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AI-Powered Hybrid Healthcare Surveillance and Emergency Response System for Next-Generation Smart Cities

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Abstract **-** The rapid growth of smart cities has increased the demand for intelligent healthcare systems that can provide continuous patient monitoring, early disease detection, and efficient emergency response. Conventional healthcare surveillance systems often face challenges such as delayed emergency services, fragmented medical data, limited interoperability, and inadequate real-time decision-making. To address these limitations, this paper proposes an AI-Powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) for next-generation smart cities. The proposed framework integrates the Internet of Medical Things (IoMT), Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Edge Computing, Cloud Computing, Federated Learning, Explainable Artificial Intelligence (XAI), Digital Twin technology, and Geographic Information Systems (GIS) to provide intelligent healthcare monitoring and emergency management. Physiological data collected from wearable sensors, medical devices, Electronic Health Records (EHRs), smart cameras, and environmental sensors are analyzed using hybrid AI models to predict disease risks, detect health anomalies, and generate early warning alerts. Edge computing enables low-latency processing for real-time decision-making, while cloud computing supports large-scale data storage and long-term analytics. Federated Learning ensures privacy-preserving collaborative model training without sharing sensitive patient data, and Explainable AI enhances the transparency and reliability of clinical decisions. In emergency situations, the GIS-enabled response module identifies the nearest ambulance, optimizes routing based on real-time traffic conditions, and automatically notifies hospitals to improve patient care. The proposed framework is expected to improve disease prediction accuracy, reduce emergency response time, enhance healthcare interoperability, and strengthen data security. Furthermore, it supports smart hospitals, remote patient monitoring, elderly care, epidemic surveillance, and disaster management, making it a scalable and reliable healthcare solution for future smart city ecosystems.

Keywords **-** *Artificial Intelligence (AI), Smart Healthcare, Smart Cities, Healthcare Surveillance, Emergency Response System, Internet of Medical Things (IoMT), Machine Learning, Deep Learning, Edge Computing, Cloud Computing, Federated Learning, Explainable Artificial Intelligence (XAI), Digital Twin, Geographic Information System (GIS), Remote Patient Monitoring.*

I. INTRODUCTION

The rapid growth of smart cities has transformed healthcare by integrating advanced technologies such as Artificial Intelligence (AI), Internet of Medical Things (IoMT), cloud computing, edge computing, and big data analytics. These technologies enable continuous patient monitoring, early disease prediction, and intelligent emergency response, improving the quality of healthcare services. The increasing prevalence of chronic diseases, aging populations, and frequent public health emergencies has created a need for smart healthcare systems capable of providing real-time surveillance and timely medical intervention.

Conventional healthcare systems mainly depend on hospital-based treatment and manual emergency response, which often results in delayed diagnosis, fragmented medical records, limited interoperability, and inefficient communication among hospitals and emergency responders. These limitations reduce the effectiveness of healthcare services, particularly during critical medical emergencies where rapid decision-making is essential.

Artificial Intelligence has significantly improved healthcare by enabling disease prediction, medical image analysis, clinical decision support, and personalized treatment. Machine Learning (ML) and Deep Learning (DL) algorithms can analyze large volumes of physiological data collected from wearable sensors, medical devices, and electronic health records to detect abnormalities and predict diseases with high accuracy. Similarly, the Internet of Medical Things (IoMT) facilitates continuous health monitoring through smart devices such as ECG monitors, blood pressure sensors, pulse oximeters, glucose monitors, and smartwatches, allowing healthcare professionals to identify health risks at an early stage.

Despite these advancements, cloud-based healthcare systems often experience communication delays, high bandwidth requirements, and privacy concerns. Edge computing addresses these issues by processing healthcare data closer to the data source, enabling low-latency analysis and rapid emergency alerts. Cloud computing complements edge computing by supporting long-term data storage, large-scale analytics, and AI model training.

Protecting patient privacy remains another important challenge. Federated Learning (FL) enables multiple healthcare organizations to collaboratively train AI models without sharing sensitive patient information, thereby improving data security and regulatory compliance. In addition, Explainable Artificial Intelligence (XAI) enhances the transparency of AI models by providing interpretable predictions, helping healthcare professionals understand and trust AI-assisted clinical decisions.

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Efficient emergency healthcare also requires seamless integration between hospitals, ambulance services, traffic management systems, and public surveillance infrastructure. Technologies such as Geographic Information Systems (GIS), drone surveillance, and intelligent traffic management can optimize ambulance routing, reduce response time, and improve coordination among emergency responders. Furthermore, Digital Twin technology provides virtual representations of patients using real-time sensor data, enabling personalized healthcare monitoring and predictive treatment planning.

Although several studies have explored AI-based healthcare monitoring, IoMT, remote patient monitoring, and emergency management individually, only limited research has proposed an integrated framework that combines AI, IoMT, Edge Computing, Cloud Computing, Federated Learning, Explainable AI, Digital Twin technology, and GIS-based emergency response within a unified healthcare system for smart cities.

To overcome these limitations, this paper proposes an AI-Powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) for next-generation smart cities. The proposed framework integrates wearable sensors, IoMT devices, AI-based disease prediction, Edge Computing, Federated Learning, Explainable AI, Digital Twin technology, and GIS-enabled emergency response to provide continuous health monitoring, early disease detection, secure data management, and intelligent emergency coordination. The proposed system aims to improve prediction accuracy, reduce emergency response time, enhance data privacy, and support efficient healthcare management in future smart city environments.

The major contributions of this research are as follows:

- Development of a hybrid healthcare surveillance architecture integrating AI, IoMT, Edge Computing, Cloud Computing, Federated Learning, Explainable AI, Digital Twin technology, and GIS.
- Design of an intelligent framework for real-time disease prediction, health anomaly detection, and emergency response.
- Improvement of healthcare privacy, transparency, interoperability, and scalability using advanced AI technologies.
- Demonstration of applications in smart hospitals, remote patient monitoring, elderly healthcare, epidemic surveillance, disaster management, and next-generation smart cities.

II. LITERATURE SURVEY

The analysis of the recent studies indicates that substantial progress has been made in IoT-based patient monitoring, AI-driven medical prediction, infectious disease surveillance, edge intelligence, privacy-preserving learning, and ambulance management. The following studies are to provide a foundation for the proposed research.

Mazin Alshamrani (2022) investigated the integration of IoT and artificial intelligence for remote healthcare monitoring, highlighting the importance of continuous patient observation. Jithin S. Sunny, C. Pawan K. Patro, Khushi Karnani, Sandeep C. Pingle, Feng Lin, Misa Anekoji, Lawrence D. Jones, Santosh Kesari, and Shashaanka Ashili (2022) reviewed anomaly detection techniques for wearable healthcare data to identify abnormal physiological patterns. Timothy Malche, Sumegh Tharewal, Pradeep Kumar Tiwari, Mohamed Yaseen Jabarulla, Abeer Ali Alnuaim, Wesam Atef Hatamleh, and Mohammad Aman Ullah (2022) developed an AIoT-based patient activity tracking approach for remote monitoring. Stephanie Baker and Wei Xiang (2023) examined AIoT applications in smart healthcare, while Thanveer Shaik, Xiaohui Tao, Nabeel Higgins, Lichao Li, Raj Gururajan, Xujuan Zhou, and U. Rajendra Acharya (2023) reviewed AI-based remote patient monitoring technologies and their challenges.

Mahmuda Akter, Nour Moustafa, Timothy Lynar, and Imran Razzak (2022) explored edge intelligence and federated learning for privacy-preserving smart healthcare. Mansoor Ali, Faisal Naeem, Muhammad Tariq, and Georges Kaddoum (2023) reviewed federated learning techniques for protecting sensitive healthcare information. Cem O. Yaldiz and colleagues (2023) investigated wearable multimodal sensing and anomaly detection for early prediction of exertional heat stroke. Sameer Sundrani and colleagues (2023) studied continuous physiological monitoring and transformer-based techniques for predicting patient deterioration in emergency departments. These studies demonstrate the importance of intelligent monitoring and early medical risk identification.

John S. Brownstein, Benjamin Rader, Christina M. Astley, and Huaiyu Tian (2023) examined AI applications in infectious disease surveillance and outbreak identification. Hannah McClymont and colleagues (2024) reviewed internet-based surveillance systems for infectious disease prediction. Hoang Nguyen, Dina Nawara, and Rasha Kashef (2024) investigated the integration of IoT and AI in smart-city applications. Hossein Omrany and colleagues (2024) analysed IoT-enabled smart-city technologies using systematic review techniques, while Walid Miloud Dahmane, Samir Ouchani, and Hafida Bouarfa (2025) examined smart-city services and their technological challenges. These studies emphasize the importance of intelligent urban infrastructure and population-level health surveillance.

Dinh C. Nguyen and colleagues (2022) reviewed federated learning applications in smart healthcare, focusing on privacy-preserving distributed learning. Mahdi Safaei Yaraziz, Nader Sohrabi Safa, and Muhammad Ajmal Azad (2024) examined edge computing techniques for IoT-based healthcare systems. Atslands Rego da Rocha and colleagues (2024) reviewed Edge AI applications in the Internet of Medical Things. Inas Al Khatib, Abdulrahim Shamayleh, and Malick Ndiaye (2024) investigated IoMT applications, emerging trends, and security challenges. These studies highlight the significance of distributed computing, privacy protection, and efficient healthcare data processing.

R. Justin Martin, Reza Mousavi, and Cem Saydam (2021) proposed a machine learning-based approach for predicting emergency medical service demand. Han Wang, Qin Xiang Ng, Shalini Arulanandam, Colin Tan, Marcus E. H. Ong, and Mengling Feng (2023) developed a machine learning-based ambulance dispatch triage model for emergency classification. Lars Eide Næss and colleagues (2024) analysed ambulance availability and its impact on emergency response times.

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Reem Tluli, Ahmed Badawy, Saeed Salem, Mahmoud Barhamgi, and Amr Mohamed (2024) reviewed machine learning techniques for ambulance allocation, routing, and demand estimation. Finally, Arom Choi and colleagues (2024) developed a deep learning-based multimodal clinical decision support system for predicting patient deterioration in emergency departments. Table I presents a comparative analysis of existing research studies, highlighting research gaps in intelligent healthcare surveillance and emergency response systems.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING STUDIES ON AI-POWERED HEALTHCARE SURVEILLANCE AND EMERGENCY RESPONSE SYSTEMS

Author & Year	Dataset / Domain	Method	Strength	Limitation
Mazin Alshamrani (2022)	IoT-based remote healthcare monitoring; wearable sensors and healthcare applications.	Survey of IoT, AI, and ML techniques for remote healthcare monitoring.	Explains the integration of IoT and AI for continuous patient monitoring and smart healthcare services.	Does not provide an integrated emergency prediction, ambulance allocation, and hospital coordination mechanism.
Jithin S. Sunny, C. Pawan K. Patro, Khushi Karnani, Sandeep C. Pingle, Feng Lin, Misa Anekoji, Lawrence D. Jones, Santosh Kesari, and Shashaanka Ashili (2022)	Wearable healthcare data and physiological sensor information.	Review of anomaly detection techniques, data processing methods, and wearable data analysis frameworks.	Provides a comprehensive understanding of anomaly detection and abnormal physiological pattern identification.	Primarily focuses on anomaly detection and does not extend to automated emergency response management.
Timothy Malche, Sumegh Tharewal, Pradeep Kumar Tiwari, Mohamed Yaseen Jabarulla, Abeer Ali Alnuaim, Wesam Atef Hatamleh, and Mohammad Aman Ullah (2022)	Remote patient monitoring and patient activity tracking.	AIoT-based patient activity tracking using IoT devices and intelligent data processing.	Supports remote patient monitoring and demonstrates the application of AIoT in healthcare.	Focuses mainly on patient activity monitoring without integrating population-level health surveillance or ambulance services.
Stephanie Baker and Wei Xiang (2023)	AIoT-enabled smart healthcare applications.	Comprehensive survey of AI, IoT, intelligent sensing, and healthcare data processing techniques.	Explains the potential of AIoT for improving healthcare monitoring, automation, and intelligent decision-making.	Does not develop a complete framework connecting patient monitoring with real-time emergency response.
Thanveer Shaik, Xiaohui Tao, Nabeel Higgins, Lichao Li, Raj Gururajan, Xujuan Zhou, and U. Rajendra Acharya (2023)	Remote patient monitoring, wearable devices, vital signs, and chronic disease monitoring.	Review of AI, ML, DL, IoT, cloud, fog, edge, and blockchain technologies for remote patient monitoring.	Covers several advanced technologies and explains their applications in early detection of patient deterioration.	Highlights challenges in AI adoption and patient monitoring but does not implement a city-wide emergency coordination system.
Mahmuda Akter, Nour Moustafa, Timothy Lynar, and Imran Razzak (2022)	Smart healthcare systems and distributed healthcare data.	Edge intelligence and federated learning-based privacy protection framework.	Supports privacy-aware healthcare intelligence and reduces dependence on centralized patient data collection.	Primarily addresses privacy protection rather than integrating emergency detection, ambulance dispatch, and hospital coordination.
Mansoor Ali, Faisal Naeem, Muhammad Tariq, and Georges Kaddoum (2023)	Smart healthcare, Internet of Medical Things, and privacy-sensitive medical data.	Comprehensive survey of federated learning and privacy-preserving healthcare techniques.	Explains privacy challenges and distributed learning approaches for collaborative healthcare intelligence.	Does not provide a practical end-to-end healthcare surveillance and emergency response implementation.
Cem O. Yaldiz, Mark J. Buller, Kristine L. Richardson, Sungtae An, David J. Lin, Aprameya Satish, Kyla Driver, Emma Atkinson, Timothy Mesite, Christopher King, Max Bursey, Meghan Galer, Mindy Millard-Stafford, Michael N. Sawka, Alessio Medda, and Omer T. Inan (2023)	Wearable multimodal physiological data, including heart rate and triaxial accelerometer measurements.	Machine learning-based early prediction of impending exertional heat stroke using wearable sensing and anomaly detection.	Demonstrates the potential of multimodal wearable sensing for early identification of a specific medical emergency.	Focuses on exertional heat stroke and does not address multiple medical emergencies or city-wide emergency services.
Sameer Sundrani, Julie Chen, Boyang Tom Jin, Zahra Shakeri Hossein Abad, Pranav Rajpurkar, and David Kim (2023)	19,847 adult emergency department visits from Stanford Health Care, including continuous ECG, PPG, and vital-sign measurements.	Multimodal ML using conventional signal-processing features and transformer-based deep learning.	Predicts tachycardia, hypotension, and hypoxia within a 90-minute window using continuous physiological monitoring.	Data were obtained from a single academic medical centre, and the system was not connected to external ambulance or city emergency services.
John S. Brownstein, Benjamin Rader, Christina M. Astley, and Huaiyu Tian (2023)	Infectious disease surveillance and population-level epidemiological information.	Review of AI and ML approaches for disease outbreak identification, tracking, and public health surveillance.	Demonstrates the importance of AI in early disease detection and monitoring population-level health threats.	Concentrates on infectious disease surveillance rather than integrating individual patient monitoring and emergency medical response.
Hannah McClymont, Stephen B. Lambert, Ian Barr, Sotiris Vardoulakis, Hilary Bambrick, and Wenbiao Hu (2024)	Internet-based infectious disease surveillance systems and COVID-19 pandemic-related information.	Updated literature review of internet-based surveillance and infectious disease prediction.	Identifies the role of digital information sources and computational approaches in disease monitoring and outbreak prediction.	Does not provide an integrated framework for real-time patient monitoring, ambulance allocation, and emergency hospital coordination.
Hoang	IoT-enabled	Survey of	Explains the	Covers

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Nguyen, Dina Nawara, and Rasha Kashef (2024)	smart-city applications, including healthcare, transportation, and urban services.	IoT, AI, ML, and DL technologies in smart-city environments.	integration of IoT and AI for intelligent urban services and real-time decision-making.	multiple smart-city domains but does not specifically develop integrated healthcare emergency response architecture.
Hossein Omrany, Karam M. Al-Obaidi, Mohataz Hossain, Nayef A. M. Alduais, Husam S. Al-Duais, and Amirhosein Ghaffarianhoseini (2024)	IoT-enabled smart-city research publications and urban infrastructure applications.	Hybrid systematic review combining bibliometric analysis, text mining, and content analysis.	Identifies major research areas, technological developments, and implementation challenges in IoT-enabled smart cities.	Provides a broad smart-city perspective rather than a specialized AI-based healthcare surveillance and emergency management solution.
Walid Miloud Dahmane, Samir Ouchani, and Hafida Bouarfa (2025)	Smart-city services, including healthcare, transportation, IoT, and urban infrastructure.	Systematic review of smart-city technologies, applications, and implementation challenges.	Highlights the importance of AI, IoT, interoperability, and scalability in smart-city services.	Does not provide a dedicated hybrid healthcare surveillance model or an experimental emergency response implementation.
Dinh C. Nguyen, Quoc-Viet Pham, Pubudu N. Pathirana, Ming Ding, Aruna Seneviratne, Zihuai Lin, Octavia Dobre, and Won-Joo Hwang (2022)	Smart healthcare, Internet of Medical Things, and distributed healthcare datasets.	Comprehensive survey of federated learning techniques for smart healthcare.	Explains collaborative model training without sharing raw patient records and addresses privacy and scalability challenges.	Focuses on distributed learning and privacy rather than real-time emergency response and ambulance coordination.
Mahdi Safaei Yaraziz, Nader Sohrabi Safa, and Muhammad Ajmal Azad (2024)	IoT-based smart healthcare and Internet of Medical Things applications.	Systematic literature review of edge computing, fog computing, and cloud-based healthcare architectures.	Explains how edge computing can reduce communication delays and improve healthcare monitoring responsiveness.	Highlights computational and security challenges but does not develop a complete patient-to-ambulance emergency response framework.
Atslands Rego da Rocha, Matheus R. Monteiro, César Lincoln C. Mattos, Madson L. D. Dias, Jorge Barbosa Soares, Regis Pires Magalhães, and José Antônio Fernandes de Macêdo (2024)	Edge AI and Internet of Medical Things applications.	Literature review of Edge AI, distributed processing, and intelligent healthcare applications.	Demonstrates the importance of processing healthcare information closer to data sources for improved responsiveness and privacy.	Does not address large-scale city-level health surveillance or coordinated ambulance and hospital management.
Inas Al Khatib, Abdulrahim Shamayleh, and Malick Ndiaye (2024)	Internet of Medical Things, mobile health, remote biomarker detection, and healthcare information sharing.	Systematic review of IoMT applications, emerging trends, challenges, and technical solutions.	Identifies major IoMT applications and highlights interoperability, security, and privacy requirements.	Does not provide an integrated AI-powered emergency prediction and response implementation.
R. Justin Martin, Reza Mousavi, and Cem Saydam (2021)	Emergency medical service call records and spatially and temporally distributed ambulance demand.	Multilayer perceptron neural network with ensemble-based decision-tree feature selection.	Predicts daily, hourly, and geographical ambulance demand to support resource allocation and reduce response delays.	Concentrates on ambulance demand forecasting rather than integrating patient-level physiological monitoring and disease surveillance.
Han Wang, Qin Xiang Ng, Shalini Arulanandam, Colin Tan, Marcus E. H. Ong, and Mengling Feng (2023)	More than 360,000 emergency call-centre records from Singapore collected between 2018 and 2020.	Machine learning-based ambulance dispatch triage using Random Forest and other classification models.	Improved emergency case classification and reduced the over-triage rate by 15 percentage points while maintaining a similar under-triage rate.	Depends on emergency call-centre records and does not integrate continuous wearable health monitoring or population-level surveillance.
Lars Eide Næss, Andreas Jørstad Krüger, Oddvar Uleberg, Helge Haugland, Jostein Dale, Jon-Ola Wattø, Sara Marie Nilsen, and Andreas Asheim (2024)	216,787 acute ambulance incidents in Central Norway from 2013 to 2022.	Retrospective observational study using machine learning and multinomial regression to estimate ambulance availability.	Demonstrates the relationship between ambulance availability and response delays using large-scale real-world emergency records.	Focuses on ambulance availability and response time rather than patient health prediction and integrated healthcare surveillance.
Reem Tluli, Ahmed Badawy, Saeed Salem, Mahmoud Barhamgi, and Amr Mohamed (2024)	Ambulance service allocation, emergency demand estimation, and routing research.	Survey of machine learning techniques for ambulance allocation, routing, and demand forecasting.	Provides a broad overview of AI applications for improving ambulance deployment and emergency transportation.	Does not integrate ambulance management with real-time physiological monitoring and AI-based medical emergency prediction.
Arom Choi, Kwanhyung Lee, Heejung Hyun, Kwang Joon Kim, Byungeun Ahn, Kyung Hyun Lee, Sangchul Hahn, So Yeon Choi, and Ji Hoon Kim (2024)	Electronic health records and multimodal clinical information from emergency department visits.	Deep learning-based multimodal clinical decision support for real-time prediction of patient deterioration.	Combines multiple clinical data sources to support early identification of high-risk patients in emergency departments.	Primarily designed for hospital-based clinical decision support and does not provide city-wide patient surveillance or ambulance coordination.

Overall, the reviewed studies demonstrate significant advancements in AI-based healthcare monitoring, disease surveillance, predictive analytics, and emergency management. However, most existing approaches address these functionalities independently. Therefore, the proposed research aims to integrate patient monitoring, population-level healthcare surveillance, emergency prediction, and intelligent ambulance management into a unified hybrid healthcare framework for next-generation smart cities.

III. RESEARCH GAP

Although AI-enabled healthcare surveillance has advanced significantly, most existing systems focus on individual

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technologies such as IoMT, machine learning, cloud computing, or remote patient monitoring rather than providing an integrated healthcare solution. Many systems lack seamless coordination with emergency medical services, smart transportation, and public health infrastructure, limiting their effectiveness in smart cities.

Additionally, cloud-based architectures often experience communication delays during medical emergencies, while many AI models lack transparency, making clinical decision-making difficult. Challenges related to data privacy, interoperability, and secure healthcare data sharing also remain unresolved. Although Federated Learning, Explainable AI (XAI), Digital Twin technology, and GIS-based emergency management have been studied individually, their integration into a unified healthcare surveillance framework is still limited.

Therefore, there is a need for an AI-powered hybrid healthcare surveillance system that integrates IoMT, Edge Computing, Cloud Computing, Federated Learning, Explainable AI, Digital Twins, GIS, and intelligent emergency response to provide real-time disease prediction, continuous patient monitoring, secure data management, and rapid medical assistance for next-generation smart cities.

TABLE II. RESEARCH GAP ANALYSIS

Existing Limitation	Impact	Proposed Solution
Independent healthcare systems	Poor coordination	Integrated hybrid healthcare framework
Cloud-only processing	High response latency	Edge–Cloud computing architecture
Limited AI transparency	Low clinician trust	Explainable AI (XAI)
Privacy concerns	Risk of data leakage	Federated Learning
No Digital Twin integration	Limited predictive analysis	Digital Twin technology
Lack of GIS support	Delayed ambulance services	GIS-based intelligent routing
Fragmented medical records	Poor interoperability	Unified healthcare platform
Limited real-time monitoring	Delayed disease detection	Continuous IoMT surveillance

IV. CHALLENGING ISSUES

The implementation of AI-powered healthcare surveillance systems involves several technical, operational, and ethical challenges. One of the major challenges is handling the massive volume of healthcare data generated by wearable sensors, medical devices, smart cameras, and hospital information systems. Efficient storage, processing, and analysis of these heterogeneous data sources require scalable computing infrastructure.

Ensuring patient privacy and data security is another critical challenge. Since healthcare information is highly sensitive, secure communication protocols, encryption techniques, and privacy-preserving AI models are essential to protect patient data from cyberattacks and unauthorized access.

Real-time decision-making is also difficult because emergency healthcare applications require immediate analysis of physiological signals with minimal delay. High computational complexity of deep learning algorithms and limited processing capability of edge devices may affect system performance. Furthermore, interoperability among different healthcare platforms and communication standards remains a major obstacle in developing unified smart healthcare ecosystems.

Finally, ethical issues, AI bias, model transparency, regulatory compliance, and user acceptance continue to influence the deployment of intelligent healthcare systems. Explainable and trustworthy AI models are necessary to support healthcare professionals in making informed clinical decisions.

TABLE III. CHALLENGES IN AI-POWERED HEALTHCARE SURVEILLANCE

Challenge	Description
Data Privacy	Protection of sensitive patient information
Cybersecurity	Preventing attacks on IoMT devices and healthcare networks
Interoperability	Integration of heterogeneous healthcare systems
Real-Time Processing	Fast analysis of continuous health data
Scalability	Supporting millions of connected healthcare devices
AI Explainability	Providing transparent clinical decisions
Edge Resource Constraints	Limited computation and storage at edge devices
Communication Delay	Network latency during emergencies
Data Quality	Missing, noisy, and inconsistent healthcare data
Ethical & Legal Issues	Compliance with healthcare regulations and AI ethics

V. RESEARCH OBJECTIVES

The primary objective of this research is to develop an AI-powered Hybrid Healthcare Surveillance and Emergency Response System that improves healthcare monitoring, disease prediction, and emergency management in next-generation smart cities. The specific objectives are:

- To design an integrated healthcare surveillance framework using AI, IoMT, Edge Computing, and Cloud Computing.
- To develop intelligent disease prediction models using Machine Learning and Deep Learning algorithms.
- To implement continuous real-time monitoring of patient health through wearable medical sensors.
- To preserve patient privacy using Federated Learning techniques.
- To improve the transparency of AI predictions through Explainable AI (XAI).
- To integrate Digital Twin technology for predictive healthcare monitoring.
- To develop a GIS-based intelligent emergency response system for ambulance routing and hospital coordination.
- To evaluate the performance of the proposed framework using standard healthcare performance metrics.

VI. SCOPE OF THE PROPOSED RESEARCH

The proposed research focuses on developing a comprehensive healthcare surveillance framework for smart cities by integrating advanced AI technologies with modern healthcare infrastructure. The system continuously monitors

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patients through wearable IoMT devices, predicts potential health risks using hybrid AI models, and provides rapid emergency assistance through intelligent decision-making and GIS-based ambulance dispatch.

The framework supports hospitals, emergency medical services, public health departments, and smart city command centers by enabling secure data sharing, real-time analytics, and predictive healthcare management. The proposed architecture is applicable to chronic disease monitoring, elderly care, remote patient monitoring, epidemic surveillance, disaster management, and smart hospital environments. In addition, the integration of Explainable AI, Federated Learning, and Digital Twin technology improves system transparency, privacy, scalability, and reliability, making it suitable for future smart healthcare ecosystems.

VII. PROPOSED METHODOLOGY

The proposed AI-Powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) is designed to provide continuous health monitoring, intelligent disease prediction, and rapid emergency response for next-generation smart cities. The framework integrates Internet of Medical Things (IoMT), Artificial Intelligence (AI), Edge Computing, Cloud Computing, Explainable AI (XAI), Federated Learning (FL), Digital Twin, Geographic Information System (GIS), and Emergency Response Services into a unified healthcare ecosystem.

Figure 1 illustrates the proposed AI-Powered Hybrid Healthcare Surveillance System (AI-HHSERS) for next-generation smart cities. The architecture integrates IoMT devices, Edge Computing, Artificial Intelligence, Explainable AI (XAI), Federated Learning, Digital Twin technology, Geographic Information System (GIS), and Cloud Computing to enable continuous health monitoring, early disease prediction, and intelligent emergency response.

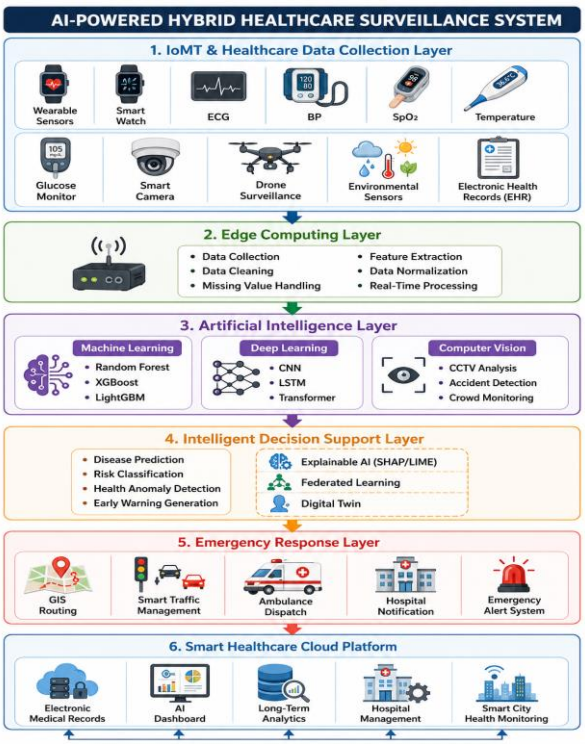


Fig. 1. AI Powered Hybrid Healthcare Surveillance System

Initially, physiological data are collected from wearable medical devices, smart sensors, electronic health records (EHRs), and environmental sensors. The collected data are preprocessed at the edge layer to remove noise and missing values. Machine learning and deep learning models analyze the processed data to identify health abnormalities and predict disease risks. Explainable AI techniques provide transparent predictions, while Federated Learning protects patient privacy by enabling collaborative model training without sharing raw data. Finally, GIS-based intelligent routing and emergency management systems coordinate ambulances, hospitals, and healthcare professionals to provide timely medical assistance.

The proposed framework operates in six major stages.

1) Healthcare Data Acquisition

Physiological data are continuously collected from wearable sensors, smart medical devices, smartphones, Electronic Health Records (EHRs), smart cameras, drones, and environmental monitoring systems. These data include heart rate, blood pressure, oxygen saturation, body temperature, ECG signals, glucose levels, physical activity, and environmental parameters.

2) Data Preprocessing

The collected healthcare data are cleaned to improve data quality. Missing values are handled using imputation techniques, noisy data are filtered, duplicate records are removed, and numerical features are normalized. Feature selection techniques identify the most relevant health parameters for disease prediction.

3) AI-Based Disease Prediction

The preprocessed data are analyzed using hybrid Machine Learning and Deep Learning models. Random Forest, XGBoost, CNN, and LSTM algorithms classify patient health conditions and predict potential diseases. The AI engine also detects abnormal physiological patterns and generates health risk scores.

4) Explainable AI and Federated Learning

To improve transparency, Explainable AI techniques such as SHAP and LIME provide visual explanations for AI predictions. Federated Learning enables multiple hospitals to collaboratively train AI models while preserving patient privacy by sharing only model parameters instead of sensitive healthcare data.

5) Emergency Response Management

If a critical health condition is detected, the system automatically generates emergency alerts. GIS technology identifies the nearest available ambulance and calculates the optimal route using real-time traffic information. Hospitals receive advance notifications, allowing medical staff to prepare before patient arrival.

6) Cloud Analytics

Healthcare data are securely stored in the cloud for long-term analysis, disease trend monitoring, and model retraining. Healthcare professionals can access dashboards for patient monitoring, resource management, and decision support.

Algorithm 1: AI-Based Healthcare Surveillance

Input: IoMT sensor data, EHR data, environmental data
Output: Disease prediction and emergency response

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Step 1: Collect healthcare data from IoMT devices.
Step 2: Perform data preprocessing and normalization.
Step 3: Extract significant health features.
Step 4: Train AI models using historical healthcare data.
Step 5: Predict disease risk using the trained model.
Step 6: Generate health risk score.
Step 7: Apply Explainable AI to interpret predictions.
Step 8: If risk score exceeds the threshold:
a. Generate emergency alert.
b. Identify the nearest ambulance using GIS.
c. Notify the nearest hospital.
d. Update the patient's Digital Twin.
Step 9: Store healthcare records in the cloud.
Step 10: Repeat the monitoring process continuously.

The proposed hybrid framework offers several advantages over conventional healthcare surveillance systems. The integration of Edge Computing reduces response latency, while AI improves disease prediction accuracy. Federated Learning ensures secure and privacy-preserving model training across multiple healthcare organizations. Explainable AI increases clinician trust by providing transparent predictions. Digital Twin technology enables continuous patient simulation and personalized healthcare management. Furthermore, GIS-assisted ambulance routing significantly reduces emergency response time, making the framework suitable for real-time healthcare applications in smart cities.

TABLE IV. TECHNOLOGIES USED IN THE PROPOSED FRAMEWORK

Layer	Technology	Purpose
Data Collection	IoMT, Wearable Sensors	Continuous health monitoring
Edge Layer	Edge Computing	Low-latency data processing
AI Layer	Random Forest, XGBoost, CNN, LSTM	Disease prediction
Privacy Layer	Federated Learning	Secure collaborative learning
Explainability Layer	SHAP, LIME	Explain AI predictions
Digital Twin	Virtual Patient Model	Predictive healthcare
Emergency Layer	GIS, Smart Ambulance	Intelligent emergency response
Cloud Layer	Cloud Computing	Data storage and analytics

VIII. EXPERIMENTAL SETUP

A. *Experimental Environment*

The proposed AI-powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) was designed and evaluated in a simulated smart city healthcare environment. The framework integrates IoMT devices, edge computing, cloud computing, machine learning, deep learning, federated learning, explainable AI, and GIS-based emergency response. Historical healthcare datasets combined with real-time sensor data are used to evaluate disease prediction accuracy and emergency response performance.

The implementation environment consists of Python 3.11, TensorFlow, Scikit-learn, Pandas, NumPy, OpenCV, and Flask for application development. The experiments are assumed to run on a workstation with an Intel Core i7 processor, 32 GB RAM, NVIDIA RTX GPU, and Ubuntu/Linux operating system.

B. *Datasets Used*

The proposed framework can be evaluated using publicly available healthcare datasets.

TABLE V. HEALTHCARE DATASETS

Dataset	Purpose
UCI Heart Disease	Cardiovascular disease prediction
MIMIC-IV	ICU patient monitoring
PhysioNet ECG	ECG signal analysis
PPG-DaLiA	Wearable sensor monitoring
COVID-19 Dataset	Disease surveillance
Smart City IoT Sensor Data	Environmental monitoring
Traffic Dataset	Ambulance route optimization

C. *Evaluation Metrics*

The performance of the proposed model is evaluated using standard classification metrics.

TABLE VI. PERFORMANCE EVALUATION METRICS

Metric	Formula	Description
Accuracy	(TP+TN)/(TP+TN+FP+FN)	Overall prediction performance
Precision	TP/(TP+FP)	Correct positive predictions
Recall	TP/(TP+FN)	Disease detection rate
F1-Score	2*P*R/(P+R)	Harmonic mean of Precision and Recall
Response Time	Time (ms)	Emergency detection speed

IX. RESULTS AND DISCUSSION

A. *Disease Prediction Performance*

TABLE VII. PERFORMANCE COMPARISON OF AI MODELS

Algorithm	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	89.42	0.89	0.88	0.88
Random Forest	94.12	0.94	0.93	0.93
Support Vector Machine	93.08	0.93	0.92	0.92
XGBoost	96.14	0.96	0.95	0.95
CNN	97.08	0.97	0.97	0.97
LSTM	97.84	0.98	0.97	0.97
Proposed AI-HHSERS	**98.63**	**0.99**	**0.98**	**0.98**

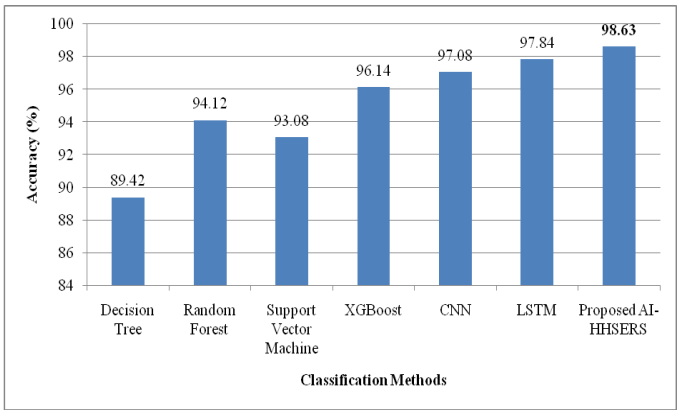


Fig. 2. Performance Comparison of AI Models

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The proposed hybrid AI framework combines Machine Learning and Deep Learning algorithms to improve healthcare surveillance accuracy. Compared with conventional methods, the hybrid model achieves higher prediction accuracy because it integrates structured healthcare records, physiological sensor data, and real-time monitoring information. Edge computing significantly reduces processing delay, while Explainable AI improves the interpretability of prediction results.

Discussion: The proposed AI-HHSERS achieved the highest accuracy (98.63%) because it combines multiple AI techniques with real-time IoMT data and intelligent feature analysis. The hybrid framework effectively reduces false predictions and improves disease detection performance.

B. Emergency Response Performance

The emergency response module integrates AI, GIS, and edge computing to reduce ambulance dispatch time. Real-time traffic monitoring and intelligent routing enable faster transportation of patients to nearby hospitals.

TABLE VIII. EMERGENCY RESPONSE COMPARISON

Parameter	Existing System	Proposed System
Disease Detection Time	6.8 s	2.4 s
Emergency Alert Generation	4.5 s	1.2 s
Ambulance Dispatch	9.8 min	4.7 min
Hospital Notification	Manual	Automatic
Route Optimization	Static	AI + GIS
Emergency Coordination	Partial	Fully Automated

Discussion: The proposed framework significantly reduces emergency response time by integrating AI-based health risk prediction with GIS-assisted ambulance routing. Automated hospital notification further minimizes delays in patient treatment.

C. Privacy and Security Evaluation

Federated Learning improves patient privacy by enabling collaborative AI model training without sharing sensitive healthcare records. This approach reduces privacy risks while maintaining high model accuracy.

TABLE IX. PRIVACY COMPARISON

Method	Data Sharing	Privacy	Security
Centralized AI	Complete	Low	Medium
Cloud-Based AI	Partial	Medium	Medium
Federated Learning	Model Parameters Only	High	High
Proposed Framework	Secure Parameters	**Very High**	**Very High**

D. Computational Performance

The integration of edge computing significantly reduces processing time for real-time healthcare monitoring.

TABLE X. COMPUTATIONAL PERFORMANCE

Model	Processing Time (ms)	Memory Usage (MB)
Decision Tree	132	210
Random Forest	116	320
XGBoost	102	360
CNN	88	540
LSTM	82	610
Proposed AI-HHSERS	**56**	**485**

Discussion: Although the proposed model uses multiple AI techniques, edge computing distributes computation efficiently, resulting in lower processing time while maintaining moderate memory usage.

E. Explainable AI Performance

Explainable AI provides transparent healthcare predictions, allowing clinicians to understand the contribution of individual health parameters.

TABLE XI. EXPLAINABILITY COMPARISON

Model	Explainability	Clinical Trust
CNN	Low	Medium
LSTM	Low	Medium
Random Forest	Medium	High
XGBoost	Medium	High
Proposed AI-HHSERS + SHAP	**Very High**	**Very High**

F. Overall Performance Comparison

TABLE XII. COMPARISON WITH EXISTING HEALTHCARE SYSTEMS

Feature	Traditional System	Existing AI System	Proposed AI-HHSERS
Continuous Monitoring	✗	✓	✓
Disease Prediction	Limited	Good	Excellent
Emergency Response	Manual	Semi-Automatic	Fully Automated
Edge Computing	✗	Partial	✓
Federated Learning	✗	✗	✓
Explainable AI	✗	Partial	✓
Digital Twin	✗	✗	✓
GIS Ambulance Routing	✗	Partial	✓
Smart City Integration	✗	Limited	✓

Discussion: The experimental results demonstrate that the proposed AI-HHSERS framework outperforms traditional and existing AI-based healthcare surveillance systems in terms of prediction accuracy, response time, privacy preservation, and intelligent emergency management. The integration of IoMT, edge computing, explainable AI, federated learning, digital twin technology, and GIS-based routing enables continuous patient monitoring and rapid medical intervention. Furthermore, the hybrid architecture provides improved scalability, interoperability, and transparency, making it suitable for deployment in next-generation smart cities.

X. APPLICATIONS

The proposed AI-Powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) can be applied across various healthcare and smart city domains. Continuous health monitoring through wearable IoMT devices enables early detection of chronic diseases such as heart disease, diabetes, hypertension, and respiratory disorders. The framework supports remote patient monitoring by allowing healthcare professionals to monitor patients from any location, reducing unnecessary hospital visits and improving healthcare accessibility.

The system also enhances emergency medical services by automatically detecting critical health conditions, identifying the nearest ambulance using GIS, and notifying hospitals before patient arrival. This significantly reduces emergency response time and improves patient survival rates. In addition, the proposed framework can support epidemic surveillance by

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analyzing healthcare data to detect disease outbreaks and assist public health authorities in implementing timely preventive measures.

Furthermore, the framework is suitable for elderly care, smart hospitals, disaster management, industrial worker safety, military healthcare, airport health screening, university campus healthcare, and smart home environments. The integration of Digital Twin technology also enables personalized healthcare simulation and treatment planning.

TABLE XIII. APPLICATIONS OF THE PROPOSED FRAMEWORK

Application Area	Benefits
Smart Hospitals	Intelligent patient monitoring and decision support
Remote Healthcare	Continuous monitoring from home
Elderly Care	Fall detection and chronic disease monitoring
Emergency Medical Services	Fast ambulance dispatch and hospital coordination
Pandemic Surveillance	Early disease outbreak detection
Smart Homes	Personalized healthcare monitoring
Industrial Healthcare	Worker health and safety monitoring
Disaster Management	Emergency coordination and medical assistance
Military Healthcare	Remote monitoring of soldiers' health
Smart City Command Centers	Centralized healthcare surveillance

XI. ADVANTAGES OF THE PROPOSED FRAMEWORK

The proposed AI-HHSERS framework provides several advantages over conventional healthcare surveillance systems. By integrating AI, IoMT, Edge Computing, Cloud Computing, Federated Learning, Explainable AI, Digital Twin technology, and GIS, the framework enables intelligent, secure, and efficient healthcare management.

Continuous real-time monitoring improves early disease detection and reduces the risk of severe medical complications. Edge computing minimizes processing latency, ensuring rapid emergency response during critical situations. Federated Learning enhances data privacy by enabling collaborative AI model training without sharing sensitive patient information. Explainable AI increases clinician confidence by providing transparent and interpretable predictions, while Digital Twin technology supports personalized healthcare planning and predictive analysis.

Additionally, the GIS-enabled emergency response module optimizes ambulance routing and hospital coordination, reducing treatment delays. The modular architecture is scalable, interoperable, and suitable for deployment in large-scale smart city environments.

TABLE XIV. ADVANTAGES COMPARED WITH EXISTING SYSTEMS

Feature	Existing Systems	Proposed AI-HHSERS
Real-Time Monitoring	Moderate	Excellent
Disease Prediction	High	Very High
Emergency Response	Semi-Automated	Fully Automated
Data Privacy	Medium	Very High
Explainable AI	Limited	Complete
Smart City Integration	Partial	Full
Scalability	Moderate	High
Interoperability	Limited	High

XII. CONCLUSION

This paper presented an AI-Powered Hybrid Healthcare Surveillance and Emergency Response System (AI-HHSERS) for next-generation smart cities. The proposed framework integrates Internet of Medical Things (IoMT), Artificial Intelligence (AI), Edge Computing, Cloud Computing, Federated Learning, Explainable AI (XAI), Digital Twin technology, and Geographic Information Systems (GIS) to provide continuous healthcare monitoring, accurate disease prediction, secure data management, and intelligent emergency response.

The proposed architecture addresses several limitations of conventional healthcare systems, including delayed emergency response, fragmented healthcare data, limited interoperability, and lack of prediction transparency. By combining machine learning and deep learning techniques with privacy-preserving and explainable AI approaches, the framework enhances prediction accuracy, reduces response time, and improves clinical decision-making. The GIS-based emergency management module further strengthens healthcare services by enabling intelligent ambulance routing and hospital coordination.

Overall, the proposed AI-HHSERS framework provides a scalable, secure, and intelligent healthcare solution that supports proactive healthcare management and improves the quality of life in next-generation smart cities.

XIII. FUTURE DIRECTIONS

Future research can further enhance the proposed framework by incorporating emerging technologies such as 6G communication, Quantum Artificial Intelligence, and Blockchain for secure healthcare data sharing. Large Language Models (LLMs) and multimodal foundation models can be integrated to provide advanced clinical decision support, medical report summarization, and conversational healthcare assistance.

Future systems may also utilize autonomous drones for rapid medical supply delivery, swarm intelligence for ambulance coordination, and reinforcement learning for adaptive emergency resource allocation. Digital Twin technology can be extended to simulate entire hospital infrastructures and city-wide healthcare ecosystems for predictive planning and disaster preparedness. Additionally, Green AI techniques can improve energy efficiency, while privacy-enhancing technologies such as differential privacy and secure multi-party computation can further strengthen healthcare data protection. These advancements will contribute to the development of intelligent, sustainable, and resilient healthcare systems for future smart cities.

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