. 1364-1374,March 2023, doi: 10.1109/JBHI.2022.3227585.

[6] T. Fernando, H. Ghaemmaghami, S. Denman, S. Sridharan, N. Hussain and C. Fookes, "Heart Sound Segmentation Using Bidirectional LSTMs With Attention," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 6, pp. 1601-1609, June 2020, doi: 10.1109/JBHI.2019.2949516.

[7] Zhang H, Zhang P, Wang Z, Chao L, Chen Y, Li Q. Multi-Feature Decision Fusion Network for Heart Sound Abnormality Detection and Classification. IEEE J Biomed Health Inform. 2024 Mar;28(3):1386-1397. doi: 10.1109/JBHI.2023.3307870. Epub 2024 Mar 6. PMID: 37610909.

[8] Susic D, Gradisek A, Gams M. PCGmix: A Data-Augmentation Method for Heart-Sound Classification. IEEE J Biomed Health Inform. 2024 Nov;28(11):6874-6885. doi: 10.1109/JBHI.2024.3458430. Epub 2024 Nov 6. PMID:39255074.

[9] R. Katarya and P. Srinivas, "Predicting Heart Disease at Early Stages using Machine Learning: A Survey," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020,pp. 302-305, doi: 10.1109/ICESC48915.2020.9155586.

[10] J. Chen, X. Dang and M. Li, "Heart Sound Classification Method based on Ensemble Learning," 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP), Xi'an, China, 2022, pp. 8-13, doi: 10.1109/ICSP54964.2022.9778383.

[11] R. S. V, B. Karan, G. Thakur, A. Rath and S. S. Sahu, "Heart Sound Abnormality Detection using Wavelet Packet Features and Machine Learning," 2021 International Symposium of Asian Control Association on Intelligent Robotics and Industrial Automation (IRIA), Goa, India, 2021,pp. 310-314, doi: 10.1109/IRIA53009.2021.9588724.

[12] J. Lee et al., "Deep Learning Based Heart Murmur Detection Using Frequency-time Domain Features of Heartbeat Sounds," 2022 Computing in Cardiology (CinC), Tampere, Finland, 2022, pp. 1-4, doi: 10.22489/CinC.2022.071.

[13] M. Habijan, I. Galić and A. Pizurica, "Heart Sound Classification using Deep Learning," 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech), Split/Bol, Croatia, 2023, pp. 1-6, doi: 10.23919/SpliTech58164.2023.10193726.

[14] T. S. Roy, J. K. Roy, N. Mandal, S. C. Mukhopadhaya, D. Majumder and S. Ghosh, "Valvular Heart Disease Prediction Using CNN-based Residual Network," 2023 16th International Conference on Sensing Technology (ICST), HYDERABAD, India, 2023, pp. 1-6, doi: 10.1109/ICST59744.2023.10460788.

[15] Banerjee, Megha & Majhi, Sudhan. (2020). Multi-class Heart Sounds Classification Using 2D-Convolutional Neural Network. 1-6. 10.1109/ICCCS49678.2020.9277204.

[16] Qiao, PAN & Yu, ZHANG & Jingyi, ZHANG & Zhuo, CHEN. (2020). A method for diagnosing heart sounds in adolescents based on wavelet analysis and random forest. 69-74. 10.1109/ICBAIE49996.2020.00021.

[17] Xinqi Bao, Yujia Xu, Hak-Keung Lam, Mohamed Trabelsi, Ines Chihi, Lilia Sidhom, Ernest N. Kamavuako, Time-Frequency distributions of heart sound signals: A Comparative study using convolutional neural networks,Biomedical Engineering Advances,Volume 5, 2023, 100093, ISSN 2667-0992,

[18] E. Grooby et al., "Neonatal Heart and Lung Sound Quality Assessment for Robust Heart and Breathing Rate Estimation for Telehealth Applications," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 12, pp. 4255- 4266, Dec. 2021, doi: 10.1109/JBHI.2020.3047602.

[19] K. -H. Tsai et al., "Blind Monaural Source Separation on Heart and Lung Sounds Based on Periodic-Coded Deep Autoencoder," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 11, pp. 3203-3214, Nov. 2020, doi: 10.1109/JBHI.2020.30