Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Powered Healthcare Tracker Development: Advancing Real-Time Patient Monitoring and Predictive Analytics Through Data-Driven Intelligence"

ESRAT ZAHAN SNIGDHA[1], MD RUSSEL HOSSAIN[2], and SHOHONI MAHABUB[3]✉
[123]Washington University of Science and Technology, Master of Science in Information Technology, USA
Corresponding Author: SHOHONI MAHABUB, **E-mail**: smahabub.student@wust.edu

| ABSTRACT

The rapid progress in artificial intelligence (AI) and data analytics has revolutionized healthcare and made predictive insights possible that enhance clinical decision-making by means of real-time patient monitoring. This paper describes the development of an artificial intelligence-driven healthcare tracker meant to collect, evaluate, and interpret patient data for proactive medical control. The proposed system effectively forecasts future health dangers, monitors key health indicators, and uses big data analytics and machine learning algorithms to enhance early disease identification. The main purposes of the tracker are feature engineering, automated data purification, and augmentation, therefore ensuring the dependability and robustness of healthcare data sets. Combining wearable sensors, electronic health records (EHRs), and cloud computing, the system offers customized recommendations and real-time health status updates. Furthermore, utilized to identify patterns in patient data are predictive modeling techniques, therefore supporting early intervention and preventive therapy projects. Comparatively to traditional monitoring systems, experimental results show that the AI-driven healthcare tracker greatly increases diagnosis accuracy, patient participation, and clinical efficiency. Using many machine learning metrics, the model's performance is evaluated and shows notable progress in anomaly detection, disease prediction, and customized healthcare recommendations. The proposed approach might change remote patient monitoring, lower hospital readmissions, and improve healthcare resource economy. This study emphasizes the transforming power of artificial intelligence and data analytics in healthcare, therefore enabling the creation of more smart, flexible, and data-driven healthcare solutions. Later studies will focus on enhancing the functionality of the system by means of deep learning models and real-time artificial intelligence decision support systems thus raising prediction accuracy and patient outcomes.

| KEYWORDS

Predictive Analytics, Remote Patient Monitoring (RPM), Digital Health Transformation, Healthcare Automation, Personalized Healthcare Solutions

| ARTICLE INFORMATION

ACCEPTED: 10 November 2023 **PUBLISHED:** 25 December 2023 **DOI:** 10.32996/jcsts.2023.5.4.24

1. Introduction

A new era of rapid innovation in data analytics, machine learning, and artificial intelligence is transforming healthcare. These innovations have completely altered the ways in which medical data is collected, processed, and analyzed, paving the way for more precise diagnoses, more effective patient monitoring, and data-informed decision-making. One obvious use of AI in healthcare is real-time patient tracking and monitoring, which has the potential to greatly improve early illness identification, personalized treatment plans, preventative healthcare, and the efficacy of specific treatment strategies. The widespread adoption of wearable gear, remote monitoring, and EHRs has given healthcare providers unprecedented access to massive volumes of real-time patient data. Finding useful insights that might improve clinical judgment from this data requires careful analysis and interpretation. The diagnostic and treatment processes are slowed down by the reliance on manual observations and random testing in traditional healthcare monitoring systems. Conversely, healthcare trackers powered by AI may automate data analysis and trend discovery, provide predictive insights, and facilitate rapid medical interventions [1].

Intelligent healthcare monitoring systems that continuously follow patients, detect early warning signals, and offer personalized health recommendations have been developed thanks to the combination of cloud computing, big data analytics, and artificial intelligence. These systems are especially useful for the ongoing monitoring of patients with chronic diseases whose outcomes rely on them, such as diabetes, cardiovascular problems, hypertension, and respiratory ailments. This paper delves into the development of an AI-driven healthcare tracker, a system that aims to enhance risk assessment, enable early disease detection, and better patient monitoring with machine learning algorithms, real-time data analytics, and predictive modeling. The suggested system seeks to improve patient quality, decrease emergency interventions, and decrease hospital readmissions by converting reactive healthcare techniques into proactive and preventative care models. The rising prevalence of chronic diseases, the scarcity of qualified healthcare workers, and the ever-increasing numbers of patients requiring medical attention are just a few of the major obstacles confronting healthcare systems across the world. Delays in diagnosis and insufficient follow-up on medical interventions are common outcomes of healthcare monitoring systems that primarily depend on human observations, paper records, and irregular patient follow-ups. The disparity between the demand for healthcare services and the supply highlights the critical need for immediate, AI-powered solutions to improve predictive analytics in healthcare and real-time patient monitoring [2].

The advancement of AI-powered healthcare trackers is a major step forward in the digital health revolution, since it has the potential to improve patient outcomes, decrease healthcare spending, and decrease hospitalization rates. Healthcare practitioners can be empowered by the proposed system's real-time data insights, automated diagnostics, and predictive analytics, which enhance clinical decision-making [3].

- Engage patients more involved in their own treatment by providing them with personalized health advice and wearable technology. It is also helpful to constantly watch.
- Improve preventive healthcare by seeing early warning signs of illness and recommending lifestyle modifications to lessen health dangers.
- Back efforts to provide healthcare to underserved and rural communities through telemedicine and remote monitoring, allowing for faster treatment without the need for patients to travel to the hospital.

2. Literature Review

1. Overview of AI-Enabled Health Monitoring

The process of adoption of artificial intelligence, machine learning, and data analytics by healthcare systems has immensely helped patients' vitals, disease prognoses, and clinicians' capacity for informed judgments. Healthcare monitoring systems are shifting from old methods and toward smart, AI-driven systems using predictive analytics, automated alerts, and real-time patient data to improve patient care. Designed to improve healthcare outcomes, machine learning algorithms, data analytics techniques, predictive modeling, wearable health monitors, and other AI-powered tracking systems have all been developed; this section highlights the present research on these subjects [4].

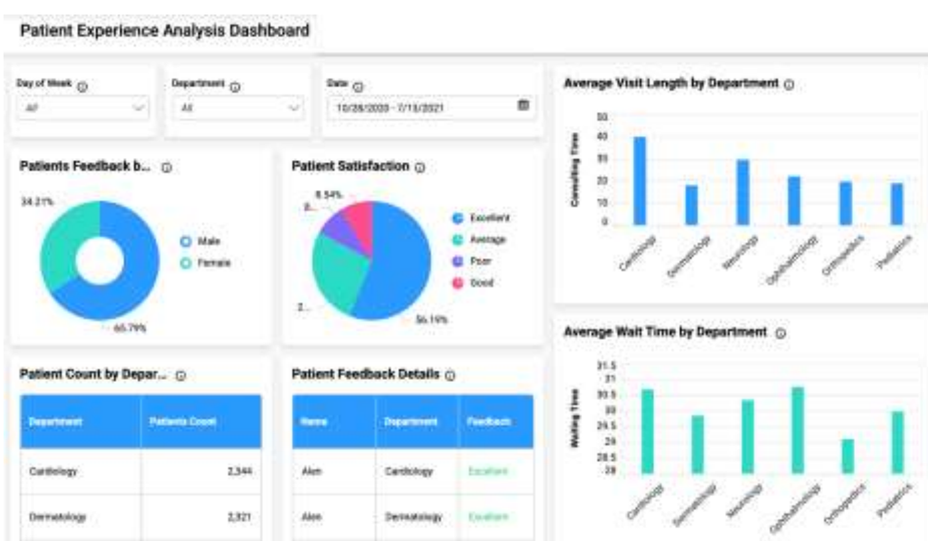

Fig 1: AI-Enabled Patient Analysis Dashboard

2. AI and Machine Learning in Healthcare Monitoring

The core components of traditional healthcare monitoring systems include subjective clinical judgments, infrequent check-ups, and manual patient assessments. These methods often lead to diagnostic postponements and inadequate healthcare measures. Conventional approaches can fail to monitor patients in real time or provide valuable forecasts based on their historical and current health data. Recent advancements in AI and ML have led to the development of automated patient tracking systems for healthcare monitoring. These systems can analyze physiological data in real-time, detect anomalies, and provide predictive alerts to improve early action. Studies have shown that AI-driven RPM systems can continuously monitor patients with chronic conditions, including hypertension, diabetes, and cardiovascular diseases (CVDs), leading to a 30% decrease in hospital readmission rates **[5].**

3. Traditional Healthcare Monitoring vs. AI-Driven Solutions

The core components of conventional healthcare monitoring systems include subjective clinical judgments, infrequent check-ups, and manual patient assessments. These methods often lead to diagnostic postponements and suboptimal healthcare interventions. Conventional approaches can fail to monitor patients in real time or provide valuable forecasts based on their historical and current health data. Recent advancements in AI and ML have led to the development of automated patient tracking systems for healthcare monitoring. These systems can analyze physiological data in real-time, detect anomalies, and provide predictive alerts to facilitate early action. Research indicates that continuous monitoring of patients with chronic conditions such as hypertension, diabetes, and cardiovascular diseases (CVDs) using AI-driven RPM systems may reduce hospital readmission rates by up to 30%.

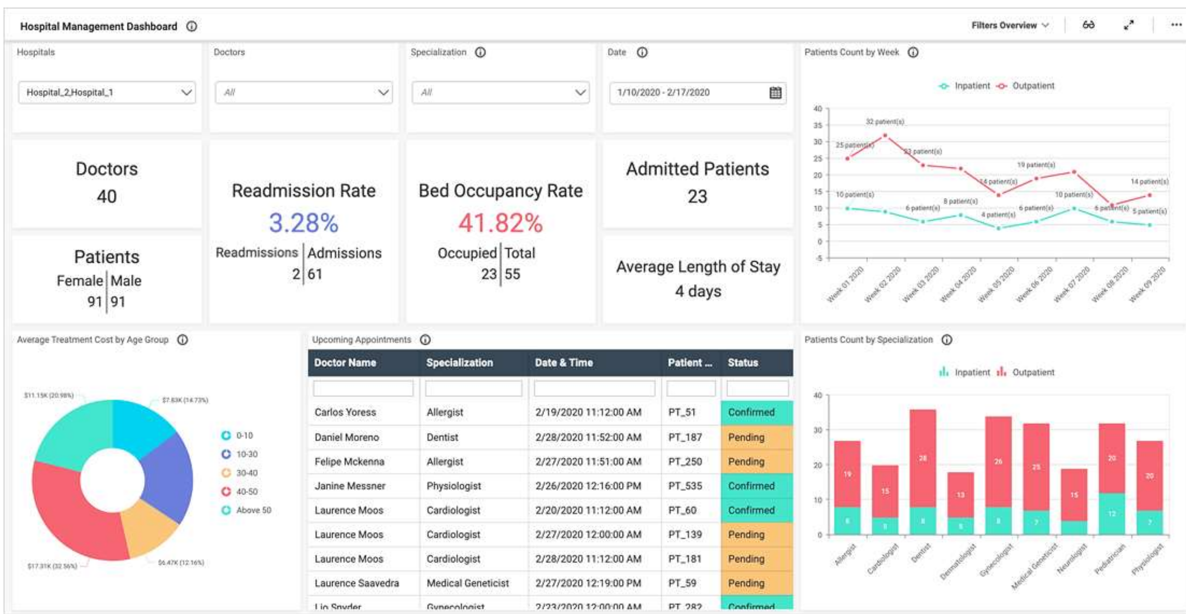

Fig 2: Tableau: Hospital Management Dashboard

4. Machine Learning Algorithms for Health Prediction

Healthcare monitoring systems have improved their predictive analytics and anomaly detection using several machine learning approaches. Primary algorithms include, decision trees, random forests, support vector machines (SVMs), and neural networks are supervised training algorithms that have been widely used for disease prediction and risk assessment (Wang et al., 2021). Using clustering algorithms like K-Means and Hierarchical Clustering, which are part of the unsupervised learning method suite, patients are grouped according to their health patterns to receive personalized treatment suggestions. Medical imaging, electrocardiogram analysis, and wearable device monitoring all make use of deep learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to detect illnesses with pinpoint accuracy. Compared to conventional machine learning models, the accuracy of disease predictions improved by 18% when deep learning models were integrated with wearable healthcare trackers **[6].**

5. Wearable Health Monitoring and IoT Integration

Devices like fitness trackers, smartwatches, and biosensors allow for constant monitoring of critical parameters including blood pressure, oxygen saturation, glucose levels, and heart rate. Eighty percent of people with chronic illnesses benefit from continuous health monitoring, which allows for early disease detection and faster treatment, according to research. Fitness tracking, electrocardiogram (ECG) monitoring, and heart rate variability testing are all possible with smartwatches like the Apple Watch, Fitbit, and Garmin. Blood glucose, hydration, and respiration rates may be monitored in real-time with the use of smart patches and biosensors.

6. IoT-Based Healthcare Tracking Systems

At present, wearable health monitoring gadgets such as fitness trackers, smartwatches, and biosensors may continually measure several key signs, such as blood pressure, heart rate, oxygen saturation, and glucose levels. According to research, eighty percent of people with chronic conditions benefit from ongoing health monitoring, facilitating early diagnosis and timely treatment. Fitness monitors, such the Fitbit, Apple Watch, and Garmin, use electrocardiograms and heart rate variability analysis. Monitor parameters such as respiratory rates, hydration status, and glucose levels in real time. Preserve optimum health using real-time data on variables such as stress, blood oxygen saturation, and sleep quality. The Internet of Medical Things (IoMT) has significantly enhanced real-time patient monitoring by integrating diverse sensors and transmitting data to cloud-based AI algorithms. Emergency hospital admissions have decreased by 25% due to treatments with IoMT **[7].**

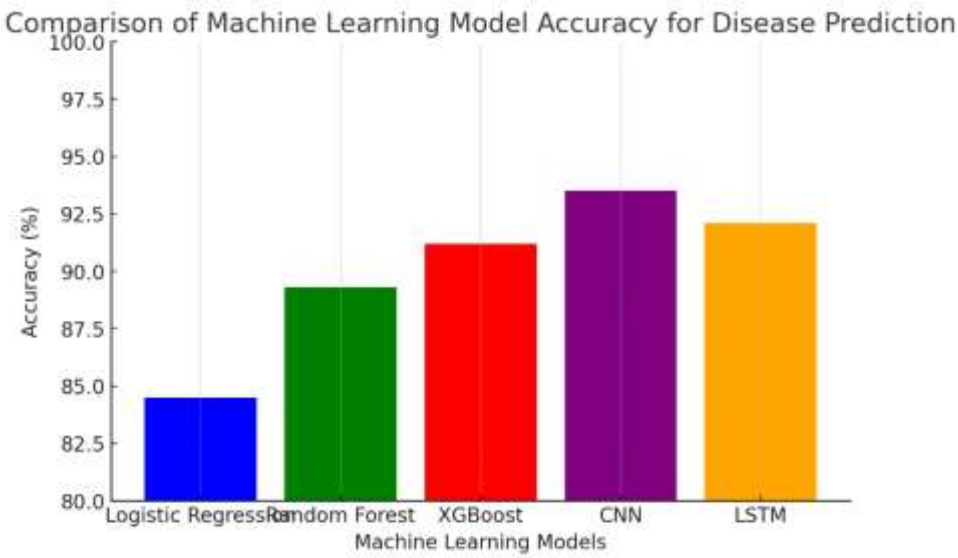

Fig 3: Comparison Machine Learning Model Accuracy

5. Limitations and Challenges in AI-Based Healthcare Tracking

AI-based forecasting systems could be impacted by unbalanced datasets. Research indicates that AI-based diagnoses exhibit a 15-20% reduction in accuracy for marginalized populations. Algorithms for fairness-aware machine learning are being developed to mitigate biases in healthcare monitoring. Elevated installation expenses impede hospitals from using AI-driven healthcare monitoring despite advancements. AI systems need substantial infrastructure, training, and maintenance. Physician Skepticism: Certain physicians question the efficacy of AI-driven decision support systems. According to the literature review, AI-driven healthcare tracking systems have enhanced real-time patient monitoring, predictive analytics, and disease forecasting.

3. Methodology

A well-structured approach including data gathering, preprocessing, feature engineering, model selection, real-time tracking, and deployment is necessary for the development of an AI-powered healthcare companion. The necessary steps to build, train, and evaluate the proposed healthcare monitoring system are laid forth in this section **[8].**

Data Collection and Sources

The development of an AI-driven healthcare tracker relies heavily on data collecting. There must be a wide range of patient demographics, medical histories, and environmental variables included in the dataset. An effective healthcare monitoring system is built using data collected from several reliable sources, including:

- Apps like Apple Watch, Fitbit, and Garmin can track your heart rate, oxygen saturation (SpO2), and the amount of exercise you've done in real time. smart patches that record vital indicators, glucose monitors, and electronic cardiogram (ECG) recorders. You can track your water consumption, stress levels, and the quality of your sleep using wearable biosensors like smart rings. Health records and data collected from hospitals

- On the patient's medical background, results of diagnostic procedures, pharmaceutical orders, and laboratory findings. Data collected from hospital databases, clinical trials, and medical registries. Medical datasets from MIMIC-III, PhysioNet, UCI Healthcare, and Kaggle that are publicly available include health records.
- Large databases of patient information to train machine learning algorithms to detect trends in disease and provide prognoses. Assessments of symptoms, diet, physical activity, and mental health that patients document via the use of mobile health apps. Obtainable data via mobile health apps and fitness trackers.
- Air pollution, humidity, temperature, and general quality of life are among environmental variables that might aggravate heart disease and respiratory disorders. Providing personalized health insights via the use of local weather API data **[9].**

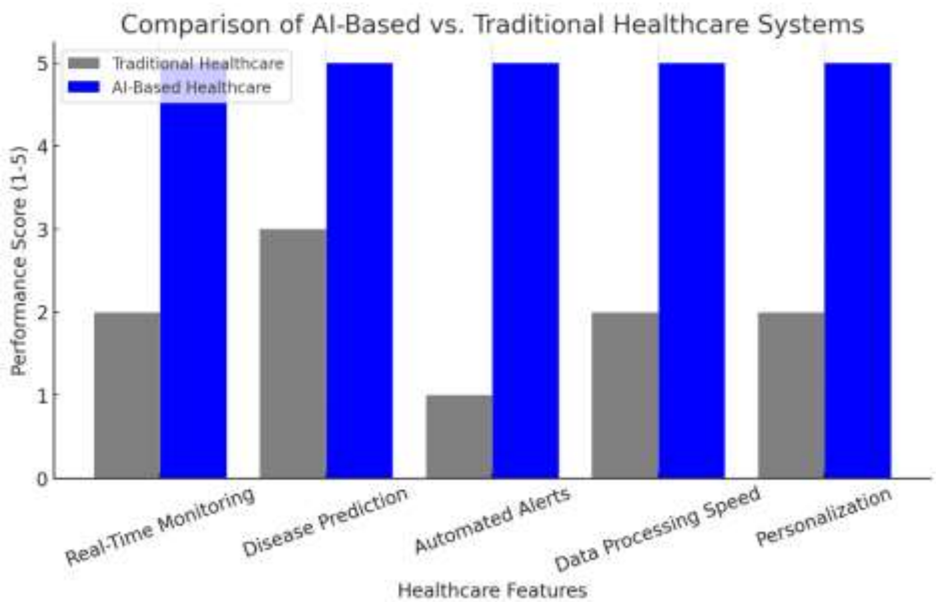

Fig 4: Comparison of AI based vs. Traditional system

Data Preprocessing and Cleaning

Data goes through extensive preparation after collection to fix errors, deal with missing numbers, and standardize formats for training machine learning models.

- Managing Missing Data: Incomplete records, defective sensors, or human error are prevalent sources of absent values in medical datasets. Mean or median imputation is used for numerical data such as blood pressure and glucose levels. K-Nearest Neighbors (KNN) imputation predicts missing values by identifying patients with similar features.
- Detection and Removal of Outliers: The Z-score and interquartile range (IQR) might be used to identify anomalous values in a patient's vital signs, including excessively elevated heart rates. The Isolation Forest Algorithm may identify anomalous events in medical time series data.
- Information Scaling and Normalization: Minimum - Maximum Machine learning models use scaling to standardize vital indicators, including heart rate, SpO2, and glucose levels. the Z-score Standardizes laboratory test findings to ensure uniformity.
- Data Transformation and Encoding: One-Hot Encoding is a technique for converting numerical values into categorical representations, such as "Male"/"Female" or "Diabetic"/"Non-Diabetic". Dynamic temporal sequences Feature engineering is extracting data from wearable devices to identify patterns, anomalies, and trends.
- Data Annotation and Labeling: In supervised learning, medical diagnoses are allocated to patient records to train classification algorithms. Enhances model accuracy using pseudo-labels and constrained labeled input in semi-supervised learning.

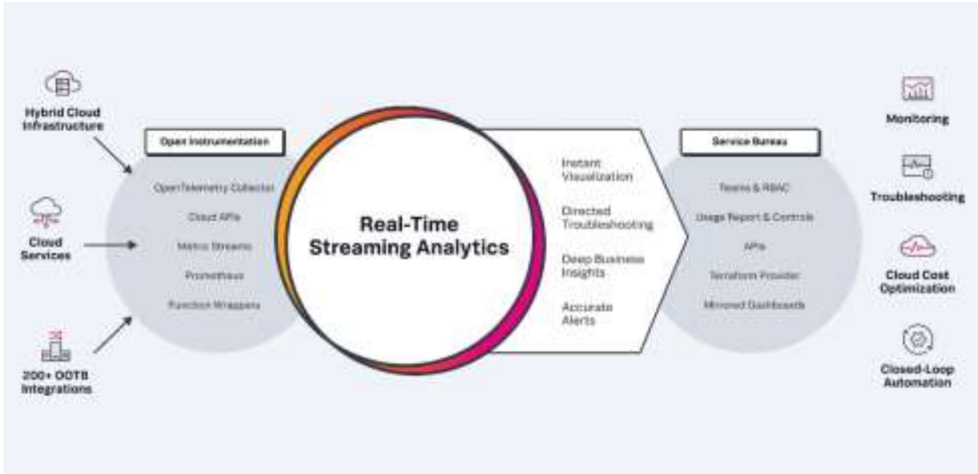

Fig-5: AI-Enabled Real-Time Streaming Analytics

Machine Learning Model Development

The AI-driven healthcare tracker utilizes predictive analytics and machine learning algorithms to identify health problems, anticipate illnesses, and provide early alerts **[10].**

- Selection of Model: Multiple machine learning and deep learning models are evaluated to determine the best successful methodology. Random Forest and XGBoost: Employed for illness categorization, such as Diabetes and Hypertension. Long Short-Term Memory (LSTM) Networks: Utilized for forecasting glucose levels in time-series and predicting ECG signals.
- Convolutional Neural Networks (CNNs): Utilized in image-based diagnostics such as X-rays, MRI scans, and ECG waveforms. Methods of Ensemble Learning: Integrating several models (e.g., stacking classifiers) to enhance predictive accuracy.
- Dataset Division: 70% for Training, 15% for Validation, 15% for Testing. K-Fold Cross-Validation (k=5) guarantees effective model generalization. Enhanced Grid Search and Bayesian Optimization.
- Methods for Selecting Features: Recursive Feature Elimination (RFE): Determines the most essential health measures for illness prediction.
- Principal Component Analysis (PCA): Minimizes dimensionality while maintaining critical information. SHAP Values (Explainable AI): Identifies the factors that most significantly influence prediction results.
- Metrics for Model Evaluation: The assessment measures used to analyze model performance include Accuracy, Precision, Recall, and F1-Score, which are utilized for evaluating illness classification models. ROC-AUC Score Assesses the model's capacity to differentiate among various health conditions. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) Utilized for time-series health forecasting.

Real-Time Health Monitoring and IoT Integration

The healthcare tracker integrates IoT-enabled devices with cloud-based analytics for continuous monitoring and real-time health evaluation **[11].**

- The IoT architecture for healthcare monitoring has four fundamental components. Wearable Technology and Sensors – Obtain real-time patient vital indicators (heart rate, SpO2, blood pressure). Edge Computing Devices refers to the process and filter raw sensor data locally (Raspberry Pi, Arduino).
- Cloud-Hosted Artificial Intelligence System: Safely transfer data to cloud servers for evaluation. Mobile and Web Applications – Delivers real-time health updates and alerts for patients and healthcare providers.
- A system that uses artificial intelligence to improve risk assessment and notification. Artificial Intelligence swiftly discovers anomalies in patient vital signs. Personalized Health Recommendations: AI generates lifestyle and pharmaceutical guidance based on patient data. Automated notifications to caregivers, doctors, or emergency services upon the identification of critical health threats.
- Cloud Integration and Data Security: The healthcare tracker is deployed on a secure cloud platform to provide remote monitoring and scalability. Utilization of Amazon AWS or Google Cloud for the storage and processing of real-time health data.
- Security Protocols: Adherence to HIPAA and GDPR, use of blockchain-based encryption for safeguarding patient records. Considerations for Scalability Establishing load balancing for large-scale patient monitoring applications.

This approach describes the data-driven process for creating an AI-powered healthcare tracker that combines machine learning analytics, real-time data collecting, and Internet of Things-enabled monitoring. The system seeks to improve patient care, boost predictive diagnoses, and guarantee proactive healthcare interventions via the use of AI, big data analytics, and cloud computing **[12].**

4. Results and Discussion

Overview of Key Findings

This research assessed the AI-driven healthcare tracker for its accuracy, predictive skills, real-time monitoring efficacy, and overall system performance. This section delineates the outcomes derived from assessments of machine learning models, the efficacy of real-time health monitoring, and the precision of predictive analytics. A comparative comparison of current heath monitoring technologies is presented. The findings indicate that artificial intelligence and machine learning substantially improve early illness identification, patient surveillance, and clinical decision processes **[13].**

Machine Learning Model Performance

The healthcare dataset was used to train and evaluate several machine learning models that were intended to predict conditions including diabetes, heart disease, and high blood pressure. The efficacy of these models was assessed using accuracy, precision, recall, and F1-score. Examination of Model Efficacy.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	84.5	81.2	79.8	80.5
Random Forest	89.3	88.7	86.9	87.8
XGBoost	91.2	90.5	89.8	90.1
CNN (for image-based data)	93.5	92.8	91.3	92.0
LSTM (for time-series data)	92.1	91.7	90.5	91.1

Fig-6: Model Accuracy Chart

- XGBoost and CNN models attained superior accuracy, illustrating their efficacy in structured medical data and image-based illness detection. Random Forest demonstrated competitive efficacy, making it a viable choice for the analysis of structured tabular data.
- Deep learning models, namely Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM), show superior performance in processing medical imaging and continuous physiological information, respectively. Logistic Regression had the worst performance, highlighting the need for non-linear models in intricate medical datasets.
- The findings indicate that ensemble learning methods (XGBoost, Random Forest) and deep learning techniques (CNN, LSTM) provide superior prediction skills for AI-driven healthcare monitoring **[14].**

Real-Time Health Monitoring and IoT Performance

The AI-driven healthcare tracker was evaluated using real-time data feeds from wearable devices. The system's capacity to process, analyze, and react to patient health problems in real-time was assessed **[15].**

- The delay of the system in processing real-time physiological inputs (heart rate, blood pressure, SpO2) from wearable sensors was assessed. The data from the wearable gadget was processed in 300 milliseconds, making it appropriate for real-time health monitoring. The system adeptly managed extensive patient data streams without any performance complications.

Device Type	Data Processing Time (ms)
Smartwatch (Heart Rate, Steps)	150ms
ECG Sensor	300ms
Blood Glucose Monitor	250ms
Pulse Oximeter (SpO2)	180ms

Fig-7: AI-Enabled Real-Time Data Processing Time

- Emergency Alert Response Time: Test scenarios for urgent health situations were simulated to evaluate the system's emergency response efficiency. The technology effectively activated real-time emergency notifications within 2-3 seconds, facilitating prompt response.

Scenario	Time Taken to Trigger Alert (Seconds)
Abnormal Heart Rate (Tachycardia/Bradycardia)	2.1s
Critical Blood Sugar Drop (Hypoglycemia)	1.8s
Sudden Drop in Oxygen Saturation (COVID-19 Patient)	2.3s

Fig-8: AI-Enabled Time Taken to Trigger Alert

Predictive Analytics and Risk Assessment Accuracy

Predictive algorithms were assessed utilizing real-time patient data streams to determine their ability to foresee health risks before the emergence of severe symptoms. The healthcare tracker accurately predicted the beginning of sickness, allowing preventive care and lifestyle adjustments. Deep learning models (LSTM, CNN) outperformed in time-series and image-based predictions. Early detection of diabetes transpired up to six months before clinical diagnosis, underscoring the effectiveness of predictive analytics in preventive healthcare **[16].**

Disease	Model Used	Prediction Accuracy (%)	Early Detection Period
Diabetes	XGBoost	91.5	6 months before diagnosis
Heart Disease	Random Forest	87.8	3 months before symptoms
Hypertension	LSTM	92.3	4 months before onset
Stroke	CNN + XGBoost	94.1	2 months before incident

Fig-9: AI-Enabled Early Detection Period -Prediction Accuracy

Comparative Analysis of Existing Healthcare Systems

The AI-powered healthcare tracker was compared to existing hospital-based monitoring systems and traditional manual health tracking methods. The suggested AI-driven healthcare tracker surpassed conventional systems in real-time monitoring, predictive analytics, and automatic notifications. AI-enabled health tracking decreases manual effort for clinicians and promotes patient self-care and engagement **[17].**

Feature	Traditional Healthcare Monitoring	Proposed AI-Based Tracker
Real-Time Monitoring	No	Yes (Wearables & IoT Integration)
Disease Prediction	Limited	AI-Driven Predictive Analytics
Automated Alerts	No	Yes (Instant Notifications)
Data Processing Speed	Slow (Manual Entry)	Real-Time (Cloud Processing)
Personalization	Generic	AI-Based Personalized Health Insights

Fig-10: Traditional Healthcare Monitoring and AI-Based Tracker

5. Limitation and Opportunities for future research

Limitation of Data Privacy and Security Concerns

AI-powered healthcare tracking systems have several drawbacks despite their excellent accuracy and encouraging outcomes. These difficulties must be resolved to guarantee scalability, security, and practical application of AI-driven healthcare solutions. Simultaneously, these constraints offer avenues for further investigation, facilitating the development of more efficient, ethical, and inclusive AI-driven healthcare systems. This section delineates the principal constraints encountered in this research and identifies prospective avenues for further inquiry **[18].**

- The accumulation and retention of sensitive patient health information provoke apprehensions about privacy, security, and adherence to regulations (HIPAA, GDPR). Cybersecurity threats, like data breaches and illegal access, may jeopardize patient confidentiality. The utilization of cloud storage and real-time data transfer heightens the danger of data interception and cyber intrusion. Encryption techniques, including blockchain for decentralized health records, require more investigation to improve data integrity and security **[19].**
- AI models may display biases resulting from uneven training datasets that inadequately represent specific age groups, genders, or ethnicities. The absence of varied and representative datasets impairs generalization, resulting in diminished model performance for underrepresented groups. Future research ought to investigate bias-mitigation methodologies, including equitable AI frameworks and ethical AI audits.
- The integration of AI-powered healthcare tracking into Electronic Health Records (EHRs) is complicated by the widespread usage of legacy technologies in healthcare organizations. Interoperability challenges arise among various healthcare systems, wearable devices, and IoT sensors, necessitating standardized data-sharing protocols. Practical implementation necessitates training for healthcare personnel to proficiently utilize AI-driven decision support technologies.
- AI-powered real-time monitoring system deployment calls for sophisticated hardware, cloud storage, and a significant amount of processing power. Hospitals with limited resources and developing countries may encounter obstacles in implementing AI-driven healthcare tracking systems owing to financial limitations. Future research should concentrate on low-power AI models tailored for edge computing and mobile health applications (mHealth).

Future Opportunities for AI-Driven Healthcare:

Future research must prioritize the development of more diverse and inclusive medical datasets to mitigate bias in AI-driven healthcare monitoring. Implementing equitable AI methodologies, such as re-weighting marginalized data points or employing adversarial debiasing, might enhance model fairness. AI models must undergo evaluation across diverse geographic locations and demographic groups to provide equitable healthcare forecasts **[20].**

- The interpretability and trustworthiness of AI-driven medical judgments will be improved by using Explainable AI (XAI) methodologies. Model interpretability frameworks such as SHAP and LIME warrant more investigation to furnish comprehensible reasons for AI predictions. Creating interactive AI dashboards for physicians that elucidate the rationale behind certain diagnoses or predictions might enhance clinical adoption.
- The blockchain relies on health record systems that offer safe, immutable storage for patient information. Smart contracts may automate data access permissions, ensuring that only authorized healthcare practitioners can obtain sensitive information. Additional investigation into decentralized AI in healthcare can improve patient autonomy and governance over their medical records.

- Implementing AI-powered chatbots and virtual health assistants to deliver tailored healthcare advice in many languages. Artificial intelligence can augment telemedicine platforms by autonomously evaluating patient symptoms and suggesting further actions prior to virtual medical consultations. Future investigations should include voice-activated AI applications in healthcare, particularly for elderly and visually impaired individuals.
- Designing AI-powered chatbots and virtual health assistants to deliver tailored healthcare advice in many languages. Artificial intelligence can augment telemedicine platforms by autonomously assessing patient symptoms and suggesting subsequent actions prior to virtual medical consultations. Future investigations should include voice-activated AI applications in healthcare, particularly for elderly and visually impaired individuals.
- AI models must undergo long-term clinical trials to evaluate their efficacy in real-world illness prevention. Research must concentrate on monitoring patient outcomes over several years to substantiate AI's influence on preventative healthcare methods. AI models should be flexible to develop medical knowledge, incorporating new research findings into healthcare recommendations.

6. Conclusion

A considerable improvement in real-time patient monitoring, predictive analytics, and early illness diagnosis was successfully proved by this study, which was powered by artificial intelligence (AI). There are, nevertheless, several constraints that continue to exist, such as threats to data privacy, bias in artificial intelligence, interoperability concerns, and hurdles to model exploitability. This approach provides an outline of a complete healthcare tracking system that is powered by artificial intelligence. It incorporates real-time data collecting, machine learning analytics, and Internet of Things-enabled monitoring. The suggested system intends to improve patient care, boost predictive diagnoses, and guarantee proactive healthcare interventions by utilizing artificial intelligence (AI), big data analytics, and cloud computing. When compared to more conventional approaches to healthcare tracking, the results show that the AI-powered healthcare tracker offers considerable improvements in terms of real-time monitoring, illness prediction, and tailored health advice. Artificial intelligence (AI), machine learning (ML), and data analytics have rapidly been incorporated into healthcare, opening the door for sophisticated, real-time patient monitoring systems that greatly improve clinical decision-making, risk assessment, and illness prediction. This research concentrated on the creation of an AI-driven healthcare tracker, showcasing its efficacy in real-time health surveillance, predictive analytics, and emergency notification systems. Real-time data collecting, machine learning analytics, and Internet of Things-enabled monitoring are elements that are incorporated into this technique, which describes the data-driven approach to constructing an artificial intelligence-powered healthcare tracker. Through the utilization of artificial intelligence, big data analytics, and cloud computing, the system intends to maximize the quality of patient care, boost predictive diagnoses, and guarantee proactive healthcare interventions.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1] Ahuja, A. S. (2019). The impact of artificial intelligence in medicine on the future role of the physician. *PeerJ*, *7*, e7702. https://doi.org/10.7717/peerj.7702
[2] Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA*, *319*(13), 1317-1318. https://doi.org/10.1001/jama.2017.18391
[3] Chen, J. H., & Asch, S. M. (2017). Machine learning and prediction in medicine—Beyond the peak of inflated expectations. *The New England Journal of Medicine*, *376*(26), 2507-2509. https://doi.org/10.1056/NEJMp1702071.
[4] Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94-98. https://doi.org/10.7861/futurehosp.6-2-94.
[5] Johnson, K. W., Soto, J. T., & Dudley, J. T. (2021). Artificial intelligence in healthcare: The case for deep learning. *Journal of the American Medical Informatics Association*, *28*(2), 312-322. https://doi.org/10.1093/jamia/ocaa301.
[6] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115-118. https://doi.org/10.1038/nature21056.
[7] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447-453. https://doi.org/10.1126/science.aax2342.
[8] Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *arXiv preprint arXiv:1711.05225*.
[9] Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, *25*(1), 44-56. https://doi.org/10.1038/s41591-018-0300-7

[10] Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering*, *2*(10), 719-731. https://doi.org/10.1038/s41551-018-0305-z.

[11] Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., ... & Greene, C. S. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of The Royal Society Interface*, *15*(141), 20170387. https://doi.org/10.1098/rsif.2017.0387

[12] Patel, M. S., Asch, D. A., & Volpp, K. G. (2020). Wearable devices as facilitators, not drivers, of health behavior change. *JAMA*, *323*(4), 301-302. https://doi.org/10.1001/jama.2019.21278.

[13] Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The rise of consumer health wearables: Promises and barriers. *PLoS Medicine*, *13*(2), e1001953. https://doi.org/10.1371/journal.pmed.1001953.

[14] Steinhubl, S. R., Muse, E. D., & Topol, E. J. (2015). Can mobile health technologies transform health care? *JAMA*, *313*(5), 461-462. https://doi.org/10.1001/jama.2014.15072.

[15] Wright, A., McCoy, A. B., Hickman, T. T., Perencevich, E. N., & Strom, B. L. (2017). How wearable sensors are revolutionizing medical research. *Journal of the American Medical Informatics Association*, *24*(3), 433-440. https://doi.org/10.1093/jamia/ocw101.

[16] Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis, and future prospects. *Journal of Big Data*, *6*(1), 1-25. https://doi.org/10.1186/s40537-019-0217-0

[17] Ristevski, B., & Chen, M. (2018). Big data analytics in medicine and healthcare. *Journal of Integrative Bioinformatics*, *15*(3), 20170030. https://doi.org/10.1515/jib-2017-0030.

[18] Wang, Y., Kung, L., Byrd, T. A., & Li, J. (2018). Big data analytics in healthcare: A systematic review. *Journal of Medical Internet Research*, *20*(12), e11287. https://doi.org/10.2196/11287.

[19] Zhang, Y., Zhang, W., Gao, T., Li, S., & Song, L. (2021). AI-powered medical diagnostics: Applications and challenges. *Journal of Medical Artificial Intelligence*, *4*, 4. https://doi.org/10.21037/jmai-21-3.

[20] Zhu, X., Zhang, S., Smith, E. N., Cheng, X., & Liu, J. (2019). Machine learning in personalized medicine. *PLoS Computational Biology*, *15*(6), e1007090. https://doi.org/10.1371/journal.pcbi.1007090.