IMU-BASED MOTION SENSORS FOR MEDICAL REHABILITATION: APPLICATIONS, ACCURACY, AND MULTIMODAL INTEGRATION

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K E Y W O R D S

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A B S T R A C T

This paper explores the use of IoT sensors and artificial intelligence (AI) technologies in healthcare. With IoT devices, patients' physiological indicators can be monitored in real time, while AI algorithms enable in-depth analysis of this data. Sensors measure heart rate, blood pressure, respiratory rate, muscle activity, or daily movements and transmit them to physicians through special applications. AI algorithms process the data, detect incorrect movements, predict risky situations, and help develop personalized treatment and rehabilitation plans. The paper also highlights the application areas of IoT and AI in healthcare, such as remote monitoring of chronic diseases, telemedicine services, mental health assessment, and virtual autopsies in forensic medicine. Additionally, the study discusses not only the advantages of these technologies but also challenges, including cost, standardization, information security, and privacy. Rehabilitation of patients with lumbar disc herniation is presented as a case study. In this condition, accurate tracking and analysis of patient movements help improve recovery efficiency. The integration of IoT and AI makes this process faster, safer, and more personalized.

Introduction

In recent years, advances in information technology have deeply penetrated the healthcare system. In particular, the Internet of Things (IoT) and artificial intelligence (AI) technologies have ushered in a new era in medicine. With these technologies, it has become possible to monitor patients' physiological conditions in real time, process large volumes of medical data, and support physicians in making objective decisions.

IoT sensors are small devices that collect various indicators from the human body or the environment and transmit them through networks. They can be used to measure heart rate, blood pressure, respiratory rate, spinal movements, muscle activity, and walking speed. For example, in studies on fall detection, sensors placed on the neck or ankle demonstrated high accuracy [1]. IoT devices are widely applied not only in healthcare but also in manufacturing, agriculture, transportation, and smart city systems [2]. However, healthcare remains one of the fields that benefit the most, as the accurate and timely collection and analysis of health-related data play a crucial role in preventing diseases, enabling early diagnosis, and providing effective treatment. The efficiency of IoT technologies increases significantly when combined with AI algorithms. Since manually analyzing large amounts of signals from sensors is challenging, AI can process them in real time, identify patterns, and predict dangerous conditions. For instance, heart-monitoring sensors can detect irregularities in cardiac rhythm at an early stage, helping prevent heart attacks.

Application of Iot and Artificial Intelligence in Healthcare

IoT and AI technologies are widely applied across various medical domains:

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- **Healthcare** — monitoring chronic diseases and developing personalized treatment plans [3].
- **Medical education and society** — representation of AI in the *Chicago Med* series has influenced public perceptions of technology [4].
- **Preventive medicine** — integration of genomics, AI, and telemedicine to prevent diseases [5].
- **Forensic medicine** — virtual autopsies and advanced imaging technologies [6].
- **Mental health** — analysis of speech and biosignals to detect stress and emotions (AudEeKA project) [7].
- **The main roles of AI in healthcare include:**

1. **Early diagnosis and treatment** — in rheumatoid arthritis and other chronic diseases.
2. **Medical imaging analysis** — automated processing of MRI, CT, and X-rays.
3. **Cognitive health assessment** — automation of CHA processes to detect dementia and Alzheimer's [9].
4. **Emotion recognition** — monitoring stress using speech and physiological signals.
5. **Rehabilitation monitoring** — controlling exercises and detecting incorrect movements.

Moreover, new scientific concepts are emerging: neuro-symbolic AI to make decision-making more explainable [10], and AGI, which shows potential in processing complex medical data and enhancing global collaboration [11].

Bibliometric analyses show that the application of autonomous (self-powered) IoT sensors and machine learning algorithms is expanding. In particular, accelerometers, ECG, motion, and temperature sensors are the most commonly used in medical applications. Research has shown that AI models in such systems can achieve accuracy rates of up to 99.92% [12]. This significantly improves early diagnosis, secure monitoring, and long-term patient observation.

However, issues of security and privacy remain pressing in IoT and AI integration. Traditional centralized data collection and processing increase cybersecurity risks and jeopardize patients' personal information. Therefore, federated learning (FL) has emerged as an important solution. In FL, data remain stored on the device, while the model is trained locally, and only updated parameters are shared. This approach ensures data privacy, reduces network load, and enhances the efficiency of IoT-based healthcare systems [13].

IoT Sensors Data Processing and Integration Methods

IoT-based smart systems are now widely applied in healthcare, industry, transportation, and environmental monitoring. However, the massive, diverse, and often noisy data collected from IoT devices pose serious challenges for processing and integration. To improve system efficiency, methods have been developed to clean, fuse, and analyze sensor data.

In many cases, IoT data collection occurs in complex environments such as smart buildings, smart factories, or smart cities. For instance, in smart buildings, multiple sensors are installed to monitor safety, energy efficiency, and resource management. These data are transmitted to cloud services, enabling remote management and analysis. Systems of this type, tested in simulators such as Cooja, have demonstrated effectiveness in enhancing safety and resource efficiency [14].

IoT sensors vary by function, measuring environmental or physiological indicators. Examples include accelerometers, gyroscopes, temperature, humidity, or ECG sensors. Studies have shown that choosing the right sensor for the right application is critical for achieving effective results.

Raw sensor data are often noisy, incomplete, or inconsistent. Therefore, data processing methods such as denoising, outlier detection, missing data imputation, and data aggregation are applied [14]. Through these processes, cleaner and more consistent datasets are generated.

The next crucial step is data fusion. Since IoT data originate from different sensors, they must be analyzed within a unified context. Methods such as direct fusion, associated feature extraction, and identity-based data fusion are employed [15], [16]. Furthermore, the integration of cloud computing, fog computing, and edge computing technologies has expanded opportunities for real-time processing and analysis of IoT sensor data.

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Method

Rehabilitation for patients with lumbar disc herniation refers to the recovery process following surgical or conservative treatment of a herniated intervertebral disc.

- The goals of rehabilitation include:
- Pain reduction – controlling back and leg pain.
- Restoring mobility – retraining patients in walking, bending, sitting, and daily activities.
- Muscle strengthening – reinforcing spinal and abdominal muscles with specific exercises to support the spine.
- Correcting improper habits – teaching correct sitting, standing, and lifting techniques.
- Preventing recurrence – promoting healthy lifestyles, physical activity, and regular monitoring.
- Rehabilitation typically involves:
- Physiotherapy – electrical stimulation, massage, heat or cold therapy.
- Physical exercises – therapeutic exercises (LFK) to enhance strength and flexibility.
- Psychological support – addressing the impact of chronic pain on mental health.
- Technological solutions – IoT sensors and AI used to monitor exercises, detect incorrect movements, and send reports to physicians.

The integration of IoT and AI in lumbar disc herniation rehabilitation consists of two main components. The first is wearable accelerometer and gyroscope sensors. These are attached to the patient's lower back, ankle, or wrist to measure motion speed, acceleration, and bending angles. The data are transmitted via Bluetooth to a smartphone application and stored on a server.

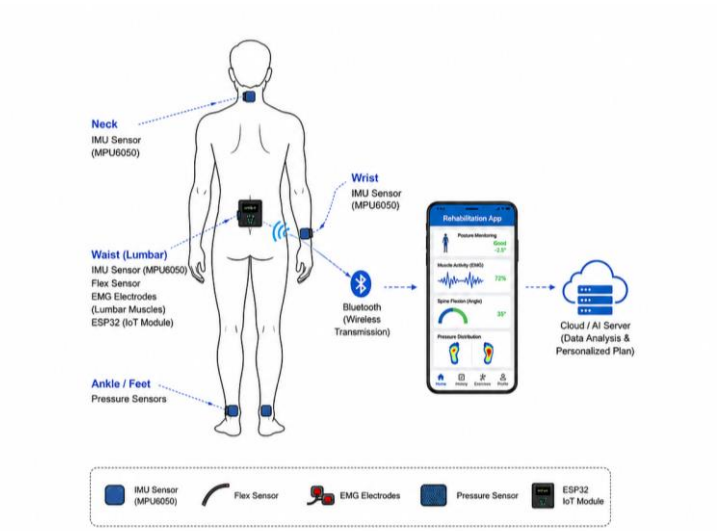


Fig-1. Placement of IoT sensors for lumbar disc herniation rehabilitation.s

In this process, the accelerometer plays a key role. It is based on a three-axis coordinate system and measures acceleration, tilt angles, and deviations of the body, enabling assessment of exercise performance. As shown in Figure 2, the G vector represents gravitational acceleration, projected onto the body's axes. The a angle shows tilt relative to the Y-axis, while the b angle shows deviation from the vertical axis. These parameters help identify whether exercises are being performed correctly or if excessive load is applied. Data collected by accelerometers are transmitted via IoT systems to mobile apps, then analyzed by AI algorithms. This provides physicians with objective insights into patient exercise performance and allows the development of personalized rehabilitation plans

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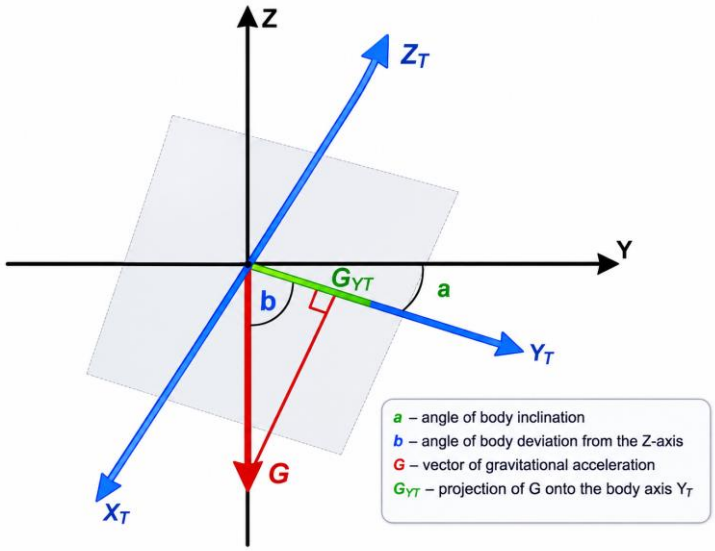


Fig-2. Body tilt angles and gravitational vector projections in the body coordinate system.

The second component involves AI-based algorithms, particularly LSTM and Random Forest. Sequential IoT data are processed by LSTM neural networks to differentiate between normal and abnormal movements, while Random Forest classifies exercises as "correct" or "incorrect." Patients receive immediate alerts via mobile apps, while physicians receive detailed reports. Additional algorithms can also be used. For example, Support Vector Machine (SVM) is effective for smaller datasets; Convolutional Neural Networks (CNNs) identify complex patterns; K-Nearest Neighbors (KNN) classifies movements based on similarity; and gradient boosting methods such as XGBoost or LightGBM efficiently analyze large-scale sensor data. In the future, reinforcement learning could be applied to track repeated exercises and develop optimal personalized recovery strategies.

Results

As a result of real-time monitoring, sensors continuously record the patient's exercises, providing the physician with objective data. During the error detection process, LSTM and Random Forest algorithms distinguish exercise mistakes with high accuracy. The mobile application support feature serves to send patients instant notifications about the correct execution of exercises. Thanks to remote physician supervision, the doctor can also monitor the patient's condition without requiring a clinic visit. Personalized rehabilitation, in turn, enables the development of an individual exercise program based on the system's analysis.

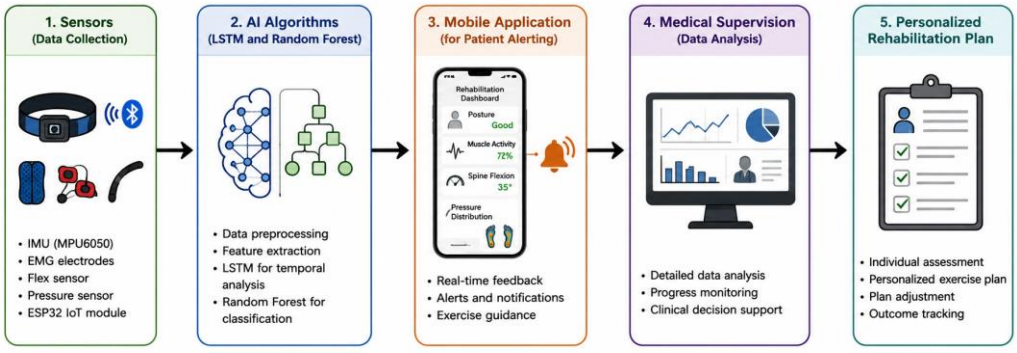


Fig-3. Proposed IoT-based rehabilitation system architecture

Conculison

The integration of IoT sensors and AI technologies has ushered in a new era in medicine.

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Specifically, in lumbar disc herniation rehabilitation, these technologies make recovery more effective and safer. IoT sensors enable real-time monitoring of physiological indicators and exercise performance, while AI algorithms analyze large datasets, assist physicians in objective decision-making, and provide patients with personalized rehabilitation plans. Compared to traditional monitoring, this approach improves efficiency and reduces errors in rehabilitation.

However, challenges such as high costs, lack of standardization, and data privacy remain barriers to widespread adoption. Therefore, future efforts should focus on developing global standards, reducing device costs, and strengthening cybersecurity. IoT and AI integration can also be applied to other areas of healthcare, ultimately improving public health, accelerating treatment, and enhancing overall quality of life.

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