



Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure from Heart Sounds

Dr. B. Shankar Nayak

Professor, Dept of
CSE(DS), CMR Technical
Campus Hyderabad,
Telangana, India
bsnaik546@gmail.com

Ms. N. Soujanya

Assistant Professor, Dept of
CSE(DS), CMR Technical
Campus Hyderabad,
Telangana, India
noundlasoujanya516@gmail.com

T.Navya Sri

UG Student, Dept of
CSE(DS), CMR Technical
Campus Hyderabad,
Telangana, India
navyasrithatikonda9@gmail.com

E.Ravi Theja

UG Student, Dept of CSE(DS),
CMR Technical Campus
Hyderabad, Telangana, India
thejaravi02@gmail.com

Ch.Akshaya Pradeepthi

UG Student, Dept of CSE(DS),
CMR Technical Campus
Hyderabad, Telangana, India
challaakshayapradeepthi@gmail.com

P.Shiva Prasad

UG Student, Dept of
CSE(DS),
CMR Technical Campus
Hyderabad, Telangana, India
shivaprasad6282@gmail.com

How to Cite this Article:

Soujanya, N., Theja, E., Sri, T., Pradeepthi, C. & Prasad, P. (2026). Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure from Heart Sounds. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04). <https://doi.org/10.55041/ijcope.v2i4.278>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i4.278>

ABSTRACT— Chronic Heart Failure (CHF) is a life-threatening cardiovascular condition that requires early and accurate diagnosis to improve patient outcomes. However, conventional diagnostic techniques such as echocardiography are expensive and require specialized medical expertise, limiting their accessibility in resource-constrained settings. This paper proposes a hybrid approach that integrates Machine Learning (ML) and end-to-end Deep Learning (DL) techniques for the automated detection of CHF using phonocardiogram (PCG) signals. Heart sound data is collected from the PhysioNet dataset and preprocessed through noise reduction, normalization, and segmentation of cardiac cycles. Time-domain and frequency-domain features are extracted and used to train a Random Forest classifier, while spectrogram representations are fed into a Convolutional Neural Network (CNN) for automatic feature learning. A hybrid model is then developed by combining the strengths of both approaches to improve classification performance. The system is evaluated using metrics such as accuracy, sensitivity, and specificity, demonstrating enhanced performance in distinguishing normal and CHF conditions. The proposed method provides a non-invasive, cost-effective, and reliable solution that can assist healthcare professionals in early diagnosis and remote monitoring of heart failure.



INTRODUCTION

Chronic Heart Failure (CHF) is a serious medical condition in which the heart is unable to pump sufficient blood to meet the body's needs. Early detection of CHF is essential to prevent complications and reduce mortality rates. Traditional diagnosis methods rely on clinical examination and laboratory tests, which may not always identify the condition at an early stage. With advancements in technology, heart sound analysis using phonocardiograms (PCG) has emerged as a non-invasive approach for detecting heart abnormalities. In this project, Machine Learning (ML) and Deep Learning (DL) techniques are used to analyze heart sound recordings and automatically classify them as normal or abnormal. By combining feature-based ML methods with end-to-end DL models, the system aims to improve detection accuracy and provide an efficient solution for early diagnosis and monitoring of CHF.

I. PROBLEM DEFINITION

Chronic Heart Failure (CHF) is a serious cardiovascular condition characterized by the heart's inability to pump blood efficiently, leading to severe health complications if not detected early. Accurate diagnosis typically relies on advanced techniques such as echocardiography, which are expensive, time-consuming, and require skilled medical professionals, making them less accessible in rural and resource-limited settings. Although heart sounds (phonocardiogram signals) contain critical information about cardiac function, manual analysis using a stethoscope is subjective and prone to human error. Therefore, there is a need for an automated, reliable, and cost-effective system that can analyze heart sound recordings and accurately classify them as normal or indicative of CHF. This project addresses this challenge by leveraging Machine Learning and Deep Learning techniques to enable early, non-invasive detection of Chronic Heart Failure.

1.2 PROJECT FEATURES

The proposed system provides a non-invasive and cost-effective solution for detecting Chronic Heart Failure (CHF) using heart sound (PCG) recordings. It employs a hybrid approach that combines Machine Learning (Random Forest) and Deep Learning (CNN) to improve accuracy and robustness. The system performs automated analysis by incorporating advanced preprocessing techniques such as noise removal, normalization, and segmentation of heart sounds (S1 and S2). It extracts both time-domain and frequency-domain features while also utilizing end-to-end deep learning to learn patterns directly from spectrograms. The model achieves high prediction performance and is evaluated using metrics like accuracy, sensitivity, specificity, and confusion matrix. Additionally, the system is scalable, adaptable to larger datasets, and has potential for real-time applications such as mobile health monitoring, ultimately assisting healthcare professionals in early diagnosis and decision-making.

Related Work

Recent studies in heart sound classification have shown significant advancements using both traditional Machine Learning and Deep Learning techniques. Conventional approaches primarily relied on handcrafted features such as Mel-Frequency Cepstral Coefficients (MFCC), wavelet transforms, and time-frequency analysis, which were then classified using algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest. However, these methods often struggled to capture complex patterns in heart sound signals. With the rise of deep learning, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been widely adopted for automatic feature extraction and classification, achieving higher accuracy and robustness. Some studies also proposed hybrid and ensemble models that combine feature-based methods with deep learning architectures, demonstrating improved performance compared to individual models. Additionally, the use of benchmark datasets such as PhysioNet has enabled standardized evaluation of models for classifying normal and abnormal heart sounds. Despite these advancements, challenges such as



data variability, noise interference, and the need for more generalized models still remain, motivating the development of more robust hybrid approaches like the one proposed in this work.

II. METHODOLOGY

The proposed system follows a structured approach to detect chronic heart failures using heart sounds.

- 1. Data Collection:**
Heart sound (PCG) signals are collected from the PhysioNet dataset.
- 2. Preprocessing:**
The raw signals are cleaned by removing noise, normalizing amplitude, and segmenting cardiac cycles (S1 and S2).
- 3. Feature Extraction:**
Time-domain and frequency-domain features are extracted from the processed signals for analysis.
- 4. Machine Learning Model:**
Extracted features are used to train a Random Forest classifier for classification.
- 5. Deep Learning Model:**
Spectrograms of heart sounds are generated and fed into a Convolutional Neural Network (CNN) for end-to-end feature learning.
- 6. Hybrid Model Formation:**
Outputs/features from both ML and DL models are combined to improve overall prediction performance.
- 7. Model Training and Testing:**
The dataset is split into training and testing sets to evaluate model performance.
- 8. Prediction:**
The system classifies input heart sounds as Normal or CHF.
- 9. Evaluation:**
Performance is measured using accuracy, sensitivity, specificity, and confusion matrix.

III. PROPOSED SYSTEM

The proposed system is an automated framework for the detection of Chronic Heart Failure (CHF) using heart sound (phonocardiogram) signals by integrating Machine Learning and Deep Learning techniques. The system accepts heart sound recordings as input and

performs preprocessing steps such as noise removal, normalization, and segmentation of cardiac cycles (S1 and S2) to improve signal quality. It then extracts relevant time-domain and frequency-domain features for analysis. A Random Forest model is employed for feature-based classification, while a Convolutional Neural Network (CNN) is used for end-to-end learning from spectrogram representations of the signals. To enhance performance, a hybrid model is developed by combining the strengths of both approaches. The system finally classifies the input as normal or indicative of CHF and provides evaluation metrics such as accuracy, sensitivity, and specificity. This approach offers a non-invasive, cost-effective, and reliable solution to support early diagnosis and assist healthcare professionals in decision-making.

IV. IMPLEMENTATION DETAILS

The proposed system is implemented using Python with libraries such as NumPy, Pandas, Scikit-learn, and TensorFlow. Heart sound (PCG) data is obtained from the PhysioNet dataset and preprocessed through noise removal, normalization, and segmentation of cardiac cycles (S1 and S2). Time-domain and frequency-domain features are extracted for training the Machine Learning model, where a Random Forest classifier is used. Simultaneously, spectrograms of the signals are generated and fed into a Convolutional Neural Network (CNN) for end-to-end learning. The outputs from both models are combined to form a hybrid model, which improves prediction accuracy. The system is evaluated using metrics such as accuracy, sensitivity, and specificity to ensure reliable detection of Chronic Heart Failure.

4.1 ALGORITHMS USED

- 1. Signal Processing (STFT / Fourier Transform):**
Converts heart sound signals from time domain to frequency domain (spectrogram) for better analysis.
- 2. Preprocessing Algorithm:**
Removes noise, normalizes signals, and segments heart sounds into S1 and S2 components.



3. **Feature Extraction Techniques:**
Extracts important time-domain and frequency-domain features from PCG signals.
4. **Random Forest Algorithm (Machine Learning):**
Uses extracted features to classify heart sounds as Normal or CHF based on decision trees.
5. **Convolutional Neural Network (CNN):**
Takes spectrogram images as input and automatically learns patterns for classification.
6. **Hybrid Model Algorithm:**
Combines outputs/features of Random Forest and CNN to improve prediction accuracy.
7. **Model Training Algorithm:**
Splits data into training and testing sets and trains ML and DL models.
8. **Prediction Algorithm:**
Classifies new input heart sounds into Normal or CHF.
9. **Evaluation Algorithm:**
Uses metrics like Accuracy, Sensitivity, Specificity, and Confusion Matrix to measure performance.



VI. CONCLUSION

In this project, a hybrid approach combining Machine Learning and end-to-end Deep Learning techniques was successfully developed for the detection of Chronic Heart Failure (CHF) using heart sound signals. The system effectively processes phonocardiogram data through preprocessing, feature extraction, and model training to accurately classify heart sounds as normal or abnormal. The integration of Random Forest and Convolutional Neural Network (CNN) models enhances overall performance, with the hybrid model achieving better accuracy, sensitivity, and specificity compared to individual approaches. This method provides a non-invasive, cost-effective, and efficient solution for early detection of CHF, making it highly beneficial for real-world healthcare applications, especially in resource-limited settings. Future work can focus on improving model generalization, incorporating larger datasets, and developing real-time monitoring systems for practical deployment.

VII. FUTURE SCOPE

The proposed system can be further enhanced by incorporating larger and more diverse datasets to improve model generalization and robustness across different patient populations. Advanced deep learning architectures such as recurrent neural networks (RNN) or transformer-based models can be explored to capture temporal dependencies in heart sound signals more effectively. The system can also be integrated with Internet of Things (IoT) devices and wearable sensors to enable real-time heart monitoring and continuous health assessment. Additionally, developing a user-friendly mobile or web application can make the system





more accessible for remote and rural healthcare settings. Future work may also focus on detecting multiple cardiovascular diseases beyond CHF and improving explainability of the model to assist clinicians in better decision-making.

VIII. ACKNOWLEDGMENT

We take this opportunity to express our gratitude to the people who have been instrumental in the successful completion of this project, we take this opportunity to express our profound gratitude and deep regard to our guide **Dr. B.Shankar Nayak**, Designation for his/her exemplary guidance, monitoring and constant encouragement throughout the project work. The blessing, help and guidance given by him/her shall carry us a long way in the journey of life on which we are about to embark.

We also take this opportunity to express a deep sense of gratitude to the Project Review Committee (PRC) coordinators **N. Soujanya**, **Shafana Bakshi**, for their cordial support, valuable information and guidance, which helped us in completing this task through various stages.

We are also thankful to **Dr. K. Murali**, Head, Department of Computer Science and Engineering (Data Science) for providing encouragement and support for completing this project successfully.

We are deeply grateful to **Dr. A. Raji Reddy**, Director, for his cooperation throughout the course of this project. Additionally, we extend our profound gratitude to **Sri. Ch. Gopal Reddy**, Chairman, **Smt. C. Vasantha Latha**, Secretary and

Sri. C. Abhinav Reddy, Vice-Chairman, for fostering an excellent infrastructure and a conducive learning environment that greatly contributed to our progress.

The guidance and support received from all the members of CMR Technical Campus who contributed to the completion of the project. We are grateful for their constant support and help.

Finally, we would like to take this opportunity to thank our family for their constant

encouragement, without which this assignment would not be completed. We sincerely acknowledge and thank all those who gave support directly and indirectly in the completion of this project.

IX. REFERENCES

[1] [M. Gjoreski et al., "Chronic heart failure detection from heart sounds using a stack of machine-learning classifiers," in 2017 International Conference on Intelligent Environments \(IE\). IEEE, 2017, pp. 14-19 .](#)

[2] [J. Voigt et al., "A reevaluation of the costs of heart failure and its implications for allocation of health resources in the United States," Clinical cardiology, vol. 37, no. 5, pp. 312-321, 2014.](#)

[3] [G. D. Clifford et al., "Classification of normal/abnormal heart sound recordings: the PhysioNet/Computing in Cardiology Challenge 2016," in 2016 Computing in Cardiology Conference \(CinC\). IEEE, 2016, pp. 609-612.](#)

[4] [X. Jiang, Y. Pang, X. Li, and J. Pan, "Speed up deep neural network based pedestrian detection by sharing features across multi-scale models," Neurocomputing, vol. 185, pp. 163-170, 2016.](#)

[5] [A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," in International Conference on Neural Information Processing Systems, 2012, pp. 1097-1105.](#)

[6] [C. Szegedy et al., "Inception-v4, inception-ResNet and the impact of residual connections on learning," in Thirty-First AAAI Conference on Artificial Intelligence, 2017.](#)

[7] [T. Young et al., "Recent trends in deep learning based natural language](#)



[processing.” IEEE Computational intelligence magazine, vol. 13, no. 3, pp. 55-75, 2018.](#)

[8] [Y. Bengio et al., “A neural probabilistic language model,” Journal of machine learning research, vol. 3, no. Feb, pp. 1137–1155, 2003.](#)

[9] [S. Amiriparian et al., “Recognition of echolalic autistic child vocalisations utilising convolutional recurrent neural networks,” in Interspeech, 2018, pp. 2334-2338.](#)

[10] [S. Amiriparian et al., “Bag-of-Deep-Features: Noise-robust deep feature representations for audio analysis,” in International Joint Conference on Neural Networks \(IJCNN\). IEEE, 2018, pp. 1-7.](#)

[11] [M. Gjoreski et al. “Deep affect recognition from R-R intervals,” in Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers. ACM, 2017, pp. 754-762.](#)

[12] [H. P. Martinez, Y. Bengio, G. N. Yannakakis, “Learning deep physiological models of affect,” IEEE Computational intelligence magazine, vol. 8, no. 2, pp. 20-33, 2013.](#)

[13] [M. Gams, “Weak intelligence: Through the principle and paradox of multiple knowledge,” Advances in computation: Theory and practice, Volume 6, Nova science publishers, inc., NY, ISBN 1-56072-898-1, pp. 245, 2001.](#)

[14] [M. Gjoreski et al., “Classical and deep learning methods for recognizing human activities and modes of transportation with smartphone sensors,” in Information Fusion. 2019, under revision.](#)

[15] [M. Gjoreski et al., “Toward early detection and monitoring of chronic heart failure using heart sounds,” Intelligent Environments, pp. 336- 343, 2019.](#)

[16] [S. Schmidt et al., “Segmentation of heart sound recordings from an electric stethoscope by a duration dependent hidden-markov model,” in 2008 Computers in Cardiology. IEEE, 2008, pp. 345-348.](#)

[17] [D. B. Springer, L. Tarassenko, and G. D. Clifford, “Logistic regression-HSSM-based heart sound segmentation,” IEEE Transactions on Biomedical Engineering, vol. 63, no. 4, pp. 822-832, 2015.](#)

[18] [M. N. Homsy et al., “Automatic heart sound recording classification using a nested set of ensemble algorithms,” in 2016 Computing in Cardiology Conference \(CinC\). IEEE, 2016, pp. 817-820.](#)

[19] [F. Plesinger et al., “Heart sounds analysis using probability assessment,” Physiological measurement, vol. 38, no. 8, p. 1685, 2017.](#)

[20] [C. Potes et al., “Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds,” in 2016 Computing in Cardiology Conference \(CinC\). IEEE, 2016, pp. 621-624](#)

[21] [M. Zabihi et al., “Heart sound anomaly and quality detection using ensemble of neural networks without segmentation,” in 2016 Computing in Cardiology Conference \(CinC\). IEEE, 2016, pp. 613- 616.](#)

[22] [E. Kay and A. Agarwal, “DropConnected neural networks trained on time-frequency and inter-beat features for classifying heart sounds,” Physiological measurement, vol. 38, no. 8, p. 1645, 2017.](#)



[23] I. J. D. Bobillo, "A tensor approach to heart sound classification," in 2016 Computing in Cardiology Conference (CinC). IEEE, 2016, pp. 629-632

[24] J. Rubin et al., "Classifying heart sound recordings using deep convolutional neural networks and mel-frequency cepstral coefficients," in 2016 Computing in Cardiology Conference (CinC). IEEE, 2016, pp. 813-816.

[25] S. Choi, Z. Jiang, "Comparison of envelope extraction algorithms for cardiac sound signal segmentation," Expert Systems with Applications, vol. 34, no. 2, pp. 1056-1069, 2008.

[26] F. Eyben, F. Wening, F. Gross, B. Schuller, "Recent Developments in openSMILE, the Munich Open-Source Multimedia Feature Extractor," In Proc. ACM Multimedia (MM), Barcelona, Spain, ACM, ISBN 978-1-4503-2404-5, pp. 835-838, October 2013.

[27] A. Gradišek et al., "Predicting species identity of bumblebees through analysis of flight buzzing sounds," Bioacoustics, pp. 63-76, 2017.

X. GITHUB LINK

<https://github.com/thejaravi02/Chronic-Heart-Failure-Project>