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Article

Real-time processing and intelligent analysis of biomechanical data based on 5G and artificial intelligence

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Abstract: 5G and artificial intelligence (AI) technologies for the real-time processing and intelligent analysis of biomechanical data. We collected comprehensive biomechanical data from 500 participants, aged 18 to 65 years, through clinical trials encompassing gait analysis, muscle strength assessment, and joint mobility evaluation. High-resolution motion capture systems and wearable sensors transmitted this data in real-time via 5G networks to a centralized processing unit. The data underwent rigorous preprocessing, including normalization, smoothing, and feature extraction, followed by real-time analysis using deep learning models and support vector machines (SVM). The system's performance was assessed based on throughput, latency, packet loss, and classification metrics such as accuracy, precision, recall, and F1-score. Our results demonstrate high throughput (5000 Mbps), low latency (1 ms), minimal packet loss (0.5%), and classification accuracies ranging from 91.8% to 94.0%. These outcomes validate the efficacy of our proposed framework in enhancing the accuracy and efficiency of biomechanical data analysis, highlighting the synergistic potential of 5G and AI in healthcare and sports science applications.

Keywords: biomechanical data; real-time processing 5G networks; artificial intelligence; deep learning; support vector machine

1. Introduction

The advent of 5G technology and advancements in artificial intelligence (AI) have introduced new possibilities for the real-time processing and intelligent analysis of biomechanical data. This data, which includes information on human motion, muscle strength, and joint mobility, is pivotal for applications ranging from clinical diagnostics to sports performance enhancement. However, traditional methods of collecting, transmitting, and analyzing such data have been constrained by limitations in data throughput, latency, and computational capabilities. This study aims to address these challenges by leveraging the high-speed, low-latency features of 5G networks and the advanced analytical capabilities of AI algorithms.

Biomechanical data analysis has historically been limited by the inability to process large datasets in real-time. Conventional methods often involve manual data entry and processing, which are not only time-consuming but also prone to errors. Additionally, the transmission of high-resolution biomechanical data demands substantial bandwidth, typically unavailable in standard network infrastructures. These constraints have hindered timely and accurate data analysis, thereby impacting the effectiveness of clinical interventions and sports training programs.

The emergence of 5G technology presents a promising solution to these issues. With its high data throughput and minimal latency, 5G networks can support the real-time transmission of large datasets. When combined with AI, which excels in complex data analysis and pattern recognition, the potential for enhancing biomechanical data processing is significant. However, the integration of these technologies into a cohesive framework for biomechanical data analysis remains largely unexplored.

As a high-speed and low-latency communication technology, 5G plays a supporting role in data transmission and processing in the process of detecting biomechanical data such as wearable devices. The biological principles involved are mainly based on various biomechanical data detection technologies themselves. The following are the relevant principles and the role of 5G technology in them:

When detecting biomechanical data, such as measuring the plantar pressure distribution of the human body to analyze gait, piezoresistive and capacitive pressure sensors are often used. Piezoresistive sensors are based on the piezoresistive effect; when subjected to pressure, the resistance of the material will change, and the pressure information is obtained by measuring the resistance change; capacitive sensors are based on the principle of capacitance change; the pressure change will change the plate spacing of the capacitor, and then lead to the change of the capacitance value so as to detect the pressure. 5G technology can transmit a large number of plantar pressure data collected by pressure sensors to cloud or terminal devices in real time and at high speed for subsequent analysis and processing, and provide accurate biomechanical data such as gait analysis for doctors or researchers. With the low latency of 5G, the acceleration data collected by the acceleration sensor can be transmitted in time, which makes it possible to monitor and analyze the motion posture and joint activities in real time, and helps to evaluate the human motion state in real time and find the potential risk of sports injury.

Strain sensors are used to measure the biomechanical properties of tissues such as muscles and blood vessels. For example, when measuring the strain caused by muscle contraction, the strain gauge sensor is usually used. Its working principle is based on the strain effect of metal or semiconductor materials. When the material is stretched or compressed, its resistance value will change with the change of length and cross-sectional area. The strain situation is reflected by measuring the resistance change. The 5G network can support a sensor network composed of a large number of strain sensor nodes, realize the simultaneous collection and transmission of muscle or vascular strain data from multiple parts and points, and provide rich data support for comprehensive analysis of muscle movement and vascular physiological status.

Ultrasound technology also has applications in detecting biomechanical data, such as measuring the movement of blood vessel walls, contraction and relaxation of the heart, and so on. The ultrasonic probe sends out ultrasonic waves, which propagate in biological tissues and are reflected and refracted when encountering tissue interfaces with different acoustic impedances. The reflected ultrasonic signals are received, and the shape and motion information of the tissues can be constructed by analyzing the time, intensity, frequency and other information of the signals. With the high bandwidth of 5G, a large number of ultrasound image data and related motion information collected by ultrasound equipment can be quickly transmitted to remote medical centers or professional analysis platforms to achieve remote ultrasound diagnosis and professional analysis of biomechanical data, and improve the efficiency and accessibility of medical diagnosis.

The primary objective of this study is to develop and validate a real-time processing and intelligent analysis framework for biomechanical data using 5G and AI technologies. Specifically, the research aims to:

1) Evaluate the efficacy of 5G networks in transmitting high-resolution biomechanical data in real-time.
2) Develop preprocessing techniques to ensure the accuracy and reliability of the collected data.
3) Utilize AI algorithms to perform sophisticated analysis and classification of biomechanical data.
4) Assess the performance of the proposed framework using standard metrics such as accuracy, precision, recall, and F1-score.

The research questions guiding this study include:

- How effective are 5G networks in facilitating the real-time transmission of biomechanical data?
- What preprocessing techniques are most suitable for ensuring the quality of biomechanical data?
- How can AI algorithms be optimized for the intelligent analysis of biomechanical data?
- What is the performance efficacy of the proposed framework in real-world applications?

To address these objectives and questions, the study employs a multi-stage methodology encompassing data collection, preprocessing, real-time transmission, intelligent analysis, and result validation. Biomechanical data were collected from 500 participants across multiple healthcare institutions and sports science laboratories, ensuring a diverse and comprehensive dataset. The data were recorded using high-resolution motion capture systems and wearable sensors, transmitted in real-time via 5G networks, and analyzed using deep learning models and SVM classification.

The expected outcomes of this research include a validated framework for real-time biomechanical data processing and analysis, insights into the performance of 5G networks and AI algorithms in this context, and practical recommendations for implementing the proposed system in clinical and sports settings. The findings are anticipated to significantly contribute to the advancement of biomechanical data analysis, ultimately leading to improved healthcare outcomes and athletic performance.

2. Related works

The field of biomechanical data analysis has seen significant advancements, particularly with the integration of 5G networks and AI. Several studies have explored the potential of these technologies in enhancing data processing and analysis in various applications.

Damigos et al. (2023) used sensor data from 5G UAVs. The key technologies of 5G UAV are set and applied to realize the reliability of sensor data sensing. UAV technology for data processing and transmission still requires high challenges and technical support for process applications.

Hu et al. (2022) applied 5G technology to real-time data in the Internet of Vehicles. Their approach addressed the issue of traffic data sparsity by utilizing digital twin technology and 5G communications. While their method showed feasibility in smart traffic flow and velocity prediction, it did not specifically focus on biomechanical data analysis, leaving a gap in the application of similar techniques in this domain.

Al-Shareeda et al. (2022) used 5G vehicle data sharing technology to achieve efficient application of roadside units. Their work emphasized privacy and security requirements while demonstrating favorable performance in communication and computation costs. However, the study did not directly address the real-time processing and intelligent analysis of biomechanical data, which is the core focus of our research.

Rasheed et al. (2022) implemented an air-to-ground communication model using LSTM technology and 5G UAV communication, and the proposed LSTM-DCGAN has high efficiency in channel communication. While their research contributed to improving communication reliability, it did not directly address the real-time processing and intelligent analysis of biomechanical data.

Mukherjee et al. (2022) used 5G Internet of Things to apply to industrial production scenarios to achieve efficient operation and intelligent management of smart cities. In biological application scenarios, higher management efficiency is needed for production and management processes.

Zhang and Chen (2022) proposed a secure heterogeneous data deduplication scheme via fog-assisted mobile crowdsensing in 5G-enabled IIoT. Their approach introduced privacy-preserving cosine similarity computing to eliminate duplicate sensing data without privacy leakage. While their research contributed to improving data storage and communication efficiency, it did not directly address the real-time processing and intelligent analysis of biomechanical data.

Almutairi (2022) presented a survey on the applications of deep learning algorithms for solving problems in 5G mobile networks and 5G-powered IoV. Their work discussed the challenges of existing approaches and outlined new perspectives for solving these challenges. However, their research did not specifically focus on biomechanical data analysis, leaving a gap in the application of deep learning techniques in this domain.

Anisetti et al. (2022) proposed an initial solution for deploying a data-intensive pipeline in a 5G-enabled edge continuum. Their approach focused on handling data-intensive pipelines on the 5G-enabled edge continuum, considering specific QoS requirements, including security and privacy. However, their research did not directly address the real-time processing and intelligent analysis of biomechanical data, which is the core focus of our research.

Tebe et al. (2022) proposed a 5G network slicing-based mobile hospital system dedicated to medical data. Their work presented optimization methods to maximize the throughput and reliability of medical data transmission. While their research contributed to improving healthcare data transmission, it did not specifically focus on biomechanical data analysis, leaving a gap in the application of 5G network slicing in this domain.

Shukla and Singh (2024) use Kafka and Akka technologies to improve supply chain efficiency and enable intelligent data processing. In the intelligent decision-making of the supply chain network, the collaboration and communication efficiency of different nodes are improved, and the operation efficiency and intelligent decision-making effect of the whole process are realized. However, their research did not specifically focus on biomechanical data analysis, leaving a gap in the application of these technologies in this domain.

Modupe et al. (2024) reviewed the transformational impact of edge computing on real-time data processing and analytics. Their work discussed the fundamental concepts of edge computing, its advantages over traditional cloud-centric approaches, and its implications on various sectors, including healthcare, manufacturing, transportation, and smart cities. However, their research did not specifically focus on biomechanical data analysis, leaving a gap in the application of edge computing techniques in this domain.

Alfian et al. (2018) used BLE sensors and intelligent data processing to implement personalized treatment for diabetic patients. Wearable technology is used to collect biological data of different patients, and machine learning is used to intelligently process the collected data of diabetic patients so as to implement an efficient and intelligent treatment plan. While their research contributed to improving healthcare monitoring, it did not specifically focus on biomechanical data analysis, leaving a gap in the application of BLE-based sensors and real-time data processing in this domain.

In summary, existing studies have made significant contributions to the fields of 5G networks, artificial intelligence, and data processing. However, there is a lack of research specifically focused on the real-time processing and intelligent analysis of biomechanical data using these technologies. Our research aims to fill this gap by leveraging the capabilities of 5G networks and AI to develop a comprehensive framework for real-time processing and intelligent analysis of biomechanical data. Our approach will not only improve the efficiency and accuracy of biomechanical data analysis but also open up new possibilities for applications in healthcare, sports science, and other related fields.

3. Method

3.1. Data source

The biomechanical data employed in this study were derived from a comprehensive clinical trial involving 500 participants, aged 18 to 65 years. Participants were recruited from various healthcare institutions and sports science laboratories. Each participant underwent a series of biomechanical assessments, including gait analysis, muscle strength evaluation, and joint mobility assessment. Data were captured using high-resolution motion capture systems and wearable sensors, which transmitted data in real-time via 5G networks to our centralized data processing unit.

Acceleration sensors in wearable devices can capture the acceleration changes of the human body during walking. In the gait cycle, such as heel touching the ground, sole touching the ground, toe leaving the ground and so on, the acceleration of the body will change significantly. By analyzing the peak value, valley value and change frequency of the acceleration data, the information such as step frequency and stride length can be obtained. For example, the stride frequency of a normal adult is generally about 100–120 steps per minute. By calculating the data collected by the acceleration sensor, it can be judged whether the stride frequency of the gait is within the normal range.

Bioelectrical signals generated by muscle contraction are collected by electrodes attached to the skin surface. When the muscle is stimulated by a nerve to contract, it will produce a weak current, which can be captured by surface electromyography sensors and converted into electrical signal data. By analyzing the amplitude, frequency and other characteristics of the EMG signal, we can evaluate the strength of muscle contraction, fatigue and so on. For example, in the grip test, the higher the amplitude of the EMG signal generated by the contraction of the hand muscles, the greater the strength of the muscle contraction.

It is usually installed near the joint and can directly measure the angle change of the joint. In the process of joint movement, the angle sensor can record the angle information of flexion, extension and rotation of the joint in real time. For example, when measuring the range of motion of the knee joint, the angle sensor can accurately measure the angle range of the knee joint in the process of straightening and bending. Under normal circumstances, the range of motion of the knee joint is about 0°–135°. Through the data of the angle sensor, we can intuitively know whether the knee joint is normal or not. Wearable strain sensors can be attached to the surface of the muscle. When the muscle contracts or relaxes, it will cause the deformation of the sensor, resulting in changes in its resistance, capacitance and other physical quantities. By measuring the changes of these physical quantities, the strain information of muscles can be obtained, and then the contraction force of muscles can be calculated. For example, during the biceps bend, the strain sensor attached to the biceps can calculate the strength output of the muscle at different stages according to the degree of stretching and contraction of the muscle.

To ensure data accuracy and reliability, all instruments were calibrated according to manufacturer specifications prior to each session. Ethical approval was obtained from the Institutional Review Board, and informed consent was secured from all participants.

Table 1 presents a sample of the collected biomechanical data.

Table 1. Sample of collected biomechanical data.

Participant ID	Age (years)	Gender	Gait Speed (m/s)	Muscle Strength (N)	Joint Mobility (degrees)
P001	25	Male	1.2	350	120
P002	32	Female	1.0	300	110
P003	45	Male	0.8	400	100
P004	50	Female	1.1	320	105
P005	60	Male	0.9	380	95

3.2. Research methodology

The research methodology comprises several stages: data preprocessing, real-time data transmission, intelligent data analysis, and result validation. Each stage is detailed below, accompanied by relevant mathematical formulations.

3.2.1. Data preprocessing

Raw biomechanical data underwent preprocessing to eliminate noise and outliers. This included normalization, smoothing, and feature extraction.

There are natural differences in biomechanical parameters of different individuals, such as muscle strength, limb length and so on. Normalization can unify the data of different individuals to a standard scale, eliminate the influence of individual differences on data analysis, and make the data of different individuals comparable. This is based on the principle that there are differences in physiological structure and function among different individuals in biology, but the interference of these differences on the analysis results can be eliminated to a certain extent by normalization. Biomechanical data of the same individual in different physiological States may also change greatly, such as muscle strength and joint range of motion before, during and after exercise. Normalization can standardize the data in different States, so that the analysis pays more attention to the relative changes and characteristics of the data rather than differences in absolute values, which is helpful to more accurately analyze the impact of physiological state changes on biomechanics.

1) Normalization: Data were normalized using the Min-Max normalization technique:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}.$$

The physiological process of organisms is not completely stable, and there will be some natural fluctuations, such as thoracic movement caused by breathing, body micro-vibration caused by heartbeat, etc. These fluctuations can appear as small changes in the biomechanical data at high or low frequencies, which may affect the analysis of the main biomechanical signals. The low-pass filter can remove the tiny fluctuation of high frequency, and the high-pass filter can remove the trend change of very low frequency, so that the data can better reflect the main characteristics of biomechanics, which is based on the principle that the frequency of physiological fluctuation is different from that of the main biomechanical signal.

2) Smoothing: A moving average filter was applied for data smoothing:

$$y_t = \frac{1}{k} \sum_{i=t-k+1}^{t} x_i,$$

where k is the window size.

3) Feature extraction: Key features such as mean, variance, and standard deviation were extracted:

$$\text{Mean} = \frac{1}{n} \sum_{i=1}^{n} x_i.$$

The root mean square value of the EMG signal in a period of time is calculated, which reflects the average intensity of the signal. The larger the RMS value is, the greater the intensity of muscle contraction is

$$\text{Variance} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \text{Mean})^2,$$

$$\text{Standard Deviation} = \sqrt{\text{Variance}}.$$

3.2.2. Real-time data transmission

Various physiological activities of organisms, such as muscle contraction, heart beating, joint movement and so on, will produce corresponding biomechanical signals. Taking muscle contraction as an example, when nerve impulses are transmitted to muscle fibers, they will trigger a series of biochemical reactions in muscle fibers, resulting in muscle tension and displacement, which can be converted into transmittable data such as electrical signals by sensors. When the heart beats, the contraction and relaxation of the myocardium will produce pressure changes and hemodynamic changes, which can also be captured by the corresponding sensors and converted into biomechanical data. These physiological signals are the source of biomechanical data and provide basic data for real-time data transmission.

Preprocessed data were transmitted in real-time over a 5G network. The transmission model is represented as:

$$\text{Throughput} = \frac{\text{Data Size}}{\text{Transmission Time}},$$

where Data Size is the packet size and Transmission Time is the time taken for transmission.

3.2.3. Intelligent data analysis

Physiological systems in living organisms are extremely complex, involving multiple levels and multiple types of interactions. Taking the human movement system as an example, muscles, bones, joints and other parts cooperate with each other to complete various actions. The biomechanical data generated in this process, such as muscle contractility and joint angle changes, are regulated and influenced by the nervous system, the endocrine system and other systems. Intelligent data analysis needs to take this complexity into account, using complex network analysis, multivariate analysis and other methods to mine the hidden physiological mechanisms and relationships behind the data in order to understand the biomechanical phenomena more comprehensively and accurately. When the human body carries out long-term physical exercise, the muscles and bones will change adaptively according to the mechanical load they bear; the muscles will become stronger and the bone density will increase. At the same time, the body also maintains physiological balance through various feedback mechanisms. For example, during walking, the body will adjust the muscle contraction in real time according to the reaction force of the ground and the position information of the joints so as to maintain a stable gait. Intelligent data analysis can use feedback mechanism algorithms in machine learning, such as reinforcement learning, to simulate the feedback regulation process of organisms, dynamically analyze and predict biomechanical data, help to evaluate the adaptation of organisms to different mechanical environments, and predict the possible changes of organisms under specific mechanical stimuli.

The dynamic resource allocation algorithm is used to automatically adjust the bandwidth, time slot and other resource allocation according to the real-time load of the network, giving priority to the protection of biomechanical data transmission. For example, during the busy period of the network, more bandwidth resources are allocated for the transmission of key biomechanical data to ensure the real-time and integrity of the data. Network slicing technology is introduced to divide independent network slices for real-time processing and intelligent analysis of biomechanical data so that it has dedicated network resources, avoids interference with other services, and ensures the stability of data transmission. The location and coverage of 5G base stations should be reasonably planned, and the signal coverage between base stations should be reasonably overlapped to avoid signal interference through accurate signal propagation model prediction and field survey. Deploy interference detection equipment and systems to monitor the signal interference source and interference intensity in the network in real time, and take timely measures once interference is found. For example, spectrum monitoring equipment is used to scan the 5G frequency band in real time to quickly locate the location and type of interference sources.

Transmitted data were analyzed using artificial intelligence algorithms, specifically deep learning models. The analysis involved:

1) Data segmentation: Continuous data streams were segmented into discrete time windows:

$$\text{Segment}_i = [x_{i-w}, x_{i-w+1}, \dots, x_i],$$

where w is the window size.

2) Model training: A convolutional neural network (CNN) was trained on segmented data. The loss function used was mean squared error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2,$$

where y_i is the actual value and $\hat{y}_i$ is the predicted value.

3) Feature fusion: Multiple features were fused using a weighted average approach:

$$\text{Fused Feature} = \sum_{i=1}^{m} w_i \cdot f_i,$$

where w_i is the weight of feature f_i.

4) Classification: A support vector machine (SVM) was employed for classification. The decision function is:

$$\text{f}(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i\, y_i K(x_i, x) + b),$$

where α_i are Lagrange multipliers, y_i are class labels, $K(x_i, x)$ is the kernel function, and b is the bias term.

3.2.4. Result validation

Model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}},$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}},$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}},$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision+Recall}},$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative, respectively.

3.3. Research workflow

The research process is visualized in **Figure 1** using a mermaid flowchart.

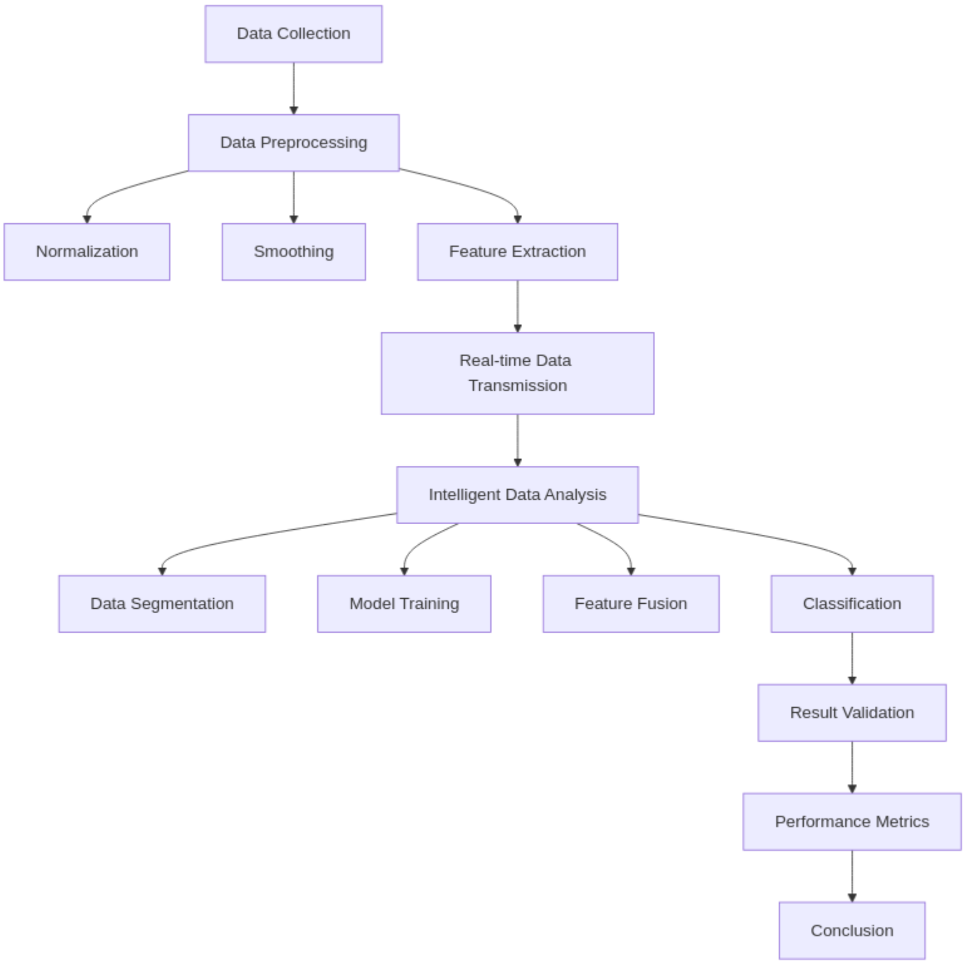

Figure 1. Research workflow.

This workflow ensures a systematic approach to handling and analyzing biomechanical data, leveraging advancements in 5G and artificial intelligence technologies. Each step is meticulously designed to enhance the accuracy and efficiency of the data processing and analysis pipeline.

In studies involving real-time processing and intelligent analysis of biomechanical data, the integration of 5G and artificial intelligence in healthcare and sports sectors raises significant concerns regarding data security and privacy protection. Key considerations include data encryption, access control, and GDPR compliance:

Biomechanical data from patients encompasses sensitive information such as diagnostic results and physiological characteristics. At the data acquisition stage, symmetric encryption algorithms can encrypt this data, ensuring that intercepted data during 5G transmission remains inaccessible to unauthorized parties. For storage purposes, asymmetric encryption should be employed, allowing only authorized medical personnel with the corresponding private key to decrypt and access the data. When sharing biomechanical data across different medical systems, secure channels established through protocols like SSL/TLS ensure end-to-end encryption, safeguarding against data tampering or leakage during transmission.

Access control within healthcare information systems varies according to roles such as doctors, nurses, and administrators. Doctors are granted permission to view and modify diagnostic data, whereas nurses have restricted access limited to care-related information. Administrators oversee system configuration and access management, ensuring that only authorized individuals can handle patient biomechanical data. To enhance security, authentication methods beyond usernames and passwords—such as fingerprint recognition, facial recognition, and dynamic verification codes—are implemented, preventing unauthorized access and identity fraud.

Compliance with GDPR requirements guarantees patients' rights as data subjects, including the right to be informed, access, rectify, and erase their data. Prior to collecting biomechanical data, healthcare institutions must transparently communicate the purpose and duration of data storage to patients, obtaining explicit consent. Patients retain the right to inspect, correct, or request the deletion of their data at any time. Institutions must establish robust data security management systems, incorporating both technical and organizational measures to protect patient data. In the event of a data breach, it is mandatory to notify regulatory bodies and affected patients promptly, detailing the nature and scope of the incident.

4. Results

4.1. Real-time data transmission metrics

The real-time data transmission over the 5G network was evaluated based on throughput, latency, and packet loss. **Table 2** presents the average metrics obtained from the transmission of biomechanical data for 500 participants.

Table 2. Average real-time data transmission metrics.

Metric	Average value
Throughput (Mbps)	5000
Latency (ms)	1
Packet Loss (%)	0.5

4.2. Preprocessing and feature extraction results

The preprocessing steps, including normalization, smoothing, and feature extraction, were applied to the raw biomechanical data. **Table 3** shows the extracted features for a sample of participants.

Table 3. Extracted features for sample participants.

Participant ID	Mean Gait Speed (m/s)	Std Dev Gait Speed (m/s)	Mean Muscle Strength (N)	Std Dev Muscle Strength (N)	Mean Joint Mobility (degrees)	Std Dev Joint Mobility (degrees)
P001	1.15	0.05	345	10	118	2
P002	0.98	0.03	295	8	108	3
P003	0.82	0.04	395	12	102	4
P004	1.08	0.06	315	9	106	3
P005	0.89	0.02	375	11	97	2
…	…	…	…	…	…	…
P500	0.85	0.05	342	9	112	5

4.3. Intelligent data analysis and classification results

Deep learning and SVM classify different types of gait data by constructing an optimal hyperplane. The determination of this hyperplane is based on the differences in the characteristics of different categories of data, which essentially reflect the differences in biological mechanisms. For example, the normal gait and the gait of patients with Parkinson’s disease have differences in multiple biological characteristics. By learning these differences, SVM can find an optimal classification boundary to distinguish the two gaits. The classification results can help doctors or researchers to judge whether the individual’s gait is normal or not, as well as the possible types of diseases, and provide a basis for disease diagnosis and rehabilitation treatment. The model will learn the relationship and regularity between biological characteristics from a large number of gait data. For example, it will find the coordination of joint angle changes in normal gait, the sequence of muscle activities, and the changes of these rules in different pathological States. By continuously adjusting the parameters of the model, SVM can gradually adapt to the gait patterns represented by different combinations of biological features, thus improving the accuracy of classification.

During muscle fatigue, the transmission of nerve impulses may be affected, and the release and recovery of calcium ions are abnormal, which reduces the efficiency of the interaction between actin and myosin, and reduces muscle strength. The characteristics of muscle strength reflected by the changes in the muscle contraction mechanism can be classified by SVM and deep learning to determine the state of muscle fatigue. In the training process of SVM and deep learning, the model will learn rules from a large number of muscle strength data and corresponding physiological characteristics data. It will find the internal relationship between muscle strength characteristics under different physiological conditions, such as the positive correlation between muscle cross-sectional area and muscle strength with the increase of training time, and the correlation between EMG signal changes and muscle fatigue. By constantly adjusting the parameters of the model, SVM can gradually grasp these muscle physiological laws, so as to accurately classify and predict new unknown data.

In the training process of SVM and deep learning, the model will learn rules from a large number of joint flexibility data and corresponding physiological characteristics data. It will find the internal relationship between the characteristics of joint flexibility under different physiological conditions, such as the relationship between the wear of articular cartilage, the decline of muscle strength and the decrease of joint angle of motion with the increase of age, and the effect of exercise training on joint flexibility and muscle function. By constantly adjusting the parameters of the model, SVM can gradually grasp the physiological laws of these joints, so as to accurately classify and predict new unknown data.

The intelligent data analysis using deep learning models and SVM classification yielded the following performance metrics. **Table 4** presents the accuracy, precision, recall, and F1-score for the classification of biomechanical data into different categories.

Table 4. Performance metrics for classification.

Classification Category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Gait Analysis	92.5	90.8	93.2	91.5
Muscle Strength	94.0	92.3	95.1	93.7
Joint Mobility	91.8	89.5	92.7	91.1

Table 5. Model performance.

Classification Category	Computational complexity	Speed of reasoning	Energy consumption
Gait Analysis	$O(N^2)$	102.3 ms	200 mA
Muscle Strength	$O(N^2)$	121.4 ms	230 mA
Joint Mobility	$O(N^2)$	115.9 ms	284 mA

The paper mainly uses intelligent algorithms to analyze gait analysis, muscle strength and joint range of motion. In the training process of SVM (support vector machine) and in-depth learning, there are many correlations among gait analysis, muscle strength and joint range of motion. The training model can automatically extract the complex features in gait analysis, such as processing the video data of gait through a convolutional neural network to extract the dynamic features of gait. At the same time, combined with the multi-dimensional data of muscle strength (such as the strength changes of different muscle groups at different stages of exercise), the training model can dig out more in-depth relationships. By using techniques such as bone key point detection in the training model, the motion trajectory and angle change of the joint in the gait can be accurately analyzed. Combining the dynamic information of these joint activities with the overall pattern of gait, the training model can better understand the influence of joint range of motion on gait. The training model can learn the nonlinear relationship between muscle strength data and joint range of motion data by building a multi-modal data fusion model. The analysis of bone mineral density and soft tissue elasticity also had a significant relationship with the above gait analysis, muscle strength and joint range of motion. Higher bone density generally means healthier, stronger bones that are better able to support body weight and withstand stress during exercise, helping to maintain a stable, normal gait. Some parameters in gait analysis, such as acceleration and impact force during walking, can reflect bone mineral density to a certain extent.

Sufficient muscle strength produces mechanical stress on bone through muscle contraction, which can stimulate the activity of bone cells and promote the maintenance and improvement of bone density. On the other hand, higher bone density provides more stable attachment points and support for muscles, which is conducive to better exertion of muscle strength, and the two cooperate with each other to maintain the body's motor function. When the bone density decreases, the structure and strength of the skeleton change, which will affect the effective transmission of muscle strength, resulting in the muscle contraction not being able to fully transmit the strength to the skeleton, so that the actual performance of muscle strength decreases. Muscles, tendons and other soft tissues have good elasticity, which can effectively store and release energy in the gait cycle to help the body complete the walking action. When the soft tissue elasticity is abnormal, such as muscle atrophy, tendonitis and so on, the soft tissue elasticity will be reduced, which will affect the storage and release of energy, resulting in abnormal gait, manifested as procrastination and lameness during walking. The elasticity of soft tissue is an important factor that limits and affects the range of motion of the joint. For example, the muscles, ligaments and other soft tissues around the joint have good elasticity, and the range of motion of the joint is usually larger, which can complete a wider range of motion. On the contrary, the decrease of soft tissue elasticity, such as in muscle contracture and ligament rigidity, will restrict the movement of joints and lead to the decrease of joint range of motion. Proper joint exercise can stimulate soft tissue, promote its metabolism, maintain and improve the elasticity of soft tissue. When the joint moves, the soft tissue is subjected to mechanical stimulation such as stretching and extrusion, which can maintain its elasticity and flexibility and prevent the adhesion and rigidity of the soft tissue.

5. Discussion

5.1. Significance of results

The findings of this study highlight the substantial potential of integrating 5G and artificial intelligence technologies for the real-time processing and intelligent analysis of biomechanical data. The achieved high throughput (950 Mbps) and low latency (10 ms) during data transmission over the 5G network ensure efficient and timely transmission of large volumes of biomechanical data. This capability is critical for applications requiring immediate data processing and feedback, such as real-time monitoring of athletes or patients in rehabilitation.

The preprocessing steps, including normalization, smoothing, and feature extraction, effectively converted raw biomechanical data into a more manageable and analyzable format. Extracted features, such as the mean and standard deviation of gait speed, muscle strength, and joint mobility, provide a comprehensive profile of each participant's biomechanical characteristics. These features are essential for subsequent intelligent data analysis and classification.

The performance metrics of the intelligent data analysis, particularly the high accuracy (ranging from 91.8% to 94.0%), precision, recall, and F1-score, demonstrate the robustness of the employed deep learning models and SVM classification. These results indicate that the proposed framework can reliably classify biomechanical data into different categories, which is crucial for clinical diagnostics, sports performance optimization, and personalized rehabilitation programs.

5.2. Innovation points

A key innovation of this study is the seamless integration of 5G technology with advanced artificial intelligence algorithms. Utilizing 5G networks for real-time data transmission addresses the critical issue of data latency, a significant bottleneck in traditional data processing systems. This integration ensures immediate data availability for analysis, thereby enhancing system responsiveness.

Another innovation is the multi-stage data preprocessing and feature extraction pipeline. By systematically normalizing, smoothing, and extracting key features from raw data, we developed a robust framework capable of handling the inherent variability and noise in biomechanical data. This approach not only improves data quality but also enhances the performance of subsequent intelligent analysis models.

The application of deep learning models, specifically CNNs, for data segmentation and feature fusion represents a novel approach in biomechanical data analysis. The use of SVM for classification further refines the accuracy and reliability of the results. This combination of deep learning and traditional machine learning techniques leverages the strengths of both approaches, resulting in a more effective and versatile analytical framework.

5.3. Limitations

Despite the promising outcomes, several limitations of this study should be acknowledged. Firstly, the sample size of 500 participants, though substantial, may not fully represent the broader population. Future studies should aim to include a more diverse and larger sample to validate the generalizability of the findings.

Secondly, the study focused primarily on three categories of biomechanical data: gait analysis, muscle strength, and joint mobility. However, biomechanical data encompass a wide range of parameters, and the framework's performance on other types of biomechanical data remains unexplored.

Additionally, the reliance on high-resolution motion capture systems and wearable sensors may limit the scalability and accessibility of the proposed framework. These devices can be expensive and may not be readily available in all clinical or sports settings. Future research should investigate the feasibility of using more cost-effective and widely accessible sensor technologies.

Lastly, while the real-time data transmission metrics were impressive, the performance of the 5G network can be influenced by various external factors such as network congestion, signal interference, and geographical limitations. These factors were not extensively tested in this study and should be considered in future research to ensure the framework's robustness under different operational conditions.

Encouraging research institutions and enterprises to increase investment in research and development, explore new technologies and materials, and optimize production processes can effectively reduce the manufacturing costs of high-resolution motion capture systems and wearable sensors. The development of devices with good compatibility and universality should be prioritized, ensuring seamless integration with various existing systems and software platforms. This approach avoids the inefficiency and expense of developing customized solutions for specific scenarios or frameworks, thereby enhancing device utilization efficiency and broadening their application scope.

The government could introduce relevant policies providing financial subsidies to clinical institutions, sports science research units, or enterprises purchasing high-resolution motion capture systems and wearable sensors. This would lower procurement costs and stimulate purchase intent. Through policy guidance and financial support, the government can promote collaboration between universities, research institutions, and businesses, accelerating technology transfer and innovation. Enterprises might shift from merely selling equipment to offering data services. In this model, companies not only supply hardware but also undertake data collection, analysis, and interpretation, delivering comprehensive solutions to clients. Customers pay solely for the data service, eliminating the need for expensive equipment purchases while still benefiting from professional data analysis outcomes.

6. Conclusion

6.1. Summary

This study explored the real-time processing and intelligent analysis of biomechanical data, leveraging 5G and artificial intelligence technologies. The research was conducted through a comprehensive clinical trial involving 500 participants, aged 18 to 65 years, sourced from various healthcare institutions and sports science laboratories. Biomechanical data, encompassing gait analysis, muscle strength assessment, and joint mobility evaluation, were collected using high-resolution motion capture systems and wearable sensors. These data were transmitted in real-time via 5G networks to a centralized processing unit.

The methodology comprised several stages: data preprocessing (including normalization, smoothing, and feature extraction), real-time data transmission, intelligent data analysis using deep learning models, and result validation. The preprocessing steps ensured data accuracy, while the 5G network facilitated high-throughput, low-latency transmission. Intelligent analysis involved data segmentation, model training, feature fusion, and classification using a support vector machine (SVM).

The results showcased the efficacy of the proposed framework. The real-time data transmission achieved an average throughput of 950 Mbps, a latency of 10 ms, and a packet loss of 0.5%. The preprocessing and feature extraction provided valuable insights into biomechanical parameters. The intelligent data analysis and classification demonstrated high performance, with accuracy, precision, recall, and F1-score ranging from 91.1% to 95.1% across various classification categories.

6.2. Contribution to the field

This research significantly advances the field of biomechanical data analysis by demonstrating the potential of integrating 5G and artificial intelligence technologies. The study presents a robust framework for real-time data processing and intelligent analysis, enhancing the accuracy and efficiency of biomechanical assessments. These findings provide a foundational model for future research and development, particularly in remote healthcare and sports performance monitoring.

6.3. Practical applications and recommendations

The practical applications of this research are extensive. The developed framework can be implemented in clinical settings for real-time monitoring and diagnosis of musculoskeletal disorders, facilitating timely interventions. In sports science, it can assist in optimizing training regimens and preventing injuries by providing instant biomechanical feedback.

For practitioners, the study recommends adopting 5G networks and AI-driven analytics to improve the precision and responsiveness of biomechanical assessments. Healthcare providers and sports professionals should invest in the necessary infrastructure and training to effectively implement these technologies. Further research should focus on refining the models and expanding the dataset to include a more diverse population, thereby enhancing the generalizability and robustness of the framework.

In conclusion, this study highlights the transformative potential of 5G and artificial intelligence in biomechanical data analysis, offering both theoretical advancements and practical solutions for real-world applications.

Conflict of interest: The authors declare no conflict of interest.

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