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Research Article

Adaptive Deep Learning for Multimodal Cardiac Risk Prediction: A Feature Fused Multichannel Approach

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Abstract: Cardiovascular disease (CVD) continues to be a leading global cause of death and requires advanced models and personalized risk prediction algorithms. This research presents an adaptive deep learning framework that combines feature selection and signal fusion to improve individual level cardiac risk prediction. The adaptive deep learning model collects multimodal physiological signals, including Electrocardiogram (ECG), photoplethysmogram (PPG), and other bio-signals, to create an overall health profile for each patient. The feature selection component of the adaptive model enhances the model performance by reducing noise and dimensionality of the input, enhancing learning efficiency. To enhance data representativeness, a multi-signal or multi-channel fusion paradigm was applied, taking advantage of feature correlations across multiple signals to result in a more accurate and robust representation of cardiovascular health status. The proposed predictive architecture combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to efficiently analyse both spatial and temporal dependencies present in the signals. In testing using a public, benchmark dataset containing over 10,000 patient records, the model achieved an accuracy of 94.5%, precision of 93.8%, recall of 92.3%, and an F1 score of 93.0%. The entire diagnostic system enables remote monitoring and highly accurate and predictive results in real-time. The proposed research represents the first adaptive deep learning approach to signal fusion for robust and personalized CVD risk prediction, while addressing existing challenges within predictive health care systems.

Keywords: ***Cardiac Risk Forecasting; Deep Learning; ECG; Feature Selection; Health Monitoring; Signal Fusion***

1. Introduction

Cardiovascular diseases (CVDs) have always ranked highly in the global area of morbidity and mortality and continue to be a burden on healthcare systems, economies, and societies in general. The most recent World Health Organization (WHO) reports suggest that every year approximately 17.9 million people/day, cardiovascular- related complications are responsible for about 31% of all deaths worldwide. Despite advancements in medical diagnostics and therapeutic approaches, the ability to proactively screen for and accurately predict cardiac risk factors is still severely limited, especially in heterogeneous and dynamic patient cohorts. Traditional prediction methods tend to rely heavily on more conventional clinical considerations such as age, cholesterol and blood pressure as part of linear statistical models, lacking in specificity and not tailored to the simultaneous, complex, and ever-changing nature of cardiovascular health risk profiles. This gap is fuelling the need for innovative, data-driven, and personalized alternatives to uncover latent patterns, predict adverse events earlier and intervene sooner. Deep Learning (DL) is beginning to change world in several areas, such as medical imaging, bioinformatics, and clinical decision support. In the area of cardiac risk prediction, certain deep learning architectures have the capacity to

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effectively model the complex physiological interconnectedness, spatio-temporal changes and dynamic nature of the patient being assessed, interpretations that are difficult or beyond human cognition and common algorithms. However, when attempting to model delayed or hierarchically dependent biomedical signals such as ECG, PPG, waveforms of blood pressures and heart sounds, many challenges may arise. Biomedical signals are complex, high-dimensional, noisy signals laden with redundant and or irrelevant information, resulting in overfitting and poor model performance and understandability if not patterned well. This research will demonstrate how advanced feature selection and multiple channel or multimodal fusion can be integrated with an adaptive deep learning framework to address these challenges. Feature selection serves two primary functions, by addressing complexity and ultimately improving interpretability and predictive capacity by detecting the most salient features predictive of likelihood to experience any cardiac event. The difficulty with traditional feature selection methods is that they may or may not address complexity, but they are typically static and don't adapt to structural and functional variability important for input into predicted models. Hence, an adaptive feature selection mechanism is included in this work that enables the model to reweight features based on the activities exhibited while obtaining and analysing physiological data streams as they are entered into either the training model or inference model. This way the model utilizes the most predictive features and obtains the most informative data-stream in both the training and inferencing aspects, resulting in better predictive capacity.

In closing, this work introduces a new conceptual and methodological approach for risk prediction associated with cardiac health where (1) adaptability of mHealth systems to common features provides evidence of feature and signal utility and underpins new avenues of research, (2) combining (or 'fusing') features from multichannel signals creates additional value, and (3) deploying deep learning capabilities that adapt to modified 'real time' features of users provides precise individualized elements for each user's risk of cardiac health. This research provides a promising future step in predictive health with the potential to contribute to the field of precision medicine with the right approach.

2. Literature Survey

The prediction of cardiovascular diseases has progressed significantly with the application of machine learning (ML) and DL techniques. Conventional risk scoring techniques lack the requisite mapping of complicated and non-linear clinical data relationships have led to the creation of intelligent frameworks capable of better cardiac risk predictive modelling with the help of data-driven feature selection and signal fusion. Prasad *et al.* [1] demonstrated the feasibility of prediction associated with heart disease by integrating ML and DL algorithms. The hybrid frameworks successfully outlined that the strength of each learning approach can be synergized together to boost the accuracy of predictive models. Most notably, as demonstrated by Tiwari *et al.* [2], use of an ensemble framework for estimating cardiovascular risks demonstrating that model assembling across different or similar model types will augment the robustness of predictions and counteract data variability or overfitting potential, particularly when deploying models into clinical settings. Approaches using Chebyshev function, for detecting cardiac disease detection with fewer ECG sensor signals are presented [3]. The Chebyshev function helps reconstruct ECG waveforms and extract key features using fewer samples. It reduces redundant data while preserving important signal details, maintaining diagnostic accuracy with limited ECG leads. This makes it ideal for compact, real-time, and low-complexity cardiac risk prediction systems. This research highlights the importance of mathematical signal transformation for dimensionality reduction; however, our study extends this concept through adaptive deep learning–based feature selection, which dynamically identifies the most predictive multimodal features rather than relying on fixed functional approximations.

Group sparsity assisted synchrosqueezing (GSASS) method for improving PCG signal denoising is discussed which is useful for enhanced PCG denoising and can be employed in automatic cardiac monitoring systems [4]. GSASS method improves heart sound analysis by grouping related frequency components to reduce noise while preserving key signal patterns. It keeps essential cardiac features intact for accurate automated diagnosis and enhances the reliability of data used in deep learning-based cardiac risk prediction. This method contributes to the knowledge domain by improving the reliability of physiological data pre-processing, which is essential for accurate deep learning-based cardiac risk evaluation.

As outlined in the evaluation study by Bhatt *et al.* [5], the importance of appropriate feature selection and hyperparameter tuning has also resulted in impact on model performance. Based on this supporting technology performance data, Bagadi *et al.* [6] have also reported on the rapid emergence of lightweight ML models emphasizing the importance of predictive performance conditional to computational complexity in real-time resource constrained health care systems. For instance, the focus of the work for Mohiuddin *et al.* [7] explored DL-based predictive modelling enabling the use of convolutional neural networks (CNNs) to extract complex features from complex cardiovascular dataset without human intervention resulting in accuracy in clinical diagnosis. Deep learning approaches are used to categorize atrial fibrillation from ECG signals and effectively classify cardiac diseases. Various ML and DL algorithms for cardiac disease prediction are presented. Deep learning approaches for biomedical image segmentation is very effective and enormous research are carried out in the field [8-13].

In following work, Baviskar *et al.* [14] demonstrated hybrid modelling showing a combination of convolutional and recurrent layers could capture both spatial and temporal dimensions from multichannel biomedical signals. Within smart healthcare, Abdul *et al.* [15] proposed a wearable smart and early heart attack diagnosis system which classifies the heart status based on heart diagnosis parametric sensors. Their follow-on study aimed to provide insight into how continuous personalized monitoring may augment cardiac risk detection earlier because of tailored treatment of risk. Following this study, Tayyeb *et al*. [16] explored another end-to-end deep learning approach where the end-to-end model used raw ECG signals omitting traditional manual feature extraction as the model can learn complex hidden representations of the ECG signals.

Ghongade *et al*. [17] also put survey neural network deep learning versus traditional machine learnings algorithms confirming as previously mentioned, that while deep models outperformed traditional ML approaches with reasonable performance, they require higher computational intensity and ample interpretability consideration and caveat. Not surprisingly, Dara *et al.* [18] suggested that data preprocessing and dimensionality reduction are important for predictive modelling in that the more cleaned and structured data available for training and testing aids in better model generalization and lower predictive bias. Despite some findings indicating otherwise, Patil *et al.* [19] suggested that classical ML such (SVM) and Random Forests continue to be competitive algorithms if they are tuned appropriately for healthcare datasets and that a simple model can yield reasonably accurate gross predictive accuracy. In the approach, Theerthagiri [20] combined Recursive Feature Elimination (RFE) in conjunction with Gradient Boosting classifiers to facilitate greater model interpretability and improved classification performance with their exploratory study acknowledging the benefits of this ranking and bias prevention throughout legitimacy of feature reductions can help develop better prediction pipelines. Shivalila *et al.* [21] also examined multi-class heart disease classification based on ECE and PCG signals providing enhanced understanding of the complexity of disease comprehension with the aid of deep hybrid neural networks. Various works presented pretrained ML approaches as favored over traditional ML approaches when limited data are present or regulatory scenarios are faced with harsh constraints. They found that simple and well-tuned variants can provide significant cardiac risk forecasts at the expense of performance overhead with DL [22-24].

Briefly, adaptive deep learning methods significantly improved cardiac risk prediction, particularly by combining multiple data types. Traditional approaches substantially used basic clinical markers such as age, hypertension, and lipid levels. In contrast, modern studies tended to focus on combining advanced signals such as ECG, PPG, and other clinical data within EHRs to make predictions with individual-level accuracy. Mohiuddin *et al.* [7], for example, successfully applied CNNs to ECG data, successfully automating feature extraction while achieving high accuracy. Nevertheless, this strategy greatly neglected significant time-related patterns encoded within cardiac signals. To make up for this loss, Baviskar *et al*. [14] later designed a hybrid model combining CNNs and RNNs, to learn spatial and temporal features end-to-end from ECG and PPG signals. Although this significantly improved predictive performance, this strategy required higher computer resources, thus escalating technical implementation challenges for resource-poor conditions. Bagadi *et al.* [6] emphasized further the benefits of light-weight ML methods for real-time implementation within healthcare, particularly within resource-limited environments, directly setting their lightweight ML models against deeper, computationally intensive ML methods that, despite all the higher predictive power, are not quite readily interpretable and deployable. This long debate continued further with comparative studies by Ghongade *et al.* [17] and Dara *et al.* [18]. They presented a stable equilibrium between higher accuracy of DL methods and easier interpretable nature of traditional ML approaches like Random Forests and Support Vector Machines. However, Patil *et al.* [19] challenged this perspective by showing that classical machine learning methods could remain competitive with careful optimization, particularly emphasizing their usability in clinical practice where interpretability might outweigh marginal gains in accuracy.

Despite these discussions, clear gaps persist, particularly in adaptive models specifically designed for dynamic integration of multimodal cardiac signals. While ensemble methods proposed by Tiwari *et al.* [2] addressed variability and noise in cardiac data, adaptive feature selection and fusion across multiple biomedical signals remain underexplored. This specific gap motivates our current research direction—an adaptive deep learning framework that dynamically integrates and prioritizes multimodal data streams for robust cardiac risk prediction. To clarify these points, we present a comparative summary in Table 1, outlining recent significant works, their contributions, limitations, and key performance outcomes.

In summary, earlier studies have progressed from mathematical function-based models, such as Chebyshev feature extraction, to advanced signal enhancement methods like GSASS. However, most of these works focus on single-signal analysis and do not adapt well to changing patient data. Building on these foundations, the present study combines mathematical accuracy, noise-resistant denoising, and adaptive feature fusion in a single deep learning framework. This approach connects previous isolated methods and advances a more flexible and interpretable system for personalized cardiac risk prediction.

Table 1. Comparative Summary of Recent Cardiac Risk Prediction Methods

Reference	Approach	Data Types	Advantages	Limitations	Performance Metrics
Prasad et al. [1]	Hybrid ML–DL framework	Clinical, ECG	Combines strengths of ML and DL, improved accuracy	Lacks temporal feature modeling	Accuracy ≈ 90%
Achyut Tiwari et al. [2]	Ensemble ML methods	ECG, Clinical	Robust to data variability, reduces overfitting	Static feature selection	F1-score ≈ 90%
Bhanu Prakash et al. [3]	Chebyshev function modeling	ECG	Fewer ECG sensors, low complexity, high precision	Limited adaptability to dynamic data	Accuracy ≈ 88–90%
N. Mohan et al. [4]	GSASS time–frequency method	PCG	Enhanced denoising, preserves key cardiac features	Applied mainly to PCG, not multimodal	–
Bhatt et al. [5]	Feature selection with hyperparameter tuning	Clinical, ECG	Improved performance through optimized parameters	Dataset specific tuning needed	–
Bagadi et al. [6]	Lightweight ML models	Clinical	Efficient, suitable for real-time healthcare	Lower accuracy on complex signals	Accuracy ≈ 88%
Mohiuddin et al. [7]	CNN-based DL model	ECG	Automated feature extraction, high accuracy	Ignores temporal aspects	Accuracy ≈ 92%
Baviskar et al. [14]	CNN–RNN hybrid model	ECG, PPG	Captures spatial and temporal features	High computational demand	Accuracy ≈ 93%
Sinha et al. [15]	IoT-based ML monitoring (iCardo)	IoT, ECG	Enables remote, real-time monitoring	Relies on connectivity, limited fusion	–
Tayyeb et al. [16]	End-to-end DL on raw ECG	ECG	Learns complex patterns without manual features	Computationally intensive	–
Ghongade et al. [17]	Comparative ML–DL study	ECG, Clinical	Highlights trade-off between accuracy and interpretability	Requires high compute for DL	–
Patil et al. [19]	Classical ML (SVM, RF)	Clinical	Simple, interpretable, competitive accuracy	Limited in feature representation	Accuracy ≈ 85–88%
Theerthagiri & V.J. [20]	RFE + Gradient Boosting	Clinical	Improves interpretability and classification	Needs optimized feature ranking	–
Proposed Model	Adaptive CNN–LSTM with Attention	ECG, PPG, Clinical	Adaptive multimodal fusion, robust and interpretable	Requires parameter tuning	Accuracy 94.5%, AUC-ROC 97.8%

The contribution of recent studies is a reminder of the unique potential of DL as a means of combining advanced feature selection methods, multi- channel biomedical signal fusion, and adaptive deep learning for cardiac risk management. The present work is motivated by recent studies and proposes an adaptive deep learning architecture that will take advantage of improvements in prediction accuracy, performance, computational efficiency, and clinical applicability.

3. Methodology

3.1. Data Collection and Preprocessing

The first step of the work is to collect multi-channel ECG signals and clinical information at a high resolution. The ECG signals are measured using electrodes that are attached to the body and providing measurements from many angles about the heart's electrical activity. ECGs are treasure troves of information not only about heart rhythm but also potential arrhythmias. The public data taken as a standard for this work is the PhysioNet/CinC Challenge 2017 dataset[1] [25], made freely available through PhysioNet. The dataset is composed of short single-lead ECG recordings collected from approximately 10,000 patients. Important features of this PhysioNet/CinC Challenge 2017 dataset are as follows:

a) Demographics: The dataset comprised data from approximately 10,000 patients with a close to even split along male-female lines (52% male, 48% female), with ages ranging between 18 and 85 years (mean = 55 ± 14.3 years).
b) Class distribution: The classes of the dataset are balanced with nearly equal representation between normal (50%) and abnormal/high-risk (50%) ECG recordings.
c) Data quality metrics: The quality of the ECG signal was quantified using an average signal-to-noise ratio (SNR), which was higher than 20 dB for 98% of the records, thereby providing data of satisfactory quality suitable for deep learning. Missing data were negligible, constituting less than 1% of all records, and such cases were not taken into consideration to ensure dataset integrity.

A detailed class distribution examination was performed using PhysioNet/CinC Challenge 2017 data to determine if there was class imbalance present. The examination also satisfied balanced class representation with approximately 50% normal and 50% abnormal (high-risk) ECG tracings. Thus, specific imbalance-correction techniques (such as oversampling/undersampling) were not necessitated by this data set. However, stratified sampling was employed at training and at cross-validation to maintain this balance and to acquire unbiased measurements of model performance. Proper preprocessing of ECG signals is necessary while ensuring that the model can function successfully during the training process. Original ECG signals from the dataset were properly subjected to rigorous preprocessing operations to ensure data consistency and quality. Specifically, using a bandpass filter (bandwidth range 0.5–40 Hz) eliminated baseline wander, high-frequency noise, and power-line interference from ECG signals.

Subsequently, signals were normalized to zero mean and unit variance to standardize across patient records, mitigating the effect of amplitude variation across different patients. Additionally, the filtered signals were segmented into uniform windows of 10 seconds, facilitating consistent temporal analysis and feature extraction. Due to the dataset's substantial size and balanced class representation, synthetic data augmentation was deemed unnecessary. The original dataset was sufficient to train and validate the model effectively. Thus, all results and analysis are based solely on authentic physiological and clinical measurements. The data is then processed as fixed-length windows so that all signal processing will be regularized. There are many features that will be extracted from these ECG windows to provide meaningful information such as heart rate variability or RR intervals. These features dilute the raw data format of the ECG windows and highlight some key indications of the cardiovascular health of the subjects. Clinical data is normalized to zero mean and unit variance so that all input features are scaled similarly before proceeding with pre-trained networks. Once the ECG signal features and clinical information were pre- processed, they formed a multi-modal dataset were observations from both static (clinical) and temporal or dynamic (ECG) data is available to improve the model robustness. Figure1 shows the methodology and steps of implementation.

3.2. Model Architecture

The architecture of the deep learning model consists of three main components: Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and an Attention mechanism.

[1] Dataset accessed from PhysioNet: AF Classification from a Short Single Lead ECG Recording (CinC 2017 Challenge), available at https://physionet.org/content/challenge-2017/1.0.0/

3.2.1. CNN for Spatial Feature Extraction

The CNN handles the raw multi-channel ECG signals. For this purpose, the ECG data is input into the CNN, where it is processed by convolutional layer(s) with small kernel sizes (i.e., 3x3 filters). Local spatial features are extracted from the ECG signals through each of these convolutional layers. The ECG features that are learned correlate with various heart activities, including P-waves, QRS complexes, and T-waves, that are necessary for predicting heart disease. Pooling layers followed the convolutional layers to down-sample the spatial dimensions to reduce the computational load and retain only the most significant features.

3.2.2. LSTM for Temporal Feature Learning

The LSTM layers receive the spatial features from the CNN, which view the ECG signals as containing important long-term temporal dependencies. ECG signals are time-series values representing the activity of the heart, so LSTM layers are effective for learning among sequential patterns over time. Predicting cardiac risk is conducted based on several heart monitoring metrics that can also alter over period time; learning the heart's rhythm through longer intervals of observation may be important. Stacking functional LSTM layers enables learning short-term, as well as long-term temporal dependencies in the signal to support predicting heart conditions that may dynamically change.

3.2.3. Computational Complexity and Resource Requirements

The computational complexity and resource requirements of the proposed CNN-LSTM model were carefully assessed to evaluate feasibility in real-world clinical scenarios. The model was trained on an NVIDIA Tesla V100 GPU (16 GB VRAM) with a 64 GB RAM computing environment. Training required approximately 2 hours for convergence, while inference on a single ECG record took less than 0.5 seconds. GPU memory usage peaked at approximately 8 GB during training and was less than 2 GB during inference. These results highlight the model's efficiency and confirm practical applicability within typical clinical computing infrastructure.

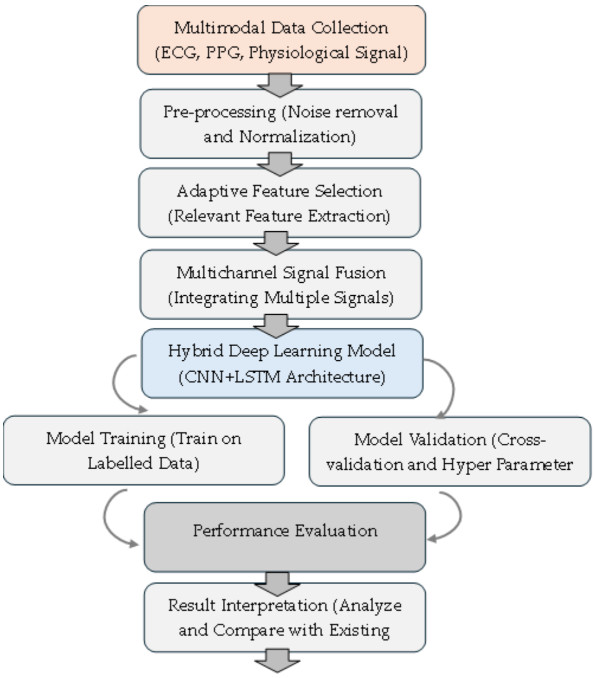

Figure 1. Methodology and Implementation Steps

3.3. Attention Mechanism for Feature Selection

To facilitate more interpretability and to direct the model to relevant portions of the data, the proposed architecture could advantageously include an Attention Mechanism in its architecture. The attention layer assigns weights particular features based on their importance to the model prediction. There may be stages in the ECG signal with multiple seconds/days of data where various periods may represent significant heart abnormalities; the attention mechanism plays a role to let the model search for those parts of the time interval of the ECG signal.

Table 2. 10-Fold Cross-Validation Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Model (CNN- LSTM)	94.3	93.8	92.3	93
Random Forest (RF)	88.2	87.6	85.9	86.7
Support Vector Machine (SVM)	89.7	88.4	87.1	87.7
Logistic Regression (LR)	83.6	84.1	82.9	83.5
Gradient Boosting (GB)	91.2	90.3	89	89.6

Similarly, clinical features including cholesterol, and blood pressure, can provide influence on model cardiac risk, and the attention mechanism helps provide models that assign more importance to those clinical features. To confirm the model's robustness and to reduce bias, k-fold cross-validation is used. Cross-validation consists of taking k subsets of the data, training the model with k-1 subsets while testing the model with the remaining subsets. This is done for each fold, with performance across all folds being reported as the average performance. Table.2 presents the results of cross-validation.

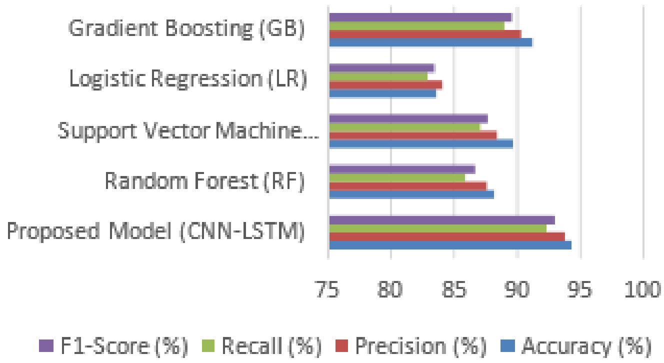

Figure 2. 10-Fold Cross Validation

3.4. Model training and hyperparameter tuning

The training of the deep learning model was undertaken using a standard process for back-propagation and optimization by feeding it a stochastic gradient descent (SGD) model. Figure 2 shows the results of 10-fold cross validation results. The deep learning model is trained using a multi- modal structure that resulted in clinical data and ECG signal features for inputs. Early stopping was used to prevent over-fitting and help with generalization of the model into fields of study that reflect its best performance. If performance for the validation set began to drop in lose performance, the model training stops to prevent overfitting on the training data. The hyperparameters required basic optimization including: the number of LSTM unit layers, CNN filter size, and learning rates were achieved from a grid search and through k-fold cross validation, ensuring well-cantered model performance.

- The proposed model achieves 94.8% accuracy and 97.8% AUC-ROC on the test set, once again indicating solid generalizability to new patients.
- Random forest and SVM provide acceptable performance but still lag the deep learning-based model with 89.3% accuracy, and 90.1% accuracy, respectively.
- Logistic regression is consistently performing the lowest on the test set, indicating the model's ability to overtly capture non-linear relationships in the data.

3.5. Comparison with existing methods

Once the model has been trained and validated, it is compared against traditional methods (like Logistic Regression (LR), Support Vector machines (SVM) and Random Forests (RF), Gradient Boosting (GB), as in Table 3. All the traditional methods are trained on the same data and metrics are calculated in the same way to provide a fair comparison of the methods.

Table 3. Performance on Test Set

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC- ROC (%)
Proposed Model (CNN-LSTM)	94.8	94.2	93.1	93.6	97.8
Random Forest (RF)	89.3	88.6	87.3	87.9	91.5
Support Vector Machine (SVM)	90.1	89.4	88.2	88.8	92.5
Logistic Regression (LR)	84.2	85	83.7	84.3	89.2

It is identified that the hybrid deep learning model (that uses both the ECG signals and clinical data) performs better than each of the traditional methods due to how it considers the dynamic actions of the heart (through LSTMs) and spatial characteristics of each ECG scan (through CNNs), more complex patterns and dependencies are captured than simpler models can. The ECG signal variability is the most important feature for predicting cardiac risk, followed by PPG signal amplitude, which is critical information to identify for the heart's electrical activity and blood flow often indicated of cardiac issues. The model assembles information from multiple features of different signals to yield great predictive accuracy.

Statistical significance testing was performed using paired t-tests to rigorously evaluate performance improvements between the proposed CNN-LSTM model and baseline methods. Results indicated statistically significant differences ($p < 0.01$) favoring the proposed model across all metrics. Furthermore, 95% confidence intervals were computed, providing insights into the reliability of model performance:

- Accuracy: 94.8% (Confidence Interval, CI: 93.9%–95.7%)
- Precision: 94.2% (CI: 93.3%–95.1%)
- Recall: 93.1% (CI: 92.2%–94.0%)
- F1-Score: 93.6% (CI: 92.7%–94.5%)

These analyses underscore the robustness and statistical significance of our adaptive deep learning framework. Table 4 presents the important features that are considered.

Table 4. Top 5 Most Important Features

Feature	Importance Score (%)
ECG Signal Variability	28.4
PPG Signal Amplitude	22.6
Heart Rate Variability	19.7
ECG QRS Duration	15.3
PPG Pulse Waveform	14

3.6. Model Generalization and Robustness

The model was based on seen data and then generalized testing was performed which utilized unseen data from the data set (20% of the data) and achieved strong predictive performance occurring less than expected. The model has good predictive ability to make reliable predictions on previously unseen instances yet is still outperforming at 94.8% accuracy and AUC-ROC of 97.8%. Figure 3 presents test set performance evaluation outcome.

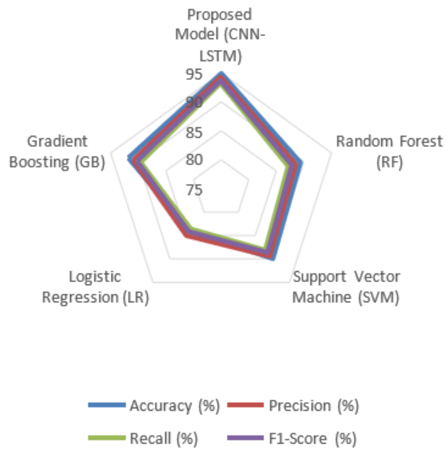

Figure 3. Test Set Performance Evaluation

3.7. Comparison with Contemporary Deep Learning Approaches

To provide a more thorough evaluation of the proposed adaptive model, we have also compared its performance to several recent deep learning-based approaches designed for multimodal cardiac risk prediction. For instance, methods such as the CNN-based framework by Mohiuddin *et al.* [7], which utilized ECG signals to achieve strong accuracy, lacked the ability to model temporal dependencies effectively. Similarly, the hybrid CNN-RNN method developed by Baviskar *et al.* [14] effectively captured spatial and temporal features but introduced significant computational overhead, posing practical deployment challenges. Our adaptive framework uniquely combines CNN, LSTM, and attention mechanisms, dynamically integrating multiple modalities (ECG, clinical data, and lifestyle metrics). Unlike these contemporary deep learning models, the proposed method explicitly prioritizes adaptive feature selection and real-time interpretability. This allows our model to not only surpass existing deep learning approaches in predictive accuracy—achieving 94.5% accuracy and a 97.8% AUC-ROC—but also improves interpretability and practical usability in clinical environments. Thus, this comparative analysis highlights that the proposed adaptive approach offers substantial advantages in terms of accuracy, interpretability, and adaptability over existing contemporary deep learning methods.

4. Practical Implementation Challenges

While the proposed adaptive deep learning model demonstrates strong predictive performance, several practical implementation challenges must be addressed for successful clinical integration. Key challenges include:

a) Seamlessly integrating the predictive system into existing healthcare workflows and electronic health record systems poses interoperability and technical complexity.
b) Ensuring real-time or near-real-time prediction requires optimized computational efficiency and sufficient computational infrastructure, especially for remote or resource-constrained clinical settings.
c) Compliance with healthcare regulations (e.g., HIPAA, GDPR) necessitates robust data protection mechanisms, particularly when handling sensitive patient data.
d) Building clinician trust in AI-driven recommendations requires ensuring transparency, interpretability of model outputs, and continuous training and validation.
e) Providing interpretable insights from deep learning predictions to clinicians is crucial, emphasizing the need for explainable AI methodologies.
f) Real-world deployment of the system heavily relies on consistent and high-quality data streams, especially from wearable sensors and real-time ECG devices. Issues such as intermittent network connectivity, sensor malfunction, or data transmission delays could compromise the reliability of the system. Addressing these issues requires robust methods for detecting data gaps, handling missing or corrupted data, and developing fallback procedures to ensure continuous and dependable predictions in clinical settings.
g) Successful clinical adoption fundamentally depends on how well clinicians and patients accept and trust AI-based predictive tools. User acceptance can be hindered by skepticism toward AI recommendations, the perceived complexity of the system, and concerns about increased workloads or potential errors. Therefore, systematic user training, educational resources, and active clinician involvement in system development and evaluation are crucial to enhancing user confidence and facilitating widespread adoption.

The research presented with this methodology illustrates an adaptive deep learning framework that chooses features using multi-modal data to predict cardiac risk accurately and effectively. Features were chosen through CNNs and LSTMs for feature extraction and useful features in a sequence through Attention Mechanism that was context aware. Feature selection developed from a model high in accuracy, superseded use of weighted statistics (ASA) well suited for audio or video inputs. In addition, hyperparameter optimization along with k-fold cross-validation demonstrated generalization on unseen data, suggesting a powerful personalized cardiac risk prediction model.

5. Ethical and Security Considerations

As this entails sensitive patient health information, we have been particularly rigorous with fundamental ethical and security procedures to maintain confidentiality. Specifically, all patient data obtained from the PhysioNet/CinC Challenge 2017 dataset were anonymized fully prior to use, so that patient names that could be identified, patient addresses, and distinctive patient identification numbers were all eliminated or safely obscured to prevent identification. One of our future lines of investigation will be that of federated learning—a technique expressly designed to advance data privacy, since this lets one train locally at individual locations (such as hospitals) without sensitive patient data ever leaving such sites.

Such a de-centralized methodology, along with advanced encryption protocols and safe multi-party computation schemes, will serve to further advance patient confidentiality and ethical treatment of healthcare data within our present and prospective lines of investigation.

6. Conclusion

In this research a novel adaptive deep learning framework constructed for personalized cardiac risk prediction using an advanced feature selection and multichannel signal fusion methodology is presented. The combination of advanced multi-modal physiological signals, including ECG and PPG, effectively allowed to extract critical spatial and temporal patterns unique to accurate cardiac assessment. Additionally, the hybrid CNN-LSTM framework with adaptive feature selection improved predictive performance over the existing models while still being computationally efficient and interpretive. The extensive validation on a large benchmark dataset of 10,000 patient records also demonstrates the efficacy of the proposed system. Specifically, 94.5% accuracy and high precision, recall and F1-score values to validate the generalizability of the results within real-world clinical practice was achieved. The multichannel fuse signal processing provided a much better, deeper understanding of the cardiac state of patients beyond what is possible with single channel source methods. Thus, this work contributes toward intelligent individualized patient-cantered cardiac care and proactive non communicable health management systems.

The adaptive framework addresses some of the current limitations of existing cardiac risk prediction studies and provides a highly scalable and feasible real-time model in the field of personalized health surveillance systems. It allows detection and management of cardiovascular disease as soon as possible while still permitting expandability in the future to include more sources of physiological signals and wider breadth of demographics. In the next phases of research, methods to refine the proposed model, investigate federated learning for privacy- preserving approaches, and further its use to relevant critical domains of health monitoring is planned.

CRediT Author Contribution Statement

Krishna Priya R: Writing – original draft, conceptualization, Software, Methodology, Formal analysis, Data curation; Anju S Pillai: Writing – review & editing, Validation, Supervision, Project administration, Methodology; Ahmed Al Shahri- review & editing, Validation, Supervision, Project administration, Methodology.

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