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Predicting Heart Blocks in Diabetic Patients: A Deep Learning Approach Integrating Stacked CNN and RNN Models

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Abstract

Cardiovascular disease (CVD) is one of the leading causes of death globally, particularly among diabetic patients who are at an elevated risk of developing heart-related complications, including high blood pressure, atherosclerosis, and stroke. This study focuses on the application of deep learning algorithms to predict heart attacks by utilizing clinical biomarkers and medical images. The integration of stacked convolutional neural networks (CNN) and recurrent neural networks (RNN), optimized using the Emperor Penguin Optimizer (EPO), allows for the efficient handling of both structured and unstructured data. The results demonstrate the potential for early diagnosis and preventive care, offering new insights into personalized medical interventions.

Keywords: Diabetics; Cardiovascular Disease; Cox Proportional Hazard Model

Abbreviations

CVD: Cardiovascular Disease; CNN: Convolutional Neural Networks; RNN: Recurrent Neural Networks; EPO: Emperor Penguin Optimizer; ML: Machine Learning; DL: Deep Learning; DNN: Deep Neural Networks; HRV: Heart Rate Variability; DBN: Deep Belief Network; ECG: Electrocardiograms.

Introduction

Diabetes is a significant risk factor for cardiovascular disease, contributing to conditions such as high blood pressure, arterial stiffness, and stroke, which ultimately increase the likelihood of a heart attack. Predicting heart attacks in diabetic patients is critical for reducing mortality, but the task is complex due to the multifactorial nature of the disease. While traditional models rely on specific biomarkers like blood pressure or cholesterol, modern advancements in deep learning allow for the integration of diverse data types, including medical images. This paper seeks to create a robust model by using deep learning to analyse datasets comprising both clinical readings and medical imaging data to accurately predict heart attacks in diabetic patients.

In recent years, machine learning (ML) and deep learning (DL) models have significantly advanced heart disease prediction, enhancing cardiovascular healthcare through early detection and personalized patient care [1]. This study aims to improve heart disease prediction in diabetic patients using integrated ML and DL models, with a particular focus on improving outcomes through timely and accurate diagnostics. Several models have been developed for cardiovascular disease (CVD) prediction [2] in diabetic populations. One notable approach, combining deep neural networks (DNNs) with heart rate variability (HRV) features, achieved remarkable success, particularly in diabetic males. The DNHRV model reported a 98.8% accuracy, outperforming earlier models across various metrics, including precision and F1-score.

Another impactful approach involves an AI-based prognostic model designed to predict heart failure risk in diabetic patients. The proposed deep neural network survival method, PHNN, surpassed the traditional Cox proportional hazard model (COX) [3] in both discrimination and calibration. This AI model effectively identified 20 key predictors, aligning with recognized trends in clinical practice, further enhancing its reliability in heart failure prediction.

Deep learning models, especially those utilizing convolutional neural networks (CNNs), have also made significant strides in heart disease prediction, achieving over 90% accuracy [4]. These CNN-based models have outperformed both classical techniques and other DL methods, underscoring their efficacy in early-stage heart disease diagnosis. Holistic machine learning approaches that integrate lifestyle, clinical, genetic, and biochemical data have further improved heart disease prediction, achieving a cross-validated accuracy of 92% [5]. These models represent a significant improvement over traditional methods, particularly in their comprehensive approach to prediction. Deep learning has also been applied effectively to diabetes prediction. Models utilizing the PIMA and MESSIDOR datasets have achieved high accuracy rates, providing better categorization outcomes for diabetes diagnosis. Cloud-based frameworks, which combine traditional ML methods with deep learning [6], have demonstrated an accuracy of 98% when tested on the Pima Indian diabetic dataset from UCI, underscoring the potential of cloud-integrated solutions for large-scale diabetes prediction.

Moreover, integrated deep learning models that leverage features from lung, diabetic, and clinical datasets have been proposed to predict heart disease more effectively [7]. These models not only improve overall performance but also reduce false-positive rates, further enhancing the accuracy and reliability of heart disease diagnostics in diabetic patients. Deep learning models have consistently demonstrated superior performance in predicting outcomes from diabetes datasets. A deep belief network (DBN) model, for example, outperformed both LSTM and RNN models, achieving an impressive 95.79% accuracy [8] while maintaining the lowest mean absolute error. This showcases the strength of deep learning models in tackling complex prediction tasks in diabetic populations. In the realm of healthcare, particularly for diabetic patients, the intersection of artificial intelligence and cardiovascular disease prediction has gained substantial attention. Numerous studies have explored the use of deep learning (DL) and machine learning (ML) techniques to enhance the accuracy and reliability of disease prediction models, particularly for identifying risks related to heart blocks in diabetic patients [9].

One significant area of exploration has been the application of stacked deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These models are well-suited to handle the complexities of medical data, which often include time-series elements (such as heart rate and glucose levels) and imaging data (such as echocardiograms). For instance, the use of CNN-RNN hybrids [10] has shown promise in accurately predicting not only cardiovascular conditions but also patterns indicative of disease progression in diabetes. By stacking these networks, researchers have been able to exploit the strengths of both models-CNNs for spatial feature extraction and RNNs for temporal sequence analysis.

Another critical area of research has been the development of predictive models that integrate both clinical and biometric data [11]. By leveraging data from electrocardiograms (ECG), glucose monitoring, and patient history, advanced machine learning models have improved diagnostic precision for conditions like myocardial infarction and atrial fibrillation. Integrating such data has become crucial in predicting heart blocks, as it allows for a more comprehensive assessment of the patient's risk profile. Recent literature highlights the effectiveness of advanced optimization techniques in boosting the performance of predictive models. Techniques like genetic algorithms, particle swarm optimization, and gradient boosting have been applied to enhance model training and feature selection [12]. These techniques help improve model accuracy while reducing the risk of over fitting, a common challenge when dealing with complex medical data.

Additionally, cloud-based and edge computing frameworks have been explored to enable real-time heart block prediction in diabetic patients [13]. The combination of DL models with IoT-enabled healthcare devices has allowed for continuous monitoring and faster predictions. This advancement is particularly important for managing diabetes-related cardiovascular risks, where timely intervention can prevent severe outcomes. In terms of real-world applications, models integrating CNN and RNN architectures have been validated using datasets like the Physio Net Challenge dataset, which includes comprehensive ECG and glucose monitoring data. Studies have demonstrated that integrating these architectures can predict adverse cardiac events more accurately than conventional methods, proving beneficial in clinical decision-making for diabetic patients [13-15]. Lastly, explainable AI (XAI) models have started to play a crucial role in this domain. Providing interpretable results is essential for gaining trust from clinicians and ensuring the models' applicability in practice. Efforts have been made to create models that not only predict heart blocks but also offer insights into which features-such as glucose variability or specific ECG markers-contribute most to the prediction. This transparency is vital for integrating AI solutions into mainstream healthcare practices for diabetic patients [16].

Despite advancements in machine learning and deep learning models, accurately predicting heart blocks in diabetic patients remains a significant challenge due to the complexity of integrating temporal and spatial medical data, such as ECG readings and clinical histories. Existing models often fail to capture the intricate patterns between diabetes and cardiovascular diseases, resulting in suboptimal prediction performance. The objective of this paper is to develop an advanced deep learning approach by integrating stacked CNN and RNN models, aimed at improving the prediction of heart blocks in diabetic patients. This model seeks to enhance accuracy by leveraging both spatial features (from medical imaging and signals) and temporal data (from time-series health monitoring), ultimately providing a more reliable diagnostic tool for early intervention and personalized treatment strategies.

Survey of Research Challenges and Solutions

Several challenges arise when using deep learning to predict heart attacks. The first is data heterogeneity, as the dataset includes both structured data (such as blood pressure and cholesterol levels) and unstructured data (such as medical images). The solution lies in using CNNs to process image data and RNNs to analyse sequential data like blood pressure readings. Another challenge is over fitting, particularly with high-dimensional datasets, which can lead to poor generalization. Techniques like data augmentation, dropout layers, and early stopping are used to reduce over fitting. Lastly, computational complexity is a concern when training deep learning models on large datasets. Efficient optimization algorithms, such as the Emperor Penguin Optimizer (EPO), are utilized to minimize computational load while improving model accuracy.

The prediction of heart attacks in diabetic patients requires a sophisticated approach that integrates both structured clinical data and unstructured medical images. The proposed methodology leverages the strengths of deep learning models, specifically convolutional neural networks (CNN) for image processing and recurrent neural networks (RNN) for sequential data, while optimizing model performance using the Emperor Penguin Optimizer (EPO). The process begins with data collection, where the dataset consists of structured data, including clinical biomarkers such as blood pressure, cholesterol, and atherosclerosis markers, along with unstructured data from medical images like angiograms and echocardiograms.

Proposed Methodology

The prediction of heart attacks in diabetic patients requires a sophisticated approach that integrates both structured clinical data and unstructured medical images. The proposed methodology leverages the strengths of deep learning models, specifically stacked convolutional neural networks (CNN) for image processing and recurrent neural networks (RNN) for sequential data, while optimizing model performance using the Emperor Penguin Optimizer (EPO). The process begins with data collection, where the dataset consists of structured data, including clinical biomarkers such as blood pressure, cholesterol, and atherosclerosis markers, along with unstructured data from medical images like angiograms and echocardiograms.

The proposed methodology aims to develop an efficient deep learning framework for predicting heart attacks in diabetic patients by combining clinical data (biomarkers) and medical images. This approach employs stacked convolutional neural networks (Stacked CNN) for image processing, recurrent neural networks (RNN) for handling sequential clinical data, and the Emperor Penguin Optimizer (EPO) for optimizing the model. Below is an elaboration of each step involved in the methodology.

Data Collection

The dataset includes two primary types of data:
Structured Data (clinical biomarkers): This data comprises medical indicators such as blood pressure readings, cholesterol levels, glucose levels, and atherosclerosis markers (arterial stiffness, plaque buildup). These biomarkers are stored in .CSV format.
Unstructured Data (medical images): Medical images like angiograms, echocardiograms, and other relevant heart scans are used to capture visual information about arterial blockages, heart structure, and blood flow anomalies. These images are key to detecting patterns that lead to heart attacks.

Data Preprocessing

Structured Data Preprocessing: The clinical biomarkers are preprocessed by applying normalization and feature scaling to ensure that the features are comparable and in a consistent range. Handling missing values is done through imputation, while outliers are identified and adjusted to avoid data distortion. Temporal features, such as blood pressure trends over time, are created by calculating rolling averages or statistical metrics to enhance the prediction model's ability to capture time-based trends.

For the medical images, preprocessing involves resizing them to a consistent resolution, converting to grayscale (if necessary), and augmenting the dataset with transformations like rotation, flipping, and contrast enhancement. These augmentations are designed to make the stacked CNN model more robust and generalizable by introducing variability in the training data. The architecture consists of a dual pipeline combining stacked CNN for processing image data and RNN for handling sequential clinical data:

Stacked CNN for Image Processing

The stacked CNN model consists of multiple convolutional layers stacked on top of each other, enabling deeper feature extraction from the medical images. Each convolutional layer is followed by an activation function (ReLU) and max-pooling to reduce dimensionality and highlight critical features. The stacked architecture allows for learning more complex hierarchical patterns in the images, facilitating the identification of heart attack risk factors.

RNN for Sequential Data

The RNN is used to process the structured, time-sequenced clinical data, such as blood pressure trends, cholesterol levels, and glucose readings over time. The RNN captures temporal dependencies and patterns in the data, allowing the model to understand how a patient's health indicators change over time.

Feature Fusion: The outputs from both the stacked CNN and RNN models are concatenated and passed through fully connected layers to form a comprehensive feature set that reflects both visual and clinical indicators of heart health. Fig.1 shows the proposed workflow of the research work.

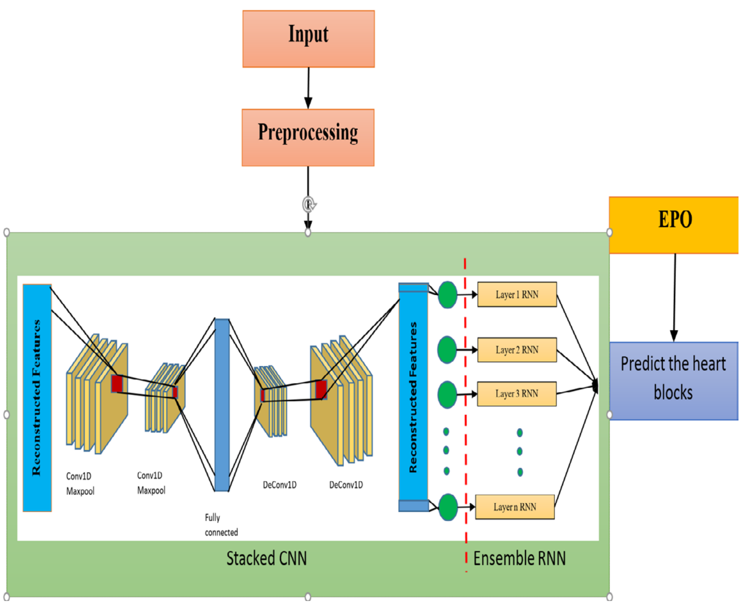

Figure 1: Workflow of the proposed work.

Optimization

The Emperor Penguin Optimizer (EPO) is employed to optimize the hyperparameters of the model. EPO simulates the collective behavior of emperor penguins in search of food, balancing exploration and exploitation during the optimization process. These results in better tuning of parameters such as learning rate, dropout rate, and the number of neurons, which ultimately enhances the accuracy and convergence of the deep learning model. The model is evaluated using key metrics such as accuracy, precision, recall, F1-score, and Area under the Curve - Receiver Operating Characteristics (AUC-ROC) to assess its ability to distinguish between high-risk and low-risk patients. A cross-validation strategy is applied to ensure the model's robustness and generalizability.

Conclusion

In this study, we proposed a robust deep learning framework for predicting heart attacks in diabetic patients by integrating structured clinical data and unstructured medical images. By employing stacked convolutional neural networks (Stacked CNN) for image processing and recurrent neural networks (RNN) for analysing temporal trends in clinical biomarkers, the model effectively captures both spatial and sequential patterns associated with cardiovascular risk.

The incorporation of the Emperor Penguin Optimizer (EPO) further enhances model performance through efficient hyper parameter tuning.

References

1. Himanshi, Pattanaik S, Nayak K (2024) Heart Diseases Prediction Using Machine Learning and Deep Learning Models. Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT), Sonepat, India, pp: 343-349.

2. Sonia SVE, Nedunchezhian R, Rajalakshmi M (2023) A multi-modal integrated deep neural networks for the prediction of cardiovascular disease in type-2 diabetic males. Automatika 64(4): 1315-1327.

3. Gandin I, Saccani S, Coser A, Scagnetto A, Cappelletto C, et al. (2023) Deep-learning-based prognostic modeling for incident heart failure in patients with diabetes using electronic health records: A retrospective cohort study. PLoS One 18(2): e0281878.

4. Kumar L, Anitha C, Ghodke VN, Nithya N, Drave VA, et al. (2023) Deep Learning Based Healthcare Method for Effective Heart Disease Prediction. EAI Endorsed Transactions on Pervasive Health and Technology 9.

5. Rakhra M, Singh P, Angra PK, Cheema GS, Bedi KS (2024) Predicting Heart Disease Holistically: A Machine Learning Approach.

6. Priyanka S, Kavitha C, Kumar MP (2023) Deep Learning based Approach for Prediction of Diabetes. 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, pp: 1-6.

7. Tarawneh M, AlZyoud F, AlSharrab Y, Khatatneh K (2022) Cloud-based Diabetic Prediction Framework: Deep Learning Approach. International Conference on Emerging Trends in Computing and Engineering Applications (ETCEA), Karak, Jordan, pp: 1-6.

8. Anwar S, Thillaigovindan SK (2022) Integrated Deep Learning Model for Heart Disease Prediction Using Variant Medical Data Sets. International Journal of Online and Biomedical Engineering, 18(9): 178-191.

9. Akinsola JET, Ajagbe SA, Olajubu EA, Lawal AO, Aderounmu GA, et al. (2023) Artificial Intelligence - Enabled Deep Learning Model for Diabetes Prediction Using Deep Belief Network with Bayesian Optimization. International Conference on Computational Science and Computational Intelligence (CSCI), pp: 353-358.

10. Jiu L, Vreman R, Wang J, Mantel-Teeuwisse A, Goettsch W (2022) PP37 A Systematic Review of Machine Learning and Statistical Models For Predicting Coronary Heart Disease In Diabetic Patients. International Journal of Technology Assessment in Health Care 38(Suppl 1): S52-S53.

11. Qiu H, Yang P, Wang L (2024) DCNeT: A disease comorbidity network-based temporal deep learning framework to predict cardiovascular risk in patients with mental disorders. Expert Systems with Applications 254: 124312.

12. Salama AA, Shitaya AM, Mohammed EL, Wahed S, Helemy S, et al. (2024) Neutrosophic Deep Learning for Student Performance Prediction: A Novel Approach with Uncertainty Integration and Ethical Considerations. Journal of Business and Environmental Sciences 3(2): 252-274.

13. Madarapu S, Ari S, Mahapatra K (2024) A deep integrative approach for diabetic retinopathy classification with synergistic channel-spatial and self-attention mechanism. Expert Systems with Applications 249(A): 123523.

14. Varshney RP, Sharma DK (2024) Optimizing Time-Series forecasting using stacked deep learning framework with enhanced adaptive moment estimation and error correction. Expert Systems with Applications 249(A): 123487.

15. Vilela LFC, Cabral NO, Destefani AC, Destefani VC (2024) Harnessing the power of artificial intelligence for early detection and management of diabetic retinopathy, age-related macular degeneration, and glaucoma: a narrative review of deep learning applications in ophthalmology. Ibero-American Journal of Humanities, Sciences and Education 10(8): 3311-3320.

16. Sangeethaa SN (2023) Presumptive discerning of the severity level of glaucoma through clinical fundus images using hybrid PolyNet. Biomedical Signal Processing and Control 81: 104347.