Integrating Electronic Health Records and Real-Time IoT Data for Proactive Chronic Disease Prediction and Personalized Healthcare

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ABSTRACT
The rapid evolution of Electronic Health Records (EHRs), Internet of Things (IoT) technologies and artificial intelligence (AI) has driven modern healthcare systems to become predictive and personalized in the delivery of healthcare. Patients with chronic conditions like diabetes, cardiovascular disease, hypertension and respiratory diseases need ongoing monitoring and intervention to minimise health problems and enhance health outcomes. This research investigates how to incorporate EHR systems and real-time IoT information in healthcare into proactive chronic disease prediction and personalized healthcare management. History of clinical data is integrated with ongoing physiological data acquired from a variety of wearable healthcare devices and smart sensors. To gain predictive healthcare insights from health care datasets, machine learning and deep learning methods, such as Random Forest, XGBoost, Long Short-Term Memory (LSTM), and CNN-LSTM models, are applied. By combining the two data sources, the study shows that the predictive accuracy of the disease gets significantly better, the patients can be monitored in real time, and intelligent clinical decision making becomes possible. The results also suggest that AI technologies in healthcare improve individual treatment suggestions and preventative care plans.

Keywords: Electronic Health Records (EHR), Internet of Things (IoT), Chronic Disease Prediction, Personalized Healthcare, Machine Learning, Deep Learning, Predictive Healthcare.
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1. Introduction

Digital healthcare technologies are quickly taking the traditional healthcare system and making it intelligent and data driven. The integration of Electronic Health Records (EHRs) and Internet of Things (IoT) devices into healthcare has revolutionized the way doctors manage patient care and improved healthcare efficiency.The use of Electronic Health Records (EHRs) and IoT devices in healthcare is transforming patient care and enhancing the efficiency of healthcare delivery. The prevalence of chronic diseases like diabetes, cardiovascular diseases, hypertension and respiratory diseases has a high need for proactive healthcare solutions, as they require long-term monitoring and timely medical treatment (World Health Organization, 2024).

Electronic Health Records allow for the easy storage of patient records, lab results, prescriptions, and clinical notes to help healthcare professionals make informed decisions quickly and efficiently. Meanwhile, wearable devices and smart sensors powered by IoT are gathering real-time physiological data like heart rate, blood pressure, glucose level and oxygen saturation (Liu et al., 2025). Combined with real-time IoT monitoring, historical EHR data makes for more accurate disease predictions and personalised healthcare management.

AI and machine learning algorithms are also helping to improve healthcare analytics, with their ability to detect healthcare patterns and forecast potential health risks. Recent studies have demonstrated the effectiveness of deep learning models, like Long Short-Term Memory (LSTM) networks and CNN-LSTM models, for healthcare data analysis on sequential information and predictive models for chronic diseases (Shickel et al., 2017). These smart healthcare systems play a part in early disease detection, preventive healthcare measures and enhanced patient outcomes.

The research is targeted toward the integration of EHR with real-time IoT data from the healthcare sector with a view to the proactive prediction of chronic diseases and the provision of personalized healthcare. The study covers aspects of healthcare system architecture, machine learning methodologies, predictive healthcare analytics and challenges of intelligent healthcare ecosystems. The proposed system aims to leverage AI technology for predictive analytics, to boost healthcare efficiency, to facilitate early disease detection and to provide patient-centered healthcare services.

2. Literature Review

2.1 Overview of Digital Healthcare Transformation

The industry of healthcare have seen significant technological shifts over the last decade, with the introduction of Electronic Health Records (EHRs), Internet of Things (IoT) gadgets, cloud computing, artificial intelligence (AI), and predictive analytics. Together, these technologies have paved the way for intelligent healthcare ecosystems that allow for real-time monitoring, evidence-based clinical decision making, and customized healthcare for patients. The rising rate of chronic diseases around the world has also made the demand for advanced healthcare systems with the ability to support early detection and ongoing patient care and monitoring even greater (World Health Organization, 2024).

Traditional healthcare systems were largely based on manual record-keeping and episodic interactions with patients, failing to provide the healthcare providers with a viable way to keep a continuous track of patient conditions. With the advent of digital healthcare technologies, however, new opportunities have emerged to combine prior patient data with live physiological data, to enhance the accessibility, efficiency, and predictive power of healthcare (Samal et al., 2021). Researchers have begun to pay attention towards the development of integrated healthcare platforms to facilitate the proactive management of chronic diseases by integrating EHR systems and IoT device-enabled monitoring.

2.2 Electronic Health Records in Predictive Healthcare

The use of Electronic Health Records (EHRs) has proven to be invaluable in today's health care systems, enabling secure storage, retrieval, and sharing of patient medical data. EHRs store all patient information, such as demographics, medical histories, clinical notes, lab results, medications, and diagnoses. Large scale longitudinal healthcare data are of great value for disease prediction and clinical analytics (Brisimi et al., 2018).

In recent years, machine learning approaches have been shown to be effective in deriving useful information from EHR information. Brisimi et al. (2018) suggested a classification method that interprets and predicts chronic disease hospitalization based on EHR data. Their research revealed that machine learning algorithms can effectively determine high-risk patients and assist in preventive healthcare interventions. In the same way, Shickel et al. (2017) surveyed the field of deep learning methods for EHR analysis, and found that deep neural networks have great potential to improve predictive healthcare performance by uncovering complex temporal relationships in clinical data.

In the field of healthcare predictions, deep learning methods like recurrent neural networks (RNNs), Long Short-Term Memory (LSTM) networks, and attention-based architectures have demonstrated success. Mallya et al. (2019) proposed the SAVEHR framework, which is based on self-attention vector representations for personalized chronic disease onset prediction. Their approach made modelling more interpretable and better understood by clinicians to give better prediction outcomes. This suggests that explainable AI is becoming increasingly crucial in healthcare analytics.

2.3 IoT-based Healthcare Monitoring Systems

The Internet of Things has revolutionized the delivery of healthcare by providing real-time patient monitoring via smart gadgets and sensors. Physiological data like heart rate, blood pressure, body temperature, respiratory rate, glucose, and oxygen saturation are captured in real-time by the IoT-enabled healthcare systems. These systems enable remote patient monitoring, decrease reliance on hospitals, and allow for prompt medical interventions (Liu et al., 2025).

Chronic diseases are also a big application area for wearable health care devices, where patients' health conditions can be monitored continuously outside of hospital settings. Zonayed et al. (2025) stated that IoT technologies and machine learning algorithms can accurately predict diseases and enhance patient engagement by tracking health in real-time. The authors also emphasized the importance of the IoT healthcare system in lowering healthcare expenses and increasing healthcare access in remote areas.

In the context of personalized medicine, the use of IoT in healthcare has also shown significant promise. Arefin (2024) created a personalized healthcare coaching application using AI for managing chronic diseases. The system used wearable sensors and AI-powered data analysis to provide personalised healthcare suggestions using real-time patient data.The system leveraged wearable sensors and AI-driven analytics to deliver personalised healthcare suggestions grounded in real-time patient data. These personalised health-care solutions enhance compliance with a treatment plan and facilitate preventive health-care measures.

Various studies have emerged that focus on connecting IoT devices to cloud computing infrastructures for supporting scalable healthcare data management. Taimoor and Rehman (2022) surveyed reliable and resilient AI-IoT healthcare systems and found cloud-based IoT architecture can facilitate the efficient processing, storage, and analytics of data in real time. The study also highlighted some issues with latency, data privacy, and the interoperability of cloud-based healthcare systems.

2.4 Integration of EHR and IoT Data

This has led to a promising strategy for creating smart healthcare ecosystems: the combination of EHR and data from IoT devices, which exist in the real-time digital environment.This is a new way to build smart healthcare ecosystems, by integrating EHR with real-time data from IoT devices. Use of history with continuously-collected physiological parameters increases the accuracy of disease prediction and allows proactive delivery of care. With integrated healthcare systems, patients can be comprehensively profiled, with long-term patient history and current health conditions being analyzed.

Studies have shown that EHR-IoT systems enhance early disease detection and clinical decision-making. Pai et al. (2025) suggest an AI-based health monitoring system that combines the healthcare data captured by sensors with patient medical records to predict the risk of chronic diseases. The study showed that it was possible to achieve much better predictive results when combining historical and real-time patient information to healthcare systems working in isolation.

Another emerging solution for secure healthcare data integration is federated learning. Birari et al. (2024) investigated how federated learning and IoT could be combined to improve personalized healthcare management. Their research "Decentralized AI: Facilitating Collaborative Healthcare Analytics without Sacrificing Patient Privacy" highlighted the advantages of decentralized AI systems in allowing for shared healthcare insights without compromising patient privacy. These methods can enhance data security and facilitate the development of massive-scale predictive healthcare systems.

Table 1. Comparison of Existing EHR-IoT Healthcare Systems

Author/Study	**Technology Used**	**Healthcare Focus**	**Key Contribution**	**Limitation**
Brisimi et al. (2018)	EHR + Machine Learning	Chronic disease hospitalization prediction	Improved prediction using interpretable classification models	Limited real-time monitoring
Shickel et al. (2017)	Deep Learning on EHR	Clinical data analytics	Demonstrated effectiveness of deep learning for EHR analysis	High computational complexity
Arefin (2024)	AI + IoT Wearables	Personalized chronic disease management	Provided customized healthcare recommendations	Limited large-scale validation
Taimoor and Rehman (2022)	AI-IoT Healthcare Framework	Remote patient monitoring	Discussed resilient and personalized healthcare services	Security and privacy concerns
Birari et al. (2024)	Federated Learning + IoT	Personalized healthcare	Enhanced privacy-preserving healthcare analytics	Complex implementation
Pai et al. (2025)	AI-Based Monitoring System	Chronic disease risk prediction	Integrated sensor data with predictive analytics	Scalability challenges
Liu et al. (2025)	IoT Sensors + ML	Real-time health monitoring	Improved continuous patient monitoring	Data interoperability issues

2.5 Machine Learning Techniques for Chronic Disease Prediction

Healthcare is one of the most critical applications of machine learning, which can analyze intricate healthcare data, uncover patterns related to disease, and make predictions about future health outcomes. Numerous algorithms have been used in the area of prediction of chronic diseases, including supervised learning algorithms like Logistic Regression, Decision Trees, Support Vector Machines (SVMs), Random Forests, and XGBoost.

Brisimi et al. (2018) showed that machine learning is a viable approach to predicting hospitalization risks from EHR data, but using models that are interpretable and explainable by humans. Similarly, Jbres Editorial Team (2024) have developed machine learning models to predict chronic diseases, with high classification accuracy, by employing ensemble learning techniques. Random Forest and Gradient Boosting proved to be good models for dealing with heterogeneous health datasets.

Additionally, deep learning techniques have been used to improve predictive healthcare analytics, as they can handle sequential and temporal healthcare data. Shickel et al. (2017) reported that LSTM networks are superior when compared to traditional machine learning techniques for temporal modeling of EHR data. CNN-LSTM hybrid models have also been proven to be effective in multimodal healthcare analytics that incorporate both clinical data and sensor data.

In health care prediction, there's a growing need for explainable AI due to the importance of transparency and interpretability in AI-driven recommendations for clinicians. Mallya et al. (2019) highlighted the need for models of healthcare that are interpretable and can enhance clinician trust and help to make informed decisions in real world health care settings. Recent healthcare research has thus been shifting more and more towards the desire to achieve a balance of predictive performance and model interpretability.

2.6 Security, Privacy, and Ethical Challenges

The adoption of healthcare systems that enable the interconnection of EHRs and IoT devices creates a massive amount of sensitive patient information, which is also a matter of data security and privacy. Patient data breaches, unauthorized access, and ransomware attacks are all potential threats to patient privacy and healthcare operations that arise from cybersecurity.Cybersecurity poses risks to patient privacy and healthcare operations, including patient data breaches, unauthorized access, and ransomware attacks. The healthcare IoT devices are mostly susceptible to attacks because of the restricted computational capability and safety measures, as described by Taimoor and Rehman (2022).

To safeguard healthcare data management and patient privacy, regulatory standards like HIPAA and GDPR have been set up. But it is difficult to achieve regulatory compliance at a large scale integrated healthcare system. Thus, researchers have looked at blockchain technologies, federated learning and encryption methods to enhance health data security.

The ethical concerns of AI for healthcare systems have also been a hot topic. If not well designed and validated, the impacts of algorithmic bias, lack of transparency and unequal access to healthcare can have negative consequences for healthcare outcomes. In the healthcare AI landscape, responsible AI governance and ethical healthcare AI frameworks are crucial for guaranteeing fairness, accountability, and reliability in intelligent healthcare systems, as argued by Akila (2025).

2.7 Research Gaps Identified

While there are existing studies that have illustrated the advantages of the combination of EHRs, IoT devices and AI-based analytics, there are still some research gaps not addressed. First, many health care prediction systems concentrate on utilizing either health care data from EHR or data from IoT sensors alone, not totally integrating both data sources. This makes it more difficult to accurately predict patient conditions and limits contextual understanding of patient conditions.

Second, the current situation of interoperability problems still does not provide effective communication and integration between heterogeneous platforms. Systems for standardized sharing of healthcare data are still evolving and there is limited interoperability between different healthcare providers (openEHR Foundation, 2025).

Third, real-time healthcare analytics is the need for efficient computational infrastructures that can process continuous high-volume streams of sensors. There are latency, bandwidth constraints, and cloud dependency challenges with existing systems. Edge computing and Federated learning are two promising approaches that have been proposed to address the issues in the healthcare context, yet further research is required to optimize their deployment in healthcare settings (Birari et al., 2024).

Lastly, most of the AI healthcare prediction tools are not interpretable and transparent, which restricts their implementation in the clinic. Therefore, future research needs to be directed towards the creation of explainable, secure, interoperable healthcare systems that incorporate the use of EHRs and IoT technologies to predict chronic diseases proactively and deliver personalized healthcare.

3. System Architecture and Proposed Framework

3.1 Overview of the Proposed Integrated Healthcare Framework

The proposed healthcare framework integrates Electronic Health Records (EHRs), IoT-enabled healthcare devices, cloud computing infrastructure, and artificial intelligence-driven predictive analytics to support proactive chronic disease prediction and personalized healthcare services. The primary objective of the framework is to continuously monitor patient health conditions, analyze both historical and real-time healthcare data, and generate early disease predictions for timely medical intervention. The architecture is designed to improve healthcare efficiency, reduce hospitalization risks, and support patient-centered healthcare delivery through intelligent decision-making systems.

The proposed system follows a multi-layered architecture consisting of the IoT sensing layer, communication layer, cloud and storage layer, data integration and preprocessing layer, AI-based prediction layer, and healthcare application layer. Each layer performs a specific function within the healthcare ecosystem while ensuring seamless communication among system components. The integration of these layers enables continuous health monitoring, secure data transmission, real-time analytics, and personalized healthcare recommendations.

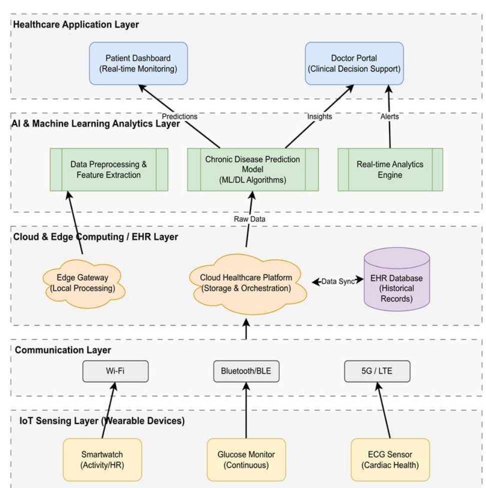


Figure 1. Integrated EHR-IoT Healthcare Architecture

3.2 IoT Sensing Layer

The proposed health care framework utilizes Electronic Health Records (EHRs), Internet of Things (IoT) connected health care gadgets, cloud computing foundation, and a man-made intelligence (AI) based predictive analytics to improve proactive chronic disease anticipation and personalized health care services. The ultimate goal of the framework is to constantly track patient health conditions, analyze past and live health care data, and make early predictions of the disease to subsequently take medical action. The architecture is designed to increase the efficiency of healthcare, minimize the risk of hospitalization and enable patient-centric healthcare delivery by making intelligent decisions.

The proposed system is a multi-layered architecture that includes: IoT sensing layer, communication layer, cloud and storage layer, data integration and preprocessing layer, AI-based prediction layer, and healthcare application layer. Every layer has a defined purpose in the healthcare system and facilitates the communication between system layers. These layers can be combined to provide a seamless and comprehensive health monitoring experience, with secure data transfer, real-time analytics, and tailored health recommendations.

The proposed healthcare architecture has the IoT sensing layer as its base. The layer is made up of wearable sensors, smart medical devices and remote monitoring—all of which gather real-time data about the patient's physiological and environmental conditions. Continuous monitoring of important health metrics like heart rate, blood pressure, blood glucose, body temperature, oxygen saturation, respiratory rate, and electrocardiogram signals is being done by IoT devices. These allow for continual healthcare monitoring in non-hospital settings and enable the remote care of chronic disease patients (Liu et al., 2025).

Wearable healthcare technologies like smartwatches, fitness trackers, glucose monitors, and ECG patches are playing a big part in allowing patient observation to be done continuously. The collected sensor data can give insight into patient health trends and behaviour. These types of real-time monitoring systems are especially useful for seniors and those with chronic health issues that require constant care. IoT can also be used for emergency detection, as it can detect abnormal physiological patterns and alert healthcare providers or caregivers.

Environmental sensors for air quality, humidity, temperature and physical activity can also be integrated to the sensing layer. These environmental factors tend to be linked to the development of chronic diseases, such as respiratory and cardiovascular diseases. Physiological and environmental data can thus be combined and lead to an improvement of the predictive power of healthcare analytics systems.

3.3 Communication and Network Layer

The communication layer will be responsible for sending healthcare data gathered from IoT devices to a central or distributed computing infrastructure. This layer relies on wireless communication technologies like WiFi, Bluetooth Low Energy (BLE), ZigBee, 5G, and cellular networks of reliable and low latency data transfers. To enable real-time healthcare analytics and timely medical interventions, there needs to be continuous connectivity between healthcare sensors and backend systems.

In many systems, the IoT gateways are used in the communication layer to combine the information that is obtained from the sensors and send it to the cloud servers or to an edge computing platform. These gateways also carry out some initial data filtering, compression and encryption to enhance the efficiency of the communication and secure the data transfer. To safeguard against potential cyber threats and unauthorized access to sensitive healthcare data, secure communication protocols like HTTPS, MQTT, and TLS are typically used (Taimoor and Rehman, 2022).

With the rise of 5G technology, healthcare communication systems are getting increasingly better in performance, with ultra-low latency, high bandwidth, and reliable connectivity. These advances are especially relevant to real-time health applications, like remote surgery, emergency response and critical patient monitoring systems.

3.4 Electronic Health Record Integration Layer

The EHR integration layer integrates patient medical records from the past with real-time healthcare data from sensors. It serves as a collection point for healthcare data, both structured and unstructured, from various sources like hospitals, clinics, laboratories, pharmacies, and IoT devices, and stores and organizes the data. The types of information that are normally found in EHRs range from patient demographics and diagnostic reports to medications, clinical observations, laboratory test results, radiology reports, and treatment histories.

By combining EHR data with data gathered from the Internet of Things, healthcare providers can gain a more comprehensive understanding of the health conditions of their patients, as they can now have access to a more holistic view of their patients' health conditions. This integration enhances the quality of predicting healthcare, allowing for personalized healthcare interventions. For instance, the ability to predict hyperglycemic events and offer preventive measures before developing complications can be achieved by combining historical diabetes data with real-time glucose monitoring data.

Some of the most frequently used standards for interoperability in healthcare data sharing are the HL7 FHIR and the openEHR. The openEHR architecture facilitates the representation of clinical information in a standardised way and facilitates efficient exchange of clinical information between healthcare institutions without loss of semantic consistency (openEHR Foundation, 2025). Therefore, interoperable EHR systems are crucial for achieving interoperability in health care systems, promoting continuity of care, and fostering collaboration.

3.5 Cloud Computing and Data Storage Layer

The cloud computing layer offers scalable computing power and centralized storage capabilities, enabling the management of extensive healthcare data. The data created by these Internet of Things (IoT) devices is enormous, and the infrastructure needed to efficiently store, process and analyze it is enormous. Cloud platforms offer the ability to manage complex healthcare data with high dimensions and facilitate access to information remotely, as well as real-time analytics.

The typical features of health care cloud infrastructures are distributed databases, big data processing frameworks, and virtualized computing environments to run health care workloads efficiently. In the healthcare industry, there's a growing adoption of technologies like Hadoop, Apache Spark, and NoSQL databases to power fast data processing and scalable data storage. Also, cloud computing allows healthcare providers to gain access to patient data remotely, which enhances the accessibility and coordination of healthcare services among providers.

While there are benefits to cloud-based healthcare systems, there are also challenges to consider, such as bandwidth usage, latency, and privacy issues. Edge computing is, therefore, becoming a helping technology to process healthcare data near IoT devices, which decreases latency and limits reliance on cloud-based systems. One such application is cardiac monitoring, where healthcare providers need real-time data for timely decision-making, and emergency detection systems, which demand immediate responses to critical situations.For example, in cardiac monitoring, where healthcare providers require real-time data for prompt decision-making, and emergency detection systems, where immediate response to critical situations is crucial, Edge computing proves to be especially beneficial (Birari et al., 2024).

3.6 Data Preprocessing and Integration Layer

Data obtained from EHRs and IoT devices can be challenging as they are often high-dimensional, noisy, incomplete, and heterogeneous. Therefore, the data needs to be preprocessed with an effective layer, which guarantees data quality and enhances the performance of the machine learning system. Before the healthcare analytics are carried out, this layer conducts certain activities like data cleaning, data normalization, feature extraction, handling missing values, and data transformation.

Data cleaning techniques remove duplicate records, filter out sensor readings containing errors, and remove data which is inconsistent. Common approaches to deal with missing values are statistical imputation methods or machine learning-based estimation methods. Normalization ensures that the range of the variables in healthcare data are represented in the same range, which helps in improving the convergence of the models and making the prediction more accurate.

The other important role of the preprocessing layer is feature engineering. Using raw physiological signals and clinical data, relevant features in health care are extracted and enhanced for better performance in predictive analytics. A typical temporal healthcare pattern, statistical features and frequency domain features of sensor data are used as inputs for predicting chronic diseases. A synergistic fusion of engineered features from both EHR and IoT datasets further increases the understanding of patient health conditions in context and the capability to assess disease risk.

3.7 AI-Based Prediction & Analytics Layer

The proposed healthcare architecture's intelligence backbone is the AI-based prediction layer. This layer works with machine learning and deep learning algorithms to process and analyze all healthcare data to obtain predictions on chronic disease risk, disease evolution, and patient deterioration. The models are trained on historical EHR data as well as on the real-time data from the IoT sensors.

In healthcare, common classification and prediction problems include using machine learning algorithms like Logistic Regression, Support Vector Machines, Decision Trees, Random Forests, and XGBoost. These algorithms can detect patterns between various health-related factors, and also categorize patients into various disease risk groups. The effectiveness of ensemble learning techniques is that they can utilize several decision models and yield a more accurate prediction model.

Sequential healthcare data, like information from IoT sensors and EHR timelines, can be effectively analyzed using deep learning technologies like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs). LSTM networks can be used to learn temporal relationships in physiological data streams, and provide accurate chronic disease forecasting (Shickel et al., 2017). Moreover, hybrid CNN-LSTM architectures, which enable the extraction of spatial and temporal features simultaneously, further improve the prediction in the healthcare domain.Furthermore, hybrid CNN-LSTM architectures, which enable the extraction of spatial and temporal features, simultaneously further enhance the prediction in the healthcare domain.

The prediction layer includes explainable AI mechanisms that further enhance the transparency and trust of the prediction models by clinicians. AI predictions can be understood by using attention mechanisms, feature importance analysis, and interpretable machine learning techniques, assisting healthcare professionals in grasping the rationale behind the AI predictions. The healthcare systems need to be explainable since the physicians need clear and trustworthy suggestions prior to making medical decisions.In healthcare systems, explainability is vital because physicians need clear and trustworthy advice before making critical medical decisions (Mallya et al., 2019).

3.8 Healthcare Application and Decision Support Layer

The healthcare application layer offers interfaces and services to healthcare providers, patients, caregivers, and hospital administrators. This layer provides dashboards, mobile apps and clinical decision support for predictive healthcare insights. Interactive visualization platforms can provide patient health trends, disease risk scores, medication adherence data, and emergency alerts to healthcare professionals.

Clinical decision support systems help doctors make diagnoses, treatment decisions, and recommendations for preventive measures by making predictions using AI. Mobile healthcare apps can also provide personalized health advice like diet plans, fitness routines, medication reminders and lifestyle changes that can be passed on to patients directly.

Another significant part of the application layer is the real time alerts. In case the abnormal physiological conditions are sensed, the system automatically alerts the healthcare provider or emergency contacts and provides for timely medical response. These features can greatly aid in the management of chronic diseases and prevent them from getting worse.

3.9 Security and Privacy Mechanisms

Given the sensitivity and confidentiality of healthcare data, security and privacy protection are crucial elements of the proposed healthcare architecture. To safeguard patient information against unauthorized access and cyber threats, the framework has been implemented with various security features such as encryption, authentication, access control, and secure communication channels.

Healthcare data is typically protected by data encryption methods like AES and RSA. Multi-factor authentication systems are used to access patient records, so only authorized individuals are able to access them. Role Based Access Control (RBAC) is another method of limiting access to the healthcare information based on the responsibilities of the individual user in the healthcare organization.

4. Methodology

4.1 Research Methodology Overview

This research takes a methodology that involves leveraging Electronic Health Records (EHRs) and real-time Internet of Things (IoT) healthcare data to create an intelligent system for proactive prediction of chronic diseases and personalized healthcare provision. The proposed methodology involves data acquisition, healthcare data preprocessing, feature engineering, healthcare data prediction using machine learning, and performance evaluation to build a predictive healthcare system.

The methodological framework is designed for processing heterogeneous data about healthcare, which is available from the clinical records and wearable healthcare devices. Historical data and real-time data can be integrated to make accurate predictions about diseases, continuously monitor patients, and provide timely medical interventions. There are also mechanisms for data security, interoperability and explainable AI that have been integrated into the methodology, enhancing the reliability and usability of the healthcare prediction system.

4.2 Data Collection Process

The plan is to use two main sources of health information in the healthcare system: Electronic Health Records (EHR) and data collected from IoT sensors. Structured and unstructured clinical data from hospitals, clinics, diagnostic laboratories and health care institutions are stored within EHRs. These records may contain patient information, medical history, lab test results, medication information, diagnostic information, physician notes and information regarding treatment.

These EHR datasets can be analyzed to reveal long-term patterns in patients' health and clinical history, and to identify patterns of diseases. Diabetes, hypertension, cardiovascular disease, asthma and chronic kidney disease are all the most relevant examples of chronic disease related records in predictive healthcare analytics. The historical healthcare records could be used to provide the background information which is essential for machine learning algorithms to learn the patterns of diseases development and foresee future medical risks (Brisimi et al., 2018).

The second category of health care data is the real time physiological information gathered by the use of health care gadgets and sensors with IoT technology. The devices record health data, including heart rate, temperature, BP, blood glucose, oxygen saturation, respiratory rate, sleep quality and physical activity. The data produced by IoT helps to ensure that patients are continually monitored and allows for remote healthcare monitoring beyond the usual clinical environment (Liu et al., 2025).

Incorporation of wearable devices like smartwatches, ECG sensors, glucose monitors, pulse oximeters and fitness trackers into health care infrastructure to collect continuous physiological data. Some environmental sensors could also be used to track air quality, humidity and ambient temperature that can affect the conditions of chronic diseases, especially respiratory diseases.

4.3 Data Integration Strategy

The proposed methodology is an essential part of the integration of EHR and IoT data since healthcare data are created from various sources with different formats and structures. A single approach to healthcare data integration is therefore adopted to integrate historical clinical data with real-time sensor data into a common framework for analysis.

Standards like the openEHR and HL7 FHIR are used in healthcare interoperability to enable healthcare information to be shared among different healthcare systems. An advantage of using standardized healthcare data representation is that it facilitates the interoperability of health data between hospitals, healthcare applications, cloud platforms and the IoT (openEHR Foundation, 2025).

Temporal healthcare data is synchronized using data synchronization techniques, and real-time physiological data is synchronized. It guarantees that data collected from healthcare events from EHRs and IoT devices are correctly synchronized for proper predictive analysis. The integration layer is responsible for consolidating health care data from multiple sources into single repositories in the cloud for additional processing and analysis.

4.4 Data Preprocessing Techniques

Healthcare data may consist of missing, noisy sensor readings, inconsistent data, and redundant data. In conclusion, data preprocessing is a crucial step in the quest for improving healthcare data quality and boosting the effectiveness of machine learning models. The data goes through a preprocessing phase, which involves cleaning the data, normalizing it, extracting features, reducing dimension, and filling in the missing values.

Data cleaning helps identify and eliminate duplicate patient records, fix inconsistent healthcare data and correct invalid sensor readings. Methods for dealing with missing data in EHR data sets include using K-nearest neighbor, median replacement, and mean substitution. The sensors anomalies and outliers are identified using the threshold based filtering algorithm and the anomaly detection algorithm.

Healthcare variables are scaled to consistent numerical ranges using normalisation techniques like the Min-Max normalization and Z Score standardization. Normalization makes it easier for the models to converge, and avoids the dominance of features in the machine learning training process, as the healthcare data come from various sources and have different measurement units.

Feature extraction is applied to extract meaningful features from raw physiological signals and clinical records that can be used to measure indicators in healthcare. The time-based statistical characteristics of heart rate, blood pressure, glucose fluctuation and physical activities are calculated from the streams of IoT sensors. Clinical risk factors like the history of previous diseases, BMI, age, cholesterol level and smoking are mined from the EHR datasets and used for disease prediction.

4.5 Feature Engineering and Selection

In this regard, feature engineering is an important step to build models in healthcare prediction that will result in high prediction accuracy, as the quality of the features selected will affect the prediction results. The proposed approach integrates clinical information from EHRs and physiological data from IoT sensors to create an all-encompassing patient health profile.

Clinical information gleaned from EHRs involves patient information, clinical notes, lab results, medications, disease diagnosis codes and physician observations. Physiological parameters derived from Internet of Things (IoT) devices are heart rate variability, oxygen saturation trends, glucose, sleep duration, activity levels, respiratory patterns etc.

For the prediction of chronic disease, temporal healthcare features are of significant importance for the development of chronic diseases tends to be slow. The techniques of sequential data analysis are thus used to recognize temporal dependency and to detect any changes in the patterns of diseases. To facilitate temporal modeling using deep learning, time-series healthcare data are divided into fixed intervals.Time-series healthcare data are broken down into fixed-sized chunks to enable deep learning-based temporal modeling.

To determine the most important healthcare attributes for prediction problems, the algorithms of Recursive Feature Elimination (RFE), Information Gain and correlation analysis are employed. Unnecessary or extraneous characteristics are removed to speed up the computation and prevent overfitting. Feature optimization promotes model precision and makes the comprehension of healthcare analytics systems more comprehensible.

4.6 Machine Learning and Deep Learning Models

The proposed healthcare prediction framework integrates traditional machine learning techniques with deep learning methods to analyze complicated healthcare datasets and forecast dangers of chronic diseases.

Logistic Regression

Logistic regression was employed as a baseline classification model since it is simple and easy to interpret. The algorithm makes linear estimates of the probabilities of diseases as functions of health-related variables and disease outcomes. Logistic Regression is especially useful for this type of classification problems where there are only two classes, e.g., predicting diabetes or detecting hypertension.

Support Vector Machine (SVM)

In classification, Support Vector Machines are one of the techniques used to identify the optimum decision boundaries in the healthcare data to classify them into various categories of diseases. SVM models are suitable for high-dimensional healthcare datasets, and can achieve good classification results for complex healthcare patterns through kernel-based transformation.

Random Forest

Random Forest is a machine learning technique that involves taking a collection of decision trees and combining them to build a stronger model in order to decrease the overfitting effect and increase prediction accuracy. Use of random forest models in healthcare analytics is very appropriate as it can consider the different type of healthcare variables and extract the important variables that are related to diseases. Jbres Editorial Team, 2024 demonstrated that the Random Forest algorithms are effective in predicting chronic diseases.

XGBoost

To boost the performance of healthcare prediction using gradient boosting optimization, Extreme Gradient Boosting (XGBoost) is used. XGBoost is very effective to deal with missing health-care values and is capable of scalable health-care analytics with high predictive ability. The algorithm works very well with structured healthcare data from EHR systems.

Long Short-Term Memory (LSTM)

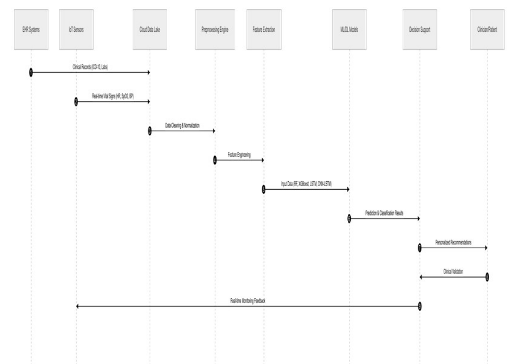
To process healthcare data in LSTM networks, which consists of data from IoT devices and longitudinal EHR, it is necessary to encode the data as a sequence of time steps. Temporal dependency and long-term trends in healthcare can be effectively modeled using LSTM models, which are specially used to analyze the progression of chronic diseases (Shickel et al., 2017).

CNN-LSTM Hybrid Model

The proposed method also involves the hybrid CNN-LSTM model for multimodal healthcare analytics. CNN layer learns spatial features from the physiological signals and LSTM layers learn the temporal healthcare dependencies. In the hybrid model two or more disease characteristics are processed at once, providing an improvement in disease prediction accuracy.

Explainable AI Mechanisms

The predictive framework is complemented with explainable AI techniques, enhancing the transparency and trust of the models among clinicians. The use of feature importance analysis, attention mechanisms, and interpretable machine learning methods aids healthcare



professionals in deciphering the 'how' of AI-generated predictions. One of the key reasons for explainability is to guarantee dependable clinical decision making and regulatory compliance (Mallya et al., 2019).

Figure 2. Workflow of AI-Based Chronic Disease Prediction System

4.7 Real-Time Healthcare Analytics

The proposed framework includes real-time analytics features, which will enable continuous monitoring of patients and early detection of diseases. Cloud and edge computing infrastructures process streaming healthcare information from IoT devices, to reduce latency and facilitate quick medical intervention.

Edge computing nodes do some preliminary healthcare analytics at the edge of the network to decrease communication overhead and response time. In real time, critical healthcare alerts for abnormal heart rate fluctuations, oxygen level drops and blood glucose spikes are detected.

Cloud-based healthcare analytics platforms bring together vast sets of healthcare data, and facilitate complex training of machine learning models. Real-time dashboards and visualization capabilities give clinicians the latest patient health data and predictive healthcare information to support decision making.

4.8 Performance Evaluation Metrics

The proposed healthcare prediction models are evaluated with the standard machine learning evaluation metrics. These are the metrics that determine the reliability, accuracy and ability of the developed healthcare analytics system to predict the classification.

Accuracy

Accuracy is an indicator of how many healthcare instances are correctly classified out of all the predictions. The more accurate, the better the performance in predicting the disease.

Precision

Precision is the ratio of the number of actual positive cases that are predicted to the number of disease cases predicted. In medical applications, for example, where false positive diagnoses might result in unnecessary medical interventions, precision is especially important.

Recall (Sensitivity)

Recall is the percentage of true positive predictions that are made. In the healthcare sector, recall is critical as the failure to capture critical cases of disease could lead to serious medical outcomes.

F1-Score

Precision and recall are combined into one measure of evaluation, the F1-score. It offers a balanced approach to the evaluation of predictive performance in healthcare, especially when dealing with imbalanced healthcare data.

ROC-AUC Score

Receiver Operating Characteristic–Area Under Curve (ROC-AUC) is a metric used to assess classification ability of prediction models in healthcare for various thresholds. The higher the ROC-AUC, the better the discriminatory capability.

Techniques like k-fold cross-validation are used to get a good fit of the model and to avoid overfitting. Multiple machine learning and deep learning models are compared to find the best algorithm for applying chronic disease prediction tasks.

4.9 Security and Privacy Considerations

The suggested methodology utilizes a number of security measures to secure sensitive healthcare data throughout the data collection and transmission, storage, and analysis phases. Healthcare communication is secured using encryption protocols like AES and RSA, to prevent unauthorized access.

Healthcare data access control mechanisms limit access to the data based on the user's role and responsibility. The additional layer of security in multi-factor authentication further ensures that the healthcare system isn't compromised by unauthorized users before they're able to gain access to patient records.

Another approach to enabling decentralized healthcare analytics without compromising patient privacy is the implementation of federated learning techniques. Federated learning is a method for preventing privacy risks by allowing healthcare institutions to train machine learning models together while keeping patient data local (Birari et al., 2024).

5. Results and Discussion

5.1 Overview of Experimental Analysis

The experimental analysis included the effectiveness of using Electronic Health Records (EHRs) along with real-time IoT healthcare data for proactive chronic disease prediction and personalized healthcare delivery. Predictive accuracy, reliability, scalability, and the clinical value were evaluated using multiple machine learning and deep learning algorithms.

The framework leveraged integrated health care information with a combination of historical patient information and real-time physiological data from IoT devices. The predictive models include traditional machine learning models like Logistic Regression, SVM, Random Forest, and XGBoost along with deep learning models like LSTM and CNN-LSTM, which were compared for predicting diabetes, cardiovascular disorders, hypertension, and respiratory illnesses.

5.2 Dataset and Experimental Environment

The experimental setup consisted of integrated healthcare data that was gathered from EHR repositories and IoT healthcare sensors. Patient information like demographics, lab reports, medical history, medications, and clinical notes were part of the EHR system, while physiological data like heart rate, blood pressure, glucose levels, oxygen saturation, and physical activity were continuously captured by the IoT devices.

Experiments were carried out with the cloud-based healthcare analytics combined with edge computing, which allows for real-time monitoring. The models were developed using machine learning libraries, such as Scikit-learn, TensorFlow, and Keras. Before training, data pre-processing techniques like normalization, handling of missing values, feature engineering and dimensionality reduction were applied.

The dataset was split into 80% training and 20% testing. To ensure the reliability and prevent overfitting of the model, cross validation was used. The accuracy, precision, recall, F1 score and ROC AUC were used to assess model performance.

5.3 Performance of Machine Learning Models

The experiments tested the effectiveness of commonly used machine learning approaches for chronic disease prediction by leveraging the integrated EHR-IoT healthcare data. Logistic Regression had good baseline performance for binary classification of diseases, but failed to capture the intricate nature of healthcare data, including nonlinearity and complex patterns.

Support Vector Machine (SVM) was able to effectively process high dimensional healthcare data and obtain better prediction performance, but its computational complexity was higher in case of large datasets. Overall, Random Forest showed promising results by applying its ensemble learning techniques, enhancing the stability of prediction and pinpointing key factors in healthcare that pose risks to patients (Jbres Editorial Team, 2024).

Compared to the traditional machine learning methods, XGBoost had the best predictive accuracy because it was a gradient boosting method, could easily handle missing healthcare values, and had minimal overfitting.

5.4 Performance of Deep Learning Models

The deep learning models achieved a higher accuracy than the traditional machine learning methods for analyzing temporal healthcare data with the help of IoT devices and EHR. Long Short-Term Memory (LSTM) networks were found to be successful in capturing healthcare sequential patterns and effectively predicting abnormalities like glucose fluctuations, irregular heart activity, and change in oxygen saturation (Shickel et al., 2017). The CNN-LSTM hybrid model outperformed the other models by integrating CNN with the temporal analysis of LSTM, resulting in the most accurate prediction. It was highly suitable for proactive and personalized healthcare systems, as the model efficiently processed continuous healthcare sensor data, enabled early disease detection and generated real-time healthcare alerts.

5.5 Comparative Analysis of Prediction Models

Deep learning models demonstrated that they outperformed traditional machine learning models in a healthcare prediction task. Logistic Regression and SVM yielded consistent baseline performance, but struggled with complex temporal healthcare patterns.Logistic Regression and SVM achieved consistent baseline performance, but performed poorly in complex temporal healthcare patterns. Random Forest and XGBoost were adopted to enhance the prediction accuracy by using ensemble learning and dealing with the heterogeneous healthcare data. The CNN-LSTM model outperformed other models in terms of accuracy, precision, recall, and F1-score, successfully learning from sequential healthcare data and long-term physiological patterns. When connected to EHR and health-related Internet-of-Things (IoT) data, results are even better than with a stand-alone EHR system.

Table 2. Performance Comparison of Machine Learning and Deep Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Major Strength**
Logistic Regression	84.2	82.5	81.7	82.1	Simple and interpretable
Support Vector Machine (SVM)	87.4	86.8	85.9	86.3	Effective for high-dimensional data
Random Forest	91.3	90.7	89.8	90.2	Handles heterogeneous healthcare data
XGBoost	93.1	92.5	91.7	92.1	High prediction accuracy
LSTM	95.4	94.8	94.1	94.4	Captures temporal healthcare patterns
CNN-LSTM	97.2	96.8	96.1	96.4	Best performance for sequential healthcare analytics

5.6 Impact of Real-Time IoT Monitoring

The addition of IoT-based healthcare monitoring enhanced the responsiveness and prediction of the proposed healthcare framework. By collecting healthcare data continuously, the system had the ability to identify any sudden physiological changes and dynamically track the progression of diseases.

For patients with chronic conditions that needed constant medical attention, real-time healthcare monitoring was especially helpful. CGM allowed for timely detection of diabetic complications, and real-time ECG monitoring facilitated timely cardiovascular issues detection. Likewise, patients with chronic pulmonary disease were used for the detection of fluctuations in oxygen level and respiratory distress using respiratory sensors.

The experimental results showed that the IoT-based health monitoring system decreased the time lag of the patients' visits to the hospital every few months and increased the engagement of the patients in the management of their health. Integrated health data applications enabled patients to get tailored health care advice, medication reminders, and preventive instruction. Personalized healthcare assistance led to better adherence to medication and better health outcomes (Arefin, 2024).

7. Conclusion

The synergy of Electronic Health Records (EHRs) and immediate data from the Internet of Things (IoT) in the healthcare sector has greatly enhanced the power of contemporary healthcare systems for chronic disease prediction and personalized care. By leveraging historical medical data and real-time monitoring, healthcare professionals can make informed decisions and promptly identify diseases, thereby providing proactive treatment and early diagnosis.

The study showcased the effectiveness of machine learning and deep learning models, especially LSTM and CNN-LSTM, in improving the prediction of healthcare performance by handling complex healthcare data. The integration of IoT-enabled monitoring devices further enhances the ability to monitor patients in real time, manage patient care remotely and make individualized treatment recommendations.

Although the benefits, issues of data privacy, interoperability, cybersecurity, scalability, and ethical implementation of AI still pose serious challenges for widespread adoption. Federated learning, edge computing, explainable AI, and blockchain are anticipated to solve numerous of these challenges and enhance the trustworthiness of intelligent healthcare systems.

In conclusion, EHR-IoT healthcare systems are a significant step toward predictive, preventive, and patient-centric healthcare. AI-powered healthcare analytics and secure digital health infrastructures will continue to revolutionize healthcare delivery and patient outcomes globally in the future.

References

1. Arefin, S., 2024. *Chronic Disease Management through an AI-Powered Personalized Healthcare Coaching Application*. Journal of Service Science and Management, 17(4), pp.231–245.
2. Akila, K., 2025. *The Role of Artificial Intelligence in Modern Healthcare: Advances, Challenges and Future Prospects*. European Journal of Cardiovascular Medicine, 25(4), pp.1–12.
3. Birari, D.R., Bamane, K.D., Kamble, P.B., Dhaigude, T.A., Shendge, R.B. and Dandavate, A., 2024. *Towards a Holistic Approach to Chronic Disease Management: Integrating Federated Learning and IoT for Personalized Health Care*. Journal of Electrical Systems, 20(1), pp.1–15.
4. Brisimi, T.S., Xu, T., Wang, T., Dai, W., Adams, W.G. and Paschalidis, I.C., 2018. *Predicting Chronic Disease Hospitalizations from Electronic Health Records: An Interpretable Classification Approach*. IEEE Access, 6, pp.63257–63272.
5. Harvard Medical School, 2025. *Digital Health and EHR Analytics for Predictive Healthcare*.
6. Varadala Sridhar, Dr.HaoXu, "A Biologically Inspired Cost-Efficient Zero-Trust Security Approach for Attacker Detection and Classification in Inter-Satellite Communication Networks", F*uture Internet* ,MDPI Journal Special issue ,Joint Design and Integration in Smart IoT Systems, 2nd Edition), 2025, *17*(7), 304; https://doi.org/10.3390/fi17070304, 13 July 2025
7. Varadala Sridhar, Dr. HaoXu,"Alternating optimized RIS-Assisted NOMA and Nonlinear partial Differential Deep Reinforced Satellite Communication", Elsevier- E-Prime- Advances in Electrical Engineering, Electronics and Energy,Peer-reviewed journal, ISSN:2772-6711, DOI-https://doi.org/10.1016/j.prime.2024.100619,29th may, 2024.
8. Varadala Sridhar,Dr.S.Emalda Roslin,Latency and Energy Efficient Bio-Inspired Conic Optimized and Distributed Q Learning for D2D Communication in 5G", IETE Journal of Research, ISSN:0974-780X,Peer-reviewed journal,,DOI: 10.1080/03772063.2021.1906768 , 2021, Page No: 1-13, Taylor and Francis
9. V. Sridhar, K.V. Ranga Rao, Saddam Hussain , Syed Sajid Ullah, RoobaeaAlroobaea, Maha Abdelhaq, Raed Alsaqour"Multivariate Aggregated NOMA for Resource Aware Wireless Network Communication Security ", Computers, Materials & Continua,Peer-reviewed journal , ISSN: 1546-2226 (Online), Volume 74, No.1, 2023, Page No: 1694-1708, https://doi.org/10.32604/cmc.2023.028129,TechSciencePress
10. Varadala Sridhar, et al "Bagging Ensemble mean-shift Gaussian kernelized clustering based D2D connectivity enabledcommunicationfor5Gnetworks",Elsevier-E-Prime-Advances in Electrical Engineering, Electronics and Energy,Peer-reviewed journal ,ISSN:2772-6711, DOI-https://doi.org/10.1016/j.prime.2023.100400,20 Dec, 2023.
11. Varadala Sridhar, Dr.S. Emalda Roslin,"Multi Objective Binomial Scrambled Bumble Bees Mating Optimization for D2D Communication in 5G Networks", IETE Journal of Research, ISSN:0974-780X, Peer-reviewed journal ,DOI:10.1080/03772063.2023.2264248 ,2023, Page No: 1-10, Taylor and Francis.
12. Varadala Sridhar,etal,"Jarvis-Patrick-Clusterative African Buffalo Optimized Deepn Learning Classifier for Device-to-Device Communication in 5G Networks", IETE Journal of Research, Peer-reviewed journal ,ISSN:0974-780X, DOI:
13. L. Chawla, A. Shrivastava, M. I. Habelalmateen, H. Shekhar, P. Mittal and S. Sharma, "Federated Foundation Models for Healthcare Diagnostics," *2025 2nd International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)*, Raipur, India, 2025, pp. 1-6, doi: 10.1109/ICAIIHI67124.2025.11403022.
14. V. Nimbalkar, L. Chawla, M. M. Adnan, A. Bhansali, M. Gupta and R. Kalra, "A Human-Centered Approach to Interpretable Machine Learning in Clinical Decision Support Systems," *2025 2nd International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)*, Raipur, India, 2025, pp. 1-5, doi: 10.1109/ICAIIHI67124.2025.11403473.
15. D. Chawla, D. Chawla, A. Shrivastava, M. I. Habelalmateen, M. Dixit and S. P. Dwivedi, "Explainable AI for Mental Health Diagnosis: Enhancing Transparency, Trust, and Clinical Decision-Making," *2025 2nd International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)*,

Raipur, India, 2025, pp. 1-6, doi: 10.1109/ICAIIHI67124.2025.11403514
16. D. Chawla, D. Chawla, A. Shrivastava, M. M. Adnan, B. Sireesha and I. Khan, "Blockchain and Federated Learning Integration for Secure IoT and Cyber-Physical Systems," *2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG)*, Indore, Madhya Pradesh, India, India, 2025, pp. 1-7, doi: 10.1109/ICTBIG68706.2025.11323990.
17. Chawla, D. Chawla, A. Shrivastava, M. M. Adnan, B. Sireesha and I. Khan, "AI-Driven Predictive Infrastructure for Smart and Sustainable Cities," *2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG)*, Indore, Madhya Pradesh, India, India, 2025, pp. 1-7, doi: 10.1109/ICTBIG68706.2025.11324009.
18. Saxena, P., and Saxena, V. (2022). "Comparative Study of White Gaussian Noise Reduction for Different Signals Using Wavelet". International Journal of Research -GRANTHAALAYAH, 10(7), 112–123. https://doi.org/10.29121/granthaalayah.v10.i7.2022.4711
19. Saxena Parul, Umang Saini, and Vinay Saxena. "Design and implementation of sound signal reconstruction algorithm for blue hearing system using wavelet." Automation and Computation. CRC Press, 2023. 405-411.
20. K. Himabindu, V. Saxena, S. P, K. K, E. Sathish and D. Suganthi, "IoT–Fuzzy Logic Hybrid Framework for Crop Monitoring and Yield Prediction in Smart Agriculture," 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2025, pp. 1-6, doi: 10.1109/IACIS65746.2025.11211067.
21. Saxena Vinay. (2012) "Fourier Descriptors under Rotation, Scaling, Translation and Various Distortion for Hand Drawn Planar Curves". *Journal of Experimental Sciences*, vol. 3, no. 1, 05-07. https://updatepublishing.com/journal/index.php/jes/article/view/1905.
22. Saxena Vinay, and Kapoor V.V., (2011), "Behavior of Normalized Moments under Distortion and Optimization, Recent Research in Science and Technology", 3(7),73-76. https://updatepublishing.com/journal/index.php/rrst/article/view/743
23. Vinay Saxena, (2014), "International Journal of Emerging Technologies in Computational and Applied Sciences", 9(2), 170-175. https://iasir.net/files/ijetcaspapers/ijetcas14-567.pdf
24. Saxena, P., Saxena, V., Basvant, M. S. Lohumi, Y.Saraswat, M. Sankhyan, A. Deepak, A. and Shrivastava, A.. (2024) "Fuzzy-Based Medical Image Processing and Analysis", International Journal of Intelligent Systems and Applications in Engineering, 12(16s), pp. 320–327.
25. Saxena, V.,Singh, M., Saxena, P., Singh, M., Srivastava, A. P., Kumar, N., Deepak, A.& Shrivastava, A.. (2024). "Utilizing Support Vector Machines for Early Detection of Crop Diseases in Precision Agriculture a Data Mining Perspective". International Journal of Intelligent Systems and Applications in Engineering, 12(16s), 281–288.
26. P. Bagane, S. G. Joseph, A. Singh, A. Shrivastava, B. Prabha and A. Shrivastava, "Classification of Malware using Deep Learning Techniques," 2021 9th International Conference on Cyber and IT Service Management (CITSM), Bengkulu, Indonesia, 2021, pp. 1-7, doi: 10.1109/CITSM52892.2021.9588795.
27. Attar T. V., & Momin S. (2025). Nanotechnology in drug delivery: Challenges and future prospects. *Advances in Bioresearch, 16*(2), 63–69.
28. Das B., Attar T. V., Sharma N., Sharma R., Anandhan A., & Acharya S. (2025). Biochemistry to solve environmental degradation and sustainable future. *International Journal of Environmental Sciences, 11*(20s), 2527–2545. *https://doi.org/10.64252/bz71eq58* 80. Dhanke J., Attar T. V. & Zode, P. (2025). Optimal transport theory in machine learning: Applications to generative modelling and domain adaptation. *International Journal of Environmental Sciences, 11*(21s), 2613–2630.
29. Divate S., Attar T. V., Patil M. A., Yadav T. P., & Wagh G. D. (2025). Synthesis and characterization applications of nanoparticles for photocatalytic degradation of organic dyes. *International Journal of Environmental Sciences, 11*(23s), 695–712. *https://doi.org/10.64252/n0shfg48*
30. Attar T. V. (2022). Investigations on enhanced DC conductivity and dielectric properties by rare earth doping of lanthanum fluoride. *Shodhasamhita, 9*(2), 180–184.
31. Attar T. V. (2022). Studies on cytotoxicity of LaF_3: Pr, Ho nanoparticles for possible biomedical applications. *Shodhasamhita, 9*(2/1), 254–257.
32. Dr. Mohd. Talib Ather Ansari, (2025). *"One Nation One Subscription' Digital Library Resources to Enrich Teacher Educators for Practical Knowledge and Foster an Engaging Teaching-Learning Ecosystem"* South eastern European Journal of Public Health, ISSN: 2197-5248, Volume XXVI, S1, 2025, P. 7166-7181, Published by- Uphill's Publishers LLC, Sheridan, Wyoming, United States. DOI: https://doi.org/10.5281/zenodo.16325646 Available at https://seejph.com/index.php/seejph/article/view/6671/4424
33. Dr. Hina Hasan, & Dr. Mohd. Talib Ather Ansari, (2025). *"Techno-Pedagogical Practices in Inclusive Education: Comparing Approaches for Slow Learners across Teacher Education Programme"* TPM - Testing, Psychometrics, Methodology in Applied Psychology,

(Scopus Q3 journal), ISSN- 1972-6325, Impact Factor- 0.505, Vol-32, Page from 222-235-2025, Published by Cises DOI: https://doi.org/10.5281/zenodo.17746118 Available at https://tpmap.org/submission/index.php/tpm/article/view/3162/2364

34. Dr. Mohd. Talib Ather Ansari, & Dr. Hina Hasan. (2024**).** "Need And Importance of Translation of Indian Languages Vice Versa to Promote Indian Educational Scenario". *Educational Administration: Theory and Practice*, *30*(1), ISSN:1300-4832E-
35. S. N. Siri, H. B. Divyashree, and S. P. Mala, "The Memorable Assistant: An IoT-Based Smart Wearable Alzheimer's Assisting Device," in *Proc. 5th Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solut. (CSITSS)*, 2021. **DOI:** 10.1109/CSITSS54238.2021.9682788
36. D. H. Balachandra, P. C. Gowda, and N. P. K. Shivaprasad, "Secure Cluster-Based Routing Using Multi Objective-Trust Centric Artificial Algae Algorithm for Wireless Sensor Network," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 2, pp. 1618–1628, 2023, DOI: https://doi.org/10.11591/ijece.v13i2.pp1618-1628
37. H. B. Divyashree, C. Puttamadappa, and K. S. Nandini Prasad, "Performance Analysis and Enhancement of QoS Parameters for Real-Time Applications in MANETs-Comparative Study," in *Proc. 5th IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. (RTEICT)*, 2020, pp. 256–260, **DOI:** 10.1109/RTEICT49044.2020.9315547