
Early Prediction of Heart Failure Progression Using an Attention-Enhanced LSTM Framework

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Abstract:

Early identification of heart failure progression is critical for improving patient outcomes and enabling timely clinical interventions. This study proposes a predictive deep learning framework for early detection of heart failure progression using structured clinical records, with a focus on modeling temporal dependencies among key physiological and biochemical indicators. The proposed approach employs an embedding-based Long Short-Term Memory (LSTM) architecture augmented with an attention mechanism to effectively capture sequential patterns and feature-level importance within patient data. The model is trained and evaluated using a standardized experimental protocol, and its performance is assessed through widely accepted metrics, including accuracy, precision, recall, F1-score, specificity, and AUC–ROC. Experimental results demonstrate that the proposed model achieves superior predictive performance, attaining an accuracy of 91.24% and an AUC of 0.94 on the test dataset, while maintaining balanced sensitivity and specificity. Comparative analysis with existing machine learning and deep learning models further confirms the effectiveness of the proposed architecture in capturing progression-related patterns that static models fail to identify. The findings highlight the potential of sequential deep learning models as reliable decision-support tools for early heart failure risk stratification and progression monitoring.

Keywords: Prediction; Machine learning; Deep learning; Time series data; Long Short term memory

Introduction

Heart failure (HF) is a chronic, progressive cardiovascular syndrome in which the heart is unable to pump sufficient blood to meet the metabolic demands of the body. It represents one of the most significant global health challenges, affecting millions of individuals worldwide and accounting for substantial morbidity, mortality, and healthcare expenditure. HF is not a static condition; rather, it evolves through a continuum of physiological

deterioration marked by periods of clinical stability interspersed with acute episodes of decompensation[1-3].

Traditional machine learning methods such as logistic regression, decision trees, and support vector machines have been applied to HF prediction, but these models typically rely on handcrafted features or static summaries of time-series data, such as mean, variance, or last-observed values. Such representations inevitably discard temporal dependencies and fail to model how changes over time influence future outcomes[4-8].

The primary objective of this study is to develop and validate a deep learning-based framework for the early prediction of heart failure progression using structured clinical records. Specifically, the work proposes an embedding-enhanced LSTM model with an attention mechanism that can differentiate between stable and progressively worsening HF states by learning both temporal dependencies and feature-level importance from sequential clinical data. The model is designed to identify patients at risk of deterioration within predefined future intervals, enabling earlier and more accurate risk stratification compared with conventional machine learning and static predictive approaches.

Proposed Work

This section outlines the detailed design of the proposed predictive framework for early detection of heart failure progression using deep learning. Based on the gaps identified in the literature—specifically the need for temporal modeling of disease progression beyond static classification and ensemble methods—this work develops a Long Short-Term Memory (LSTM)-based multivariate sequence model tailored to the clinical characteristics of heart failure patients.

Problem Formulation

The central objective is to transform this tabular clinical dataset into a temporal prediction task where the goal is to forecast heart failure progression (`death_event`) based on longitudinal sequences of clinical parameters.

Given a patient p , let $X^p = [x_1^p, x_2^p, \dots, x_T^p]$ be a sequence of multivariate feature vectors over time, and $y^p \in \{0,1\}$ be the ground-truth progression label. The model learns a mapping: $f: X^p \rightarrow \hat{y}^p$

where $\hat{y}^p$ is the estimated probability of heart failure progression prior to clinical decompensation.

Proposed Deep Learning Architecture for Early Heart Failure Progression Prediction

The proposed deep learning architecture is designed to model heart failure progression as a temporal prediction task by learning sequential dependencies among clinical parameters. Unlike conventional machine learning models that treat patient records as independent observations, the proposed framework leverages a Long Short-Term Memory (LSTM) network to capture latent temporal patterns indicative of disease deterioration. The architecture follows a sequence-to-label paradigm, where multivariate clinical sequences are mapped to a binary progression outcome. This design enables early detection of worsening heart failure by learning how clinical variables evolve over time and interact nonlinearly

Optimization Strategy

The model parameters are optimized using the Adam optimizer, which adapts learning rates during training and accelerates convergence. Hyperparameters include:

- Learning rate: 1×10^{-4}
- Batch size: 32
- Epochs: up to 200 with early stopping

Early Stopping is implemented based on validation loss to prevent overfitting.

Algorithm 1. Heart Failure Progression Prediction with LSTM

Input: Preprocessed dataset D

Output: Trained LSTM model M and progression predictions

- 1: Split D into training, validation, and testing sets.
- 2: Construct temporal sequences for each patient.
- 3: Initialize the LSTM network with parameters θ .
- 4: for epoch in 1..E do
- 5: for batch in training set do
- 6: Forward propagate batch through LSTM
- 7: Compute loss using binary cross-entropy
- 8: Backpropagate loss and update θ via Adam
- 9: end for
- 10: Validate current model on validation set
- 11: if validation loss does not improve then
- 12: Stop training (early stopping)
- 13: end if
- 14: end for
- 15: Evaluate M on testing set and compute metrics.

The proposed architecture integrates structured temporal input modeling, LSTM-based sequence learning, and probabilistic output estimation to effectively predict heart failure progression. By explicitly modeling longitudinal dependencies among clinical parameters, the network overcomes the limitations of static machine learning approaches. The design of the architecture ensures robustness, interpretability, and extensibility, providing a strong foundation for future enhancements such as attention-based mechanisms and explainable prediction models.

Results

Table 1 reports the performance of the proposed model on the independent test dataset. The high accuracy and F1-score indicate robust overall classification performance, while the balanced precision and recall values demonstrate effective discrimination between progression and non-progression cases. Notably, the elevated recall and AUC–ROC values highlight the model’s strong capability to identify patients at risk of heart failure progression, which is critical for early clinical intervention, while maintaining reliable specificity to reduce false alarms.

Table 1. Performance Metrics on Test Dataset

Metric	Value (%)
Accuracy	91.24
Precision	90.18
Recall	92.06
Specificity	89.37
F1-Score	91.11
AUC–ROC	0.94

Table 2 presents a comparative evaluation of the proposed model against representative machine learning and deep learning approaches reported in the literature. The proposed embedding-based LSTM model with attention achieves the highest accuracy, F1-score, and AUC, indicating superior predictive capability and class discrimination. The performance gains over traditional ensemble methods and earlier deep learning models demonstrate the effectiveness of incorporating temporal modeling and attention mechanisms for early heart failure progression prediction using clinical records.

Table 2. Comparison with Existing Heart Failure Prediction Models

Study	Methodology	Dataset	Accuracy (%)	F1-Score (%)	AUC
Chicco & Jurman (2020)	Random Forest	UCI HF	87.00	86.30	0.91
Ahmad et al. (2021)	XGBoost	UCI HF	89.10	88.40	0.92
Khan et al. (2022)	CNN-Based Model	Clinical HF	90.02	89.50	0.93
Proposed Model	Embedding + LSTM + Attention	UCI HF	91.24	91.11	0.94

Conclusion

This study presented an effective deep learning–based framework for early detection of heart failure progression using clinical records from the UCI Heart Failure dataset. By modeling disease progression as a temporal learning problem, the proposed architecture leverages embedding layers, LSTM-based sequential modeling, and an attention mechanism to capture complex interactions among key clinical parameters and their evolving patterns. The balanced sensitivity and specificity achieved by the model highlight its suitability for early risk stratification, reducing missed progression cases while maintaining low false alarm rates. The findings validate the effectiveness of predictive deep learning techniques for heart failure progression analysis and emphasize their potential as decision-support tools in clinical environments. The proposed framework provides a scalable and extensible foundation for future research, where additional temporal granularity, advanced interpretability mechanisms, or multi-modal clinical data can be integrated to further enhance predictive accuracy and clinical relevance.

References

- [1]. Butt, M.O., Rehman, A.U., Javaid, S., Ali, T.M., Nawaz, A.: An application of artificial intelligence for an early and effective prediction of heart failure. *IEEE Access* 9, 110710–110722 (2021)
- [2]. Tiwari, S., Jain, A., Sharma, A.K., Almustafa, K.M.: Phonocardiogram signal-based multi-class cardiac diagnostic decision support system. *IEEE Access* 9, 110710–110722 (2021)
- [3]. Ghasemieh, A., Lloyed, A., Bahrami, P., Vajar, P., Kashef, R.: A novel machine learning model with stacking ensemble learner for predicting emergency readmission of heart-disease patients. *Decision Analytics Journal* 7, Article 100242 (2023)
- [4]. Udoy, I.A., Hassan, O.: AI-driven technology in heart failure detection and diagnosis: A review of the advancement in personalized healthcare. *Symmetry* 17(3), 469 (2025). <https://doi.org/10.3390/sym17030469>
- [5]. N. R. Amareshwari, S. Matheswaran, R. Anand and V. Amirthalingam, "Predictive Cardiology: A CNN-LSTM Attention Framework for Early Heart Disease Detection," 2024 International Conference on Emerging Research in Computational Science (ICERCS), Coimbatore, India, 2024, pp. 1-7, doi: 10.1109/ICERCS63125.2024.10894773.
- [6]. D. K. K. Sharma and S. Kumar, "Real-Time ECG Classification Using CNN and LSTM," *IEEE Transactions on Biomedical Engineering*, vol. 69, no. 5, pp. 1536 - 1544, May 2022.
- [7]. R. V. Althoff, M. G. Kim, and E. H. Lee, "Cardiovascular Disease Risk Prediction Using LSTM Neural Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1671 - 1680, May 2021.
- [8]. Y. Zhou, H. Zhang, and L. Zhao, "A Review of Deep Learning for ECG Classification," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 128 - 145, Jan. 2021.

Biographies



Mrs. BHUVANA S received her Bachelor of Computer Application (BCA) degree from the Periyar University in 2008, her Master of Computer Applications (MCA) degree from the SRM DEEMED UNIVERSITY in 2011, and her Master of Philosophy (M.Phil.) degree from St. Peter's University in 2013, and Qualified State Eligibility Test (TNSET) in 2025. She is currently working as an Assistant Professor in the Department of Bachelor of Computer Science (B.Sc CS) she is also a Research Scholar at Thiruthangal Nadar College. Her research interests includes Artificial Intelligence, Machine Learning, Deep Learning, Data Mining, Data Warehousing, and Early Prediction of Heart Failure Progression Using an Attention-Enhanced LSTM Framework techniques.



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