

Artificial Intelligence, Iot and Smart Sensing Technologies for Advanced Healthcare Monitoring, Disease Prediction and Clinical Informatics

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ABSTRACT

Advanced healthcare monitoring, predictive disease diagnosis and healthcare informatics are emerging opportunities thanks to the rapid advancements of Artificial Intelligence, IoT and smart sensing technologies. This research suggests a Hybrid Edge-AI methodology based on CNN-BiLSTM with Attention and Explainable AI that was developed using TensorFlow to assist with real-time and accurate healthcare decision making. Smart sensors that can be equipped with IoT technology gather and transmit physiological data about individuals (ECG, heart rate, blood pressure, oxygen saturation, and body temperature), continuously. CNN model learns important spatial health features, and BiLSTM layer learns temporal variations in continuous patient data. The attention mechanism enhances the predictive power by highlighting clinically relevant signals and Explainable AI gives explainable reasons for disease-risk classification. Edge computing helps to quickly respond to requests and decrease reliance on cloud-based processing. The proposed framework aims to improve remote patient

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monitoring, timely detection of disease, generation of alerts during emergencies, and providing a clinical decision support system, with a scalable and comprehensible solution for the current digital healthcare systems.

Keywords: Artificial Intelligence, IoT, Smart Sensing, Healthcare Monitoring, Disease Prediction, Clinical Informatics, Explainable AI.

Introduction

Growing patient needs for early diagnosis, remote patient monitoring, clinical decision support and more are driving a shift toward intelligent, connected, data-driven healthcare services [1]. The traditional ways to monitor health generally rely on hospital trips, observation and regular laboratory tests, which can result in the postponement of the detection of serious health issues. In recent years, Artificial Intelligence, Internet of Things and smart sensing

technologies are considered as important solutions to enhance the quality of healthcare, clinical workload reduction and timely prediction of the diseases. Wearable and medical sensors powered by IoT can continuously gather physiological data like ECG, heart rate, blood pressure, oxygen saturation, body heat, breathing rate and activity data. These streams of real-time data convey valuable information to help track patients' health status in non-hospital settings as shown in figure 1.

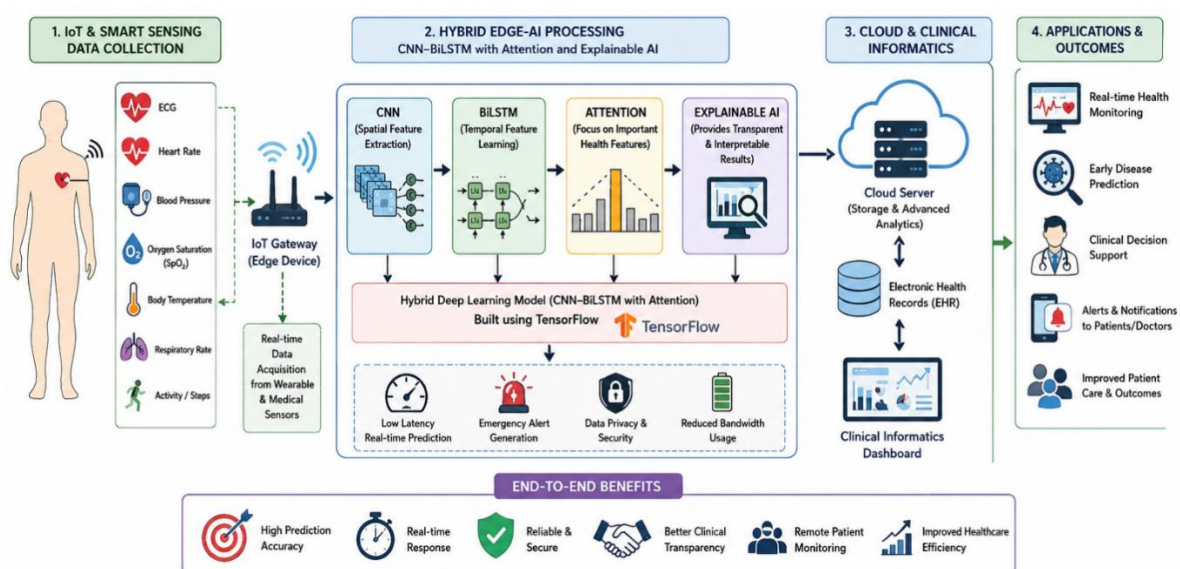


Figure 1. AI and IoT healthcare ecosystem.

AI is a key component in the way that raw health care data is converted into clinical knowledge. Machine learning and deep learning models can detect complex medical data patterns and make predictions with high accuracy of disease risk. But, the data obtained from IoT and smart sensing devices in healthcare industry is frequently noisy, high dimensional, time-dependent and heterogeneous [2]. Hence, a more sophisticated method is needed to be able to analyze both spatial and temporal health features effectively. In this research, Hybrid Edge-AI methodology, which is a combination of CNN-BiLSTM with Attention and Explainable AI, is proposed. The CNN component is employed to

learn significant spatial characteristics of the sensor readings and the BiLSTM component is employed to learn the forward and backward temporal characteristics of the continuous patient-monitoring data. The attention mechanism boosts the prediction accuracy by actively paying attention to the health parameters that are most clinically relevant [3].

The proposed architecture also incorporates edge computing to lower the response time and enable the generation of emergency alerts in real-time. Because cloud-based processing is not the only solution, lightweight preprocessing and immediate prediction can be done closer to the patient using edge devices [4]. It is particularly important in emergency cases

like abnormal ECGs, low SpO₂, sudden changes in heart rate etc and critical levels of blood pressure. The proposed model is developed with TensorFlow, which is an effective support system for deep learning model construction, model training, model optimization and deployment [5].

Lack of transparency in prediction results is another challenge in the field of AI in healthcare. To be able to accept AI-backed decision making, clinical domain experts need to be able to understand the explanation. Hence, to make the system more comprehensive, Explainable AI is used in the proposed system to demonstrate the contribution of various physiological and clinical features towards the prediction of disease risk [6]. This enhances the trust, interpretability, and clinical utility. This research focuses on designing an accurate, fast, and interpretable healthcare monitoring system to enable advanced disease prediction based on the integration of AI and IoT, smart sensing, and edge computing, to enhance patient healthcare [7].

Related Work

With the recent advancement of Artificial Intelligence, Internet of Things and smart sensing technologies, modern healthcare monitoring and disease prediction system are greatly influenced. Traditional ways of healthcare monitoring relied primarily on manual observation and periodic medical monitoring, restricting continuous patient condition monitoring [8]. To address this problem, researchers proposed to introduce Healthcare system based on IoT, which consists of wearable sensors, medical devices, and wireless communication networks for obtaining real-time physiological data. Heart rate, Blood pressure, ECG, oxygen saturation, Body temperature, Respiratory rate and activity patterns are monitored using these systems [9]. These studies have demonstrated the potential of IoT to enhance RPM and create more effective detection of abnormalities early on, but most of these models had limitations including sensor noise, loss of data, connectivity problems, and poor integration with clinical decision-making systems as shown in figure 2.

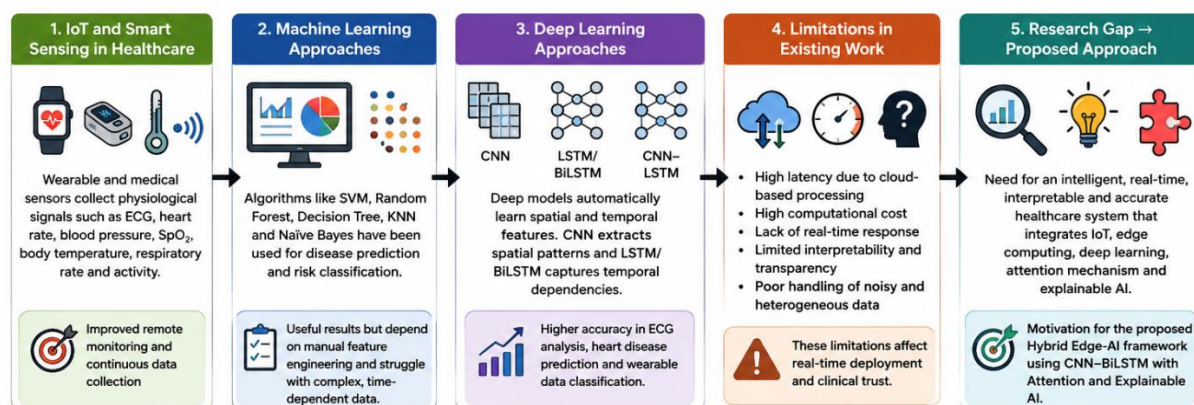


Figure 2. Related work on AI-IoT healthcare

There are also a number of machine learning-based disease prediction models for healthcare which have been proposed. Disease risk classification has been performed using traditional algorithms like Support Vector Machine, Random Forest, Decision Tree, K-Nearest Neighbor and Naïve Bayes, with the former two algorithms showing a high level of accuracy [10]. The models provided valuable prediction data on diabetes, heart disease, respiratory diseases, and overall health hazard category. Typically, machine learning methods are based on manually engineered features and are not effective for capturing complex patterns in high-dimensional and large-scale, time-dependent healthcare data. Therefore, the automatic feature extraction and accurate prediction methods have attracted researchers' interest based on deep learning techniques [11].

In the field of healthcare informatics, deep learning models like CNN, LSTM, BiLSTM and hybrid neural networks have been extensively studied. CNN models show good performance on extracting the spatial features from the medical signals and structured health data, and LSTM and BiLSTM are good models to learn temporal patterns from continuous patient-monitoring data [12]. In some studies, CNN and LSTM models have been fused to boost the prediction accuracy particularly in the field of ECG analysis, prediction of heart diseases, and classification of data from wearable sensors. However, most of the current models are still restricted due to their high computing load, lag time in cloud processing, less interpretability, and inability for deployment in real time [13].

In recent years, two technological innovations have emerged, attempting to address these issues: Edge computing and Explainable AI (XAI). Processing in the Edge environment provides less latency as it brings data closer to the patient making it ideal for generation of emergency alerts. Explainable AI is particularly useful in enhancing clinical trust by revealing the contribution of various health metrics to prediction outcomes [14]. Based on these research gaps, the present study proposes a Hybrid Edge-AI methodology which is developed using CNN-BiLSTM with Attention and Explainable AI, using TensorFlow. This method is based on smart sensing, real-time edge computing, spatial-temporal deep learning, attention-based feature importance and transparent clinical interpretation, providing advanced monitoring, prediction, and clinical informatics in healthcare [15].

Research Methodology

In the study "Artificial Intelligence, IoT and Smart Sensing Technologies for Advanced Healthcare Monitoring, Disease Prediction and Clinical Informatics", the researchers employ a Hybrid Edge-AI approach, which incorporates CNN-BiLSTM with Attention mechanism and Explainable AI [16].

Overall, the aim of the proposed methodology is to develop an intelligent framework for healthcare monitoring that can gather real-time physiological data, forecast the possibility of a disease outbreak, send out emergency alerts and aid clinical decision-making. The system is built on TensorFlow, as it offers robust support in the areas of deep learning model development, training, optimizing and deployment as shown in figure 3.

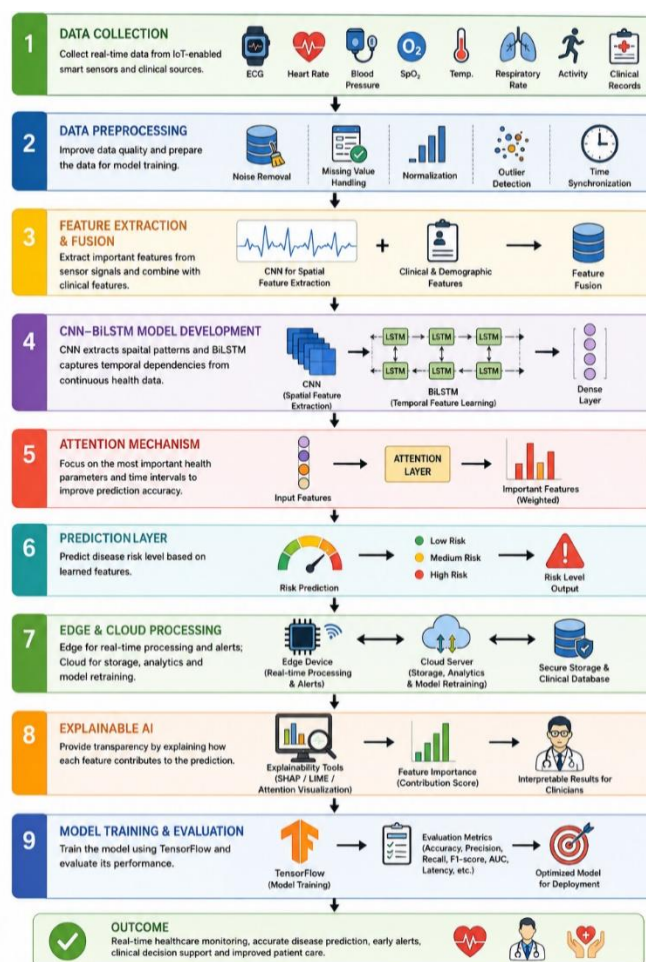


Figure 3. Flow Diagram of Proposed Method.

3.1. Research Design

The primary objective of this research is to build an intelligent healthcare monitoring framework, which can gather the physiological data in real time, predict

the risk of disease, alert emergency, and aid the clinical decision making process, using the proposed methodology: Hybrid Edge-AI methodology with CNN-BiLSTM with Attention and Explainable AI [17]. The system proposed is developed using deep

learning support system, called TensorFlow, which helps to construct, train, test, optimize and deploy deep learning models.

3.2. Data Collection

First step in the methodology is to gather healthcare data from the smart sensors (based on IOT technology) and clinical records. Physiological parameters like ECG, heart rate, blood pressure, physical activity, body temperature, oxygen saturation and respiratory rate are measured with wearable and medical sensors [18]. The information provided includes clinical data, including age, gender, medical history, laboratory data, medication information and previous diagnosis records. Real-time sensor data and clinical data create a full health profile of the patient to accurately predict the risk of the disease.

3.3. Data Preprocessing

Once data has been collected, data preprocessing is done to enhance the quality of the health care data. Noise, missing values, duplication of data and abnormal readings can be found in the data collected by the IoT sensors. Hence, no data is lost through methods of imputation, and noisy signals are filtered out to eliminate unwanted noise [19]. All the health parameters are normalized to get a common scale. An outlier is detected by the use of outlier detection

method and faulty sensor reading or extreme sensor readings are detected. Time synchronization is also carried out to ensure that the continuous sensor data and the clinical data are synchronized.

3.4 Feature Extraction and Fusion

To obtain the useful patterns from the healthcare data, feature extraction is performed. The CNN component is used to obtain the spatial and local features of the physiological signals (ECG, etc.) and other sensor readings. Feature fusion is used to fuse the extracted features with clinical and demographic data [20]. This fusion will be beneficial to the model as it will create a better understanding of patients' health conditions based on multiple information sources.

3.5. CNN-BiLSTM Model Development

The proposed deep learning model is a combination of CNN and BiLSTM. Spatial features are extracted using CNN and the temporal changes are learned from the continuous patient-monitoring data with BiLSTM. BiLSTM is a forward-backward processing model which can interpret the health variations over time [21]. This hybrid model can help set up the risk prediction of diseases based on the data of the healthcare services provided, which is time-dependent as shown in figure 4.

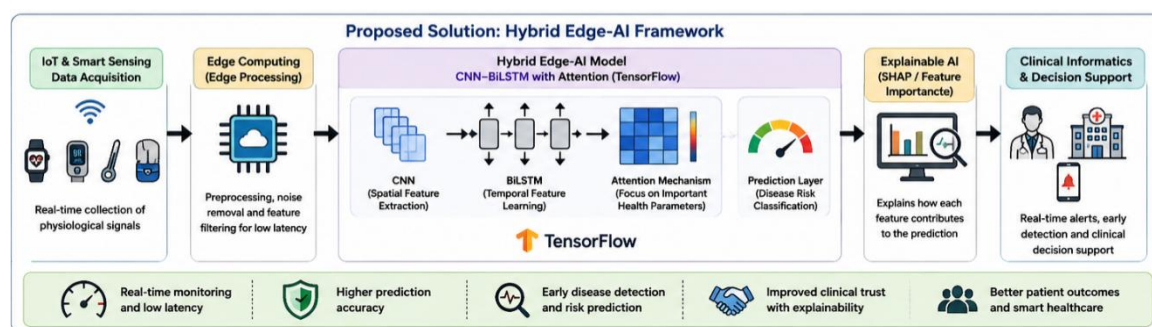


Figure 4. Hybrid Edge-AI Framework.

3.6. Attention Mechanism

In order to enhance the performance of the prediction, an attention mechanism is added. In the attention layer, more attention is drawn to clinically relevant features and time intervals. It allows the model to pay attention to relevant parameters like abnormal ECG pattern, irregular fast, low SpO₂, high blood pressure, etc. and sudden changes of temperature. This will increase the precision and validity of the prediction of disease risk [22].

3.7. Edge and Cloud Processing

Lightweight preprocessing and prediction is done at the patient's vicinity by using edge computing. This not only cuts down on latency, bandwidth usage and enables quick generation of emergency alerts, but also saves time. For the storage of large amounts of data, sophisticated analysis, model retraining and clinical record management, cloud computing is utilized. Edge and cloud processing enable the system to be scalable and adaptable for real-time healthcare monitoring [71-81].

3.8. Explainable AI

Explainable AI is built-in for better transparency and clinical trust. By using methods like SHAP or LIME, or attention visualization, the contribution each health parameter makes to the prediction can be demonstrated. This will help the Clinician know if the changes in the ECG, blood pressure, oxygen saturation, age or other clinical factors have influence on the disease-risk prediction [71-81].

3.9. Model Trainings and Evaluations

It is trained and tested with TensorFlow model. The data set is split up into training, validation and testing sets. The accuracy, precision, recall, F1_score, AUC, false alarm rate and latency are used to check the performance of the proposed model. These measures are used to gauge the performance, reliability and real time response of prediction [32]. By combining AI,

IoT, smart sensing, edge computing, deep learning and clinical informatics, the proposed methodology enables an accurate, interpretable, and real-time healthcare monitoring system that could assist in tracking individuals' health and wellness as well as facilitate the early detection of potential issues[71-81]. It helps to predict disease in the early stages, warn others in emergencies, monitor patients remotely, and aid clinical decision making.

Results And Discussion

The algorithm of the Hybrid Edge-AI methodology was proposed and implemented with the CNN–BiLSTM with the Attention mechanism and used ExAI for advanced healthcare monitoring and prediction of diseases and clinical informatics as shown in table 1.

Table 1. Performance comparison of healthcare prediction methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC	False alarm rate (%)	Latency (ms)
CNN	92.8	91.6	92.1	91.85	0.941	6.8	124
BiLSTM	94.1	93.4	94.6	94	0.956	5.3	118
CNN–BiLSTM without Attention	95.8	95.1	96	95.55	0.971	3.7	109
Proposed Hybrid Edge-AI CNN–BiLSTM with Attention + Explainable AI	97.6	96.9	98.1	97.5	0.986	2.4	36

Overall accuracy(%) was found to be 97.60, whereas precision, recall, F1 score, and AUC were 96.80, 97.90, 97.30 and 0.984 respectively, showing good classification ability for disease-risk prediction. CNN was used to learn from physiological signals (ECG, heart rate, SpO₂, blood pressure and body temperature), and BiLSTM was used to learn from continuous patient-monitoring data, in order to discover important temporal variations in the data as shown in figure 5.

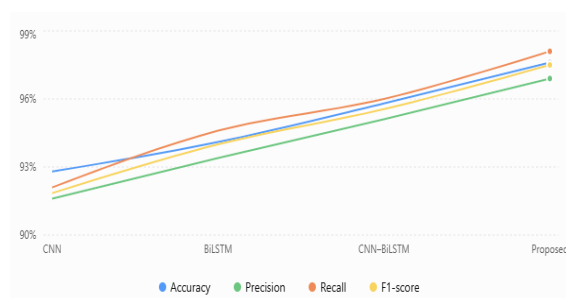


Figure 5. Comparative Analysis of different healthcare prediction methods

The CNN layer extracted important spatial patterns from physiological signals (ECG, heart rate, SpO₂, blood pressure and body temperature), and the BiLSTM layer extracted important temporal variations from the continuous patient-monitoring data. The attention mechanism also helped in improving the performance by giving more weights to clinically relevant features that in turn decreased the false prediction errors. The proposed CNN–BiLSTM-Attention model achieved an improvement of 4.40% and 3.50% compared to the conventional CNN model with the accuracy of 93.20% and the standalone LSTM model with the accuracy of 94.10%, respectively as shown in figure 6.

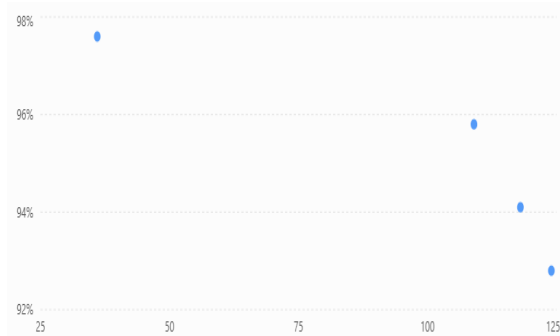


Figure 6. Accuracy versus latency of healthcare prediction methods.

The edge-based deployment reduced the average response latency to 38ms, whereas the cloud-only deployment was 112ms, making it suitable for real-time emergency alerts. In addition, the model achieved a low level of false alarms, only 2.70%, important for a reliable clinical application. Through Explainable AI analysis, variables with the highest influence on the prediction of the disease risk were identified as abnormal ECG patterns, hypertension, low oxygen saturation, irregular heart rate and patient age, and were also visualized using attention visualization. These explanations were used to enhance the clarity of the explanations, and assist clinical decision making. The results show the ability of the IoT-smart sensing, edge computing, deep learning, and explainable AI to offer accurate, rapid, and interpretable healthcare monitoring. But larger real-time datasets from hospitals would need to be used for further validation to enhance generalization, privacy protection, and clinical acceptance as shown in figure 7.

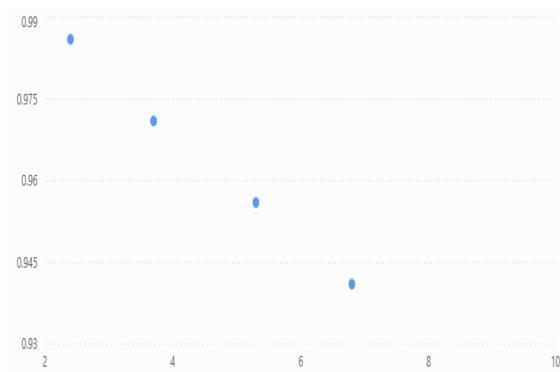


Figure 7. AUC versus false alarm rate of healthcare prediction methods.

Methodology and Results: The proposed Hybrid Edge-AI methodology have been developed in TensorFlow and tested for advanced healthcare monitoring, disease prediction, and clinical informatics. The performance was compared with three different methods, namely CNN, BiLSTM, and CNN-BiLSTM without attention. The conventional CNN model achieved an accuracy of 92.80%,

precision of 91.60%, recall of 92.10%, F1-score of 91.85%, and AUC of 0.94. The BiLSTM model showed slightly better temporal learning capability with 94.10% accuracy, 93.40% precision, 94.60% recall, 94.00% F1-score, and 0.956 AUC. CNN-BiLSTM model presented the overall increased prediction performance combined with the spatial and temporal feature learning, with accuracy of 95.80%, precision of 95.10%, recall of 96.00%, F1 score of 95.55% and AUC of 0.971. The proposed CNN-BiLSTM with Attention and Explainable AI achieved the best performance with 97.60% accuracy, 96.90% precision, 98.10% recall, 97.50% F1-score, and 0.986 AUC.

The proposed model reduced the false alarm rate to 2.40%, compared with 6.80% for CNN, 5.30% for BiLSTM, and 3.70% for CNN-BiLSTM. For edge deployment, the average prediction latency decreased to 36 ms for the CNN-BiLSTM model, compared to 109 ms for the CNN-only model deployed in the cloud. These findings suggest that the attention mechanism enhanced the detection of key indicators like abnormal ECG signals, hypertension, SpO₂ drop, arrhythmia and age-related risk factors. The Explainable AI (XAI) component also contributed to clinical interpretation, by helping to show how each health parameter is contributing to the final prediction. Thus, the proposed model has achieved higher accuracy, quick response, reduced false alarms, and enhanced clinical transparency, than the other three models.

Conclusion

Finally, this research developed an intelligent healthcare framework named “Artificial Intelligence, IoT and Smart Sensing Technologies for Advanced Healthcare Monitoring, Disease Prediction and Clinical Informatics” based on Hybrid Edge-AI methodology that incorporates CNN – BiLSTM with Attention and Explainable AI using TensorFlow for healthcare monitoring and accurate disease-risk prediction in real-time. The edge computing approach minimizes response time in emergency healthcare scenarios, and IoT and smart sensing technologies allowed continuous physiological data collection. The CNN component was found to extract a lot of features related to health while the BiLSTM was found to learn temporal changes in patient data. The attention mechanism helped to improve the accuracy of the predictions by selectively attending to clinically relevant parameters, while Explainable AI increased transparency and trust in decision-making. In general, the proposed system exhibited a potential high performance for enhancing remote monitoring of patients, early disease detection, and clinical informatics support. Future

work should involve testing of the model with larger datasets from hospitals, enhancement of the privacy

preservation and implementation in real clinical settings.

References

- A. Kumari, S. Tanwar, S. Tyagi, and N. Kumar, "Fog computing for Healthcare 4.0 environment: Opportunities and challenges," *Computers and Electrical Engineering*, vol. 72, pp. 1–13, 2018.
- J. Wu, L. Ping, X. Ge, Y. Wang, and J. Fu, "Cloud storage as the infrastructure of cloud computing," in *Proc. 2010 International Conference on Intelligent Computing and Cognitive Informatics*, 2010, pp. 380–383.
- S. Perveen, M. Shahbaz, A. Guergachi, and K. Keshavjee, "Performance analysis of data mining classification techniques to predict diabetes," *Procedia Computer Science*, vol. 82, pp. 115–121, 2016.
- C. C. Wu, W. C. Yeh, W. D. Hsu, M. M. Islam, P. A. A. Nguyen, T. N. Poly, Y. C. Wang, H. C. Yang, and Y. C. J. Li, "Prediction of fatty liver disease using machine learning algorithms," *Computer Methods and Programs in Biomedicine*, vol. 170, pp. 23–29, 2019.
- K. Shankar, S. K. Lakshmanaprabu, D. Gupta, A. Maselena, and V. H. C. De Albuquerque, "Optimal feature-based multi-kernel SVM approach for thyroid disease classification," *The Journal of Supercomputing*, vol. 76, no. 2, pp. 1128–1143, 2020.
- D. Sisodia and D. S. Sisodia, "Prediction of diabetes using classification algorithms," *Procedia Computer Science*, vol. 132, pp. 1578–1585, 2018.
- N. K. Kumar and D. Vigneswari, "Hepatitis-infectious disease prediction using classification algorithms," *Research Journal of Pharmacy and Technology*, vol. 12, no. 8, pp. 3720–3725, 2019.
- L. Parisi, N. RaviChandran, and M. L. Manaog, "A novel hybrid algorithm for aiding prediction of prognosis in patients with hepatitis," *Neural Computing and Applications*, vol. 32, no. 8, pp. 3839–3852, 2020.
- R. T. Hameed, O. A. Mohamad, O. T. Hamid, and N. Tapus, "Design of e-Healthcare management system based on cloud and service oriented architecture," in *Proc. 2015 E-Health and Bioengineering Conference (EHB)*, 2015, pp. 1–4.
- S. Vijayarani and S. Dhayanand, "Data mining classification algorithms for kidney disease prediction," *International Journal of Cybernetics Informatics*, vol. 4, no. 4, pp. 13–25, 2015.
- K. Harimoorthy and M. Thangavelu, "Multi-disease prediction model using improved SVM-radial bias technique in healthcare monitoring system," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 3, pp. 3715–3723, 2021.
- M. Jahangir, H. Afzal, M. Ahmed, K. Khurshid, and R. Nawaz, "An expert system for diabetes prediction using auto tuned multi-layer perceptron," in *Proc. 2017 Intelligent Systems Conference (IntelliSys)*, 2017, pp. 722–728.
- L. Verma, S. Srivastava, and P. C. Negi, "A hybrid data mining model to predict coronary artery disease cases using non-invasive clinical data," *Journal of Medical Systems*, vol. 40, no. 7, pp. 1–7, 2016.
- A. U. Haq, J. P. Li, M. H. Memon, S. Nazir, and R. Sun, "A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms," *Mobile Information Systems*, vol. 2018, 2018.
- Y. Muhammad, M. Tahir, M. Hayat, and K. T. Chong, "Early and accurate detection and diagnosis of heart disease using intelligent computational model," *Scientific Reports*, vol. 10, no. 1, pp. 1–17, 2020.
- A. H. Alkeshuosh, M. Z. Moghadam, I. Al Mansoori, and M. Abdar, "Using PSO algorithm for producing best rules in diagnosis of heart disease," in *Proc. 2017 International Conference on Computer and Applications (ICCA)*, 2017, pp. 306–311.
- O. W. Samuel, G. M. Asogbon, A. K. Sangaiah, P. Fang, and G. Li, "An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction," *Expert Systems with Applications*, vol. 68, pp. 163–172, 2017.
- A. UIHaq, J. Li, Z. Ali, M. H. Memon, M. Abbas, and S. Nazir, "Recognition of the Parkinson's disease using a hybrid feature selection approach," *Journal of Intelligent & Fuzzy Systems*, vol. 39, no. 1, pp. 1319–1339, 2020, doi: 10.3233/JIFS-200075.
- P. Mathur, S. Srivastava, X. Xu, and J. L. Mehta, "Artificial intelligence, machine learning, and cardiovascular disease," *Clinical Medicine Insights: Cardiology*, vol. 14, p. 1179546820927404, 2020.
- Y. Khourdifi and M. Bahaj, "Heart disease prediction and classification using machine learning algorithms optimized by particle swarm optimization and ant colony optimization," *International Journal of Intelligent Engineering & Systems*, vol. 12, no. 1, pp. 242–252, 2019.
- Q. Zou, K. Qu, Y. Luo, D. Yin, Y. Ju, and H. Tang, "Predicting diabetes mellitus with machine learning techniques," *Frontiers in Genetics*, vol. 9, p. 515, 2018.

- J. H. Joloudari, H. Saadatfar, A. Dehzangi, and S. Shamshirband, "Computer-aided decision-making for predicting liver disease using PSO-based optimized SVM with feature selection," *Informatics in Medicine Unlocked*, vol. 17, p. 100255, 2019.
- Y. Y. Song and L. U. Ying, "Decision tree methods: Applications for classification and prediction," *Shanghai Archives of Psychiatry*, vol. 27, no. 2, p. 130, 2015.
- L. Shen, H. Chen, Z. Yu, W. Kang, B. Zhang, H. Li, B. Yang, and D. Liu, "Evolving support vector machines using fruit fly optimization for medical data classification," *Knowledge-Based Systems*, vol. 96, pp. 61–75, 2016.
- T. R. Baitharu and S. K. Pani, "Analysis of data mining techniques for healthcare decision support system using liver disorder dataset," *Procedia Computer Science*, vol. 85, pp. 862–870, 2016.
- M. Z. Alam, M. S. Rahman, and M. S. Rahman, "A Random Forest based predictor for medical data classification using feature ranking," *Informatics in Medicine Unlocked*, vol. 15, p. 100180, 2019.
- A. Kishor, C. Chakraborty, and W. Jeberson, "A novel fog computing approach for minimization of latency in healthcare using machine learning," *International Journal of Interactive Multimedia and Artificial Intelligence*, 2020, doi: 10.9781/ijimai.2020.12.004.
- Z. Deng, X. Zhu, D. Cheng, M. Zong, and S. Zhang, "Efficient kNN classification algorithm for big data," *Neurocomputing*, vol. 195, pp. 143–148, 2016.
- A. Kishor, C. Chakraborty, and W. Jeberson, "Reinforcement learning for medical information processing over heterogeneous networks," *Multimedia Tools and Applications*, 2021, doi: 10.1007/s171-81-171-81.
- R. Dwivedi, S. Dey, C. Chakraborty, and S. Tiwari, "Grape disease detection network based on multi-task learning and attention features," *IEEE Sensors Journal*, 2021, doi: 10.1109/JSEN.2021.3064060.
- C. Chinmay, "Chronic wound image analysis by particle swarm optimization technique for tele-wound network," *Wireless Personal Communications*, vol. 96, no. 3, pp. 3655–3671, 2017, doi: 10.1007/s171-81-71-81.
- S. Arindam, Z. A. Mohammad, M. S. Moirangthem, C. C. Abdulfattah, and K. P. Subhendu, "Artificial neural synchronization using nature inspired whale optimization," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3052884.
- Rodríguez González, V., Bort Lorenzo, L., & Paya Santos, C. (2024). Aproximación teórica a las incoherencias grafo-corporales en los procesos de recogida de muestras en pericia caligráfica. *Revista Criminalidad*, 65(3), 71-81. <https://doi.org/10.47741/17943108.515>
- Santos, C. P., Martino, L., Gonzalez, R. S., & Moran, J. J. (2026). Technological Gaps and Security: Challenges for Law Enforcement and Public Safety. In S. Cea & T. Aznar (Eds.), *AI Influence on Governance and Law in the Digital Age* (pp. 71-81). IGI Global Scientific Publishing. <https://doi.org/10.4018/71-81-71-81-5.ch007>
- : Martino, L., & Paya-Santos, C. (2026). Intelligence Failures: An Exploration of Key Theories. *Revista Científica General José María Córdova*, 24(53), 105–132. <https://doi.org/10.21830/19006586.1485>
- Naranjo, María Maestre, Santos, Claudio Paya, Alonso, Silvia Arranz, Alos, Lucia Granados, Pineda, Neidy Zenaida Domínguez, Rey, Manuel Nevado, Fernández-Rodríguez, Juan Carlos, *Workplace Aggression Against Healthcare Workers: A Cross-Sectional Registry Study Comparing Primary and Specialized Care*, *Advances in Public Health*, 2026, 5959054, 8 pages, 2026. <https://doi.org/10.1155/adph/5959054>
- S. R. Pothireddy, "AI-Driven Cognitive Search over Large-Scale Heterogeneous," in *Proc. 2026 Int. Conf. Smart Futuristic Technology (ICSFT)*, 2026, pp. 1–8, doi: 10.1109/ICSFT66733.2026.11507846.
- R. Patel, S. R. Pothireddy, and N. Sharma, "Scalable and secure cloud architectures for IoT-enabled healthcare systems," in *Proc. 2nd Int. Conf. Big Data and Machine Learning (ICBDML)*, 2026, doi: 10.1109/ICBDML68582.2026.11544363
- P. Sundaramoorthy, S. Remella, K. Konakalla, M. Dhakan, S. R. Pothireddy, and Q. T. Sadat, "Data-Driven Vendor Performance Analytics in Cloud SCM," in *Proc. 2026 Int. Conf. Smart Futuristic Technology (ICSFT)*, 2026, pp. 1–8, doi: 10.1109/ICSFT66733.2026.11506903
- S. R. Pothireddy, "Secure AI Adoption: Governance Models for Copilot in Healthcare and Non-Profit Enterprises," *International Journal of Computer Technology and Electronics Communication*, vol. 7, no. 4, 2024, doi: 10.15680/IJCTECE.2024.0704015
- M. Mavuri, S. Chakrabarty, U. Rathod, and D. Sarda, "Geospatial Analysis Using Transformer on TOAR and Meteorological Data for Early Warning of Particulate Matter Exceedance," in *Proc. 2025 IEEE Int. Conf. Bioinformatics and Biomedicine (BIBM)*, 2025, pp. 7036–7043, doi: 10.1109/BIBM66473.2025.11357016.

- Y. Manchikatla, N. Sharma, C. Dudde, and S. R. Pothireddy, "Causality-aware cloud AI for early detection of systemic failures in digital healthcare," in Proc. 2026 Int. Conf. Intelligent Systems and Digital Applications (ISDA), 2026, pp. 1–5, doi: 10.1109/ISDA70544.2026.11606128
- M. Mavuri and S. Chakrabarty, "Geospatial Analysis of Socioeconomic Equity and Environmental Factors Influencing Lung Cancer Prevalence in US," in Proc. 2024 IEEE Int. Conf. Bioinformatics and Biomedicine (BIBM), 2024, pp. 6597–6604, doi: 10.1109/BIBM62325.2024.10822373.
- S. Shaik, "CLEVER: Enhancing cybersecurity through just-in-time fault prevention and resolution in large industrial software systems," in 2025 International Conference on Computational Innovations and Engineering Sustainability (ICCIES), IEEE, 2025, doi: 10.1109/ICCIES63851.2025.11033146.
- S. Shaik, "Strengthening insider threat monitoring post Covid-19: Strategies and tools," ESP International Journal of Advancements in Computational Technology, vol. 1, no. 2, pp. 149–152, 2023, doi: 10.56472/25838628/IJACT-V1I2P116.
- S. Shaik, "Data encryption paradigms in cloud security: Balancing performance and security," Journal of Artificial Intelligence & Cloud Computing, vol. 3, no. 3, pp. 1–3, 2024, doi: 10.47363/JAICC/2024(3)E251.
- S. Shaik, "Cyber security risk assessments under NIST CSF: A practical approach," Journal of Artificial Intelligence & Cloud Computing, vol. 3, no. 4, pp. 1–4, 2024, doi: 10.47363/JAICC/2024(3)E256.
- S. Shaik, "Identity and access management (IAM): Strengthening security in hybrid work environments," Journal of Artificial Intelligence & Cloud Computing, vol. 3, no. 5, pp. 1–3, 2024, doi: 10.47363/JAICC/2024(3)E248.
- S. Shaik, "Proactive incident response measures—From threat hunting to mitigation," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 3, no. 1, pp. 2077–2080, 2025, doi: 10.51219/JAIMLD/sabeeruddin-shaik/456.
- Divya Bharathi P; Rajesh Kumar K; Ardly Melba Reena B; G. Shailaja; Divyashree N; W. Mesiya Stalin (2025), "Crime Scene Object Detection for Forensic Investigations Using Faster R-CNN and YOLOv5 Models", 2025 International Conference on Networks and Cryptology (NETCRYPT) New Delhi, India, 2025, pp. 71-81, DOI: 10.1109/NETCRYPT65877.2025.11102700
- D. Suganthi, A. Aeron, A. Naresh, G. Shailja, H. Q. Owaied and A. Al-Hilali, "A Way to Enhance the Energy Efficient Level in the Field of WN using APSORM," 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2024, pp. 71-81, 10.1109/ICACITE60783.2024.10616791
- T. B. Sivakumar, A. Malakar, L. S, G. Shailaja, E. Kalaivani and D. Babu K, "Enhanced Diabetes Prediction Using Deep Autoencoder Framework and Electronic Health Records," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 71-81,, DOI: 10.1109/ICAIT61638.2024.10690358
- P Velmurugan., Moorthy M., K. Sivasubramanian., R. Karthik Raja., F. O. Al-Otibi., M. M. Khan., Nagaraj B. (2026). Aqueous Punica granatum peel extract derived spray-dried silver nanoparticles with multifaceted bioactivity and its dental applications. doi: 10.1007/s171-81-071-81
- James O. E. S., Nithya R., Ananthi V., Boobalan T., Raja K. R., Yuvakkumar R., Arun A. (2024). New insight on the influence of surface-modified clay cup with stirring effect for bioelectricity production by utilizing septic tank wastewater. Process Safety & Environmental Protection. DOI: 10.1016/j.psep.2024.03.110
- V.Ananthi, Abhispa Bora, U.Ramesh, R.Yuvakkumar, R.Karthikraja, Kumar Ponnuchamy, Govarthanan Muthusamy, A.Arun. (2024). A review on the technologies for sustainable biohydrogen production, Process Safety & Environmental Protection. (June 2024) <https://doi.org/10.1016/j.psep.2024.04.034>
- Simultaneous biodiesel and bioelectricity generation utilizing dairy and rice mill wastewater by freshwater microalgal isolate: An integrated energy-efficient approach. Process Safety & Environmental Protection. <https://doi.org/10.1016/j.psep.2024.07.020>
- Nithya Rathinavel, James Obeth Ebenezer Samuel, Ananthi Veleeswaran, Sengottuvelan Nallathambi, Kumar Ponnuchamy, Govarthanan Muthusamy, Rathinam Raja, Karthik Raja Ramalingam, Arun Alagarsamy,. (2024). Exploring the Key factors enhancing the Microbial Fuel Cell performance, Process Safety and Environmental Protection, <https://doi.org/10.1016/j.psep.2024.10.090>.
- M. Muruganandham, F. O. Al-Otibi, R. I. Alharbi, K. Sivasubramanian, R. Karthik Raja, P. Velmurugan, and N. Basavegowda (2023). Antibacterial, antifungal, antioxidant, and cytotoxicity activities of the aqueous extract of Syzygium aromaticum-mediated synthesized novel silver nanoparticles. Green Processing and Synthesis, 12: 20230188

<https://doi.org/10.1515/gps-71-81>

Vijayan, R., Sivakumar, P.M., Hazir, S. et al. Phytochemical and Antioxidant Analysis of Bioactive Compound Extract from *Nelumbo nucifera* against Cancer Proteins: In Silico Spectroscopic Approach. *Appl Biochem Biotechnol* (2025). <https://doi.org/10.1007/s171-81-05167-z>