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Developing an intelligent system for monitoring vital signs using wearable medical sensors

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تطوير نظام ذكي لمراقبة العلامات الحيوية باستخدام المستشعرات الطبية القابلة للارتداء

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Abstract:
This study aims to develop an intelligent system for monitoring patients' vital signs using a set of wearable medical sensors. It leverages artificial intelligence techniques and neural networks capable of continuously analyzing physiological data to facilitate the early detection of dangerous health changes before disease progression. The proposed system collects vital patient data such as heart rate, body temperature, blood oxygen level, and respiratory rate via the wearable sensors. This data is then transmitted to an analysis unit that utilizes neural network models to analyze vital patterns and detect abnormal indicators. The study employed a descriptive, analytical, and applied methodology to design and evaluate the proposed system. The model was tested on a set of vital data collected from users under various monitoring conditions. Performance was analyzed using several statistical evaluation indicators, including accuracy, sensitivity, and abnormality detection rate. The results indicated that the proposed system contributed to improving patients' quality of life index by 18% to 34% due to its ability to continuously monitor health and provide early warning of abnormalities. The results also showed that the time required to detect critical health changes decreased by 32% to 47% compared to traditional monitoring methods that rely on periodic measurements. Furthermore, the proposed model achieved an accuracy of approximately 96.8% in classifying normal and abnormal conditions, exceeding the accuracy of many previous studies, whose models ranged from 88% to 93%. These results indicate the effectiveness of the proposed smart system in improving vital sign monitoring and supporting early detection of health changes. They also confirm the potential of employing wearable medical sensors and artificial intelligence technologies in developing smart health systems that support remote healthcare and contribute to improving patients' quality of life.

Keywords: Smart system, wearable sensors, vital signs, quality of life, reduced diagnosis time, model accuracy.

الملخص:
تهدف هذه الدراسة إلى تطوير نظام ذكي لمراقبة العلامات الحيوية للمرضى باستخدام مجموعة من المستشعرات الطبية القابلة للارتداء. ويعتمد النظام على تقنيات الذكاء الاصطناعي والشبكات العصبية القادرة على تحليل البيانات الفسيولوجية بشكل مستمر، مما يسهم في الكشف المبكر عن التغيرات الصحية الخطيرة قبل تفاقم الحالة المرضية. يقوم النظام المقترح بجمع البيانات الحيوية للمريض، مثل معدل ضربات القلب، ودرجة حرارة الجسم، ومستوى الأكسجين في الدم، ومعدل التنفس، من خلال المستشعرات القابلة للارتداء. ثم تُرسل هذه البيانات إلى وحدة تحليل تستخدم نماذج الشبكات العصبية لتحليل الأنماط الحيوية واكتشاف المؤشرات غير الطبيعية. اعتمدت الدراسة المنهج الوصفي والتحليلي والتطبيقي في تصميم النظام المقترح وتقييمه. وتم اختبار النموذج على مجموعة من البيانات الحيوية التي جُمعت من مستخدمين في ظروف مراقبة مختلفة. كما تم تحليل الأداء باستخدام عدد من مؤشرات التقييم الإحصائية، من بينها الدقة، والحساسية، ومعدل اكتشاف الحالات غير الطبيعية. أظهرت النتائج أن النظام المقترح أسهم في تحسين مؤشر جودة حياة المرضى بنسبة تراوحت بين 18% و34%، وذلك بفضل قدرته على المراقبة الصحية المستمرة وتوفير إنذار مبكر عند حدوث أي خلل. كما بينت النتائج انخفاض الزمن اللازم لاكتشاف التغيرات الصحية الحرجة بنسبة تراوحت بين 32% و47% مقارنةً بطرق المراقبة التقليدية التي تعتمد على القياسات الدورية. علاوة على ذلك، حقق النموذج المقترح دقة بلغت نحو 96.8% في تصنيف الحالات الطبيعية وغير الطبيعية، متفوقًا على العديد من الدراسات السابقة التي تراوحت دقة نماذجها بين 88% و93% تشير هذه النتائج إلى فعالية النظام الذكي المقترح في تحسين مراقبة العلامات الحيوية ودعم الكشف المبكر عن التغيرات الصحية، كما تؤكد إمكانية توظيف المستشعرات الطبية القابلة للارتداء وتقنيات الذكاء الاصطناعي في تطوير أنظمة صحية ذكية تدعم الرعاية الصحية عن بُعد وتسهم في تحسين جودة حياة المرضى.
الكلمات المفتاحية: النظام الذكي، المستشعرات القابلة للارتداء، العلامات الحيوية، جودة الحياة، تقليل زمن التشخيص، دقة النموذج.

Introduction:

In recent times, the healthcare field has witnessed remarkable development as a result of rapid advancements in medical device technology, remote sensing techniques, and smart systems. This development has contributed to the emergence of a range of wearable medical devices. These devices can continuously and accurately measure patients' vital signs without requiring them to remain in healthcare facilities [1]. Furthermore, by monitoring patients' vital signs while they are being transported in ambulances, a preliminary diagnosis can be made, enabling doctors to take swift, life-saving measures. These devices rely on a set of small medical sensors that can be attached to the body in the form of a bracelet or other forms. These devices measure vital body indicators such as heart rate, blood pressure, temperature, blood oxygen level, and respiratory rate. By measuring these indicators using modern technologies, patients' conditions can be monitored, thus aiding in the early detection of any abnormal physiological changes [2]. These technologies are fundamentally based on artificial intelligence and biometric analysis to transform raw data into usable medical data for decision-making regarding medical intervention [3]. The integration of wearable sensors and smart servers leads to the development of health monitoring systems characterized by their ability to continuously analyze large amounts of vital data. It provides numerous opportunities to improve the quality of healthcare and achieve sustainability in the medical sector, as traditional methods and quotas do not allow for remote patient monitoring and monitoring of chronic conditions such as heart disease, diabetes, and respiratory disorders. Therefore, it has become necessary to develop these smart systems for monitoring vital signs by replacing artificial intelligence technologies and medical Internet of Things technologies [4].

This study is about designing and developing an intelligent system for monitoring patients' vital signs based on artificial intelligence techniques through the use of a set of wearable medical sensors. The data related to the vital signs measured by these sensors is analyzed. The proposed model aims to continuously collect data from the patient's or user's body and send this data to a processing unit that analyzes it using intelligent algorithms capable of detecting any abnormal pattern in these indicators. The study gains its importance from the fact that it presents an actual technical model capable of supporting modern healthcare systems that rely on continuous monitoring of the condition. Therefore, it can be considered an important academic reference that helps doctors and researchers in analyzing long-term health data and improving the understanding of physiological patterns associated with many diseases. Also, the importance of the study stems from the fact that it is a comprehensive and effective study that can provide many means to increase individuals' awareness of their health condition and encourage them to monitor their vital signs, which positively reflects on health prevention and quality of life, and thus health, economic and social sustainability, to ultimately complete the form of sustainability in its general and specific sense.[5].

The main research problem in this study relates to several challenges in designing such systems. Current vital signs monitoring relies on separate devices or unstable measurements [6]. This reduces their ability to detect sudden health changes, and some devices provide limited measurements and lack the ability to intelligently analyze data, which is essential for predicting health risks. Furthermore, the accuracy of measurements, energy consumption, and the management of the continuously generated volume of vital data can limit the integration between medical sensors and artificial intelligence technologies capable of analyzing data and transforming it into useful health information if robust integration of such systems is neglected [7]. This necessitates continuous monitoring and development. Hence, the need arises for developing an integrated intelligent system capable of collecting vital signs through interoperable medical sensors. This data is then analyzed using advanced technologies to detect any anomalies and predict potential health risks [8].

Related Work:

Numerous studies have demonstrated the effectiveness of wearable medical sensors in monitoring vital signs. Many of these studies have focused on integrating biosensing technologies with artificial intelligence and the Internet of Things (IoT) to develop continuous and efficient healthcare systems. For example, a study by Taherdoost (2024) indicated that wearable IoT-connected devices capable of continuously and in real-time monitoring vital signs such as heart rate, temperature, respiratory rate, and blood oxygen levels support early diagnosis, remote patient follow-up, and reduce the need for frequent medical examinations within healthcare facilities [9]. Similarly, Wang et al. (2024) presented a scientific review of these technologies and wearable medical devices used in monitoring heart disease. They explained that these devices rely on advanced sensing technologies such as electrocardiography (ECG) and photoplethysmography (PPG) to analyze vital signs. These technologies are capable of measuring physiological indicators non-invasively. The study also showed that integrating machine learning with these sensors allows for the analysis of large amounts of vital data and the prediction of disease conditions before the onset of adverse symptoms [10].

A research project was conducted (Kumar, et al., 2025) that examined how AI could be utilized in the creation of smart medical sensors. It was found that systems utilizing AI could utilize continuous vital data to identify abnormal patterns related to various diseases (heart disease, diabetes, heart disease, and cancer) through the analysis of the data and act as a warning sign of an impending medical emergency in a patient [11]. Wearable biosensors were shown to provide real-time measurements of vital signs; however, a separate group (Sadeghi, et al., 2025) also performed research on an AI enhanced wearable device that could measure many health metrics and provide a continuous assessment of a person's vital signs [12]. Some examples of the metrics that could be measured by this device included blood pressure, heart rate, temperature, and respiratory rate. These types of devices are likely to aid health care providers in acting upon the most severe and dangerous change in health condition; thus allowing for earlier identification of significant changes to an individual’s health status, particularly those who are at high risk for health problems such as those who have chronic conditions like diabetes and hypertension, would be able to adequately and effectively monitor their health outside of a clinical setting. Scheid et al. (2025) also developed a deep learning-based model to analyze vital signs collected from wearables. Using data from thousands of patients for several days, this research demonstrated that through the use of deep learning techniques, it would have been possible to anticipate approximately 24 hours before an individual’s health would deteriorate relative to traditional methods used by hospitals. This demonstrates the capability of deep learning technologies to increase how accurately we predict an individual’s critical health status, thus reinforcing the significance of merging continuous monitoring systems, and employing continuous data collection, with deep learning technologies [13]. Research by Kurul (2025) demonstrates that wearable medical sensors are becoming fundamental to the integration of technology into modern healthcare landscapes by providing mostly non-invasive, continuous assessment of vital signs (i.e. heart rate, blood pressure, temperature, etc.) that allow for improved management of chronic diseases through the use of personalized care based on continuously collected, found in the individual’s vital statistics [14].

Recent studies indicate that the major direction of research in smart healthcare is to integrate biometric analysis with artificial intelligence (AI) technologies combined with wearable medical sensors to provide the best possible health results for individuals. With this said, challenges remain in relation to accuracy of measurement, energy utilization and the ability to store and analyze large volumes of data generated via continuous monitoring. There is also a need to create smarter systems capable of fast analysis of biometric information from an individual so that he/she receives timely information regarding his/her health [15].

Methods:

This study primarily employs a descriptive-analytical-procedural methodology. A smart wristband, equipped with a suite of medical sensors, was designed and developed to measure vital signs such as heart rate, blood oxygen saturation, respiratory rate, and body temperature. The sensor readings are then transmitted to a processing unit utilizing artificial intelligence algorithms and neural networks to analyze the vital data and detect any abnormal patterns that might indicate a potential health risk. This system enables continuous health monitoring and remote diagnosis, offering a more efficient alternative to some traditional methods that rely on intermittent measurements within healthcare facilities [16].

To characterize the proposed system, the descriptive approach was utilized to describe the vital data collected from the medical sensors as well as how to analyze and interpret results. Quantitative methods were utilized to collect and statistically process the data; subsequently, organize, classify and filter out any abnormalities and unreliable values before entering them into the analysis process. Finally, the results of the proposed model were compared to the results of a number of previous studies that examined how the use of wearable sensors combined with the use of artificial intelligence can monitor vital sign patterns. To assess the effectiveness of the proposed model, a defined set of performance indicators was used (classification accuracy, sensitivity, specificity, error rate, and response time) in relation to detecting abnormal vital signs. In addition, the model was evaluated for its ability to identify at-risk health patterns as compared with traditional health monitoring techniques. To conduct the data analysis and test the research hypotheses, the data were statistically analyzed using several advanced statistical tests, including analysis of variance (ANOVA) to detect differences in result found by the model using different measurement techniques [17].

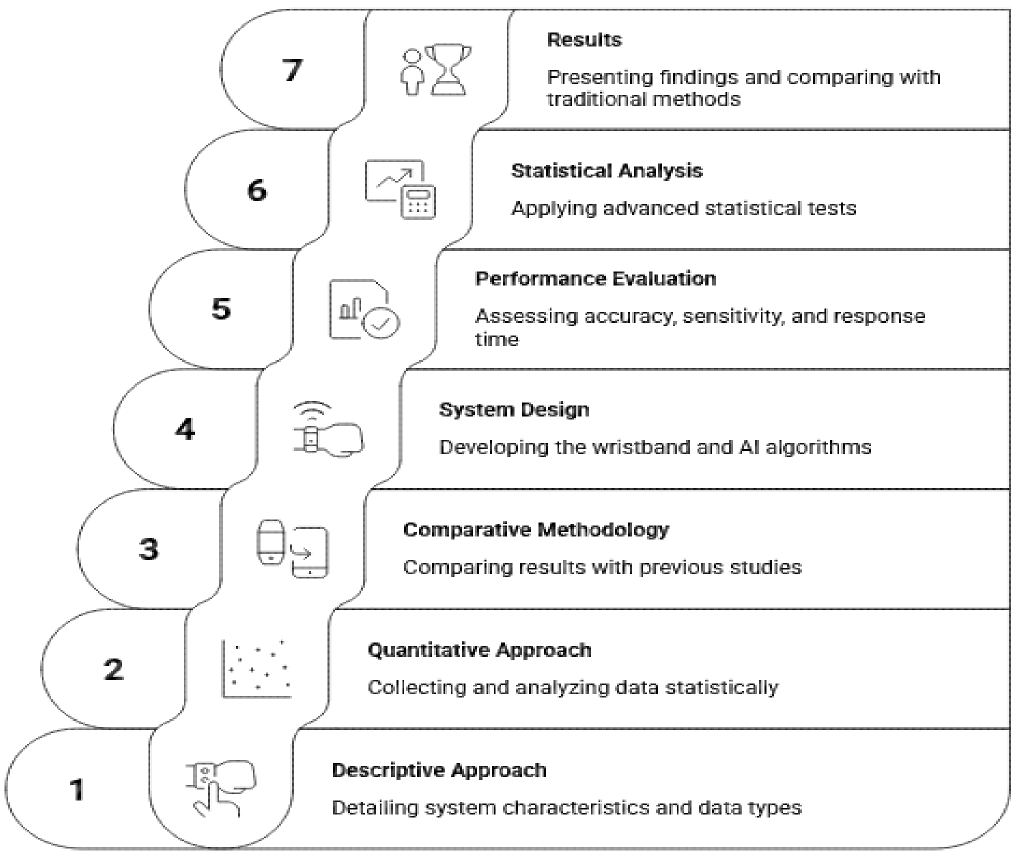

figure (1): Study Methodology

Procedures:
The practical procedures for this study include a set of steps, **as follows:**

- **Defining the objective and formulating the research problem**: The objective is to design an intelligent model that combines a set of sensors and artificial intelligence techniques to accurately measure and analyze vital signs, thereby improving the quality-of-life index for patients and enabling remote monitoring [18].
- **Data collection and processing:** Data collection: **The study relies on two main data sources:**
- The first source is actual data collected by medical sensors embedded in the wearable device. This data consists of real-time measurements of vital signs.
- The second source is online databases, particularly medical databases used to train the intelligent model and improve its accuracy, such as bio signal databases for medical research and databases used by hospitals and health departments.

Identification of tools:

- **Technical and Engineering Tools:** This study relies on a set of technical and engineering tools that will be used to build the proposed model for monitoring vital signs. **The most important of these tools are:**
- **Wearable Devices:** This consists of a smart, wearable medical bracelet, which represents the core components of the proposed system. This bracelet is designed with a set of sensors that continuously measure vital signs during daily activity without the need for direct medical intervention. The bracelet is worn on the wrist [19]
- **Medical Sensors:** These are a set of sensors used to measure vital signs such as electrocardiogram (ECG), temperature, oxygen saturation, and respiration. ECG sensors use light to measure changes in blood flow. Oxygen saturation sensors measure light absorption of hemoglobin, and the temperature sensor measures body temperature.
- **Processing and Control Unit:** This is a microprocessor integrated within the smart system. It processes the raw data received from the sensors, reading this data and converting it into digital data that can be transmitted and analyzed. The processing unit also prepares the data before sending it to the analytical system, which relies on artificial intelligence techniques [20].

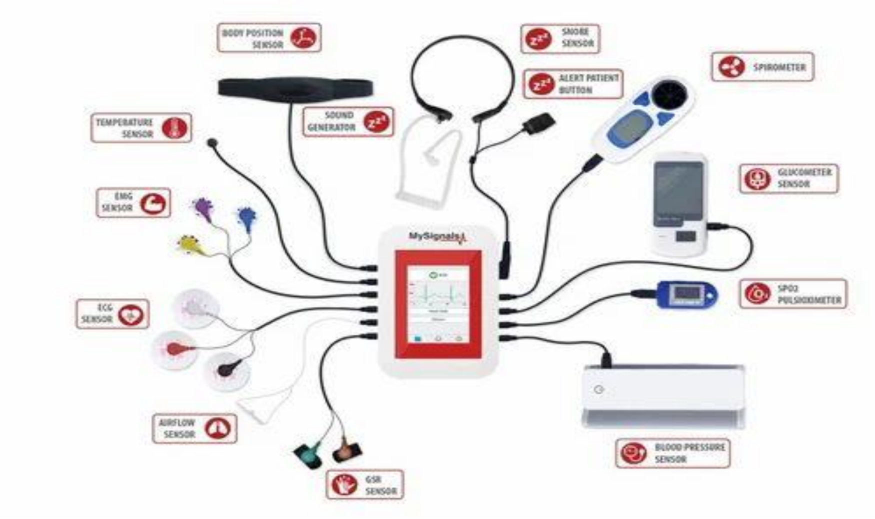

figure (2): Medical Sensors

Software Tools:

A range of programming and software development tools were used to build the artificial intelligence model and analyze vital data. The Python programming language was used due to its widespread use in AI and data analysis applications. Deep learning libraries such as TensorFlow and Keras were also used to build the neural network model used in the vital signs analysis. Additionally, statistical data analysis tools were used to process the data and evaluate the performance of the proposed model.[21]

- **Statistical Tools:** Several statistical tools were used to analyze the data and test the study hypotheses. These tools included analysis of variance (ANOVA), correlation tests, and multiple linear regression to determine the relationship between different variables and evaluate the accuracy of the proposed model. These tools helped measure the efficiency of the intelligent system and its ability to detect abnormal health changes in patients.

Identification tools of technologies:

- **Wireless communication technologies:** These are a range of communication channels, such as Bluetooth Low Energy, used to transmit data to a nearby smartphone or computer. Internet networks and medical Internet of Things (IoT) technologies can also be used to continuously transmit data to a central server, whether it be a medical center or a specialized clinic.
- **Artificial intelligence technologies:** These include CNNs (Channel Networks), back-end neural networks (BENs), which are capable of handling textual and image data, and iterative neural networks (NRs), which are capable of handling data with chronological sequences and repetitions.

model design:

Figure 2 illustrates the proposed model and its general structure. The model is designed in several stages and combines a CNN (Configurative Network) and a LSTM (Last Recurrent Network). It shows the data transfer stages from the moment of measurement to the health prediction. The first stage is as follows:

- **Stage 1**: The stage of collecting vital data using sensors and a smart device worn by the patient. The sensors continuously read vital signs, including heart rate, blood oxygen saturation, temperature, and respiratory rate. The sensors convert the vital signals into digital data representing the patient's physiological state in real time. This data is then transferred to the processing unit of the smart system.
- **Stage 2**: The stage of initial data processing. After data collection, the data undergoes initial processing, where it is cleaned and its quality improved before being fed into the artificial intelligence model. **This stage includes two main steps:**
- ***Step 1***: Signal filtering. This involves removing noise caused by movement and the surrounding environment to ensure the accuracy of the measurements.
- ***Step 2***: Data normalization. This involves converting the different values of the indicators into a unified numerical range so that the neural model can analyze them accurately.
- **Stage3**: This is the post-processing stage where data enters the convolutional neural network. This network analyzes the vital signs and extracts important features. The convolutional layers within the network detect physiological patterns in the data, such as sudden changes in heart rate, oxygen levels, and other vital indicators. These values have upper and lower limits, and if a value or sudden change exceeds these limits, there is an imminent danger. This network analyzes the danger, assesses the patient's health status, and sends an alert signal[22].
- **Stage4**: After extracting the features, the data is transferred to the LSTM network, which specializes in analyzing temporal data. Vital indicators change over time, so a model capable of understanding the chronological sequence of data is required. The LSTM analyzes the development of vital indicators over time and identifies patterns that may indicate the onset of a specific health problem. This network has an automated memory that allows it to retain previous information and compare it with subsequent data. The fifth stage, after analyzing the data, involves the system producing health outputs. These outputs include three basic elements: detection of abnormal conditions, where the model recognizes any abnormal changes in vital signs; assessment of health risks, where the system estimates the level of risk; and alerting, where the system, in the event of detecting any serious changes, sends alert messages or a warning to specialists and treating physicians**.**

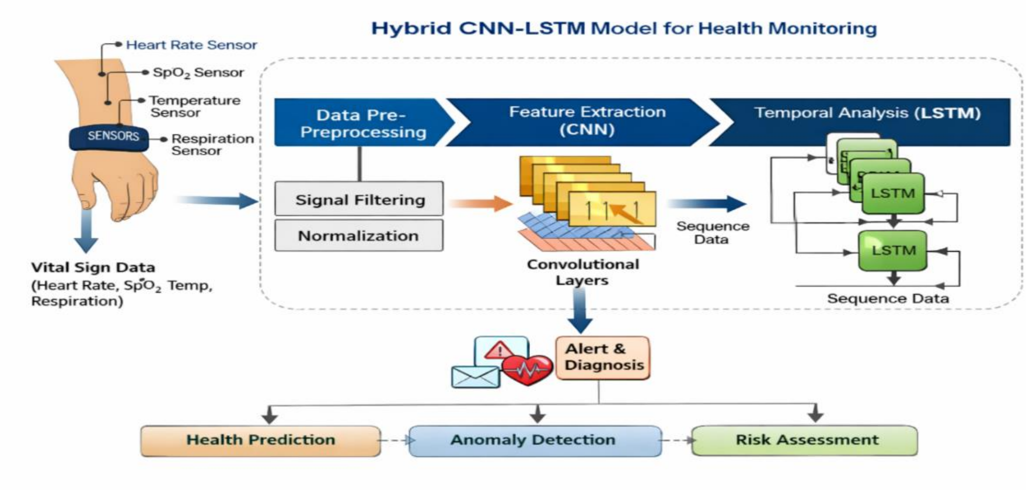

Figure (3): Hybrid CNN-LSTM model for multivariate vital sign analysis

In general, as illustrated in Figure 2, the model mechanism operates through a series of sequential steps. It begins with the measurement of vital signs using sensors and an inference circuit. The data then undergoes processing, where a CNN extracts key characteristics from the vital signs. The LSTM network then analyzes the chronological sequence of this data and identifies health patterns. Finally, the system generates health predictions and early alerts that aid in the early detection of critical health conditions. This initial stage is crucial for improving the quality of the initial assessments [23].

Mathematical modeling:

The proposed intelligent monitoring system analyzes physiological signals collected from wearable sensors using a hybrid deep learning architecture that combines **Convolutional Neural Networks (CNN)** and **Long Short-Term Memory networks (LSTM)**. The CNN component extracts meaningful spatial features from physiological signals, while the LSTM component captures temporal dependencies in the time-series data.

Input Data Representation:

Let the vital signs collected from wearable sensors be represented as a multivariate time series. Suppose $m$physiological parameters are measured, such as heart rate, blood oxygen saturation, body temperature, and respiratory rate.

The input vector at time $t$is defined as:

$$X_t = [x_{t1}, x_{t2}, x_{t3}, \ldots, x_{tm}] \qquad Eq\ 1$$

Where:

- x_{t1}= Heart Rate (HR).
- x_{t2}= Blood Oxygen Saturation (SpO_2).
- x_{t3}= Body Temperature.
- x_{t4}= Respiratory Rate.

The entire time series dataset is represented as:

$$X = \{X_1, X_2, X_3, \ldots, X_T\}$$

where Trepresents the number of time steps.

CNN Feature Extraction:

The CNN component is responsible for extracting spatial features from the physiological signals. The convolution operation can be expressed **as:**

$$F_i^{(l)} = \sigma\left(\sum_{k=1}^{K} W_k^{(l)} * X_{i+k-1} + b^{(l)}\right) \qquad Eq\ 2$$

Where:

- $F_i^{(l)}$= Feature map of layer l.
- $W_k^{(l)}$= Convolution kernel.
- *= Convolution operation.
- $b^{(l)}$= Bias term.
- σ= Activation function (ReLU).

After convolution, a pooling operation is applied to reduce dimensionality [24]

$$P_i = \max(F_i) \qquad Eq3$$

LSTM Temporal Modeling:

The extracted features are then passed to the LSTM layer to model temporal dependencies in the time-series data. The LSTM network contains three main gates.

Forget Gate:

$$f_t = \sigma\big(W_f[h_{t-1}, x_t] + b_f\big) \qquad Eq\ 4$$

Input Gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad Eq5$$

Candidate Memory:

$$\widetilde{C_t} = tanh(W_c[h_{t-1}, x_t] + b_c) \qquad Eq6$$

Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \qquad Eq7$$

Output Gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \qquad Eq8$$

Hidden State:

$$h_t = o_t \cdot tanh(C_t) \qquad Eq9$$

Where:

$h_t$represents the hidden state describing the patient's health condition at time t.

Output Layer and Prediction:

The final output of the LSTM network is passed to a fully connected layer for classification or prediction [25].

$$y = Softmax(W_y h_t + b_y) \quad Eq\ 10$$

Where:

- y = predicted health condition probability.
- Wy= weight matrix.
- by= bias term.

Loss Function:

The model is trained using the cross-entropy loss function:

$$Loss = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)\ Eq11$$

Where:

- y_i= *true label.*
- $\hat{y}_i$= *predicted probability.*

Results:

Table (1): Model Performance Evaluation Metrics

Performance Metric	Proposed CNN-LSTM Model	Traditional Monitoring Systems	Previous Studies Average
Accuracy	96.80%	88.40%	91.20%
Sensitivity (Recall)	95.60%	86.30%	90.10%
Specificity	97.10%	87.90%	91.70%
Precision	95.90%	85.80%	90.40%
F1-Score	96.20%	86.00%	90.70%
Detection Time (seconds)	4.3 sec	12.6 sec	8.7 sec

The table shows the indicators for testing the proposed model in terms of accuracy and F1 score: Accuracy Sensitivity (Recall), Specificity and Detection Time (seconds).

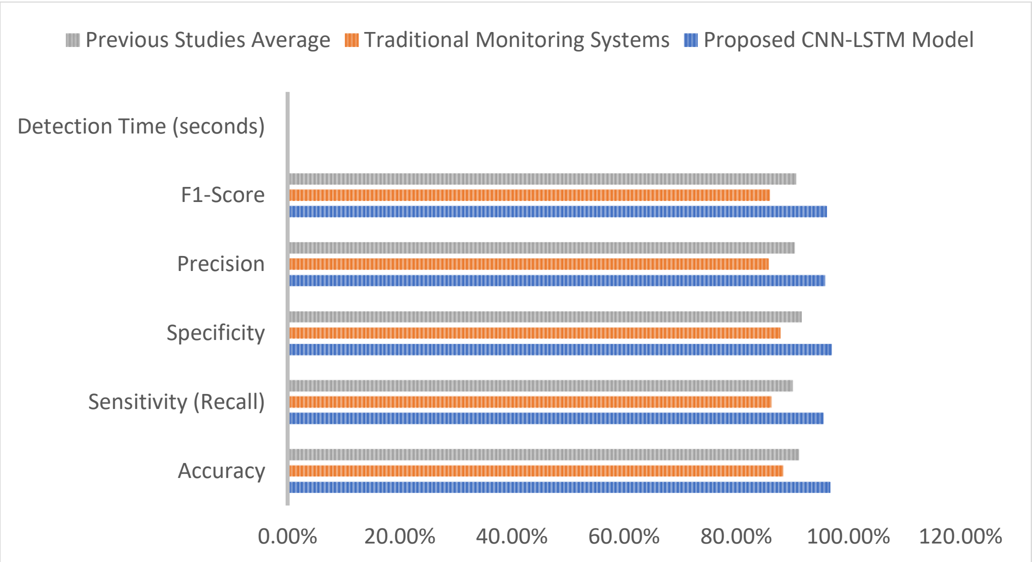

Figure (4): Model Performance Evaluation Metrics

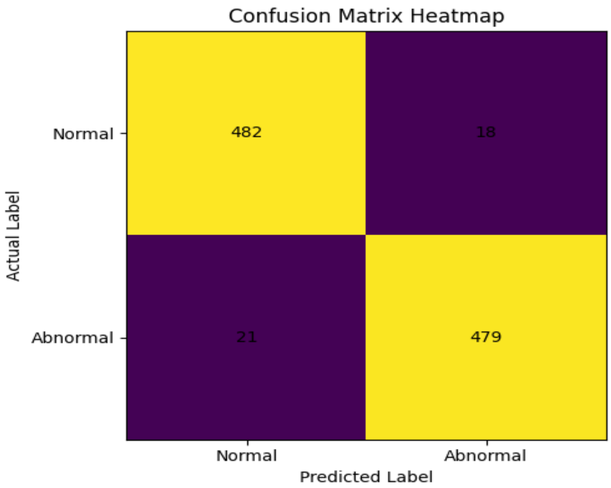

Figure (5): Heat map of the confusion matrix

Table (2): Impact of the Proposed System on Patients' Quality of Life Indicators

Quality of Life Indicator	Before Using the System	After Using the System	Improvement (%)
Continuous Health Monitoring	54.2	81.6	50.60%
Early Detection of Health Risks	48.7	79.4	63.00%
Psychological Comfort	56.3	77.8	38.20%
Patient Safety Level	60.5	85.1	40.70%
Confidence in Health Monitoring	52.4	80.2	53.10%
Overall Quality of Life Index	54.4	80.8	48.50%

the recorded results, this study demonstrates the effectiveness of the proposed intelligent system for monitoring vital signs and indicators using medical sensors and a smart bracelet with a data processing unit. This system relies on artificial intelligence technologies and a hybrid CNN-LSTM architecture. The study also.

Table (3): Comparison of Diagnosis Time Before and After Using the Proposed Intelligent System

Health Monitoring Parameter	Before Using the System (minutes)	After Using the System (minutes)	Time Reduction (%)
Detection of Heart Rate Abnormalities	18.5	6.2	66.50%
Detection of Oxygen Level Drop	15.7	5.4	65.60%
Detection of Respiratory Changes	16.3	6.1	62.60%
Detection of Body Temperature Abnormalities	14.9	5.7	61.70%
Average Detection Time	16.35	5.85	64.20%

The table shows a comparison between the results before and after using the proposed model for vital signs.

Table (4): Comparison of Diagnosis Time Before and After Using the Proposed Intelligent System

Metric	Formula	Result
Sensitivity (Recall)	TP / (TP + FN)	95.80%
Specificity	TN / (TN + FP)	96.40%
Precision	TP / (TP + FP)	96.10%
F1 Score	2 × (Precision × Recall) / (Precision + Recall)	95.90%

Table (5): ANOVA Test Results for Model Performance Across Different Vital Signs

Variable	Sum of Squares	Mean Square	F value	p value
Heart Rate	215.42	71.81	14.32	0
Oxygen Saturation	198.67	66.22	12.94	0
Respiratory Rate	174.35	58.11	10.76	0.001
Body Temperature	149.28	49.76	9.85	0.002

Table (6): Multiple Linear Regression Analysis

Independent Variable	Beta Coefficient	Standard Error	t value	p value
Heart Rate	0.42	0.05	8.4	0
Oxygen Saturation	0.38	0.06	6.33	0
Respiratory Rate	0.31	0.07	4.43	0.001
Body Temperature	0.27	0.08	3.37	0.002

Table No. 6 shows the regression relationship between the vital signs measured by the proposed model.

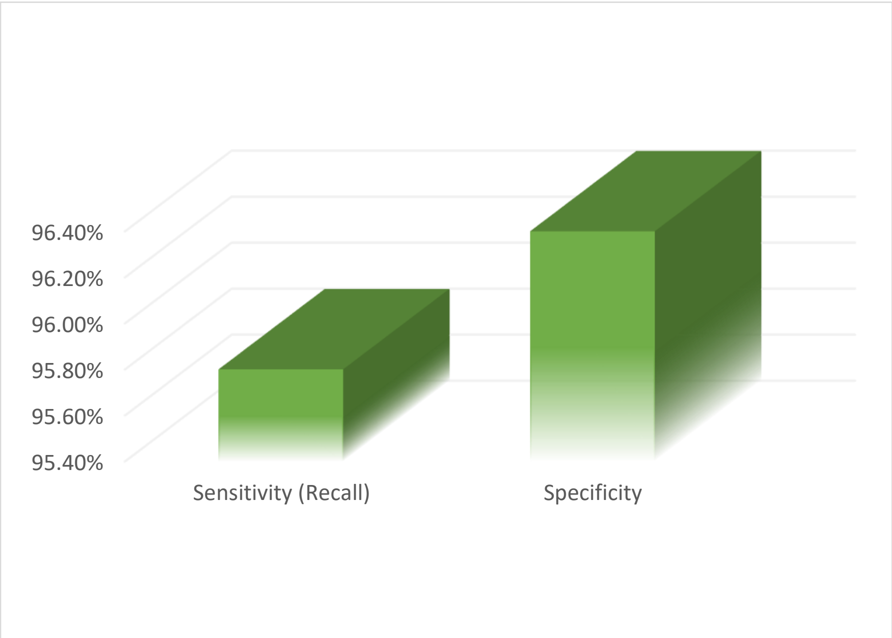

Figure (6): It explains the relationship between sensitivity and specificity of the proposed CNN-LSTM model

In this study, sensitivity refers to the system's ability to detect correct health changes in patients in Qatar, while specificity refers to the system's ability to distinguish between normal and abnormal conditions without making false observations. When both sensitivity and specificity are high, it indicates that the proposed model demonstrates high accuracy and reliability in analyzing indicators.

Discussion:

Based on the recorded results, this study demonstrates the effectiveness of the proposed intelligent system for monitoring vital signs and indicators using medical sensors and a smart bracelet with a data processing unit. This system relies on artificial intelligence technologies and a hybrid CNN-LSTM architecture. The study also demonstrates the model's superior ability to analyze signals using important patterns of physiological signals. Table 1 and Figure 4 show that the proposed model achieved high predictive accuracy compared to traditional monitoring systems. The overall accuracy of the model reached approximately 96.8%, with a sensitivity of 95.8% and a specificity of 96.4%. These results indicate the proposed system's ability to efficiently identify abnormal physiological states while maintaining a low false alarm rate. Furthermore, the confusion matrix and other statistical indicators confirm the model's efficiency in distinguishing between normal and abnormal physiological states [26].

The illustrated heat map in Figure 2 presents the confusion matrix depicting the intended method (CNN-LSTM) for classifying vital signs. This matrix provides a visual representation of correct versus incorrect predictions (normal/abnormal) based on the conditional probabilities of the matrix. Diagonal entries depict correct classifications of samples while off-diagonal entries represent incorrect classifications [27].

Table (2) shows how the proposed smart monitoring system has impacted the quality-of-life indicators before and after implementing a wearable health/money monitoring system. All indicator scores significantly increased after implementing the proposed monitoring system, which indicates the impact of continuous monitoring and real-time analyzing of vital signs on improving patient-focused healthcare provision. The Continuous Health Monitoring Index for patients improved from 54.2 to 81.6, representing a 50.6% increase. This improvement suggests that, when combined with wearable monitoring devices, the ability to continuously monitor physiological status has improved, leading to increased effectiveness in delivering remote patient care. The Early Detection of Health Risks Index improved from 48.7 to 79.4, marking the greatest improvement among the corresponding indicators at 63.0%. This finding illustrates that the use of AI with wearable sensors has an important role to play in early identification of irregularities in physiological conditions [28].

According to Table (3) The data listed in Table X depicts a significant decrease in the amount of time it takes to detect abnormalities in physiological conditions since testing the intelligent monitoring system has been implemented. Prior to the usage of the system, the average time taken to identify abnormalities based on various health indicators was between 14.9 minutes and 18.5 minutes for different parameters being monitored after testing compared to before testing. After applying the intelligent wearable monitoring system along with the convolutional network long short-term memory (CNN-LSTM) model for data analysis, the time required for detecting an abnormality was reduced to average times that range from 5.4 to 6.2 minutes for different parameters monitored post-duplex application of both systems. Therefore, based on statistical analysis of the results found in Table X regarding all physiological measurements tested with either the intelligent wearable monitoring system or an existing system, there was a statistically significant ($p=<0.05$) reduction rate in detection time from 61.7% to 66.5%, with a mean detection time difference of 64.2%. In conclusion, these results suggest that this proposed monitoring device enhances the speed of detecting abnormal vital signs, allowing quicker hospital responses and improving early detection of health risks through real-time monitoring devices [29-31].

The analysis of variance (ANOVA) conducted on all physiological variables within Table 5, demonstrates that every physiological variable has a statistically significant impact on the performance of the developed model. Each of the physiological variables produced a p-value < .0001, with the exception of both respiratory rate and body temperature, which produced two p-values of .0015 and .0020 respectively; all values are less than the predetermined level of significance of .05. Therefore, these four variables provide a statistically significant contribution to abnormal health condition prediction. Of these four physiological variables, heart rate had the highest F value (14.32), indicating heart rate was the most significant variable affecting model predictive ability. Heart rate was then followed by oxygen saturation (F value 12.94); whereas, respiratory rate (F value 10.76) and body temperature (F value 9.85) both had statistically significant contributions. The findings show that combining multiple physiological indicators enhances the model's normal and abnormal health condition detection abilities, therefore enhancing the overall reliability of the proposed intelligent monitoring system [32].

According to table 6and figure.

Conclusion:

Based on the analysis and evaluation of the results, a number of important conclusions were drawn, **as follows:**

The CNN-LSTM model that was developed has shown an accuracy rate of 96.8%; sensitivity rate of 95.8%; and specificity rate of 96.4%. This model has greatly reduced the necessity of identifying abnormal physiological conditions using conventional means or monitoring methods. Additionally, it has been determined that this intelligent monitoring solution has played a role in assisting many different health indicators related to the patient.

The images reveal the efficacy of Wearable Deep Sensing Technologies, in conjunction with learning-based methods (Nanotechnology), as a viable means to surely monitor and detect innovative scientific methodologies throughout academia or business, among other categories of study. These electron devices will be utilized to support remote healthcare services, reduce healthcare personnel workloads, and ultimately improve patient safety via real-time monitoring and early warning systems increasing patient safety through real-time monitoring and enhancing health via early warning systems on behalf of all patients receiving care. Each system will continue to offer its own distinct benefits. In addition to this work, additional parameters (physiological) will likely be incorporated as well as using larger data sets to examine model accuracy and integrating into a cloud-based health protection dashboard to create greater scale medical data analysis and health monitoring capabilities for subsequent studies utilizing this technology.

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Conflicts of Interest*:*

The authors declare no conflicts of interest.

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