International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 1, Jan-Feb 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Interpretable Multimodal AI Framework for Predicting Chronic Disease Progression

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Abstract:

Chronic disease prediction has gained significant momentum with the rapid advancement of Internet of Medical Things (IoMT) and Healthcare 5.0, enabling continuous patient monitoring and large-scale health data acquisition. The integration of deep learning and machine learning models has shown strong potential in early disease diagnosis, progression analysis, and personalized treatment planning. While these intelligent systems improve predictive accuracy and clinical efficiency, their increasing complexity introduces challenges related to model interpretability, data heterogeneity, scalability, and clinical trust. This survey presents a structured and analytical review of chronic disease prediction methodologies in IoMT-enabled healthcare systems, with primary emphasis on multimodal data fusion, deep neural architectures, temporal health data modeling, and explainable AI frameworks. Mathematical formulations are discussed to provide theoretical grounding for feature extraction, temporal dependency learning, and disease risk estimation models. Furthermore, commonly used healthcare datasets, evaluation metrics, system architectures, open challenges, and emerging research directions are critically examined from a Healthcare 5.0 and clinical decision-support perspective. This study aims to serve as a comprehensive reference for researchers and practitioners working on trustworthy, interpretable, and scalable AI-driven healthcare systems, with Alzheimer's disease considered as a representative chronic disease case study.

Keywords — **D IoMT, Chronic Disease Prediction, Healthcare 5.0, Deep Learning, Multimodal Learning, Explainable AI, Alzheimer's Disease**

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I. INTRODUCTION

The way healthcare systems understand and manage long-term illnesses has undergone a steady but profound transformation. Chronic diseases do not arrive suddenly or fade quickly; instead, they unfold over years, quietly reshaping a person's daily life. Conditions such as diabetes, heart disease, kidney disorders, and neurodegenerative illnesses demand constant attention rather than occasional care. Each day produces new physiological signals—changes in glucose levels, heart rhythms, sleep cycles, or cognitive patterns—that often go unnoticed until damage accumulates. Though symptoms may seem manageable at first, their long-term impact carries heavy personal, social, and economic costs.

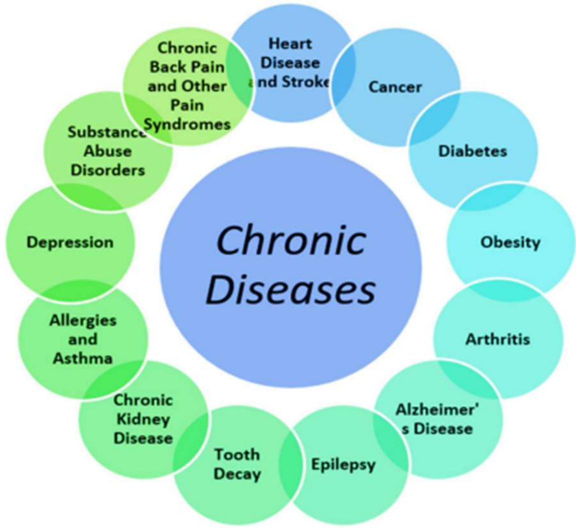
For decades, healthcare relied on scheduled hospital visits, clinician judgment, and retrospective analysis of patient records. While effective to an extent, this approach struggles to keep pace with diseases that evolve continuously.

Delays between appointments can allow subtle warning signs to pass undetected, and reliance on manual assessment places a heavy burden on already strained healthcare systems. As populations age and chronic conditions rise globally, these traditional models reveal clear limitations in scalability, timeliness, and personalization.

The rise of the Internet of Medical Things (IoMT) marks a critical shift in how health data is gathered and interpreted. Wearable devices, implantable sensors, smart diagnostic tools, and connected imaging systems now stream data in real time, capturing the body's behavior beyond the clinic walls. This constant flow of heterogeneous data—ranging from numerical sensor readings to medical images and clinical notes—creates both opportunity and challenge. While rich in insight, such data is too vast and complex for human analysis alone.

This is where machine learning and deep learning step in, offering tools capable of uncovering hidden patterns, predicting disease progression, and supporting early intervention. Modern AI models can learn from multimodal inputs, track subtle trends over time, and adapt as patient conditions change. Yet despite their promise, many existing solutions operate as opaque black boxes, making it difficult for clinicians to understand or trust their decisions. In high-stakes medical settings, lack of interpretability can be just as limiting as lack of accuracy.

Against this backdrop, the need for intelligent, transparent, and adaptive predictive systems becomes clear. This survey explores how AI-driven approaches are being applied to chronic disease prediction within IoMT-enabled healthcare environments. By examining evolving methodologies, real-world constraints, and open research gaps, it highlights how future systems can move beyond static predictions toward continuous, explainable, and clinically meaningful decision support.



II. REVIEW OF EXISTING RESEARCH PAPERS

Chronic disease prediction has attracted increasing attention from researchers due to the growing availability of continuous health data generated by IoMT-enabled devices. Early studies in this domain focused on traditional machine learning techniques that relied on manually engineered clinical features derived from electronic health records, laboratory results, and basic sensor readings. Common representations included statistical summaries, threshold-based indicators, and handcrafted health indices. These features were typically fed into classical classifiers such as Logistic Regression, Naive Bayes, Support Vector Machines (SVM), and Random Forest models. While these approaches demonstrated reasonable performance for structured datasets, they struggled to generalize across diverse patient populations and often failed to capture subtle disease progression patterns present in longitudinal health data.

As IoMT systems began producing large-scale, continuous, and heterogeneous data streams, researchers moved toward deep learning techniques to overcome the limitations of manual feature design. Neural network-based models such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks became popular due to their ability to learn temporal dependencies in physiological signals. LSTM-based architectures proved particularly effective for modeling time-series health data such as heart rate variability, glucose levels, EEG signals, and activity patterns. Studies reported improved prediction accuracy for chronic conditions including diabetes, cardiovascular disease, and neurodegenerative disorders, as these models could capture long-term trends that traditional methods overlooked.

Convolutional Neural Networks (CNNs) were also adopted in chronic disease research, especially for medical imaging and sensor signal transformation tasks. CNNs demonstrated strong performance in extracting local spatial features from medical images such as MRI scans, CT images, and retinal photographs. In IoMT environments, CNNs were applied to transformed physiological signals, enabling effective detection of disease-specific patterns. However, CNN-only approaches often lacked the ability to model temporal evolution, making them less suitable for diseases characterized by gradual progression over time.

Recent advancements have introduced hybrid deep learning architectures that combine CNNs with LSTM or GRU models, aiming to capture both spatial and temporal characteristics of IoMT data. These hybrid models showed notable improvements in predicting disease onset and progression, particularly in complex conditions such as Alzheimer's disease. By integrating CNN-based feature extraction with LSTM-based temporal modeling, researchers achieved better robustness and adaptability across different patient profiles. Nevertheless, many of these systems still function as black-box models, limiting their interpretability and clinical acceptance.

More recently, attention has shifted toward explainable and transformer-based models to improve trust and performance in healthcare applications. Transformer architectures and attention mechanisms have been explored to focus on critical time intervals and dominant physiological indicators influencing disease outcomes. Although these models demonstrate strong representational power, they are computationally intensive and often difficult to deploy in real-time IoMT settings. Furthermore, most existing studies focus primarily on binary disease classification, neglecting severity grading, progression stages, and early warning alerts that are crucial for proactive healthcare management.

A careful review of the literature reveals several gaps in current research. Many models lack scalability across multimodal IoMT data sources, while others fail to provide real-time prediction and alerting capabilities. Interpretability remains a significant challenge, and few systems support multi-stage disease severity assessment. These limitations highlight the need for adaptive, hybrid, and explainable deep learning frameworks that can operate efficiently in real-world IoMT-enabled healthcare environments.

A. A Retrospective View of Existing Approaches

When examining prior research on chronic disease prediction, existing methodologies can broadly be categorized into three groups: traditional machine learning approaches, deep learning-based models, and advanced hybrid or attention-driven architectures. Each category exhibits distinct strengths and limitations depending on data complexity and clinical requirements.

Traditional machine learning models primarily rely on structured clinical features such as laboratory measurements, demographic attributes, and basic statistical summaries. These features are commonly processed using algorithms like SVM, Decision Trees, and Random Forests. While computationally efficient and easy to interpret, these methods often fail to capture non-linear relationships and long-term disease progression trends inherent in chronic conditions.

Deep learning approaches introduced architectures such as CNNs, RNNs, and LSTMs that automatically learn hierarchical features from raw IoMT data. CNNs excel at spatial feature extraction from medical images and transformed sensor data, whereas LSTMs effectively model temporal dependencies in longitudinal health records. These models generally outperform traditional approaches in terms of prediction accuracy; however, they require large labeled datasets and are sensitive to noise and data imbalance.

Hybrid deep learning models and attention-based mechanisms represent the current state of the art.

By combining CNNs for feature extraction with LSTMs or attention layers for temporal modeling, these systems provide improved performance and adaptability. Despite their effectiveness, most existing implementations focus on prediction accuracy alone, with limited emphasis on explainability, severity estimation, or real-time alert generation.

Overall, the literature suggests that integrated hybrid architectures tailored for IoMT environments offer the most promising direction for chronic disease prediction. Future systems must balance accuracy, interpretability, scalability, and real-time responsiveness to support effective clinical decision-making and early intervention.

III. STRENGTHS AND WEAKNESSES OF EXISTING APPROACHES

A. Strengths

The existing approaches for chronic disease prediction in IoMT-enabled healthcare systems exhibit several notable strengths. Traditional machine learning techniques such as Logistic Regression, Naive Bayes, Support Vector Machines (SVM), and Random Forests are computationally efficient and relatively easy to implement. These models perform well on structured clinical datasets containing demographic information, laboratory test results, and basic physiological measurements. Their fast training time and lower hardware requirements make them suitable for early-stage decision-support systems and resource-constrained healthcare environments.

Deep learning-based approaches have significantly improved predictive performance by eliminating the need for manual feature engineering. Convolutional Neural Networks (CNNs) are particularly effective in extracting spatial features from medical imaging data such as MRI and CT scans, enabling accurate detection of disease-specific patterns. Recurrent models such as Long Short-Term Memory (LSTM) networks are capable of modeling temporal dependencies in longitudinal IoMT data, including continuous vital signs, activity logs, and historical health records. This ability to learn disease progression trends over time enhances early diagnosis and prognosis accuracy.

Recent advancements using transfer learning and hybrid architectures further strengthen chronic disease prediction systems. Pre-trained deep learning models such as ResNet and U-Net significantly reduce training time and data requirements by leveraging prior knowledge from large-scale datasets. When integrated within IoMT frameworks, these models enable scalable and continuous health monitoring, supporting proactive and personalized healthcare. Such approaches have demonstrated high accuracy, robustness, and adaptability across diverse patient datasets.

B. Weaknesses

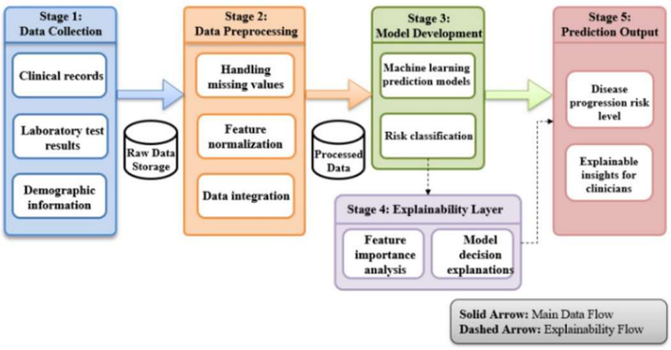
Despite their advantages, existing approaches also present several limitations. Traditional machine learning models depend heavily on handcrafted features, which may fail to capture complex non-linear relationships and subtle disease progression patterns. Their performance often degrades when applied to heterogeneous, high-dimensional, or noisy IoMT data, limiting their generalizability across different populations and healthcare settings.

Deep learning models, while powerful, require large volumes of labeled data and substantial computational resources. CNN-based architectures alone struggle to capture long-term temporal dependencies, whereas LSTM-based models can be computationally expensive and slow during training and inference. Additionally, many datasets used in chronic disease research suffer from class imbalance, particularly when predicting early or rare disease stages, which can negatively affect model reliability.

Although transfer learning and advanced deep architectures have improved performance, they introduce new challenges related to interpretability and clinical trust. Many deep learning systems operate as black-box models, providing limited insight into how predictions are made. This lack of explainability restricts adoption in real-world clinical environments, where transparent decision-making is critical. Furthermore, most existing models focus on binary disease classification and do not adequately support multi-stage severity assessment, real-time alerts, or continuous monitoring within IoMT ecosystems.

These strengths and weaknesses collectively indicate the necessity for hybrid, explainable, and scalable prediction frameworks. An effective solution should combine spatial and temporal feature learning, leverage IoMT-generated multimodal data, support disease severity analysis, and enable timely clinical interventions to improve chronic disease management.

IV. PROPOSED SYSTEM ARCHITECTURE



V. DIFFERENCE BETWEEN ACUTE AND CHRONIC DISEASEE

VI. CONCLUSION

Chronic diseases continue to pose a significant challenge to global healthcare systems due to their long-term nature, high treatment costs, and increasing prevalence. Early detection and continuous monitoring are essential to reduce disease progression, improve patient outcomes, and optimize healthcare resources. This study reviewed and analyzed existing machine learning and deep learning approaches used for chronic disease prediction in IoMT-enabled healthcare environments.

Traditional machine learning techniques such as Naive Bayes, Support Vector Machines, and Random Forests have demonstrated effectiveness in structured clinical datasets and low-resource settings. However, their dependency on handcrafted features and inability to model complex temporal and multimodal relationships limit their applicability in modern IoMT systems. With the rapid growth of wearable sensors, medical imaging devices, and real-time monitoring tools, healthcare data has become increasingly heterogeneous, high-dimensional, and time-dependent.

Deep learning approaches, including CNNs and LSTM-based models, have shown improved predictive performance by automatically learning spatial and temporal patterns from medical data. CNNs excel in medical image analysis, while LSTMs effectively capture disease progression through sequential patient records. Transformer-based and attention-driven models further enhance contextual understanding, enabling more accurate disease risk assessment. Nevertheless, challenges such as high computational costs, lack of explainability, data imbalance, and limited real-time deployment remain prevalent.

This survey highlights the growing shift toward hybrid deep learning architectures that integrate semantic feature extraction, temporal modeling, and multimodal learning within IoMT frameworks. Such hybrid models demonstrate superior accuracy, robustness, and adaptability compared to standalone approaches. Moreover, incorporating explainable AI mechanisms and severity-level prediction enhances clinical trust and supports timely medical intervention.

In conclusion, IoMT-enabled healthcare combined with advanced deep learning techniques offers a promising pathway toward proactive and personalized chronic disease management. Future systems must emphasize scalability, real-time responsiveness, data privacy, and interpretability to ensure practical clinical adoption. The findings of this study serve as a foundation for developing intelligent, reliable, and patient-centric chronic disease prediction systems capable of transforming modern healthcare delivery.

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