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An interpretable framework based on deep learning and the Internet of Things for predicting risk dynamics in chronic patients

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Abstract

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Introduction: Effective management of chronic conditions necessitates analytical approaches capable of capturing temporal dynamics within physiological data streams. Conventional machine learning methodologies frequently encounter limitations in this domain, functioning as opaque "black boxes" that obscure decision-making processes.

Objective: This investigation introduces an interpretable framework integrating Internet of Things (IoT) infrastructure with deep learning architectures to forecast health deterioration risks among individuals with chronic conditions.

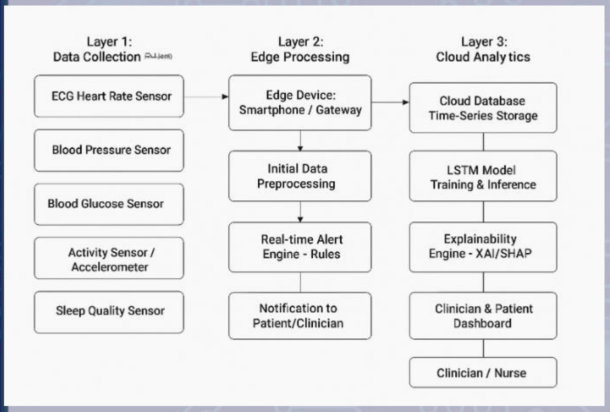
Methods: Temporal data were obtained from the established PhysioNet repository. A long short-term memory (LSTM) network was developed and optimized to anticipate critical health events. Model performance was evaluated against four baseline approaches (artificial neural network and random forest). Furthermore, the SHAP (SHapley Additive exPlanations) methodology was employed to elucidate model predictions and identify predominant risk determinants.

Results: The LSTM architecture demonstrated superior predictive capability relative to baseline models, attaining 95% accuracy with an area under the ROC curve (AUC) of 0.97. SHAP-based analysis identified diminished sleep quality and abrupt alterations in physical activity patterns as the most significant predictors of patient risk.

Conclusion: The developed framework not only enhances predictive precision but also fosters confidence in and adoption of intelligent health systems through clinically relevant explanatory capabilities.

Research method

Framework Architecture



This investigation utilized the "eICU Collaborative Research Database" repository from PhysioNet .

Time-series data presented challenges including irregular sampling intervals and missing observations. Data preparation employed linear interpolation techniques for brief temporal gaps and forward-filling methods for extended missing sequences.

conclusion

This investigation successfully demonstrated that integration of deep learning architectures (LSTM) with post-hoc explainability methods (SHAP) enables development of intelligent, accurate, and potentially trustworthy health monitoring systems for chronic disease patients. The LSTM model achieved 95% accuracy with 0.97 AUC, significantly outperforming baseline approaches. SHAP analysis provided clinically meaningful explanations identifying hypotension, reduced activity levels, and sleep quality as key risk determinants. This approach not only enhances predictive accuracy but also addresses the "black box" challenge in AI-based clinical decision support. However, important limitations regarding temporal explainability and clinical validation requirements are acknowledged. Future work should prioritize temporally-aware explanation methods and real-world pilot studies to validate clinical utility.

The purpose of the research

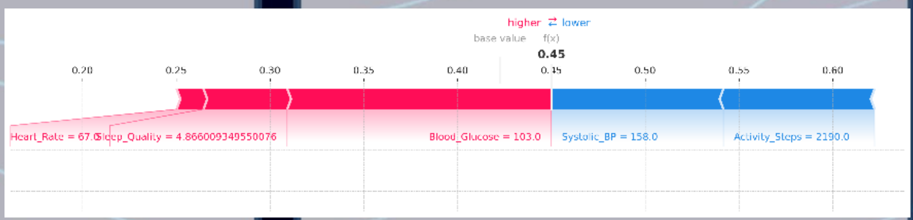
Data collection alone proves insufficient; the principal challenge resides in sophisticated analysis of this voluminous information and extraction of clinically meaningful patterns to support therapeutic decision-making. Artificial intelligence and machine learning algorithms provide powerful analytical capabilities for this purpose; however, their inherent "black box" nature constrains clinical adoption due to concerns regarding clinician trust and regulatory requirements for algorithmic transparency and accountability

Practical or simulation results

Comparative model performance with 95% confidence intervals

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Random Forest	91 (89-93)	89 (86-92)	92 (90-94)	0.92
ANN	92 (90-94)	90 (87-93)	93 (91-95)	0.94
Simple RNN	93 (91-95)	91 (88-94)	94 (92-96)	0.95
TCN	94 (92-96)	92 (89-95)	95 (93-97)	0.96
LSTM	95 (93-97)	94 (91-97)	96 (94-98)	0.97

Statistical Analysis Procedures



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