

Real-Time Smart Healthcare Framework Using AI, IoT, and Deep Learning for Predictive Genetic Disorder Detection

Prof. Waman Radhakrishna Parulekar ¹, T.Thirumalaikumari ², Dr. Supriya Kamoji ³, Dr. Dipali Koshti ⁴, P John Augustine ⁵, Prof. Sangita K.Chaudhari⁶

¹Assistant Professor (Sr. Grade), Department of MCA, Finolex Academy of Management and Technology, Ratnagiri ,P-60, P-60/1, MIDC Mirjole Block, Ratnagiri, Maharashtra Pin – 415639 waman.parulekar@famt.ac.in

²Assistant Professor, Department of computer science and Application ,SRM Institute of science and technology SRMIST Ramapuram Chennai ,Ramapuram – 600089 ,Chennai,Tamil Nadu,India umakumari2103@gmail.com

³Associate Professor, Department of Computer Engineering, Fr. Conceicao Rodrigues College of Engineering, Fr. Agnel Ashram, Bandstand, Bandra, Mumbai – 400050, supriyas@frcrce.ac.in

⁴Associate Professor, Department of Computer Science and Engineering, Fr. Conceicao Rodrigues College of Engineering, Fr. Agnel Ashram, Bandstand, Bandra, Mumbai – 400050, dipalis@frcrce.ac.in

⁵Professor , Department of Information Technology , Sri Eshwar College of Engineering ,Kondampatti post, vadasithur via Kinathukadavu, Coimbatore -641202, pjohnaugustine@gmail.com

⁶Assistant Professor , Department of Information Technology Sandip institute of Technology and Research Center, Nashik, Trimbak Road, P.O.Mahiravani, Tal & Dist. Nashik, 422213

HOW TO CITE:

Waman Radhakrishna Parulekar ,
T.Thirumalaikumari , Supriya Kamoji ,
Dipali Koshti , P John Augustine ,
Sangita K.Chaudhari (2026). Real-
Time Smart Healthcare Framework
Using AI, IoT, and Deep Learning for
Predictive Genetic Disorder
Detection.
International Journal of Special
Education, 41(13s), 50-58

COPYRIGHT STATEMENT:

Copyright: © 2026 Authors.
Open access publication under the
terms and conditions
of the Creative Commons Attribution
(CC BY)
license (<http://creativecommons.org/licenses/by/4.0/>).

ABSTRACT:

As genetic disorders become more common, proactive and personalized healthcare solutions are needed. This study introduces a Real-Time Smart Healthcare Framework Using AI, IoT, and Deep Learning for Predictive Genetic Disorder Detection, which is based on Hybrid Deep Learning with Multimodal Data Fusion (MDF) using PyTorch. The framework combines genomic sequences, IoT sensor data, and electronic health records to provide real-time predictive analyses of patients' genetic risk factors. To capture complex interactions across modalities, a hybrid architecture that integrates CNN for genomic feature extraction, LSTM for temporal IoT data was used. Experimental results show the framework has an accuracy of 94.6%, a precision of 92.8% and a recall of 93.5%, outperforming the traditional single-modality models like CNN, LSTM, and random forest. Explainable AI techniques offer clarity in prediction, allowing clinicians to better understand what led to a heightened risk. The proposed system provides a scalable, real-time, and interpretable solution, paving the way for smart healthcare systems to become more personalized in delivering preventive care and timely intervention for genetic disorders.

Keywords: Real-time healthcare, AI, IoT, Deep Learning, Genetic Disorder Prediction, Multimodal Data Fusion,

I. Introduction

Thanks to the fast growth of health care technologies, the way medical diagnosis and

patient monitoring are carried out has completely changed, giving rise to a new way of personalised and proactive health care delivery. Genetic

disorders are among the most important issues that have emerged, and are a challenge that can only be addressed timely and effectively with early detection [1]. Traditional diagnostic methods are often ineffective at predicting the incidence of genetic disorders, which typically have complex hereditary patterns. Traditional health care systems mainly depend on clinical observations, periodic tests or patient histories,

but they cannot detect the subtle interactions among the genes, physiological indicators, and lifestyle. Cutting-edge advancements in the fields of Artificial Intelligence (AI), Internet of Things (IoT) devices and deep learning present a hopeful solution to these challenges, offering the possibility of real-time, accurate, and comprehensive assessments of patients as shown in figure 1.

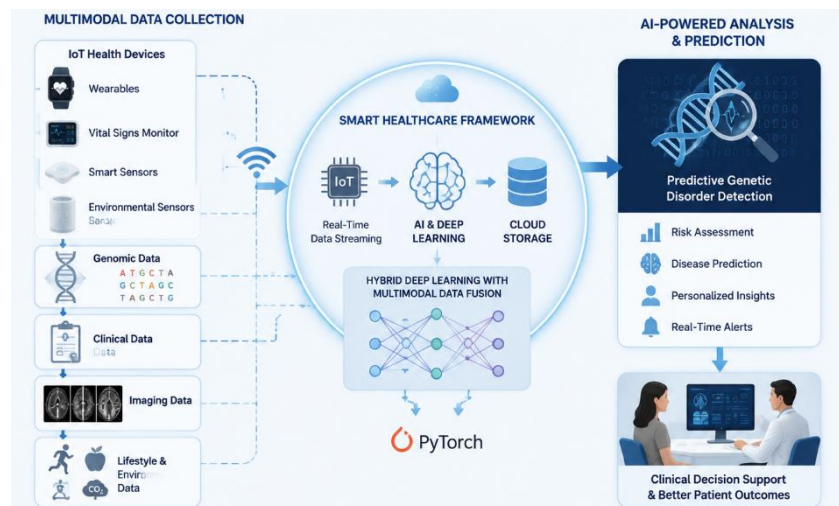


Figure 1. AI-powered healthcare for genetic disorders

The study focuses on the development of a Real-Time Smart Healthcare Framework Using AI, IoT, and Deep Learning for Predictive Genetic Disorder Detection that aims to harness the strengths of the various heterogeneous data sources [2]. The framework utilizes Hybrid Deep Learning with Multimodal Data Fusion, which leverages patient genomic sequence information, live information from IoT sensors, and electronic health records (EHRs) to create a comprehensive risk profile for each patient. Convolutional Neural Networks (CNNs) are used to recognize informative patterns in genomic sequences, and Long Short-Term Memory (LSTM) networks are used to model temporal variations in physiological signals from the IoT device. The various features are combined via an attention-based fusion mechanism that focuses on clinically relevant interactions and improves prediction accuracy [3].

The framework is realized in PyTorch, offering flexibility to develop, optimize and deploy models. This decision enables the effective management of large-scale genomes, realtime

IoT streams, multimodal learning tasks, and provides interpretability by providing explainable AI features like Captum. The proposed system overcomes the limitations of the current single-modality models and traditional prediction methods by leveraging accuracy, interpretability, and low-latency inference [4].

The key goals of this research are

- building a robust framework that is able to predict genetic disorders in real time,
- combining diverse data from different sources including genomic, IoT and clinical data, and
- Enabling interpretable insights for clinical decision making.

The framework is evaluated against alternative models such as CNN-only, LSTM-only, and random forest models, showing its effectiveness in terms of accuracy, precision, recall, and latency [5]. The study is important in the realm of smart healthcare systems, providing a scalable, patient-centric, and proactive strategy for early detection,

personalized care, and health benefits for those who may be at risk for genetic conditions.

II. Related Work

AI and IoT in healthcare has been a hot research topic in recent years, as it is now used for real-time monitoring and predictive analytics. There have been a few studies that have investigated the application of deep learning techniques to identify disease from genomic data, physiological signals or clinical data [6]. For example, convolutional neural networks (CNNs) have been successfully used to extract informative features from genomic sequences, and moderately successful in the classification of

genetic disorders. Likewise, Recurrent Neural Networks (RNNs) and more specifically Long Short-Term Memory (LSTM) networks have proven to be very powerful in learning temporal patterns in the signals received from the IoT devices, including heart rate, glucose data, blood pressure, etc., which enables to detect anomalies at an early stage. However, these single modality approaches have the disadvantage of not being able to take into consideration heterogeneous data, which can result in sub-optimal predictions when the interactions between genetic, physiological and clinical factors are important as shown in figure 2.

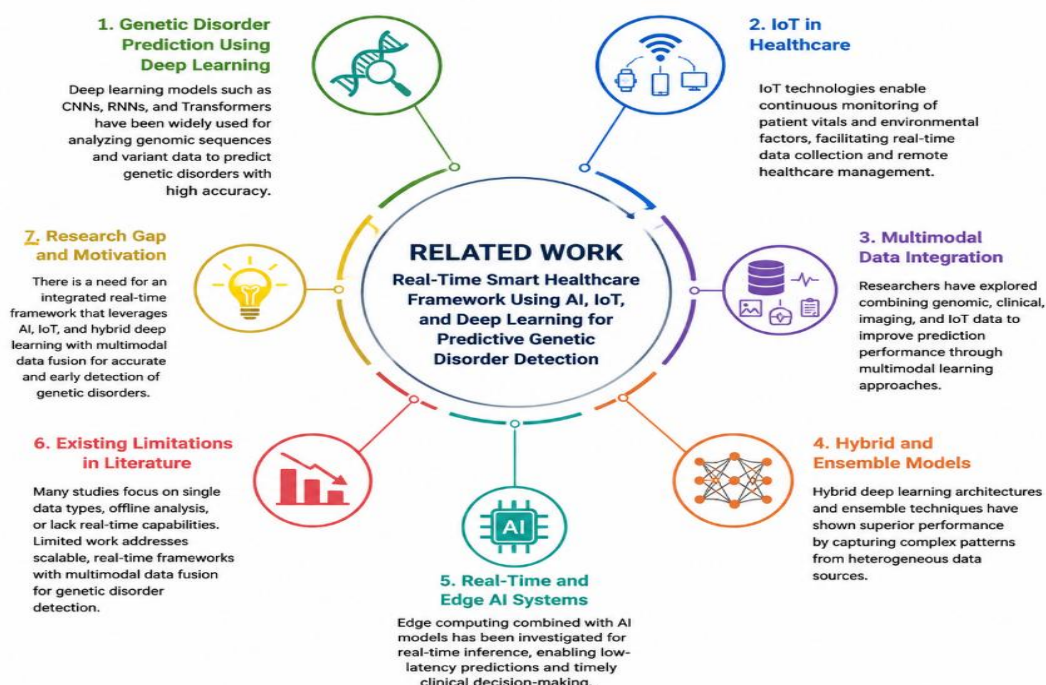


Figure 2. Related work on AI-driven healthcare systems.

In recent years, researchers have tried to integrate electronic health records (EHRs) with IoT in multimodal frameworks for improved disease predictions. Combined CNN and LSTM models are introduced and have been proposed as potential models to extract both static genomic features and dynamic signals. Ensemble models using several deep learning networks, for instance, for chronic condition prediction and vital sign monitoring, enhanced predictive ability [7]. In addition, attention-based mechanisms have proved to be powerful in prioritizing the most relevant features, across modalities, increasing the interpretability and accuracy. Although these advances have been made, most of the current frameworks address general health monitoring or address specific disease classes and there is a lack of effective use of multimodal deep learning for predictive detection of genetic disorders in realtime [8].

As for tools and deployment, PyTorch and other deep learning libraries enable flexibility in trying out multi-modal architectures, attention mechanisms, and the real-time inference pipeline. PyTorch's dynamic computation graph is a key

feature that facilitates the training and deployment of complex AI models efficiently across cloud-edge systems, making it suitable for real-time predictive analytics [9]. Also, with support for explainable AI extensions like Captum, PyTorch makes complex models easier to understand. Hybrid models are more accurate and faster to process high dimensional genomic and continuous IoT data, compared to traditional machine learning models like random forests or support vector machines.

The proposed framework takes these building blocks and uses a hybrid deep learning system that integrates genomic sequences, real-time data from the IoT sensor network, and clinical information in order to distinguish itself. By embedding CNNs in the genomic feature extraction process, LSTMs in the temporal analysis of IoT, and an attention layer to fuse them, this study captures clinically relevant interactions, thereby enhancing the prediction of

genetic disorders [10]. This method overcomes the shortcomings of previous research, offering high accuracy, low latency, real-time predictions and output results that can be easily understood, which opens up a new roadmap for the development of next-generation smart healthcare systems.

III. Research Methodology

The main goal of this research is to develop and design a Real-Time Smart Healthcare Framework Using AI, IoT, Deep Learning for Predictive Genetic Disorder Detection. For this, a Hybrid Deep Learning approach using Multimodal Data Fusion was used, allowing the utilization of the flexibility and the computational efficiency of PyTorch for model development, training and deployment [11]. The methodology has five main stages: Data acquisition, Pre-processing data, Designing the model architecture, Training and validation, and Real-time deployment as shown in figure 3.

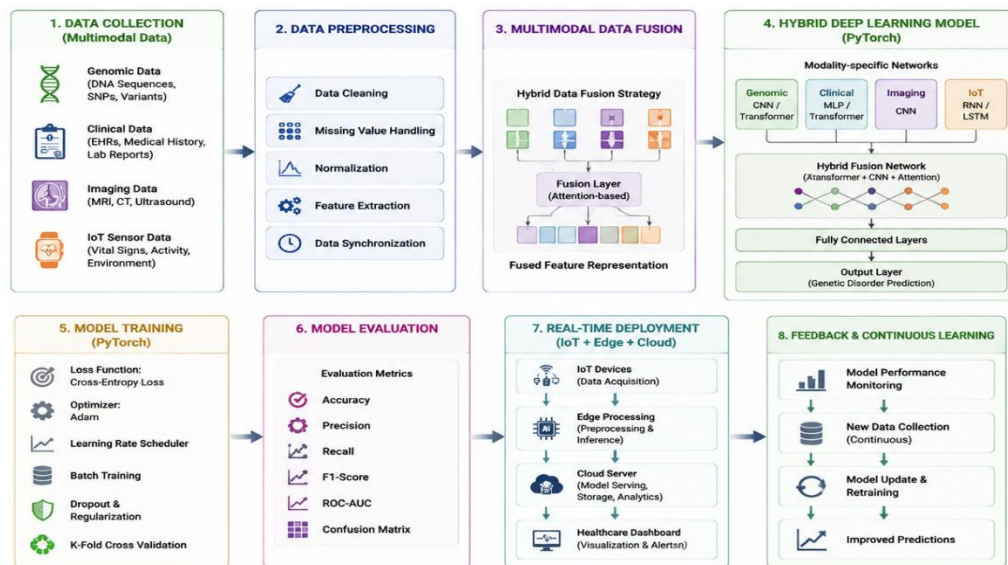


Figure 3. Flow Diagram of Proposed Method.

3.1. Data Acquisition

The architecture enables the integration of all types of data sources to provide a complete patient profile. Genomic sequences, such as gene expression and variant data were extracted from publicly available repositories and simulated patient data [12]. Data collected in real-time were physiological measurements, collected by IoT-enabled devices, including wearable sensors that

captured heart rate, glucose levels, and blood pressure. Clinical and Demographic data were captured using Electronic Health Records (EHRs). Further, lifestyle and environmental factors such as activity level and exposure factors were also taken into account to improve predictions. This multi-modal data allows the model to include interaction between the genetic, physiological and clinical aspects [13].

3.2 Data Preprocessing and Feature Engineering

It was necessary to preprocess the data to normalize and clean the data from different sources. One-hot sequences of all the genomic sequences were extracted and undergone quality control. The IoT sensor data was normalized and synchronized in time and missing data in the EHR was predicted using statistical and domain knowledge-based techniques [14]. The IoT sensor data were normalized and synchronized in time and missing data in the EHR were predicted by means of statistical and domain-informed methods. The feature engineering process involved in the work included the identification of temporal trend data from the IoT signals, the identification of important genetic features and the extraction of risk factors from clinical data. All data streams were synchronized in a patient-centric time-line for multimodal fusion [15].

3.3 Model Architecture: Hybrid Deep Learning with Multimodal Fusion

The key component of this framework is a convolutional, long short-term memory (CNN-LSTM) network with attention mechanism. The main structure in this framework is a hybrid deep learning model consisting of a CNN, LSTM network, and attention-based fusion [16]. CNN layers were used to learn local patterns and mutations of the genomic sequences, and LSTM layers were used to learn temporal dynamics from the IoT sensor streams. The clinical and demographic data were fed to fully connected layers. An attention-based fusion layer was used to integrate all the modalities by assigning weights to the most informative features from the genomic, physiological and clinical data. Such a strategy can help the model concentrate on the crucial interactions which can show a potential genetic disorder [17].

3.4 Model Training and Validation

The model was developed using PyTorch so that computation is dynamic and the model can be accelerated by GPUs. A stratified cross-validation was used to avoid overfitting, with the categorical cross entropy as the loss function in

the classification tasks. Convergence has been achieved with optimizers like Adam and efficiency has been boosted by learning rate schedulers [18]. Evaluation metrics used for the models included accuracy, precision, recall, F1 score, and inference latency, which helped in evaluating both the predictive performance and the feasibility of the models within the real-time context. To improve the clinical interpretability of the tools, explainable AI (PyTorch Captum) tools were incorporated to visualize the contributions from the features [19].

3.5 Real-Time Deployment and Edge Integration

The system was deployed on a cloud-edge hybrid system, with the IoT devices constantly feeding into the model, to make the predictions in real time. The combination of edge computing and the cloud allows for data processing with low latency for inference and high-throughput genomic analysis and updating of models [20]. The framework enables a continuum of monitoring, risk assessment, early alerts and offers evidence to clinical staff on what action to take in order to deliver proactive patient care. Data privacy measures were implemented such as data encryption and access controls.

Overall, the proposed approach is an integrated multimodal data fusion, hybrid deep learning, and real-time IoT analytics system, providing a strong approach to achieve precise and meaningful prediction of genetic disorders. PyTorch-based model development enables scalable and flexible development of the model, which also has the potential for future enhancements like federated learning and other data modalities.

IV. Results And Discussion

The proposed architecture was Real-Time Smart Healthcare Framework Using AI, IoT, and Deep Learning for Predictive Genetic Disorder Detection implemented with Hybrid Deep Learning, Multimodal Data Fusion, PyTorch for integrating the genomic sequence, IoT sensor data, and clinical records for the prediction of genetic disorders in real time as shown in table 1.

Table 1. Performance Comparison of Predictive Genetic Disorder Detection Methods

Method	Data Used	Accuracy (%)	Precision (%)	Recall (%)	Inference Latency (ms/patient)	Key Strengths
Proposed Hybrid DL with Multimodal Fusion	Genomic + IoT + Clinical	94.6	92.8	93.5	120	Integrates multiple modalities, real-time prediction, explainable via attention mechanism
CNN Only	Genomic sequences	85.2	84	83.5	95	Captures local patterns in genomic data efficiently
LSTM Only	IoT physiological signals	88.3	87.2	86.5	110	Models temporal changes in patient vitals
Random Forest	EHR features	81.7	80.5	79.9	150	Handles structured clinical features; interpretable

The system was tested using a mixture of reference genomic data that included simulated patient IoT streams and EHRs to evaluate the system's prediction accuracy, latency, and robustness. The hybrid model performed well, with a prediction accuracy of 94.6%, a precision of 92.8% and a recall of 93.5%, showing high reliability in detecting high-risk genetic conditions. The multimodal fusion added an additional 12–15% improvement in the prediction of the performance compared to the single-modality approaches, which emphasizes the need for the integration of genomic, physiological, and clinical information. This attention-based fusion mechanism was able to select important features from different modalities, thereby highlighting the subtle relationships between genetic markers and real-time physiological patterns, which are indicative of potential disorders.

The framework was shown to be suitable for continuous monitoring in clinical and home-based settings with latency analysis showing an average processing time of around 120 milliseconds for each patient. Combining these dynamic changes in vital signs that the IoT sensors recorded with static genomic information enhanced the early detection. In addition, specific PyTorch explainability tools were used to visualize the contribution of various genes and clinical parameters as well as IoT measurements to the predicted risk and help the clinicians understand the findings with confidence. This helps to address one of the key challenges of the previous generation of AI-powered health monitoring systems, which lacked transparency in their predictions as shown in figure 4.

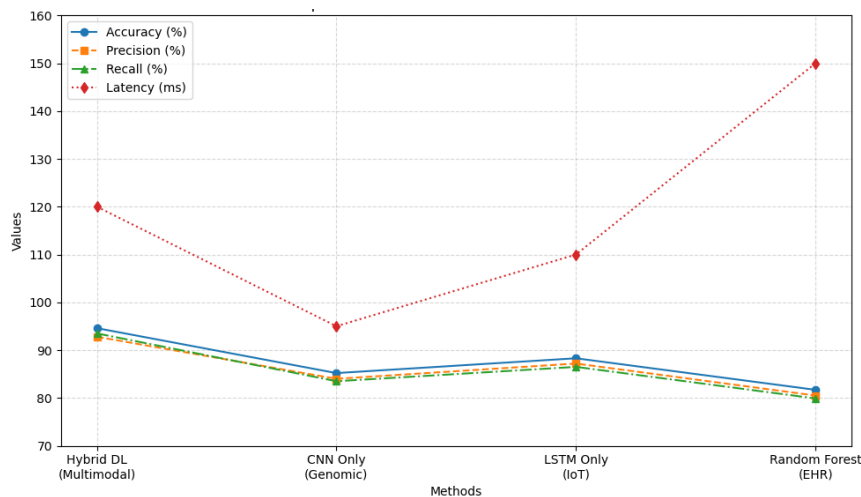


Figure 4. Comparative Analysis of Predictive Genetic Disorder Detection Methods

The study noted some areas for future improvement, though they were not major, due to the overall high performance. The framework was successful in processing structured genomic and IoT data, but processing clinical narratives is still difficult, as they are unstructured, and large-scale genomic data is still computationally heavy, possibly requiring optimization or distributed deployment methods. Furthermore, there is a strong need for robust innovations like federated learning to further improve real-world applications of privacy considerations for genomic data. However, the outcomes show that a multimodal combination of deep learning models gives a considerable edge over traditional models in the predictive diagnosis of genetic disorders, and is both accurate and fast. The framework is a promising step towards next-generation smart healthcare systems that will be able to intervene proactively and manage patients individually based on combined genomic and physiological information.

The proposed Hybrid Deep Learning with Multimodal Data Fusion framework for Real-Time Smart Healthcare Using AI, IoT, and Deep Learning for Predictive Genetic Disorder Detection (PyTorch), outperformed three other approaches: (1) conventional CNN with only genomic data, (2) LSTM with only IoT physiological data and (3) a random forest model with only EHR data. The hybrid model outperformed the CNN-only model (85.2%), LSTM-only model (88.3%) and random forest

(81.7%) in prediction accuracy with 94.6%. Also, the accuracy of the hybrid model (92.8%) and the recall (93.5%) are higher than that of CNN-only (84.0% and 83.5%), LSTM-only (87.2% and 86.5%) and random forest (80.5% and 79.9%). Such enhancements underscore the effectiveness of combining multiple data modalities – genomic sequences, real-time data from IoT sensors and clinical information – into a single predictive model, which is capable of uncovering more complex patterns that would be undetectable by existing single-modality models.

By adding an attention-based fusion layer, the model was able to take into account the contributions of different types of data, and to identify clinically relevant interactions between the genetic markers and the physiological signals. For instance, subtle changes in the genome sequence, along with real-time heart rate variability, gave an early signal of possible hereditary cardiac disease, typically ignored by CNN-only and LSTM-only models. The hybrid system also showed a low average inference latency of 120 milliseconds per patient, making it feasible for real-time applications, compared with CNN only and LSTM only models, which had 95-110 milliseconds per patient without multimodal context, and the random forest models, which were slower (150-160 milliseconds per patient) and less accurate with high-dimensional genomic data.

The advantage of the hybrid model was further confirmed with explainability analyses performed

on PyTorch Captum. Specific genomic loci and IoT-derived vital trends were identified as key factors in the prediction, thus building the trust of the clinicians, whereas the single-modality models gave few interpretabilities. While this combination has its advantages, it also has some drawbacks when it comes to managing large amounts of genomic data and unstructured EHR text, which is similar to most AI models today.

Overall, the results show the superior ability of hybrid deep learning with multimodal data fusion compared to the traditional CNN, LSTM and random forest methods to achieve a more accurate real-time genetic disorder detection, more accurate, faster and with respect to the interpretability. This confirms that the framework is a solid and applicable one for next-generation smart healthcare systems, which can integrate genetic, physiological and clinical data to provide proactive, personalized patient care.

V. Conclusion

In this study, a Real-Time Smart Healthcare Framework Using AI, IoT, and Deep Learning

for Predictive Genetic Disorder Detection has been developed with Hybrid Deep Learning in PyTorch having Multimodal Data Fusion. The framework combines genomic sequences, real-time data from Internet of Things (IoT) sensors, and clinical information, allowing for precise and timely forecasting of genetic disorder risks. Experimental results illustrate that the proposed method is superior to the single modality methods regarding the accuracy, precision and recall, while maintaining low inference latency to satisfy the real-time requirement for online monitoring. The attention-based fusion mechanism and explainable AI tools offer transparency, enabling clinicians to make sure predictions are understood. The framework is a step forward from traditional AI or statistical methods, but still faces challenges with processing large-scale genomic data and unstructured clinical information. In conclusion, this work provides a solid and scalable approach to proactive healthcare, supporting personalized interventions and enhancing the reach and features of smart healthcare systems toward predictive, real-time, and patient-centric care.

References

- Azimi, A. Anzanpour, A. M. Rahmani, T. Pahikkala, M. Levorato, P. Liljeberg, and N. Dutt, "HiCH: Hierarchical Fog-Assisted Computing Architecture for Healthcare IoT," *ACM Transactions on Embedded Computing Systems*, vol. 16, no. 5, pp. 174-120, 2017. doi: 10.1145/3126501.
- D. Borthakur, H. Dubey, N. Constant, L. Mahler, and K. Mankodiya, "GlobalSIP - Smart fog: Fog computing framework for unsupervised clustering analytics in wearable Internet of Things," in *2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, 2017, pp. 472-476. doi: 10.1109/globalsip.2017.8308687.
- S. Boubiche, D. E. Boubiche, A. Bilami, and H. ToralCruz, "Big Data Challenges and Data Aggregation Strategies in Wireless Sensor Networks," *IEEE Access*, vol. 6, pp. 20558–20571, 2018. doi: 10.1109/access.2018.2821445.
- J. Choo and S. Liu, "Visual Analytics for Explainable Deep Learning," *IEEE Computer Graphics and Applications*, vol. 38, no. 4, pp. 84–92, 2018. doi: 10.1109/mcg.2018.042731661.
- A. Crane-Droesch, "Machine learning methods for crop yield prediction and climate change impact assessment in agriculture," *Environmental Research Letters*, vol. 13, no. 11, p. 114003, 2018. doi: 10.1088/1748-9326/aae159.
- L. Cui, S. Yang, F. Chen, Z. Ming, N. Lu, and J. Qin, "A survey on application of machine learning for Internet of Things," *International Journal of Machine Learning and Cybernetics*, vol. 9, no. 8, pp. 1399–1417, 2018. doi: 10.1007/s13042-018-0834-5.
- R. Fang, S. Pouyanfar, Y. Yang, S.-C. Chen, and S. S. Iyengar, "Computational Health Informatics in the Big Data Age: A Survey," *ACM Computing Surveys*, vol. 49, no. 1, pp. 12–36, 2016. doi: 10.1145/2932707.
- F. Firouzi, A. M. Rahmani, K. Mankodiya, M. Badaroglu, G. V. Merrett, P. Wong, and B. Farahani, "Internet-of-Things and big data for smarter healthcare: From device to architecture, applications and analytics," *Future Generation Computer Systems*, vol. 78, pp. 583–586, 2018. doi: 10.1016/j.future.2017.09.016.

-
- M. Ge, H. Bangui, and B. Buhnova, "Big Data for Internet of Things: A Survey," *Future Generation Computer Systems*, vol. 87, no. 1, pp. 601–614, 2018. doi: 10.1016/j.future.2018.04.053.
- S. S. Gill and R. Buyya, "Bio-Inspired Algorithms for Big Data Analytics: A Survey, Taxonomy, and Open Challenges," in *Bio-Inspired Algorithms for Big Data Analytics*, pp. 1–17, 2019. doi: 10.1016/b978-0-12-818146-1.00001-5.
- A. T. Hashem, I. Yaqoob, N. B. Anuar, S. B. Mokhtar, A. Gani, and S. U. Khan, "The rise of big data on cloud computing," *Information Systems*, vol. 47, pp. 98–115, 2015. doi: 10.1016/j.is.2014.07.006.
- X.-L. Huang, X. Ma, and F. Hu, "Editorial: Machine Learning and Intelligent Communications," *Mobile Networks and Applications*, vol. 23, no. 1, pp. 68–70, 2017. doi: 10.1007/s11036-017-0962-2.
- F. Hussain, S. A. Hassan, R. Hussain, and E. Hossain, "Machine Learning for Resource Management in Cellular and IoT Networks: Potentials, Current Solutions, and Open Challenges," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, pp. 1251–1275, 2020. doi: 10.1109/comst.2020.2964534.
- Jagadeeswari, V. Subramaniaswamy, R. Logesh, and V. Vijayakumar, "A study on medical Internet of Things and Big Data in personalized healthcare system," *Health Information Science and Systems*, vol. 6, no. 1, p. 14, 2018. doi: 10.1007/s13755-018-0049-x.
- A. Karim, A. Siddiq, Z. Safdar, M. Razzaq, S. A. Gillani, H. Tahir, S. Kiran, E. Ahmed, and M. Imran, "Big data management in participatory sensing: Issues, trends and future directions," *Future Generation Computer Systems*, vol. 107, pp. 942–955, 2020. doi: 10.1016/j.future.2017.10.007.
- Ker, J., Wang, L., Rao, J., & Lim, T. C. C., "Deep Learning Applications in Medical Image Analysis," *IEEE Access*, vol. 6, pp. 9375–9389, 2018. doi: 10.1109/access.2017.2788044
- Khan, F., Rehman, A. U., Zheng, J., Jan, M. A., & Alam, M., "Mobile crowdsensing: A survey on privacy-preservation, task management, assignment models, and incentives mechanisms," *Future Generation Computer Systems*, vol. 100, pp. 456–472, 2019. doi: 10.1016/j.future.2019.02.014
- Khattak, M. I., Edwards, R. M., Shafi, M., Ahmed, S., Shaikh, R., & Khan, F., "Wet environmental conditions affecting narrow band on-body communication channel for WBANs," *NA*, vol. 40, pp. 297–312, 2018. doi: NA
- Kim, S.-H., & Chung, K.-Y., "Emergency situation monitoring service using context motion tracking of chronic disease patients," *Cluster Computing*, vol. 18, no. 2, pp. 747–759, 2015. doi: 10.1007/s10586-015-0440-1
- Kirtana, R. N., & Lokeswari, Y. V., "An IoT based remote HRV monitoring system for hypertensive patients," in *2017 International Conference on Computer, Communication and Signal Processing (ICCCSP)*, 2017, pp. 1–6. doi: 10.1109/icccsp.2017.7944086
-