The Use of Artificial Intelligence and Wearable IMUs in Medicine: A Systematic Review

Ricardo Smits Serena, Florian Hinterwimmer, Rainer Burgkart, Rudiger von Eisenhart-Rothe, Daniel Rueckert

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Abstract

Background: Artificial Intelligence (AI) has already revolutionized the analysis of image, text, and tabular data, bringing significant advances across many medical sectors. Now, by combining with Wearable Inertial Measurement Units (IMUs), AI could transform healthcare again by opening new opportunities in patient care and medical research.

Objective: This systematic review aims to evaluate the integration of Artificial Intelligence (AI) with Wearable Inertial Measurement Units (IMUs) in healthcare, identifying current applications, challenges, and future opportunities. The focus will be on the types of AI models used, the characteristics of the datasets, and the potential for expanding and enhancing the use of this technology to improve patient care and advance medical research.

Methods: This systematic review examines this synergy of AI and IMU data by employing a systematic methodology, following PRISMA guidelines, to explore three core questions: Which medical fields are most actively researching AI and IMU data? Which AI models are being utilized in the analysis of IMU data within these medical fields? and what are the characteristics of the datasets used for AI training in this fields?

Results: The median dataset size is of 50 participants, which poses significant limitations for AI methods given their dependency on large datasets for effective training and generalization. Moreover, our analysis reveals the current dominance of Machine Learning models in 76% on the surveyed studies, suggesting a preference for traditional models like linear regression, support vector machine, and random forest, but also indicating significant growth potential for Deep Learning models in this area. Impressively, 93% of the studies employed Supervised Learning, revealing an underutilization of Unsupervised Learning, and indicating an important area for future exploration on discovering hidden patterns and insights without predefined labels or outcomes. Additionally, there was a preference for conducting studies in clinical settings (77%), rather than in real-life scenarios, a choice that, along with the underutilization of the full potential of wearable IMUs, is recognized as a limitation in terms of practical applicability. Furthermore, the focus of 65% of the studies on neurological issues suggests an opportunity to broaden research scope to other clinical areas such as musculoskeletal applications, where AI could have significant impacts.

Conclusions: In conclusion, the review calls for a collaborative effort to address the highlighted challenges, including improvements in data collection, increasing dataset sizes, a move that inherently pushes the field towards the adoption of more complex Deep Learning models, and the expansion of the application of AI on IMU data methodologies across various medical fields. This approach aims to enhance the reliability, generalizability, and clinical applicability of research findings, ultimately improving patient outcomes and advancing medical research.

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Keywords: Artificial Intelligence; Wearables; Accelerometer; Gyroscope; IMUs; Time Series Data

Introduction

The integration of advanced computational methods such as artificial intelligence (AI) in medicine represents a significant leap in the pursuit of more accurate, efficient, and personalized healthcare [1]. The increasing popularity of wearable devices has led to a surge in the collection of various physiological signals, including accelerometer data from wristbands, smartwatches, and other sensors [2]. While these wearables offer valuable insights into our daily activities, Inertial Measurement Units (IMUs) stand out for their unique ability to capture three-dimensional motion data, including acceleration, angular velocity, and orientation. Moreover, IMUs are also highly accessible and widely available, making them an attractive choice for researchers and clinicians alike. This combination of precision and accessibility has led to a surge in the adoption of IMUs across various medical fields, from neurology to emergency medicine, where they are increasingly being used to track complex motor behaviors, such as those seen in neurological disorders or injuries.

The ability of AI to extract meaningful patterns from complex, multi-dimensional movement data offers unprecedented opportunities in diagnostics, patient monitoring, and treatment efficacy assessment. However, despite the potential benefits, there are many challenges in applying these technologies in a medical context [1]. These include issues related to data preprocessing, model selection, dataset size, and study setting (dataset bias), which can significantly impact the validity and reliability of the results. Additionally, integrating AI systems into existing clinical workflows poses significant logistical and ethical challenges, including data privacy concerns, the need for extensive validation, and the training of healthcare professionals to effectively utilize these tools.

This systematic review aims to provide a comprehensive overview of the current state of AI applications in processing IMU data for medical purposes. By examining a variety of studies across different medical specialties, this review seeks to understand the common methodologies, tools, and challenges faced in this rapidly evolving field. In doing so, it aims to identify gaps in the current knowledge base, suggest areas for future research, and provide insights into the practical implications of these technologies in clinical settings. Ultimately, the goal is to foster a deeper understanding of how AI and IMUs can be harnessed to improve patient outcomes and streamline healthcare delivery.

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Methods

Search Strategy

The design of this systematic review was centered around three fundamental research questions, all pertaining to the application of AI in analyzing IMU data within various medical fields. The first question aimed to identify which medical fields are most actively incorporating AI techniques with IMU data. The second question focused on determining the specific AI models that are employed in the analysis of IMU data. Lastly, the third question tries to understand the characteristics of the datasets used in training AI algorithms. To address these questions, this review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [3] to ensure a methodical approach to data collection and analysis.

The literature search was conducted on November 15, 2023, using two major scientific databases: PubMed and Web of Science [Figure 1]. PubMed yielded 327 articles with the search string:

("Artificial Intelligence"[Mesh]) AND (health OR medical OR clinical OR patient) AND (wearabl OR smartphone OR smartwatch) AND (magnetometer OR accelerom* OR gyroscope OR "imu" OR "imus" OR "Inertial measurement unit") AND (health OR medical OR clinical OR patient) NOT (Review[Publication Type] OR Systematic Review[Publication Type]).*

Web of Science yielded 853 articles with the search string:

("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND (health OR medical OR clinical OR patient) AND (wearabl OR smartphone OR smartwatch) AND (magnetometer OR accelerom* OR gyroscope OR "imu" OR "imus" OR "Inertial measurement unit") AND (health OR medical OR clinical OR patient).*

Study Selection

The retrieved articles were screened by two Computer Scientists [RSS, FH] based on their titles and abstracts to assess their relevance to the research questions.

Inclusion criteria:

- Study uses one or more IMUs.
- Study targets a clinical condition.
- Study focuses on ML or DL algorithms for data analysis.
- Study published in English.
- Studies with available full-text articles.
- Studies with more than 20 participants.

Exclusion criteria:

- Review articles.
- Studies not related to medical applications.
- Studies not using IMU data.

- Study not mentioning details on the ML or DL techniques used.

Data Extraction

In each included study, relevant data were extracted, concentrating on several key aspects. This included the medical field of application, the specific purpose of utilizing ML/DL, and the ML/DL methods employed. Additionally, the size of the study dataset and the study setting were utilized. The synthesized data from this extraction process provided a comprehensive overview, highlighting the current state of ML/DL applications in processing IMU data for medical purposes.

Results

This systematic review analyzed a total of 122 papers, diving into the use of ML and DL techniques on IMU data for various medical applications. The results are organized based on the predefined research questions, providing a detailed overview of the current landscape, prevalent trends, and challenges in this domain.

Distribution of papers

Neurology stood out as the most represented field, with a substantial count of 79(64.7%) papers, underscoring its significant role in the application of IMU data. Geriatric Medicine followed, with 12(9.8%) papers, reflecting a growing interest in this area for elderly care. Pulmonary and Cardiology Medicine, with 10(8.1%) papers, indicated their importance in chronic disease management using these technologies. Musculoskeletal and Orthopedic Care was another notable field, represented by 8(6.5%) papers, emphasizing the role of AI in diagnosing and treating musculoskeletal disorders. Pediatric Medicine and Psychiatry also featured in the analysis, with 4(3.2%) and 2(1.6%) papers respectively, highlighting their emerging roles. Additionally, fields such as Emergency Medicine, General and Preventive Medicine, Internal Medicine, Oncology, Otolaryngology, Sleep Medicine, and Vestibular Medicine each appearing only once (0.8%), demonstrating the wide-ranging applications of IMU data across various medical disciplines.

In analyzing the applications of ML on medical IMU data, disease monitoring emerged as the primary focus, with 38(31.1%) papers dedicated to this aspect. This indicates a strong trend towards using AI for ongoing patient care and management. Disease Detection and Disease Severity Assessment were also prominent, with 19(15.5%) and 24(19.6%) papers respectively, highlighting the role of AI in early diagnosis and evaluation of disease progression. Functional and Mobility Assessment, covered in 13(10.6%) papers, pointed to the importance of AI in evaluating patients' physical abilities. Rehabilitation and Recovery Monitoring, with 10(8.1%) papers, further emphasized the use of AI in patient recovery processes. Risk Prediction and Preventive Analysis, represented by 18(14.7%) papers, showed a proactive approach in using AI for forecasting health risks and preventing diseases.

Table 1: List of studies' references ordered by Medical Field and Machine Learning Purpose

Medical Field	AI Purpose	Studies
Neurology	Disease Monitoring	[4, 11, 16, 17, 19, 23, 28, 32, 36, 39, 51, 52, 56, 58, 60, 61, 67, 71, 76, 83, 92, 95, 96, 100, 101, 116, 119, 120]
	Disease Severity Assessment	[5, 12, 15, 33, 38, 44, 45, 48, 49, 53, 70, 81, 85, 87, 94, 97, 99, 105]
	Disease Detection	[8, 20, 26, 31, 63, 68, 75, 82, 86, 90, 93, 118]
	Functional and Mobility Assessment	[9, 14, 18, 47, 64, 69, 84, 102]
	Risk Prediction and Preventive Analysis	[10, 46, 59, 62, 66, 114, 115]
	Rehabilitation and Recovery Monitoring	[30, 50, 65, 78, 88, 117]
Geriatrics	Risk Prediction and Preventive Analysis	[13, 24, 54, 89, 91, 104, 108, 124]

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	Functional and Mobility Assessment	[73, 106]
	Disease Monitoring	[6]
	Disease Severity Assessment	[107]
Cardiorespiratory	Disease Detection	[42, 74, 79, 111, 112, 113]
	Disease Monitoring	[7, 43, 55, 110]
	Rehabilitation and Recovery Monitoring	[29]
Orthopedics	Disease Monitoring	[34, 122]
	Disease Severity Assessment	[26, 57]
	Rehabilitation and Recovery Monitoring	[40, 121]
	Functional and Mobility Assessment	[125]
	Risk Prediction and Preventive Analysis	[22]
Pediatrics	Functional and Mobility Assessment	[27, 41]
	Disease Monitoring	[37]
	Disease Severity Assessment	[123]
Psychiatry	Disease Monitoring	[72, 98]
Emergency Medicine	Risk Prediction and Preventive Analysis	[77]
Preventive Medicine	Rehabilitation and Recovery Monitoring	[21]
Oncology	Risk Prediction and Preventive Analysis	[109]
Otolaryngology	Disease Detection	[103]
Sleep Medicine	Disease Severity Assessment	[80]
Vestibular Medicine	Disease Severity Assessment	[35]

ML and DL Models Used in IMU Data Analysis

In total, 326 models were identified across the reviewed papers, averaging 2.67 tested models per paper. The analysis of the AI models employed for analyzing IMU data revealed distinct trends in the usage of both ML and DL approaches. The results are presented in two subsections detailing the prevalence and variety of models observed in the reviewed papers.

A significant majority of the models used, 232(71.1%) in total, were supervised ML models, showcasing their widespread adoption in IMU data analysis. In contrast, unsupervised ML models were less commonly used, with only 15(4.6%) papers reporting their application. Among these ML models, five methods stood out in terms of frequency: Support Vector Machine (SVM) was the most prevalent, used in 61(50%) studies, Random Forest (RF) followed, with 43(35.2%) studies, k-Nearest Neighbors (kNN) was utilized in 25(20.4%) studies. Logistic Regression (LR) and Decision Trees (DT) were each used in 17(13.9%) papers.

In the realm of DL, 72(22%) models were supervised, indicating a growing interest in this area. However, unsupervised Deep Learning was considerably less common, with only 7(2.1%) models used. The top five Deep Learning methods identified were: Convolutional Neural Networks (CNN), leading with usage in 20(16.3%) papers, Multilayer Perceptron (MLP), used in 10(8.1%) studies, Long Short-Term Memory (LSTM) networks, featured in 9(7.3%) papers, Neural Networks (NN), applied in 8(6.5%) studies, CNN-LSTM hybrid models, which were used in 4(3.2%) papers.

Table 2: List of studies sorted by Artificial Intelligence model used in the study. If the study used more than one model it will appear more than once. (Full description of the method names in the Appendix)

Name	Studies	Name	Studies
SVM	[5, 6, 11, 16, 18, 19, 20, 21, 22, 23, 25, 28, 29, 32, 33, 35, 36, 40, 41, 42, 44, 45, 46, 47, 48, 49, 51, 53, 55, 56, 56, 59, 61, 62, 66, 67, 68, 69, 70, 75, 78, 79, 82, 85, 87, 89, 91, 92, 94, 95, 96, 97, 98, 103, 106, 110, 113, 118, 118, 119, 121]	RR	[124]
RF	[6, 8, 16, 18, 19, 21, 25, 27, 28, 41, 44, 45, 47, 48, 52, 55, 56, 59, 62, 63, 64, 65, 68, 69, 74, 79, 81, 82, 85, 88, 89, 92, 93, 94, 97, 101, 103, 107, 110, 115, 121, 123, 124]	ASRF	[105]
kNN	[5, 18, 20, 23, 33, 48, 49, 59, 61, 68, 70, 71, 78, 81, 82, 86, 89, 94, 96, 103, 107, 118, 121, 123, 124]	BEDT	[125]
CNN	[6, 9, 14, 16, 17, 19, 24, 26, 30, 31, 34, 43, 45, 56, 58, 76, 77, 80, 101, 116]	NN-DTW	[88]
LR	[4, 8, 15, 20, 21, 44, 45, 55, 68, 81, 88, 94, 96, 108, 112, 121, 124]	RNN	[37]
DT	[5, 23, 25, 44, 45, 46, 48, 49, 59, 61, 74, 78, 79, 82, 103, 121, 123]	CT	[20]
NB	[5, 20, 23, 33, 45, 46, 62, 68, 70, 82, 84, 91, 92, 94]	GK	[20]
MLP	[22, 25, 45, 54, 57, 73, 81, 107, 111, 123]	GRU	[14]

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NN	[35, 46, 74, 91, 96, 110, 120, 122]	t-SNE	[29]
LSTM	[6, 10, 12, 37, 39, 80, 101, 104, 109]	MLSTM-FCN	[34]
XGB	[6, 16, 79, 110, 122]	MALSTM-FCN	[34]
SVR	[57, 85, 99, 124]	LRCF	[13]
BT	[28, 68, 78, 118]	NMF	[102]
CNN-LSTM	[12, 19, 56, 114]	MDS	[102]
AdaBoost	[19, 55, 56, 82]	Transformer	[101]
LDA	[20, 25, 78, 94]	BW	[100]
GPR	[57, 84, 117]	RFC	[98]
Lasso	[90, 103, 124]	LMT	[92]
DA	[48, 49, 70]	J48	[92]
GBT	[12, 21, 39]	NN-Clustering	[71]
LGBM	[63, 121]	GNB	[59]
PCA	[36, 102]	FFNN	[85]
InceptionTime	[18, 60]	MLGP	[38]
GMM	[83, 100]	RBFN	[47]
BDT	[41, 73]	M5P	[81]
HMM	[85, 100]	BEL	[77]
DAE	[19, 56]	GAN	[76]
K-means	[22, 72]	AMM	[73]
DNN	[15, 101]	BDS	[73]
FCN	[18, 34]	SCA	[72]
ResNet	[6, 34]	ELM	[50]
TE	[5, 70]	NBC	[69]
ET	[121]	SEM	[68]
GB	[107]	BRR	[57]
Seq2Seq	[105]	GBA	[59]
GP	[123]	CRNN	[7]
BR	[124]		

Dataset Size

The median dataset sizes varied significantly across different medical fields. The field of General and Preventive Medicine utilized the smallest median dataset size at 24(IQR not applicable), followed by Pediatric Medicine with 36(IQR 4). Musculoskeletal and Orthopedic Care, Neurology, and Sleep Medicine had median sizes of 38.5(IQR 30), 45(IQR 49), and 69(IQR not applicable) respectively. Vestibular Medicine and Sleep Medicine both showed a median dataset size of 60(IQR not applicable). Larger median dataset sizes were observed in Emergency Medicine at 89(IQR not applicable), Geriatric Medicine at 91.5(IQR 81), Psychiatry at 91.5(IQR 35), and Pulmonary and Cardiology Medicine at 93.5(IQR 87). The largest median dataset size was noted in Otolaryngology, with 103(IQR not applicable) participants.

When examining the dataset sizes based on the purpose of ML application, varying trends were observed. Rehabilitation and Recovery Monitoring had the smallest median dataset size at 31.5(IQR 18). This was followed by Functional and Mobility Assessment at 38 (IQR 21), Disease Severity Assessment at 49(IQR 51), Disease Monitoring at 49.5(IQR 74) and Disease Detection at 58 (IQR 43). The largest median dataset size, at 74(IQR 58), was for Risk Prediction and Preventive Analysis.

The study settings also influenced the median dataset sizes. In clinic and Real-Life mixed settings, the median dataset size was 35(IQR 40). Laboratory settings showed a similar median size of 35.5(IQR 52). The Clinic setting alone had a median size of 54.5(IQR 45). Finally, the Real-Life setting presented the largest median dataset size of 60(IQR 123).

Overall, the median dataset size across all studies was 50.5(IQR 54), indicating a moderate scale of data employed in training AI algorithms in these diverse settings and purposes.

Discussion

One of the most significant findings is the overall median dataset size of 50.5(IQR 54) participants, and it raises significant concerns about the practical effectiveness of ML and, more so, DL methodologies in this context. These algorithms are known for their dependency on extensive datasets not only to train effectively but also to ensure the generalizability of their outcomes across diverse populations and conditions. The relatively small size of datasets in current research could severely restrict the ability of ML and DL technologies to derive substantial insights and achieve a high degree of accuracy in their predictions, diagnoses, or assessments of treatment outcomes.

These findings about dataset size also highlight a prevalent perspective among medical researchers regarding the equivalence of "data width" and "data length" in the context of IMU data utilization of ML in healthcare. "Data width" refers to the acquisition of a broad spectrum of data from subjects (e.g. 2 subjects and 1000 datapoints per subject), which could potentially lead to overfitting due to the emphasis on big multidimensional arrays of features such as temporal patterns, spatial movements, or biometric signals. This focus might inadvertently prioritize the complexity of the dataset over its generalizability, suggesting that it could be less beneficial, and possibly even detrimental, compared to "data length", which focuses on increasing the dataset by adding more subjects and not more data per subject (e.g. 50 subjects and 40 datapoints per subject). Therefore, with a balance between 'data length' and 'data width,' alongside efforts to significantly increase dataset sizes, researchers could better leverage ML and DL methodologies to their full potential in this field.

The challenges highlighted above underline the need for combined efforts to expand the scope and scale of data collection in future studies. To assemble larger and more diverse datasets, researchers should consider multi-institutional collaborations and/or employing new technologies for data collection and sharing. Moreover, even with successful collection of wearable IMU data or data from other wearable devices, a significant obstacle remains in integrating this data into hospital systems or electronic health records (EHRs). The current lack of infrastructure and protocols for efficiently transferring and storing wearable device data within medical records systems impedes its immediate use in clinical decision-making and complicates long-term patient monitoring and data analysis. There's a critical need for developing standardized protocols and systems capable of handling the varied data types produced by wearable technologies to ensure this valuable information is integrated into patient care workflows and health records management seamlessly. Finally, advancements in ML and DL techniques that are adept at working with smaller datasets, or that improve data augmentation practices, could play a crucial role in navigating these challenges. Such innovations could provide a pathway to maximize the utility of wearable technologies in improving patient outcomes and propelling medical research forward, despite the current limitations posed by dataset sizes and integration issues.

Another finding indicates a substantial reliance on supervised machine learning methods, observed in 71.1% of the studies, which may also be attributed to the limited size of datasets. This suggests a reliance on labeled data for model training and validation. However, the labor-intensive process of data labeling, especially with complex medical datasets, poses significant challenges. In this context, unsupervised learning would be a compelling alternative, offering the advantage of discovering hidden patterns and correlations in data without the need for pre-labeled instances. The application of unsupervised learning techniques can mitigate the bottleneck of data labeling, enabling researchers to leverage larger datasets more efficiently. This approach would not only facilitate a deeper understanding of the underlying data structures but also aid in identifying novel biomarkers and disease subtypes.

On the other hand, DL contains enormous potential for analyzing IMU medical data, particularly when fueled by larger datasets. DL's capacity to model complex, non-linear relationships, and its prowess in feature extraction from high-dimensional data make it exceptionally suited for IMU data analysis. The challenge of assembling substantial, well-annotated datasets in the medical domain, however, limits the full exploitation of deep learning's capabilities. The availability of larger datasets, potentially facilitated by unsupervised learning and other innovative data gathering and processing techniques, would not only address this limitation but also propel forward the development of more sophisticated and accurate deep learning models. By enabling access to more extensive and diverse data, the research community could accelerate the advancement of deep learning methodologies, leading to breakthroughs in predictive accuracy, diagnostic reliability, and ultimately, patient outcomes.

Another interesting finding is that, on average, each study utilizes 2.67 ML and DL techniques. This statistic highlights the field's ongoing experimental nature and its search for direction, as researchers actively explore a variety of algorithms and model architectures to identify the most effective methods for processing IMU data in medical applications. Furthermore, the varied use of ML/DL methodologies across research projects emphasizes the need for clear benchmarks to ensure reproducibility and facilitate the comparison of ML/DL models in the context of medical research using IMU data. The absence of standardized benchmarks is a significant barrier to effectively comparing and synthesizing results from various studies, thereby underlining the importance of establishing reproducibility and enabling scalable research methods.

To address these challenges, it is advised that the research community works together to develop benchmarking standards. This collaborative effort could be enhanced by actively including discussions and presentations on these topics in existing conferences and congresses. By integrating these studies into broader scientific gatherings, it would promote consensus-building among researchers and clinicians, fostering the exchange of insights and best practices. Ultimately, the creation of baseline results and standardized evaluation metrics would streamline research efforts and markedly improve the reliability, generalizability, and clinical applicability of the findings.

The predominance of machine learning studies analyzing IMU data within controlled environments such as clinics and laboratories, which represents 77% of the research reviewed, highlights a critical focus on obtaining high-quality, precise data for specific disease studies. While beneficial for eliminating external variables that might affect the data's integrity, this approach starkly contrasts with the unpredictable nature of daily life where wearable IMUs are most impactful. The real value of wearable IMUs lies in their potential to continuously monitor health conditions in natural settings, capturing nuanced data on disease manifestation and progression. However, the transition from controlled environments to real-life application faces significant challenges, primarily due to technological limitations such as inadequate battery life and insufficient data storage capacity in wearable devices, alongside difficulties ensuring patient compliance outside of clinical settings.

Addressing these challenges requires advancements in wearable technology to enhance device usability and reliability in everyday settings, alongside strategies to improve patient engagement and adherence to usage protocols. Enhancing battery life and expanding storage without compromising device comfort, coupled with the development of intuitive interfaces, could significantly boost patient compliance and data collection quality. Moreover, leveraging machine learning algorithms to manage data and power more efficiently, and implementing patient education and motivation strategies, could bridge the gap between controlled studies and the dynamic context of real-world scenarios. By overcoming these technological and logistical problems, researchers can unlock deeper insights into health conditions through wearable IMUs, paving the way for more personalized and effective healthcare solutions that reflect the complexity of real-life patient experiences.

Lastly, the fact that 64.7% of the studies focused on neurological conditions underscores a notable trend in the scientific community, particularly regarding the use of Inertial Measurement Units (IMUs) for analyzing movement disorders related to Parkinson’s disease. This focus is likely because neurological disorders exhibit distinct movement disorders, which can be readily detected and analyzed by Inertial IMUs and ML algorithms, leveraging their capacity to identify clear patterns in movement data. However, this concentration on neurology suggests an unintentional narrowness in application, potentially overlooking the vast possibilities in other medical fields.

Expanding the application of IMUs and ML/DL to include other medical areas, like musculoskeletal care, represents a promising avenue to harness the full potential of these technologies. To rectify this imbalance and encourage a broader application spectrum, targeted funding initiatives and interdisciplinary research collaborations could be established. These efforts would incentivize exploration into how IMUs and ML/DL can revolutionize diagnostics, treatment planning, and outcome monitoring. By diversifying research directions, the medical community can ensure a more equitable distribution of technological advancements across various domains, maximizing the impact of these cutting-edge tools in improving patient care and treatment outcomes.

Limitations

Despite its strengths, our systematic review has some limitations. While we focused primarily on studies utilizing inertial measurement units (IMUs), future reviews could explore the intersection between different wearable technologies. Our strict inclusion criteria ensured high-quality research but may have excluded some studies. Additionally, the variability in study quality is a common challenge in systematic reviews, and we prioritized datasets with larger sample sizes to increase confidence in our conclusions.

Conclusions

In conclusion, this systematic review has provided valuable insights into the current state of ML and DL applications on IMU data in the medical field. The key findings highlight several critical aspects: the relatively small median dataset size of 50.5 participants, the dominance of supervised ML methods, the exploratory nature of method selection in research, the preference for clinical settings over real-life data collection, and the focus on neurological problems.
These findings suggest that while the integration of ML and DL in medical research is progressing, there is still considerable room for growth and optimization. The challenges identified, such as limited dataset sizes and the need for more real-world data, must be addressed to fully realize the potential of these technologies in healthcare.

Conflicts of Interest

None declared.

Abbreviations

AI: Artificial Intelligence
DD: Disease Detection
DL: Deep Learning
DM: Disease Monitoring
DSA: Disease Severity Assessment
FMA: Functional and Mobility Assessment
IMU: Inertial Measurement Unit
IQR: Interquartile Range
ML: Machine Learning
RPPA: Risk Prediction and Preventive Analysis
RRM: Rehabilitation and Recovery Monitoring

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Supplementary Files

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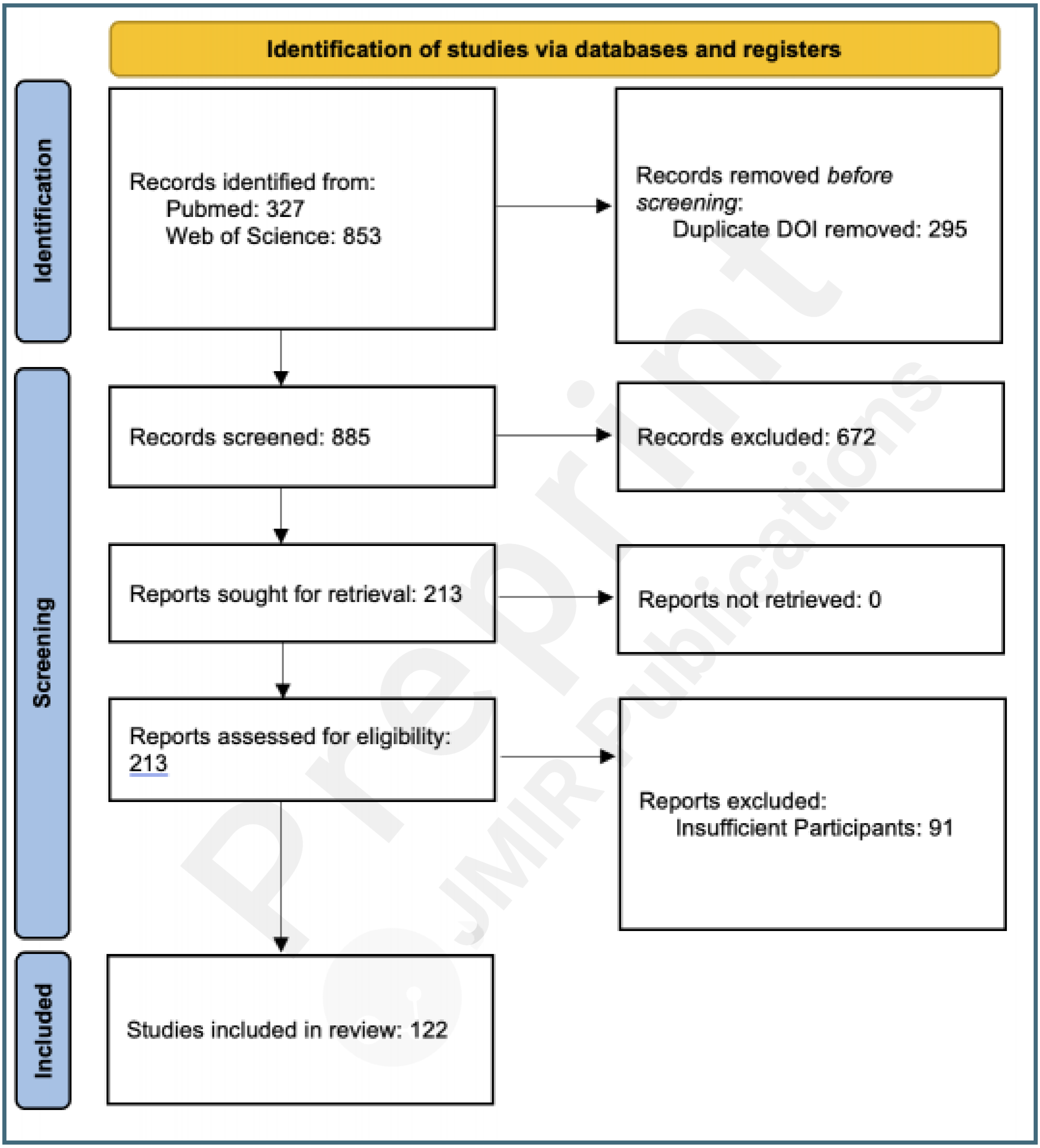
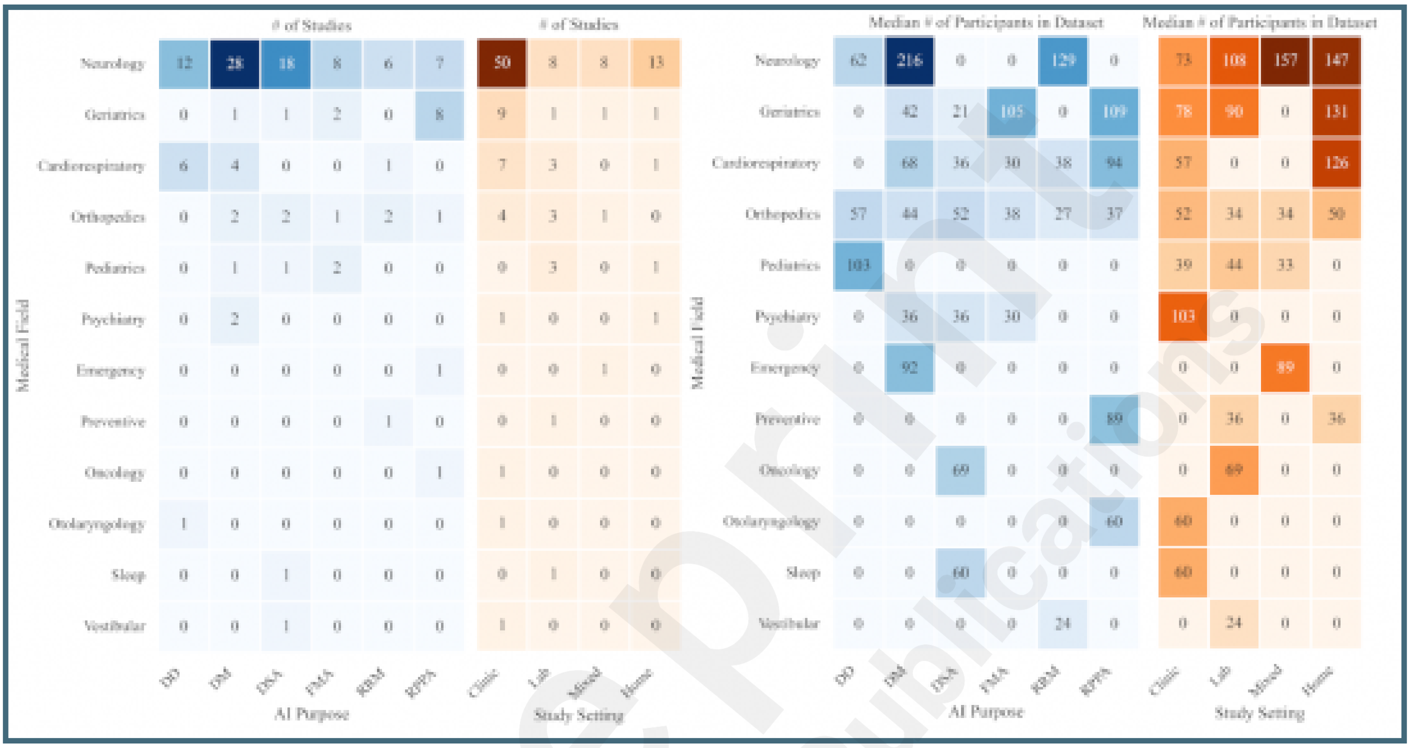
Figures

Diagram of the PRISMA filtering procedure applied to bibliographic search results.



The left heatmap quantifies the volume of studies, while the right heatmap displays the median number of participants within datasets employed across these studies. The blue sides illustrate the diversity of machine learning applications— Disease Detection (DD), Disease Monitoring (DM), Disease Severity Assessment (DSA), Functional and Mobility Assessment (FMA), Rehabilitation and Recovery Monitoring (RRM), and Risk Prediction and Preventive Analysis (RPPA)—across various medical specialties. The orange sides visualize the data collection settings for ML training datasets, encompassing clinical, laboratory, home, and hybrid environments.



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Multimedia Appendixes

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Description for all Artificial Intelligence Models reviewed.
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