

Review

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Review

Large Language Models for Wearable Sensor-Based Human Activity Recognition, Health Monitoring, and Behavioral Modeling: A Survey of Early Trends, Datasets, and Challenges

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Abstract: The proliferation of wearable technology enables the generation of vast amounts of sensor data, offering significant opportunities for advancements in health monitoring, activity recognition, and personalized medicine. However, the complexity and volume of this data present substantial challenges in data modeling and analysis, which have been tamed with approaches spanning time series modeling to deep learning techniques. The latest frontier in this domain is the adoption of Large Language Models (LLMs), such as GPT-4 and Llama, for data analysis, modeling, understanding, and generation of human behavior through the lens of wearable sensor data. This survey explores current trends and challenges in applying LLMs for sensor-based human activity recognition and behavior modeling. We discuss the nature of wearable sensors data, the capabilities and limitations of LLMs to model them and their integration with traditional machine learning techniques. We also identify key challenges, including data quality, computational requirements, interpretability, and privacy concerns. By examining case studies and successful applications, we highlight the potential of LLMs in enhancing the analysis and interpretation of wearable sensors data. Finally, we propose future directions for research, emphasizing the need for improved preprocessing techniques, more efficient and scalable models, and interdisciplinary collaboration. This survey aims to provide a comprehensive overview of the intersection between wearable sensors data and LLMs, offering insights into the current state and future prospects of this emerging field.

Keywords: wearable sensors; large language models; human activity analysis

1. Introduction

The rapid advancement of wearable technology has led to an explosion in the availability of sensor data, providing unprecedented opportunities for monitoring and understanding human behavior and health. Wearable sensors, ranging from fitness trackers to advanced medical devices, generate vast amounts of data that can be leveraged for various applications, including health monitoring, activity recognition, and personalized medicine. However, the complexity and volume of this data present significant challenges in data modeling and analysis.

Large Language Models (LLMs), such as GPT-4 and Llama, have recently emerged as powerful tools in the field of data analysis, demonstrating remarkable capabilities in understanding and generating human-like text. These models, trained on diverse datasets, have shown potential in handling the complexity of wearable sensors data, offering new possibilities for extracting meaningful insights. This survey aims to explore the current trends and challenges associated with modeling wearable sensors data using LLMs.

1.1. Background on Wearable Sensors

Wearable sensors have become an integral part of modern technology, playing a crucial role in monitoring and understanding various aspects of human behavior and health. These sensors are embedded in devices such as fitness trackers, smartwatches, and medical devices, providing continuous data on physiological and behavioral metrics. Common types of wearable sensors include accelerome-

ters, gyroscopes, heart rate monitors, electrocardiograms (ECG), and photoplethysmography (PPG) sensors [1,2].

These devices are widely used in applications ranging from fitness and lifestyle management to clinical diagnostics and chronic disease management. Wearable sensors can detect the impact of atypical events, which is crucial for understanding daily fluctuations in user states [3]. For instance, accelerometers and gyroscopes are used to track physical activities and movements, heart rate monitors provide insights into cardiovascular health, and ECG sensors are employed in detecting cardiac anomalies. The ability to collect real-time data enables continuous monitoring, early detection of health issues, and personalized healthcare interventions [4,5].

1.2. Importance of Data Modeling in Wearable Technology

The vast amount of data generated by wearable sensors necessitates effective data modeling to derive meaningful insights. Data modeling involves transforming raw sensor data into structured information that can be analyzed and interpreted. This process is critical in applications such as human activity recognition (HAR), health monitoring, and behavioral analysis [6,7].

Traditional machine learning techniques have been employed extensively for HAR, leveraging algorithms such as support vector machines (SVM), decision trees, and k-nearest neighbors (KNN). These methods typically require extensive preprocessing and feature extraction steps, which involve converting raw sensor data into a format suitable for analysis. While these techniques have shown success in various applications, they often struggle with scalability and adaptability, especially when dealing with complex and heterogeneous data from different sensor modalities [5].

Deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have emerged as powerful tools for HAR and other wearable sensor data applications. These models can automatically extract features from raw data, reducing the need for manual preprocessing and feature engineering. However, they require large labeled datasets and substantial computational resources, posing challenges for real-time and resource-constrained environments [7].

1.3. Emergence of Large Language Models (LLMs) in Data Analysis

Large Language Models (LLMs), such as GPT-4 and BERT, have revolutionized data analysis across various domains, including natural language processing, computer vision, and recently, wearable sensor data analysis. LLMs are trained on vast amounts of text data, enabling them to understand and generate human-like text with remarkable accuracy and fluency [8,9].

The application of LLMs in wearable sensor data analysis is relatively new but promising. These models can process and analyze multimodal data, including text, audio, and sensor signals, offering a more comprehensive understanding of the data. For instance, *PhysioLLM* integrates physiological data from wearables with contextual information to provide personalized health insights, demonstrating improved user understanding and motivation for health improvement [8]. Similarly, *HARGPT* leverages LLMs for zero-shot human activity recognition, outperforming traditional models in recognizing activities from raw IMU data [10].

LLMs' ability to handle complex queries and generate insightful responses makes them ideal for tasks that require high-level reasoning and contextual understanding. By integrating LLMs with wearable sensor data, researchers can develop more sophisticated models that not only classify activities but also provide personalized recommendations and insights based on the data. This integration opens new avenues for enhancing the effectiveness of wearable technology in health monitoring, personalized healthcare, and beyond [11].

2. Wearable Sensors Data

Wearable sensors have revolutionized the way we monitor and understand human health and behavior. By providing continuous, real-time data, these devices enable a deeper insight into various

physiological, biomechanical, and environmental parameters. This section explores the different types of wearable sensors, the nature of the data they generate, and their wide-ranging applications. Understanding these aspects is crucial for leveraging wearable technology to its fullest potential and addressing the challenges associated with data analysis and interpretation.

2.1. Types of Wearable Sensors

Wearable sensors encompass a diverse range of devices designed to monitor various physiological, biomechanical, and environmental parameters. These sensors can be broadly classified into several categories based on their function and application.

Physiological sensors are primarily used to monitor vital signs and other physiological parameters. Examples include heart rate monitors, electrocardiograms (ECG), blood pressure monitors, and pulse oximeters. Studies like [12] have utilized these sensors to gather data for health monitoring and disease prediction (see Table 1, Physiological Sensors).

Motion sensors, including accelerometers, gyroscopes, and magnetometers, are commonly used to track movement and orientation. They are essential in applications like activity recognition and sports science. Research by [13] demonstrates the effectiveness of motion sensors in human activity recognition (see Table 1, Motion Sensors).

Environmental sensors detect environmental conditions such as temperature, humidity, and light. These sensors are often integrated into wearable devices to provide context-aware services. The study by [14] highlights the use of environmental sensors in enhancing the accuracy of activity recognition systems (see Table 1, Environmental Sensors).

Biochemical sensors are advanced devices that can measure biochemical markers such as glucose levels, lactate, and electrolytes. They are particularly valuable in medical diagnostics and continuous health monitoring. Recent advancements in biochemical sensors have been discussed in [8] (see Table 1, Biochemical Sensors).

Multisensor systems integrate multiple sensor types into a single device to provide comprehensive monitoring capabilities. Examples include smartwatches and fitness trackers that combine physiological, motion, and environmental sensors. The integration of multisensor data for improved health insights is explored in [9] (see Table 1, Multisensor Systems).

These categories highlight the versatility and wide-ranging applications of wearable sensors, making them indispensable tools in health monitoring, activity recognition, and environmental sensing.

Table 1. Types of Wearable Sensors.

| Sensor Type | Description | Refs |
|-----------------------|---|------|
| Physiological Sensors | Monitor vital signs and other physiological parameters. Examples include heart rate monitors, electrocardiograms (ECG), blood pressure monitors, and pulse oximeters. | [12] |
| Motion Sensors | Includes accelerometers, gyroscopes, and magnetometers, used to track movement and orientation. Essential in applications like activity recognition and sports science. | [13] |
| Environmental Sensors | Detect environmental conditions such as temperature, humidity, and light. Often integrated into wearable devices to provide context-aware services. | [14] |
| Biochemical Sensors | Measure biochemical markers such as glucose levels, lactate, and electrolytes. Valuable in medical diagnostics and continuous health monitoring. | [8] |
| Multisensor Systems | Integrate multiple sensor types into a single device to provide comprehensive monitoring capabilities. Examples include smartwatches and fitness trackers. | [9] |

2.2. Nature of Data Generated

The data generated by wearable sensors is characterized by its high volume, variety, and velocity. Understanding the nature of this data is crucial for effective analysis and application. Wearable sensors produce various types of data, each with its unique characteristics and challenges.

Most wearable sensors generate continuous streams of time-series data, capturing dynamic changes over time. This type of data requires specialized techniques for preprocessing, segmentation, and feature extraction to be effectively analyzed. Techniques for handling time-series data from wearable sensors are discussed in [10] (see Table 2, Time-Series Data).

Wearable devices often generate multimodal data by combining inputs from different types of sensors. For instance, a smartwatch may collect both motion and physiological data simultaneously. Integrating and synchronizing these data streams is a complex task that is essential for accurate analysis. The challenges and methodologies for multimodal data integration are explored in [9] (see Table 2, Multimodal Data).

The raw data from wearable sensors can be high-dimensional, particularly when multiple sensors are used. Dimensionality reduction techniques, such as Principal Component Analysis (PCA) and feature selection methods, are employed to manage this complexity and make the data more manageable for analysis. The application of these techniques in wearable sensor data analysis is presented in [15] (see Table 2, High-Dimensional Data).

Wearable sensors are prone to generating noisy and sometimes incomplete data due to various factors like sensor malfunction, user movement, and environmental interference. Effective data cleaning and imputation methods are critical for maintaining data quality and ensuring accurate analysis. Approaches to address data quality issues are highlighted in [16] (see Table 2, Noisy and Incomplete Data).

These characteristics of wearable sensor data highlight the need for advanced analytical techniques to handle the unique challenges posed by high volume, variety, and velocity of data generated. Understanding these aspects is essential for leveraging wearable technology to its fullest potential.

Table 2. Nature of Data Generated by Wearable Sensors.

| Data Type | Description | Refs |
|---------------------------|--|------|
| Time-Series Data | Most wearable sensors produce continuous streams of time-series data, capturing dynamic changes over time. This type of data requires specialized techniques for preprocessing, segmentation, and feature extraction. | [10] |
| Multimodal Data | Wearable devices often generate multimodal data by combining inputs from different types of sensors. For instance, a smartwatch may collect both motion and physiological data simultaneously. Integrating and synchronizing these data streams is a complex task that is essential for accurate analysis. | [9] |
| High-Dimensional Data | The raw data from wearable sensors can be high-dimensional, particularly when multiple sensors are used. Dimensionality reduction techniques, such as Principal Component Analysis (PCA) and feature selection methods, are employed to manage this complexity. | [15] |
| Noisy and Incomplete Data | Wearable sensors are prone to generating noisy and sometimes incomplete data due to various factors like sensor malfunction, user movement, and environmental interference. Effective data cleaning and imputation methods are critical for maintaining data quality. | [16] |

2.3. Common Applications

Wearable sensors have a wide range of applications across various domains, driven by their ability to provide continuous, real-time monitoring. These applications are critical in enhancing health outcomes, improving performance, and ensuring safety in various environments.

One of the primary applications of wearable sensors is in health monitoring. These sensors play a crucial role in continuous health monitoring, enabling the early detection of medical conditions and the management of chronic diseases. Wearable sensors are increasingly being used in healthcare

organizations to monitor patients longitudinally [17]. Systems leverage wearable sensor data to provide personalized health insights and interventions [8] (see Table 3, Health Monitoring).

Another significant application is human activity recognition (HAR). By analyzing data from motion sensors, systems can classify various physical activities, which is valuable in fitness tracking, rehabilitation, and elder care. Advanced HAR models, such as those discussed in [13], demonstrate the potential of wearable sensors in accurately recognizing and categorizing different activities (see Table 3, Activity Recognition).

In the realm of sports and fitness, wearable sensors are used extensively to monitor athletes' performance, track training progress, and prevent injuries. The integration of physiological and motion sensors provides comprehensive insights into an athlete's condition and performance. Studies like those conducted by [9] showcase the benefits of wearable sensors in enhancing sports performance and optimizing training regimens (see Table 3, Sports and Fitness).

Mental health applications are also benefiting from wearable sensor technology. Accurate estimation of affective states is crucial for mental health applications. Wearable sensors offer a reliable method for this purpose [18]. These sensors monitor physiological indicators of stress, anxiety, and depression, providing real-time data that can be used to develop personalized interventions and support mental well-being. The MindShift project, for example, illustrates how wearable sensors can be employed to reduce smartphone addiction and improve mental health outcomes [19] (see Table 3, Mental Health).

Additionally, wearable sensors are employed in workplace ergonomics to improve safety and productivity. By monitoring workers' movements and posture, these sensors help design ergonomic interventions that prevent musculoskeletal disorders and enhance overall productivity. Research by [14] highlights the importance of wearable sensors in occupational health, emphasizing their role in creating safer and more efficient work environments (see Table 3, Workplace Ergonomics).

These diverse applications demonstrate the versatility and impact of wearable sensors in various fields, underscoring their importance in modern health and performance monitoring systems.

Table 3. Common Applications of Wearable Sensors.

| Application | Description | Refs |
|----------------------|--|------|
| Health Monitoring | Wearable sensors play a crucial role in continuous health monitoring, enabling the early detection of medical conditions and the management of chronic diseases. Systems like PhysioLLM leverage wearable sensor data to provide personalized health insights and interventions. | [8] |
| Activity Recognition | Human activity recognition (HAR) is one of the most prominent applications of wearable sensors. By analyzing data from motion sensors, researchers can classify various physical activities, which is valuable in fitness tracking, rehabilitation, and elder care. | [13] |
| Sports and Fitness | In sports science, wearable sensors are used to monitor athletes' performance, track training progress, and prevent injuries. The integration of physiological and motion sensors provides comprehensive insights into an athlete's condition and performance. | [9] |
| Mental Health | Wearable sensors are increasingly used in mental health applications to monitor physiological indicators of stress, anxiety, and depression. Real-time data from these sensors can be used to develop personalized interventions and support mental well-being. | [19] |
| Workplace Ergonomics | Wearable sensors are employed to improve workplace ergonomics by monitoring workers' movements and posture. This data helps in designing ergonomic interventions to prevent musculoskeletal disorders and enhance productivity. | [14] |

3. Large Language Models (LLMs)

Large Language Models (LLMs) have emerged as a transformative technology in the field of artificial intelligence, demonstrating unprecedented capabilities in understanding and generating human language. These models, built on sophisticated deep learning architectures, have significantly advanced natural language processing (NLP) and opened new possibilities for data analysis and inter-

pretation. This section provides an in-depth exploration of LLMs, including an overview of prominent models like GPT-4 and Llama, their capabilities and limitations, and their diverse applications in data analysis.

3.1. Overview of Recent LLM-based Systems

Large Language Models (LLMs) have revolutionized natural language processing (NLP) by leveraging deep learning techniques to understand and generate human-like text. Prominent examples include GPT-4 by OpenAI and Llama by Meta AI. These models are built on transformer architectures, which utilize self-attention mechanisms to capture long-range dependencies in text data [20]. The transformer architecture allows LLMs to process and generate text efficiently, handling complex language tasks with high accuracy.

GPT-4, a state-of-the-art model, boasts an impressive number of parameters, enabling it to generate coherent and contextually relevant text across various domains [21]. Similarly, Llama has been designed to achieve competitive performance with a more efficient architecture, making it suitable for applications with limited computational resources [22,23]. These models have set new benchmarks in NLP, excelling in tasks such as text generation, translation, summarization, and question-answering.

3.2. Capabilities and Limitations

LLMs like GPT-4 and Llama exhibit remarkable capabilities in understanding and generating text, making them powerful tools in data analysis. However, they also have inherent limitations that need to be addressed for their effective application.

One of the key capabilities of LLMs is their ability to comprehend complex language patterns. This makes them suitable for tasks such as sentiment analysis, entity recognition, and language translation. Their contextual understanding and ability to generate relevant responses have been demonstrated in various studies, including those focusing on health data interpretation [8,24] (see Table 4, Natural Language Understanding).

The text generation capabilities of LLMs are unparalleled, allowing them to produce coherent and contextually appropriate text for diverse applications. This has been effectively leveraged in generating health-related content, educational materials, and even creative writing [21] (see Table 4, Text Generation).

Additionally, LLMs can be integrated with other data modalities to provide comprehensive insights. For example, the LLaSA model combines text data with inertial measurement unit (IMU) data to enhance human activity recognition [9] (see Table 4, Multimodal Data Integration).

However, the use of LLMs comes with significant limitations. Training and deploying these models require substantial computational resources, which can be prohibitive for many applications. Efficient model architectures and optimization techniques are necessary to mitigate these challenges [13] (see Table 4, Computational Requirements).

Moreover, LLMs rely heavily on large, high-quality datasets for training. The quality and diversity of the training data significantly impact the model's performance and generalizability. Incomplete or biased data can lead to inaccurate predictions and outputs [10,25] (see Table 4, Data Dependency).

Another critical limitation is the interpretability of LLMs. These models operate as black-box systems, making it difficult to understand their decision-making processes. This lack of transparency is particularly problematic in critical applications such as healthcare, where understanding the rationale behind predictions is crucial [11] (see Table 4, Interpretability).

Finally, the use of LLMs raises ethical issues related to data privacy, security, and potential misuse. Ensuring compliance with data protection regulations and implementing privacy-preserving techniques are essential to address these concerns [26] (see Table 4, Ethical Concerns).

These capabilities and limitations highlight the importance of ongoing research and development to enhance the effectiveness and ethical deployment of LLMs in data analysis.

Table 4. Capabilities and Limitations of LLMs.

| Aspect | Description | Refs |
|--------------------------------|---|--------|
| Natural Language Understanding | LLMs can comprehend complex language patterns, making them suitable for tasks such as sentiment analysis, entity recognition, and language translation. Their ability to understand context and generate relevant responses has been demonstrated in various studies, including those focusing on health data interpretation. | [8,27] |
| Text Generation | The text generation capabilities of LLMs are unparalleled, allowing them to produce coherent and contextually appropriate text for diverse applications. This has been leveraged in generating health-related content, educational materials, and even creative writing. | [21] |
| Multimodal Data Integration | LLMs can be integrated with other data modalities, such as sensor data, to provide comprehensive insights. For example, the LLaSA model combines text data with inertial measurement unit (IMU) data to enhance human activity recognition. | [9] |
| Computational Requirements | Training and deploying LLMs require substantial computational resources, which can be prohibitive for many applications. Efficient model architectures and optimization techniques are necessary to mitigate these challenges. | [13] |
| Data Dependency | LLMs rely heavily on large, high-quality datasets for training. The quality and diversity of the training data significantly impact the model's performance and generalizability. Incomplete or biased data can lead to inaccurate predictions and outputs. | [10] |
| Interpretability | LLMs operate as black-box models, making it difficult to interpret their decision-making processes. This lack of transparency is a significant limitation, especially in critical applications such as healthcare, where understanding the rationale behind predictions is crucial. | [11] |
| Ethical Concerns | The use of LLMs raises ethical issues related to data privacy, security, and potential misuse. Ensuring compliance with data protection regulations and implementing privacy-preserving techniques are essential to address these concerns. | [26] |

3.3. Applications of LLMs in Data Analysis

The integration of Large Language Models (LLMs) into data analysis workflows has significantly expanded the potential for extracting meaningful insights from large and complex datasets. LLMs offer versatile applications across various domains, demonstrating their utility in interpreting and generating content tailored to specific needs.

In the field of health data analysis, LLMs are utilized to interpret and generate health-related content, providing personalized health insights and recommendations. Systems such as PhysioLLM leverage wearable sensor data to deliver context-aware health analyses and interventions, enhancing the relevance and accuracy of health monitoring (see Table 5, Health Data Analysis) [8].

Human activity recognition has also benefited from the integration of LLMs. By combining text data with sensor inputs, LLMs improve the accuracy of activity recognition systems. The LLaSA model, for instance, integrates inertial measurement unit (IMU) data with language models to enhance activity classification, demonstrating the effectiveness of this combined approach (see Table 5, Human Activity Recognition) [9].

LLMs are increasingly employed in mental health monitoring, where they analyze mental health indicators through both text and sensor data. The MindShift project illustrates the use of LLMs to create dynamic and personalized mental health interventions based on real-time data from wearable devices, offering a new avenue for mental health support (see Table 5, Mental Health Monitoring) [19].

In educational settings, LLMs have shown promise in generating educational content, providing tutoring assistance, and enhancing e-learning platforms. By offering personalized feedback and resources based on student interactions, LLMs contribute to more effective and tailored learning experiences (see Table 5, Educational Tools) [21].

Lastly, LLMs play a crucial role in business intelligence by assisting in the analysis of business data, generating reports, and extracting actionable insights. They process large volumes of textual data from various sources, such as customer reviews, social media, and financial reports, to inform strategic decisions and drive business growth (see Table 5, Business Intelligence) [27].

These applications underscore the versatility and power of LLMs in transforming data analysis across different fields, making them indispensable tools in modern data-driven environments.

Table 5. Applications of LLMs in Wearable Sensor-Based Data Analysis.

| Application | Description | Refs |
|----------------------------|---|------|
| Health Data Analysis | LLMs are used to interpret and generate health-related content, providing personalized health insights and recommendations. Systems like PhysioLLM leverage wearable sensor data to deliver context-aware health analyses and interventions. | [8] |
| Human Activity Recognition | By combining text data with sensor inputs, LLMs enhance the accuracy of human activity recognition systems. The LLaSA model demonstrates the effectiveness of this approach, integrating IMU data with language models to improve activity classification. | [9] |
| Mental Health Monitoring | LLMs are employed in monitoring and analyzing mental health indicators through text and sensor data. The MindShift project illustrates how LLMs can be used to create dynamic and personalized mental health interventions based on real-time data from wearable devices. | [19] |
| Educational Tools | LLMs can generate educational content, provide tutoring assistance, and enhance e-learning platforms by offering personalized feedback and resources based on student interactions. | [21] |
| Business Intelligence | LLMs assist in analyzing business data, generating reports, and extracting actionable insights. They can process large volumes of textual data from various sources, such as customer reviews, social media, and financial reports, to inform strategic decisions. | [27] |

4. Trends in Modeling Wearable Sensors Data with LLMs

This section aims to provide an in-depth analysis of the recent trends, case studies, applications, and integration of LLMs with other AI techniques in modeling wearable sensor data.

4.1. Recent Advancements

Recent advancements in the field of wearable sensor data modeling have seen the innovative application of Large Language Models (LLMs) to enhance human activity recognition (HAR) and health monitoring systems. The hybrid learning models, such as those proposed by Athota et al. [28] and Wang et al. [12], have demonstrated significant improvements in the accuracy and robustness of HAR systems by combining various machine learning techniques. These models effectively address the complex nature of wearable sensor data by leveraging the strengths of both traditional and deep learning methods.

The introduction of transformer models in HAR, as discussed by Augustinov et al. [29] and Suh et al. [15], has shown promise in capturing long-range dependencies in sequential data. These models utilize self-attention mechanisms to enhance the recognition accuracy of complex activities. For example, the Transformer-based Adversarial learning model TASKED [15] integrates adversarial learning and self-knowledge distillation to achieve cross-subject generalization, significantly improving the performance of HAR systems using wearable sensors.

Furthermore, the application of zero-shot learning in models like HARGPT [10] underscores the potential of LLMs to recognize human activities from raw sensor data without extensive training datasets. This approach significantly reduces the need for large labeled datasets, making it a cost-effective solution for HAR.

4.2. Case Studies and Applications

Preliminary studies have demonstrated the practical applications of LLMs in analyzing wearable sensor data. For instance, the PhysioLLM system [8] integrates physiological data from wearables with contextual information using LLMs to provide personalized health insights. This system outperforms traditional methods by enhancing users’ understanding of their health data and supporting actionable health goals, particularly in improving sleep quality.

Similarly, the MindShift project [19] leverages LLMs to generate dynamic and personalized persuasive content based on users' real-time smartphone usage behaviors, physical contexts, and mental states. This approach has shown significant improvements in reducing smartphone addiction and increasing self-efficacy, demonstrating the versatility of LLMs in mental health interventions.

In the context of human activity recognition, the LLaSA model [9] combines LIMU-BERT with Llama to enhance activity recognition and question-answering capabilities. By integrating multimodal data, including inertial measurement unit (IMU) data and natural language, this model achieves superior performance in various healthcare and sports science applications.

4.3. Integration of LLMs with Other AI Techniques

The integration of LLMs with other AI techniques has opened new avenues for improving the analysis and interpretation of wearable sensor data. Hybrid models, such as those proposed by Alharbi et al. [16], employ a combination of convolutional neural networks (CNNs) and transformers to enhance the accuracy of HAR systems. These models address class imbalance and data quality issues by employing advanced sampling strategies and data augmentation techniques.

The Data Efficient Vision Transformer (DeSepTr) framework introduced by McQuire et al. [13] combines vision transformers with knowledge distillation to achieve robust HAR using spectrograms generated from wearable sensor data. This approach demonstrates improved accuracy and generalization compared to existing models.

Moreover, the integration of task-specific deep learning approaches, as seen in models like PhysioLLM and Health-LLM [11], enhances the relevance and accuracy of predictions by incorporating contextual information from wearable sensors [30]. These models utilize fine-tuning and transfer learning techniques to adapt LLMs for specific health-related tasks, providing more comprehensive and personalized insights.

5. Challenges in Using LLMs for Wearable Sensors Data

Despite the promising advancements and applications of Large Language Models (LLMs) in the field of wearable sensor data analysis, several challenges persist that hinder their full potential. These challenges encompass various aspects of data quality, computational requirements, model interpretability, and privacy concerns. Addressing these issues is critical to enhance the performance, reliability, and ethical deployment of LLMs in real-world applications. In the following subsections, we delve into each of these challenges in detail, exploring the technical intricacies and potential solutions highlighted in the literature.

5.1. Data Quality and Preprocessing

Ensuring high data quality and effective preprocessing is crucial for the success of LLMs in wearable sensor data analysis. Wearable sensors often generate noisy, incomplete, and inconsistent data due to various factors such as sensor malfunctions, user movement, and environmental conditions [5,7,31]. These issues can significantly impact the performance of LLMs, which require clean and well-preprocessed data to function effectively.

Preprocessing techniques, such as noise reduction, normalization, and feature extraction, are essential to transform raw sensor data into a suitable format for LLMs. For instance, hybrid sampling strategies, like those proposed by Alharbi et al. [16], have been employed to address class imbalance and improve the quality of the training data. Additionally, advanced data augmentation techniques can enhance the robustness of the models by creating synthetic data that mimics real-world variations [13,32].

Data quality challenges also extend to multimodal data integration, where different sensor modalities need to be synchronized and aligned for accurate analysis. Models like LLaSA [9] demonstrate the importance of effective data fusion techniques in combining IMU data with natural language inputs, ensuring the consistency and reliability of the integrated dataset.

5.2. Computational Requirements

The deployment of LLMs, such as GPT-4 and Llama, for wearable sensor data analysis requires substantial computational resources. Training and fine-tuning these models involve significant computational power, memory, and storage, which can be prohibitive for many organizations and applications [11]. The high computational requirements also impact the feasibility of using LLMs for real-time data analysis, where quick processing and low latency are critical.

Efforts to optimize model architectures and training algorithms are essential to reduce the resource requirements of LLMs. For example, the Data Efficient Vision Transformer (DeSepTr) framework introduced by McQuire et al. [13] combines vision transformers with knowledge distillation to achieve robust HAR using wearable sensor data, demonstrating improved accuracy and generalization with reduced computational overhead.

Moreover, the integration of LLMs with other AI techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can help distribute the computational load and enhance the efficiency of the overall system. Hybrid models, like those proposed by Wang et al. [12], leverage the strengths of different architectures to achieve better performance while optimizing computational resource usage.

5.3. Interpretability and Transparency

One of the significant challenges in using LLMs for wearable sensor data analysis is the lack of interpretability and transparency. LLMs operate as black-box models, making it difficult to understand and explain their decision-making processes [11]. This opacity can be problematic, especially in critical applications such as healthcare, where understanding the rationale behind a model's predictions is essential for trust and accountability.

Efforts to improve interpretability, such as using attention mechanisms and visualizing model outputs, can provide some insights into how LLMs process and analyze data. For instance, the TASKED framework [15] incorporates self-attention mechanisms to highlight the most relevant parts of the input data, offering a degree of transparency in the model's decision-making process.

Furthermore, developing explainable AI (XAI) techniques that can elucidate the inner workings of LLMs is crucial for enhancing their trustworthiness. These techniques can help stakeholders understand the factors influencing the model's predictions and make more informed decisions based on the outputs. The integration of LLMs with traditional machine learning models can also improve interpretability by providing a more comprehensive understanding of the data and the relationships between different features [8].

5.4. Privacy and Security Concerns

The use of LLMs for analyzing wearable sensor data raises significant privacy and security concerns. Wearable devices collect sensitive personal information, such as health metrics, location data, and behavioral patterns, which can be vulnerable to breaches and misuse [12]. Ensuring the confidentiality and integrity of this data is crucial to protect users' privacy and maintain their trust.

Implementing robust encryption methods, secure data storage solutions, and access control mechanisms are essential to safeguard wearable sensor data from unauthorized access and cyberattacks [19]. Additionally, adherence to data protection regulations, such as GDPR and HIPAA, is necessary to ensure compliance and protect user rights.

Privacy-preserving techniques, such as federated learning and differential privacy, can also be employed to minimize the risk of data exposure while still enabling the effective use of LLMs for data analysis [11,33]. These techniques allow for decentralized data processing, where the raw data remains on the user's device, and only the aggregated model updates are shared with the central server, reducing the likelihood of data breaches.

Moreover, interdisciplinary collaborations between computer scientists, legal experts, and ethicists are crucial to develop comprehensive frameworks that address the ethical and privacy concerns

associated with wearable sensor data [26]. These collaborations can help ensure that LLMs are deployed responsibly and ethically, balancing the benefits of advanced data analysis with the need to protect individual privacy.

6. Future Directions

As the field of wearable sensor data analysis continues to evolve, it is essential to explore the future directions that can further enhance the capabilities and applications of Large Language Models (LLMs). The integration of LLMs with wearable sensor technology holds great promise, but it also presents unique challenges and opportunities. This section delves into potential improvements in LLMs, emerging trends in wearable technology, and interdisciplinary research opportunities that can drive the next wave of innovation in this domain.

6.1. Potential Improvements in LLMs

Future advancements in Large Language Models (LLMs) are essential to enhance their performance and applicability in wearable sensor data analysis. One significant area of improvement lies in the development of more efficient and scalable models. For instance, optimizing model architectures and training algorithms can reduce the computational resources required for training and deployment [13]. Techniques such as knowledge distillation, used in the Data Efficient Vision Transformer (DeSepTr), can help create lightweight models that maintain high accuracy while being more computationally efficient.

Another promising direction is the enhancement of interpretability and transparency in LLMs. Developing methods to visualize attention mechanisms and model decisions can provide insights into how these models process and analyze data, thereby increasing trust and reliability [15]. Additionally, incorporating explainable AI (XAI) techniques can help elucidate the decision-making processes of LLMs, making them more accessible and understandable to users and stakeholders.

Furthermore, the integration of self-supervised and semi-supervised learning approaches can significantly improve the ability of LLMs to learn from limited labeled data. This is particularly relevant in the context of wearable sensors, where obtaining large, annotated datasets can be challenging [10]. By leveraging unlabelled data, LLMs can achieve higher generalization capabilities and better performance in real-world scenarios.

6.2. Emerging Trends in Wearable Technology

The landscape of wearable technology is continuously evolving, with several emerging trends that have the potential to impact data modeling and analysis. The integration of advanced sensors, such as flexible and stretchable electronics, provides more accurate and comprehensive physiological measurements [14]. These sensors can capture a wider range of data, including biochemical signals, which can be integrated with LLMs to offer deeper insights into health and activity patterns.

Another emerging trend is the development of real-time feedback and intervention mechanisms in wearable devices. For instance, biofeedback-enabled wearables can monitor physiological parameters and provide immediate feedback to users, promoting healthier behaviors and improving overall well-being [34]. This requires sophisticated data analysis models that can process and interpret sensor data in real-time, an area where LLMs can play a crucial role.

Additionally, the increasing adoption of wearable technology in potentially sensitive domains, such as sports science, mental health, and workplace ergonomics, highlights the need for robust data modeling techniques. For example, the PhysioLLM system integrates wearable sensor data with contextual information to provide personalized health insights, demonstrating the potential of LLMs in enhancing user understanding and engagement with their health data [8,14]. However, these approaches should always account for the potential risks associated with the malfunctioning of LLMs [25,35].

6.3. Interdisciplinary Research Opportunities

The intersection of wearable sensor technology and LLMs presents numerous interdisciplinary research opportunities. Collaboration between fields such as computer science, biomedical engineering, psychology, and data science can lead to innovative solutions for complex problems. For instance, integrating psychological theories and behavioral science with wearable sensor data can enhance the development of personalized health interventions [4,19].

In the realm of human activity recognition, combining expertise from robotics, AI, and human-computer interaction can lead to more effective models and applications. The LLaSA model, which integrates multimodal data from IMUs and LLMs, showcases the benefits of such interdisciplinary approaches in advancing human activity understanding and interaction [9].

Moreover, addressing the ethical and privacy concerns associated with wearable sensor data requires collaboration between legal experts, ethicists, and technologists. Developing frameworks and guidelines to ensure data security and user privacy is crucial for the responsible deployment of these technologies [26]. Privacy-preserving techniques, such as federated learning and differential privacy, can be employed to balance the need for data analysis with the protection of user privacy [11,36].

Interdisciplinary research not only drives technological advancements but also ensures that the solutions developed are holistic, user-centric, and ethically sound. By fostering collaboration across disciplines, researchers can harness the full potential of LLMs and wearable sensor technology to address pressing societal challenges and improve human well-being.

7. Conclusions

This survey has highlighted the trends and challenges associated with modeling wearable sensor data using Large Language Models (LLMs). While the potential of LLMs in this field is evident, several obstacles need to be addressed to realize their full capabilities. Continued research and innovation will be essential in harnessing the power of LLMs to enhance the analysis and interpretation of wearable sensor data, ultimately contributing to the advancement of wearable technology and its applications.

7.1. Summary of the State of the Art

Our review underscores the transformative potential of LLMs in the realm of wearable sensor data analysis. LLMs such as GPT-4 and Llama have demonstrated remarkable capabilities in handling complex and multimodal data, offering personalized health insights, improving activity recognition accuracy, and providing context-aware interventions.

Hybrid learning models have significantly improved the accuracy and robustness of Human Activity Recognition (HAR) systems by combining various machine learning techniques to address the complex nature of wearable sensor data [12,28]. Transformer models have also shown promise in enhancing HAR, leveraging their ability to capture long-range dependencies in sequential data [15,29].

The application of LLMs in HAR is a relatively new but rapidly growing area of research. Studies have highlighted the potential of LLMs to perform zero-shot recognition of activities, significantly reducing the need for large labeled datasets [5,31]. Moreover, LLMs can integrate multimodal data, including text and sensor data, to provide more comprehensive and accurate activity recognition [37,38].

Case studies such as *PhysioLLM* and *Health-LLM* have demonstrated how LLMs can be fine-tuned for specific health-related tasks, enhancing the accuracy and relevance of predictions by incorporating contextual information [8,11]. Additionally, the use of zero-shot learning in models like *HARGPT* underscores the ability of LLMs to recognize human activities from raw sensor data without extensive training datasets [10]. Other examples like *MindShift* and *LLaSA* further illustrate the versatility of LLMs in providing mental health support and advanced human activity analysis [9,19].

7.2. Challenges and Future Directions

Despite these advancements, several challenges remain. Ensuring data quality and addressing class imbalance are critical for improving HAR system performance. Hybrid sampling strategies and

data-efficient models, such as those utilizing vision transformers, have been proposed to tackle these issues [13,16]. Furthermore, the development of optimized deep learning models that can operate efficiently on resource-constrained devices is paramount [39,40].

Future research should focus on addressing these challenges while exploring new frontiers in HAR. This includes the development of more robust and scalable models, the integration of additional sensor modalities, and the application of task-specific deep learning approaches [41]. Additionally, interdisciplinary collaborations will be essential to ensure the ethical and effective deployment of these technologies [26].

Emerging trends in wearable technology, such as the integration of advanced sensors and real-time feedback mechanisms, will further enrich the data available for analysis. This, combined with the multimodal capabilities of LLMs, will lead to more comprehensive and accurate insights, benefiting fields like sports science, mental health, and workplace ergonomics [14,34,37].

Interdisciplinary research will also be crucial in addressing the ethical and privacy concerns associated with wearable sensor data. Collaborations between computer scientists, healthcare professionals, legal experts, and ethicists will help develop frameworks that protect user privacy while enabling the effective use of LLMs for data analysis [31].

In conclusion, the integration of LLMs in wearable sensor data modeling holds significant potential to revolutionize health monitoring, activity recognition, and various other applications. By building on recent advancements and addressing current challenges, researchers can develop more accurate, efficient, and versatile HAR systems. Continued research and collaboration across disciplines will be essential to realize the full potential of these technologies, ensuring they are used effectively and ethically to enhance human well-being.

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