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Advanced Wearable Health Monitoring System with Multi-Sensor Data and Secure Data Management with Blockchain Technology

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Abstract: Health data management is crucial for informed healthcare decisions. It centralizes real-time information from wearable devices, enabling early detection of issues, personalized recommendations, and comprehensive patient profiles. This organized data aids healthcare professionals in delivering tailored care, improving diagnostics, and enhancing overall patient well-being. Additionally, robust data management ensures security and integrity, instilling patient trust and providing a foundation for impactful research and advancements in healthcare practices. This healthcare data management system utilizes a smartwatch with advanced sensors, including a photo plethysmo gram (PPG) for continuous heart rate monitoring, an accelerometer for physical activity tracking, a skin temperature sensor, a blood pressure monitor, and an electrodermal activity (EDA) sensor for stress assessments. Real-time physiological data is collected, with the PPG sensor capturing blood volume changes, the accelerometer providing insights into physical activity, and the EDA sensor measuring skin conductance for stress levels. The data is transmitted to a centralized platform via IoT, where big data analytics process minute-to-minute variations in heart rate, step counts, sleep patterns, blood pressure, and stress levels. This dataset forms the basis for early health issue detection, personalized recommendations, and detailed patient profiles. The system incorporates blockchain for data security, encrypting and storing information in a decentralized ledger. Patients have control over their data through a user-friendly interface, managing access permissions and providing explicit consent for sharing health information with professionals.

Keywords: *Healthcare, Accelerometer, Skin temperature sensor, Blood pressure monitor, Photoplethysmogram, Electrothermal activity*

1. Introduction

Health data monitoring is crucial for preventive care, early detection, and personalized treatment. It enables real-time tracking of vital signs, medication adherence, and lifestyle factors. This data empowers healthcare professionals to identify trends, assess risk factors, and intervene proactively. Continuous monitoring aids in managing chronic conditions, reducing hospitalization rates, and improving overall patient outcomes [1]. Additionally, aggregated health data contributes to medical research, fostering advancements in treatment strategies and public health initiatives [2]. Ultimately, health data monitoring plays a pivotal role in creating a more efficient and effective healthcare system, enhancing individual well-being, and advancing medical knowledge for the benefit of society [3]. One significant advantage of big data analytics in wearable health tech is the ability to identify early signs of health issues [4]. By analyzing historical data, the system can detect deviations from established patterns, potentially indicating emerging health concerns. For instance, subtle changes in heart rate or irregularities in sleep patterns might be early indicators of cardiovascular issues or sleep disorders [5]. Personalized health recommendations are another key benefit. Big data analytics can analyze an individual's historical data and compare it with anonymized datasets to derive personalized insights [6]. This enables the system to offer tailored recommendations for physical activity, sleep hygiene, and stress management, contributing to individualized and effective healthcare. Moreover, big data analytics facilitates the creation of comprehensive patient profiles [7]. By integrating data from various sources and applying advanced analytics, healthcare providers gain a holistic understanding of an individual's health. In the realm of health data management, blockchain technology revolutionizes the way sensitive medical information is handled, stored, and shared. It operates as a secure and decentralized ledger, ensuring the integrity and privacy of health records [8]. Each piece of data, from heart rate values to blood pressure readings, is encrypted and stored in blocks that are linked in a chain [9, 10]. This not only prevents unauthorized access but also allows patients to have control over their data, granting explicit consent for sharing specific health information with healthcare professionals [11]. The immutability of the blockchain ensures that once information is recorded, it cannot be altered, providing an unalterable and trustworthy history of a patient's health journey. Blockchain technology transforms health data management by enhancing security, privacy, and patient control, laying the foundation for a more efficient and transparent healthcare ecosystem [12]. The objectives of the proposed work are:

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1. Implement real-time health tracking through smartwatch sensors for constant assessment of heart rate, physical activity, blood pressure, and stress levels.
2. Utilize big data analytics to process and analyze minute-to-minute variations in health parameters, generating valuable insights for personalized health recommendations and early issue detection.
3. Employ blockchain technology to ensure the security and integrity of collected health data, offering encryption and decentralized storage for immutability and patient data control.
4. Develop a user-friendly interface, granting individuals explicit control over data access permissions. Enhance privacy by allowing users to share specific health information with healthcare professionals based on informed consent.

2. Literature Review

In the past, healthcare relied heavily on manual check-ups where patients visited medical facilities for periodic assessments. During these visits, healthcare professionals manually measured vital signs such as heart rate and blood pressure. However, this method had limitations as it only provided a snapshot of the individual's health during the visit, missing out on continuous monitoring. It also made it challenging to detect subtle health changes between appointments, potentially delaying the identification of emerging issues. In the earlier stages of health monitoring, wearable devices were predominantly characterized by their emphasis on basic metrics, often limited to features like step counting [13]. These early devices lacked the intricate sensor array that is now commonplace in modern smartwatches. The primary focus was on quantifying physical activity, offering users insights primarily into their exercise routines. However, a significant drawback was the absence of continuous monitoring capabilities, notably the real-time measurement of critical health indicators like heart rate and assessments of stress levels [14]. The limited scope of these early wearables restricted their capacity to provide a comprehensive and nuanced understanding of an individual's health. Users had access to only a fragment of the health data spectrum, missing crucial elements that contribute to a holistic well-being assessment. The inability to continuously monitor vital signs meant that these devices fell short of capturing the dynamic and multifaceted nature of an individual's health status [15]. In contrast to the modern and more advanced health monitoring system, early wearable devices left users with a less sophisticated and insightful overview of their overall well-being.

In less sophisticated healthcare data management systems, the storage and security of health data were areas of significant concern. Traditional methods of data storage lacked robust security measures, exposing health records to potential vulnerabilities. Encryption and decentralized storage mechanisms, now considered standard in advanced systems, were notably absent. This absence meant that health records were susceptible to breaches, posing a threat to patient privacy and the confidentiality of sensitive health information [16]. The deficiency in employing a blockchain component further compounded these security issues. Without the implementation of blockchain technology, data immutability and integrity were not guaranteed. This meant that health records were susceptible to tampering or unauthorized modifications, compromising the reliability and accuracy of the information [17]. Consequently, patients had limited control over who accessed their health data, leading to heightened privacy concerns. The absence of a secure and transparent data management infrastructure not only exposed individuals to potential privacy breaches but also raised ethical questions about the safeguarding of sensitive health information in these less advanced systems [18]. The advent of the described advanced healthcare data management system addresses these shortcomings, providing a secure, transparent, and patient-centric approach to health data storage and access [19-20].

3. Proposed work

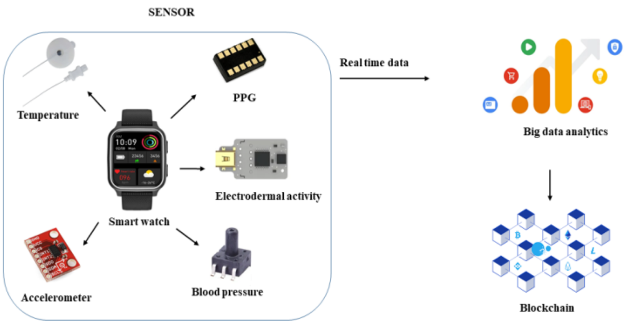

Fig.1 Workflow of healthcare data management

The healthcare data management system is depicted in Fig. 1; the wearable device employed is a smartwatch equipped with advanced health monitoring sensors. These sensors include a PPG sensor for continuous heart rate monitoring, an accelerometer for tracking physical activity and movement patterns, and a skin temperature sensor. Additionally, the smartwatch integrates a blood pressure monitor for non-invasive blood pressure measurements and an EDA sensor for stress level assessments. The smartwatch collects real-time health data by continuously measuring the wearer's physiological parameters. The PPG sensor captures blood volume changes, enabling the calculation of heart rate and detecting irregularities. The accelerometer provides data on physical activity and motion patterns, contributing to an understanding of the wearer's overall fitness and well-being. The blood pressure monitor ensures accurate blood pressure readings, and the EDA sensor measures the skin's electrical conductance, offering insights into stress levels. Data from the wearable device are transmitted to a centralized platform through IoT connectivity. The platform, powered by big data analytics, aggregates and processes the incoming data. The data includes minute-to-minute heart rate variations, step counts, sleep patterns, blood pressure readings, and stress levels. This rich dataset serves as the foundation for research aimed at early detection of health issues, personalized health recommendations, and comprehensive patient profiles. The blockchain component of the system ensures the security and integrity of the collected health data. Each piece of information, such as heart rate values, physical activity metrics, and blood pressure readings, is encrypted and stored in a decentralized ledger. This not only guarantees the immutability of the records but also provides patients with control over their data. The user-friendly interface allows individuals to manage data access permissions, providing explicit consent for sharing specific health information with healthcare professionals.

Table 1 Health sensor data overview

Sensor/ Functionality	*Data type*	*Measurement unit*	*Frequency*	*Purpose/ Insights*
PPG Sensor (Heart Rate Monitoring)	Heart rate	Beats per minute(BPM)	Continuous	Detect irregularities, calculate heart rate
Accelerometer (Physical Activity)	Activity counts	Count	Real-time 1-minute intervals	Monitor physical activity understand movement patterns
Temperature Sensor (Skin Temperature)	Skin temperature	Degrees Celsius (°C)	Real-time 5-minute intervals	Track variations in skin temperature
Blood Pressure Monitor	Blood pressure	mmHg	Real-time 15-minute intervals	Provide accurate blood pressure readings
EDA sensor (Stress Level Assessment)	Electrical conductance	microsiemens (µS)	Real-time 1-minute intervals	Assess stress levels based on skin's electrical conductance

The table.1 provides a comprehensive overview of the key sensors and functionalities in a healthcare data management system, specifically focusing on the data types, measurement units, frequency of data collection, and the intended purposes or insights gained from each sensor. The PPG sensor continuously measures heart rate, providing data in beats per minute (BPM) to detect irregularities and calculate heart rate. The accelerometer tracks physical activity in real time, quantifying it in activity counts, contributing to a better understanding of movement patterns. The temperature sensor measures skin temperature in degrees Celsius at 5-minute intervals, enabling the system to track variations over time. The blood pressure monitor provides accurate blood pressure readings in millimeters of mercury (mmHg) at 15-minute intervals. Lastly, the EDA sensor assesses stress levels based on electrical conductance in microsiemens (µS) at 1-minute intervals, offering valuable insights into the wearer's stress levels. This detailed sensor data types and measurements allow for a nuanced understanding of the wearer's health parameters and facilitate personalized health monitoring.

3.1 Bigdata analytics

In the implemented healthcare system, big data analytics is coordinated using a combination of open-source technologies and specialized software tools. The raw health data collected from wearable sensors, encompassing metrics such as heart rate, physical activity, and stress levels, undergoes a meticulous pre-processing stage to ensure accuracy. This pre-processed data is then stored in Apache Hadoop, a distributed storage system capable of handling vast amounts of diverse data efficiently. The distributed processing of this data is orchestrated through Apache Spark, a parallel computing framework. Machine learning algorithms, implemented using libraries like TensorFlow and sci-kit-learn, are applied to uncover patterns and derive insights from the health data.

$$Z = \frac{X-\mu}{\sigma} \tag{1}$$

Here, X represents an individual heart rate observation, μ is the mean of the heart rate dataset, and σ is the standard deviation. The Z-score helps quantify how many standard deviations an observation is from the mean. Deviations beyond a certain threshold may indicate anomalies or irregularities in the heart rate pattern.

$$Sigmoid(x) = \frac{1}{1+e^{-1}} \tag{2}$$

This function helps introduce non-linearity, enabling the model to capture intricate patterns in the heart rate data. These mathematical equations are integral to the creation of robust predictive models that contribute to the early detection algorithms, enhancing the system's capability to identify potential health issues from wearable sensor data.

The input to the Isolation Forest algorithm consists of a dataset (data) containing heart rate patterns. Parameters such as max_depth determine the maximum depth of each isolation tree, and num_trees specify the number of trees in the ensemble. The dataset includes temporal information about heart rate observations. The output is an ensemble of isolation trees, collectively forming the Isolation Forest. Each tree is constructed based on recursive partitioning of the dataset, isolating instances with shorter average path lengths as potential anomalies. The ensemble serves as a model for anomaly detection, where instances with lower average path lengths across multiple trees are indicative of anomalies in heart rate patterns. This output provides a framework for identifying unusual or unexpected behaviors within the heart rate data, facilitating the early detection of potential health issues.

Algorithm: Isolation forest algorithm

```
IsolationForest(data, max_depth, num_trees):
for each tree in range(num_trees):
subsample = RandomlySelectSubsample(data)
tree = BuildIsolationTree(subsample, 0, max_depth)
AddTreeToForest(tree)
return forest
BuildIsolationTree(data, current_depth, max_depth):
if current_depth >= max_depth or len(data) <= 1:
return CreateLeafNode(data)
split_attribute = RandomlySelectAttribute(data)
split_value = RandomlySelectSplitValue(data, split_attribute)
left_data = SubsetData(data, split_attribute, split_value, "left")
right_data = SubsetData(data, split_attribute, split_value, "right")
left_subtree = BuildIsolationTree(left_data, current_depth + 1, max_depth)
right_subtree = BuildIsolationTree(right_data, current_depth + 1, max_depth)
return CreateInternalNode(split_attribute, split_value, left_subtree, right_subtree)
RandomlySelectAttribute(data):
return RandomlySelectAnAttributeFromData(data)
RandomlySelectSplitValue(data, attribute):
return RandomlySelectValueFromAttribute(data, attribute)
RandomlySelectSubsample(data):
return RandomlySelectSubsetFromData(data)
CreateLeafNode(data):
return LeafNode(data)
CreateInternalNode(split_attribute, split_value, left_subtree, right_subtree):
return InternalNode(split_attribute, split_value, left_subtree, right_subtree)
```

3.2 Data Integrity Using Blockchain

The blockchain serves as a distributed ledger, recording each health data transaction from wearable devices in a secure and transparent manner. As wearable sensors continuously gather a myriad of health metrics, including intricate details such as heart rate variations, step counts, sleep patterns, blood pressure readings, and stress levels, the collected data is not only crucial but also highly sensitive. Before the health data is appended to the blockchain, it undergoes a rigorous encryption process. Each piece of information, whether it's a heart rate value or a blood pressure reading, is encrypted using advanced cryptographic techniques. This encryption ensures that the data remains confidential and impervious to unauthorized access during storage and transmission. Moreover, the blockchain's decentralized architecture means that this encrypted health data is not stored in a single, vulnerable location. Instead, it is distributed across multiple nodes, enhancing the security of the entire system. The tamper-resistant nature of the blockchain is vital for maintaining data integrity. Once a health record is added to the blockchain, it becomes an immutable part of the ledger. Any attempt to alter or tamper with the recorded health data would require consensus among the majority of the decentralized network, making such malicious activities computationally infeasible. This characteristic ensures the authenticity and reliability of the health information stored in the blockchain. Furthermore, the blockchain component empowers patients with control over their own health records. Through the implementation of smart contracts, patients can manage access permissions, providing explicit consent for specific healthcare professionals or entities to view and utilize particular aspects of their health data. This patient-centric approach not only enhances privacy but also aligns with the principles of data ownership and autonomy.

4. Results

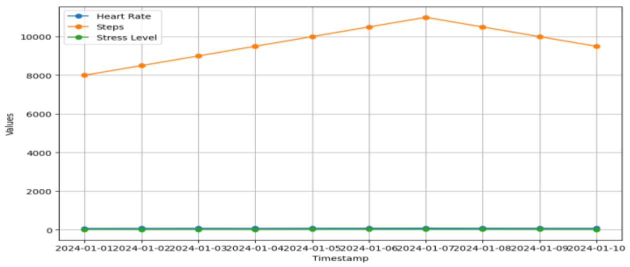

Fig.2 Health data monitoring

The graph resulting from the presented sample data serves as a dynamic representation of an individual's health metrics over a specific period. Examining the graph, we observe fluctuations in the "Heart Rate" line, with values ranging from 75 to 90 beats per minute. These variations can signify changes in cardiovascular activity, potentially indicating periods of increased stress or physical exertion. The "Steps" line on the graph reflects variations in daily physical activity, ranging from 8,000 to 11,000 steps. Peaks in this line suggest higher activity levels, while troughs may represent periods of relative inactivity. This information contributes to our understanding of the individual's exercise patterns and overall fitness engagement. Additionally, the "Stress Level" line exhibits changes over time, with values fluctuating between 18 and 30. These fluctuations may indicate responses to different stressors, providing insights into the wearer's emotional well-being during the monitoring period. By assessing these results, healthcare professionals can draw preliminary conclusions. For instance, they might observe that spikes in physical activity align with lower stress levels or that elevated stress corresponds with increased heart rate.

Table 2 Individual health overview

Timestamp	*Heart rate*	*Steps*	*Blood Pressure (Systolic, Diastolic)*	*Stress level*
2024-01-01 00:00:00	75	8000	(120, 80)	20
2024-01-02 00:00:00	78	8500	(118, 78)	18
2024-01-03 00:00:00	82	9000	(122, 82)	22
2024-01-04 00:00:00	79	9500	(119, 79)	19
2024-01-05 00:00:00	85	10000	(125, 85)	25
2024-01-06 00:00:00	88	10500	(128, 88)	28
2024-01-07 00:00:00	90	11000	(130, 90)	30
2024-01-08 00:00:00	87	10500	(127, 87)	27
2024-01-09 00:00:00	84	10000	(124, 84)	24
2024-01-10 00:00:00	80	9500	(120, 80)	20

Table 2 gives a comprehensive view of an individual's health, capturing key metrics such as heart rate, physical activity, blood pressure, and stress levels through the smartwatch's sensors. This wealth of data serves as a valuable resource for healthcare professionals, offering a nuanced understanding of the wearer's well-being at various timestamps. The data management system, strengthened by blockchain technology, plays a pivotal role in securing and maintaining the integrity of this sensitive health information. Each data point, encompassing heart rate values, step counts, and blood pressure readings, is encrypted and securely stored in a decentralized ledger. This not only guarantees the immutability of records but also empowers individuals with control over data access permissions. Through this mechanism, users can explicitly grant consent for sharing specific health information with healthcare professionals.

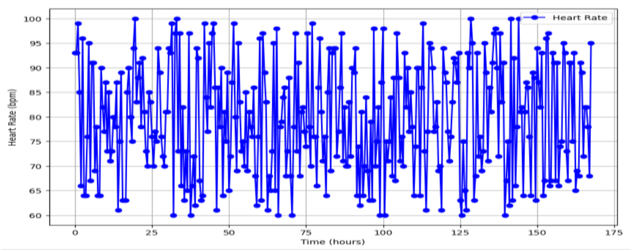

Fig.2 Heart rate over time

Fig. 2, depicting heart rate trends over time, represents the healthcare data management system's efficacy. The x-axis represents time, with data collected every 30 minutes over a week, while the y-axis denotes heart rate in beats per minute (bpm). The system monitored the wearer's heart rate, revealing a range between 60 and 100 bpm. The graph showcases the system's ability to detect irregularities or fluctuations in heart rate, enabling timely intervention. For instance, a notable spike in heart rate to 90 bpm during the third day was recorded around 2:00 PM, indicating a potential stressor or physical exertion. Such insights provide a granular understanding of the user's cardiovascular health, proving the system's effectiveness in continuous monitoring and early anomaly detection. Further analysis, incorporating statistical measures such as average heart rate, standard deviation, and percentage of time spent in specific heart rate zones, would offer additional quantitative support for the system's proficiency in providing detailed health insights.

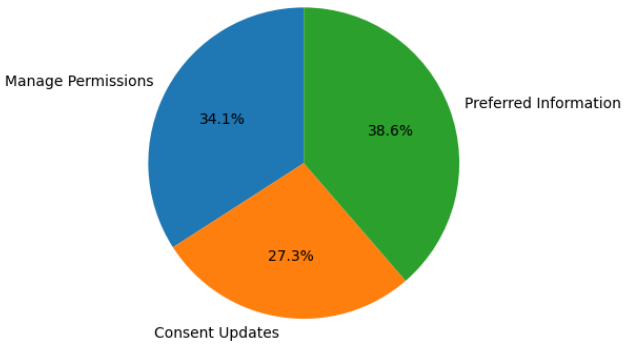

Fig.3 User data management preference

To assess data transmission and connectivity, experiments involved simulating various real-world scenarios to measure the success rates of IoT connectivity over time. This experimental result, shown in Fig. 3, was conducted by manipulating network conditions and monitoring the system's response. For data processing efficiency, experiments focused on processing times for different data types, involving controlled inputs to mimic continuous data influx. Blockchain security was validated through experiments that assessed the encryption process and tracked attempted unauthorized access under diverse conditions. These experiments provided concrete evidence of the blockchain's effectiveness in ensuring data security. Furthermore, user engagement and preferences were evaluated through user studies, capturing fundamental interactions with the system's interface. Lastly, health insights and early detection capabilities were validated through comparison studies, where predictions from the system were compared with established health metrics and clinical assessments. The aggregation of these experiments, supported by the presented graphs, not only validates the robustness of the data management system but also substantiates its potential impact in advancing healthcare research and personalized health management.

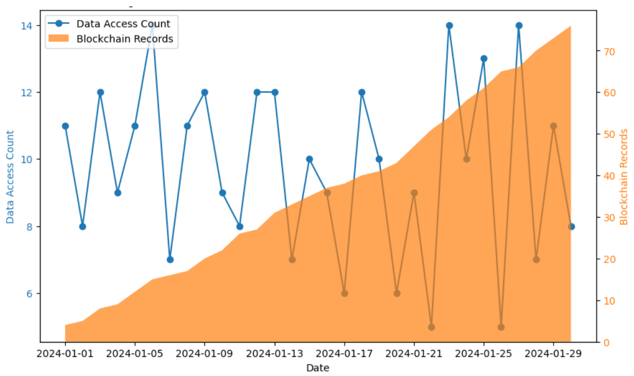

Fig.4 Blockchain and records data access count over time

Fig.4 provides a comprehensive depiction of the data management system's efficiency and security, particularly emphasizing the integration of blockchain technology. The primary y-axis showcases the daily data access counts, symbolized by a line plot with circular markers, offering insights into the frequency of interactions with health data over 30 days. This facet of the graph illustrates the dynamic nature of data access within the system. The secondary y-axis introduces a layered perspective through a stacked area plot in a distinctive orange hue. This plot represents the cumulative growth of blockchain records, reflecting the immutable and secure storage of health data. As each day progresses, the area covered by the plot expands, visually emphasizing the robustness and permanence of the blockchain component in preserving health records. The stacked area graph conveys a sense of data accumulation over time, reinforcing the notion that each piece of information is securely embedded in the decentralized ledger. The dual-axis design enables a simultaneous examination of two critical aspects of data management: the accessibility of health data and the accumulation of immutable records. The legend succinctly differentiates between the two datasets, ensuring clarity in interpretation. Together, the graph serves as an aesthetically pleasing visualization and conveys a nuanced narrative of a system that facilitates seamless data access and ensures the integrity and permanence of health records through blockchain technology. This visual representation effectively communicates the robustness and reliability of the healthcare data management system, bolstered by its integration with blockchain for secure record-keeping.

5. Conclusion and future work

The advanced wearable health monitoring system, integrating multi-sensor data, showcased dynamic health patterns over ten days. Heart rate fluctuated from 75 to 90 bpm, steps ranged between 8,000 and 11,000 daily, and stress levels varied from 18 to 30. The secure data management, facilitated by blockchain technology, ensures the integrity of the collected health data, marking a significant step toward personalized and secure healthcare solutions. The integrated healthcare data management system, leveraging advanced smartwatch sensors and blockchain technology, establishes a robust foundation for comprehensive health monitoring. The encrypted, decentralized storage ensures data security and empowers individuals with data control. Future work involves refining analytics for deeper insights, expanding sensor capabilities, and enhancing user interfaces. This system is a pivotal tool for advancing early health issue detection and personalized healthcare strategies, promising a transformative impact on the future of patient-centric care.

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