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How Deep Learning and Neural Networks can Improve Prosthetics and Exoskeletons: A Review of State-of-the-Art Methods and Challenges

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ABSTRACT Deep learning and neural networks are powerful computational methods that have been widely applied in various fields, such as healthcare and robotics. In this paper, we review some of the recent research studies that use deep learning and neural networks in healthcare and robotics, particularly focusing on their application in prosthetics and exoskeletons. The main source of data for this review is Scopus, which is a large and multidisciplinary database of peer-reviewed literature. The search criteria for this review are exoskeleton AND prosthetic AND deep AND learning. The search is limited to documents published from 2014 to 2023, as this period covers the recent developments and trends in the field4. The search results in 488 documents that match the criteria. We selected 20 papers that represent the state-of-the-art methods and applications of deep learning and neural networks in prosthetics and exoskeletons. We categorized these papers by various attributes, such as document type, subject area, sensor type, respondent, condition, etc. The main finding of this paper was that deep learning techniques and neural networks have diverse and transformative potential in healthcare and robotics, especially in the development and improvement of prosthetics and exoskeletons. The paper highlighted how these advanced computational methods can be harnessed to interpret complex biological signals, improve device functionality, enhance user safety, and ultimately improve quality of life for individuals using these devices. The paper also identified some possible future directions for this topic, such as exploring the impact of deep learning techniques and neural networks on the performance, usability, and user satisfaction of prosthetics and exoskeletons. This paper provided a valuable insight into the current state-of-the-art and future prospects of deep learning techniques and neural networks in healthcare and robotics.

INDEX TERMS Prosthetic, exoskeleton, EMG, EEG, review paper, deep learning, machine learning

I. INTRODUCTION

Deep learning and neural networks are powerful computational methods that have been widely applied in various fields, such as healthcare and robotics [1] [2]–[4]. These methods can learn from complex and high-dimensional data, such as biological signals, and provide useful insights and solutions for various problems and applications. In this paper, we review some of the recent research studies that use deep learning and neural networks in healthcare and robotics, particularly focusing on their application in prosthetics and exoskeletons. Prosthetics and exoskeletons are devices that can replace or augment the function of human limbs, either for rehabilitation or enhancement purposes [3] [5]. These devices can improve the quality of life and mobility of individuals with physical disabilities or injuries, as well as provide assistance or augmentation for healthy individuals in various tasks and scenarios. However, designing and controlling these devices pose significant challenges, such as interpreting the user's intention, ensuring the device's functionality and safety, and enhancing the user's satisfaction and comfort. One of the main challenges in prosthetics and exoskeletons is to interpret the user's intention from biological signals, such as electromyography (EMG), electroencephalography (EEG), mechanomyography (MMG), etc [6]–[13]. These signals reflect the neural activity of the user's muscles or brain, and can provide information about the user's desired movements or actions. However, these signals are often noisy, variable, and non-stationary, making them difficult to process and analyze. Moreover, different users may have different signal patterns or preferences, requiring personalized or adaptive models [14]. Deep learning and neural networks offer a promising solution for interpreting biological signals, as they can learn from large amounts of data and extract meaningful features and patterns [15] [16] [17]. Deep learning and neural networks can also handle complex and nonlinear relationships between inputs and outputs, as well as adapt to different users or contexts. Furthermore, deep learning and neural networks can be integrated with other sensors or modalities, such as vision or inertial measurement units (IMUs), to provide more robust and comprehensive information.

Several studies have demonstrated the potential of deep learning and neural networks in interpreting biological signals for prosthetics and exoskeletons [2]–[4], [18]. For instance, Foroutannia et al. utilized a deep neural network (DNN) to analyze EMG signals from 10 healthy subjects performing hip flexion and extension movements [19]. They showed that their DNN model could accurately predict the joint position of the hip exoskeleton based on the EMG signals. Similarly, Kansal et al. employed deep learning-based techniques to interpret EEG signals from 10 amputees and 10 healthy subjects performing hand gestures [20]. They showed that their model could classify the hand gestures with high accuracy and control a low-cost prosthesis for upper limb amputees. Another challenge in prosthetics and exoskeletons is to ensure the functionality and safety of the devices, as well as to enhance the user's satisfaction and comfort. These aspects depend on various factors, such as the device's design, control strategy, feedback mechanism, etc. Deep learning and neural networks can also contribute to these aspects by providing optimal or adaptive solutions based on data-driven approaches. For example, Moreno-SanJuan et al. developed an underactuated RACA hand exoskeleton for neurorehabilitation of hand function in 10 healthy subjects [21]. They used a DNN model to optimize the design parameters of the exoskeleton based on biomechanical criteria. They showed that their optimized exoskeleton could achieve better performance and comfort than a conventional design. Similarly, Contreras-Cruz et al. used a convolutional neural network (CNN) and sensor fusion for obstacle classification for powered prosthetic leg applications in 10 lower-limb amputees [22]. They showed that their CNN model could classify different types of obstacles with high accuracy and reliability based on RGB-D images and IMU data. They also showed that their model could improve the safety of the prosthetic leg by providing appropriate control commands based on the obstacle type. Deep learning and neural networks have diverse and transformative potential in healthcare

The main purpose of this review paper is to provide a comprehensive overview of the application of deep learning and neural networks in healthcare and robotics, particularly in prosthetics and exoskeletons, highlighting their potential and challenges in interpreting complex biological signals and improving device functionality, safety, and user satisfaction, while also suggesting possible future directions for this field. The contribution of this study are:

1) This paper provides a comprehensive overview of the application of deep learning and neural networks in healthcare and robotics, particularly in prosthetics and exoskeletons, highlighting their potential and challenges in interpreting complex biological signals and improving device functionality, safety, and user satisfaction.
2) This paper reviews various research studies that use deep learning and neural networks to process biological signals, such as EMG, EEG, MMG, etc., for prosthetics and exoskeletons, and compares and contrasts their methods and results, identifying the commonalities, differences, and contradictions among them.
3) This paper presents a taxonomy-based survey of deep learning techniques and neural networks for interpreting biological signals for prosthetics and exoskeletons, and evaluates their performance, usability, and user satisfaction based on various criteria and metrics.
4) This paper explores the current state-of-the-art and future prospects of deep learning techniques and neural networks in healthcare and robotics, especially in the development of rehabilitation model.

II. METHOD

The main source of data for this review is Scopus, which is a large and multidisciplinary database of peer-reviewed literature, covering various fields of science, technology, medicine, social sciences, and arts and humanities. The search criteria for this review are based on keywords that reflect the main concepts of the topic. The keywords are: Exoskeleton OR Prosthetic hand AND Deep AND Learning. These keywords are used to search within the title, abstract, and keywords fields of the documents. The search is limited to documents published from 2014 to 2023, as this period covers the recent developments and trends in the field. The search results in 488 documents that match the criteria. These documents are categorized by various attributes, such as document type, subject area, publication stage, source title, keyword, affiliation, funding sponsor, country/territory, source type, and language. These attributes can be used to further refine and filter the results according to the specific objectives and scope of the review. The final step is to synthesize and report the findings of the review, using descriptive and analytical methods. Based on the Vosviewer (FIGURE 1), it appears to be a clustering of deep learning applications in the field of exoskeletons and prosthetic hands. Here are some key clusters and concepts:

1) **Human**: This could represent the human users of exoskeletons and prosthetic hands, or the human body parts that these devices are designed to assist or replace.
2) **Develop Neural Network**: This likely refers to the development of neural networks, a type of machine learning model, for controlling exoskeletons and prosthetic hands.
3) **Prosthetics**: This represents the field of prosthetics, which involves the design, fabrication, and fitting of custom-made artificial limbs.
4) **Learning**: This could represent the process by which the neural networks learn to control the exoskeletons and prosthetic hands effectively.
5) **Robotics**: This likely refers to the broader field of robotics, which includes the design, construction, operation, and application of robots.

The edges connecting these nodes represent relationships or associations between these concepts. For example, an edge connecting "Human" and "Prosthetics" might represent the use of prosthetic devices by humans. Similarly, an edge connecting "Develop Neural Network" and "Learning" might represent the process of training neural networks.

The data provided offers a fascinating insight into the global landscape of academic publications. Leading the pack is China, with an impressive 101 publications, demonstrating its robust intellectual output and commitment to research and development. Following closely is the United States, with 75 publications, reflecting its longstanding tradition of academic excellence and innovation. India, with 45 publications, underscores its emerging role as a significant player in the global academic arena. The United Kingdom and Canada, with 32 and 26 publications respectively, continue to make substantial contributions, reflecting their rich intellectual histories and vibrant academic communities. Japan, Italy, Germany, Turkey, Australia, South Korea, and Switzerland also make notable contributions. These countries, each with their unique strengths and areas of expertise, add to the diversity and richness of global knowledge. Countries such as Iran, Pakistan, New Zealand, Spain, Sweden, Egypt, Hong Kong, Malaysia, Netherlands, Saudi Arabia, Taiwan, Denmark, and France may have fewer publications but their contributions are no less significant. Each publication

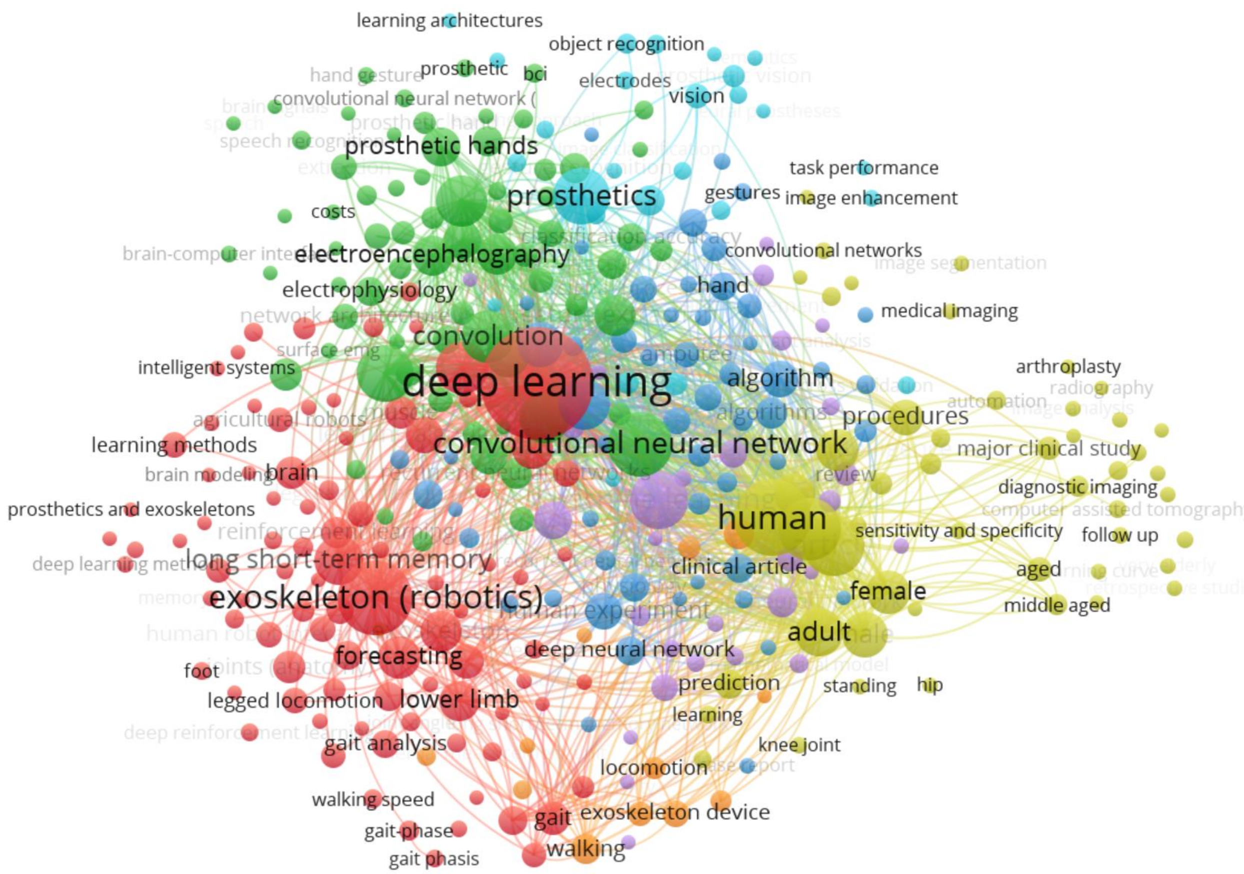
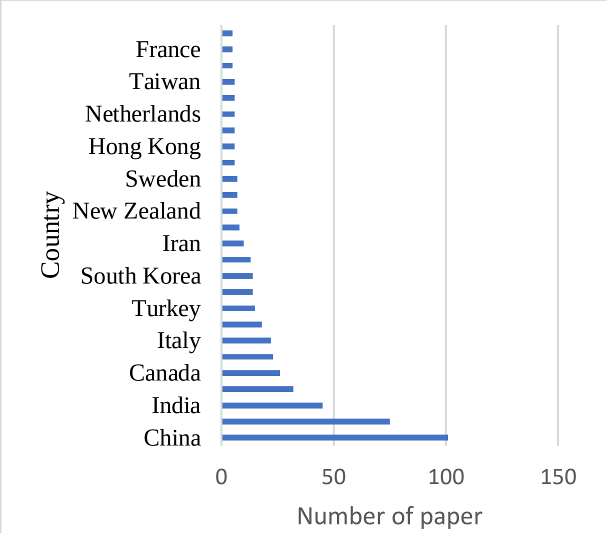
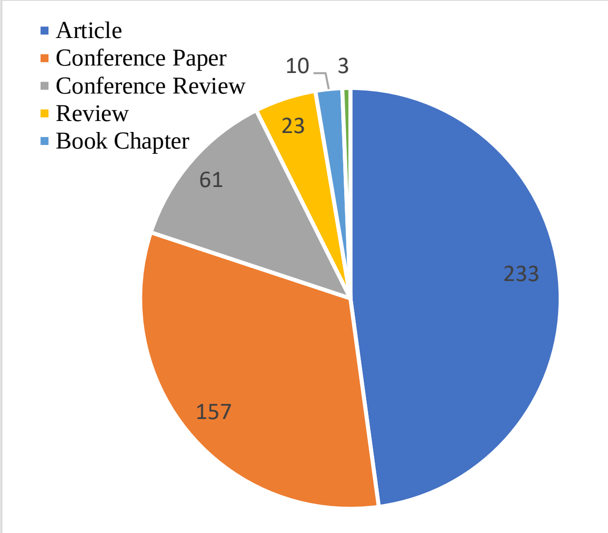
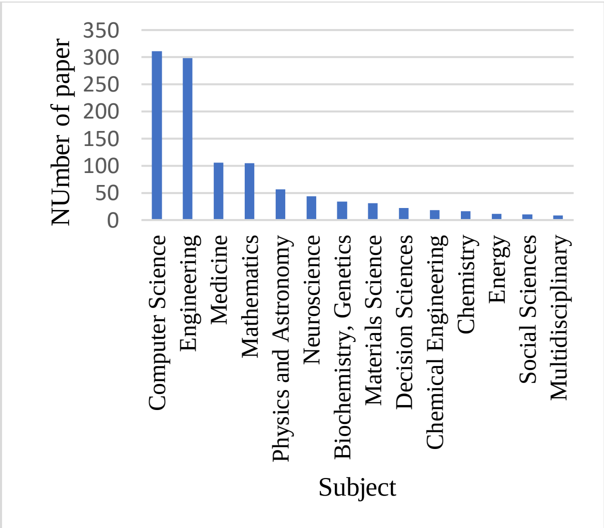


FIGURE 1. **Clustering deep learning application for medical rehabilitation**







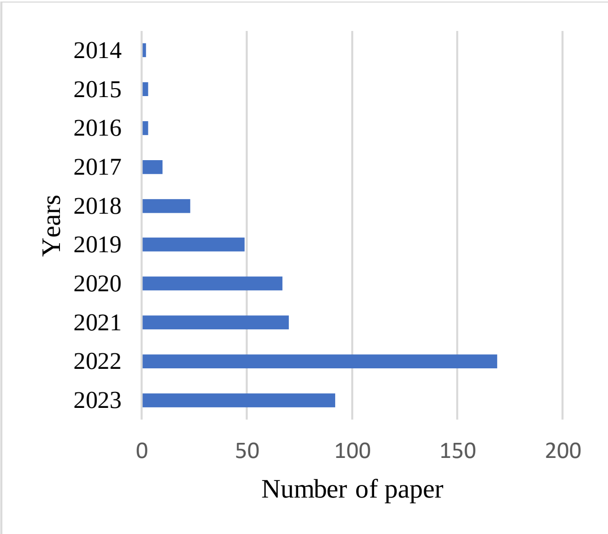


FIGURE 2. Global academic contributions: (a) publication based on country, (b) An In-depth Analysis of Publications Categorized by Document Type", (c) A Comparison of Subject Areas by Number of Publications, (d) based on years

represents a valuable addition to the global knowledge pool and reflects the intellectual vigor of these nations. This data provides a snapshot of the global distribution of academic contributions. It highlights not only the leading contributors but also the collective efforts of nations worldwide in advancing knowledge and fostering intellectual growth.

The data provided gives an intriguing overview of the distribution of academic publications based on document type. The most prevalent type is 'Article', with a total of 233 papers, indicating a strong preference for this traditional and widely accepted form of academic communication. 'Conference Paper' is the second most common type, with 157 papers. This highlights the importance of conferences as platforms for presenting new research findings and exchanging ideas. It underscores the dynamic nature of academic discourse and the value of immediate peer feedback. 'Conference Review' and 'Review' types, with 61 and 23 papers respectively, emphasize the role of critical evaluation in academia. These document types contribute to the refinement of knowledge by providing comprehensive overviews of existing literature and identifying gaps for future research. 'Book Chapter', with 10 publications, reflects the contribution of academics to broader scholarly works. It indicates a commitment to in-depth exploration of specific topics within a larger thematic framework. The 'Editorial' type, with 3 papers, represents a more discursive and opinion-based form of academic writing. It allows scholars to express viewpoints, comment on current trends, or discuss the implications of research findings. Lastly, the solitary 'Book' signifies a substantial scholarly endeavor. It represents an exhaustive examination of a particular subject and contributes significantly to the body of knowledge in that area. This data offers valuable insights into the diverse forms of academic output and their respective prevalence. It underscores the multifaceted nature of academic contributions and the various platforms through which knowledge is disseminated.

The data provided (FIGURE 2) shows the distribution of academic publications based on subject area. The data reveals that Computer Science and Engineering are the most popular subject areas, with 311 and 298 papers respectively. These subject areas reflect the growing importance of technology and innovation in the modern world. Medicine and Mathematics are the next most common subject areas, with 106 and 105 papers respectively. These subject areas reflect the relevance of health and scientific inquiry in academia. Physics and Astronomy, Neuroscience, Biochemistry, Genetics, Materials Science, Decision Sciences, Chemical Engineering, Chemistry, Energy, Social Sciences, Multidisciplinary, Dentistry, Health Professions, Environmental Science, Immunology and Microbiology, Psychology, Arts and Humanities, and Business, Management and Accounting are the other subject areas represented in the data. These subject areas cover a wide range of disciplines and topics, demonstrating the diversity and breadth of academic contributions. This data provides a comprehensive overview of the academic publications based on subject area. It highlights the dominant subject areas as well as the variety of subject areas that contribute to the global knowledge pool.

The data provided offers a detailed look at the trend of academic publications over the years. It is evident that there has been a significant increase in the number of papers published from 2014 to 2023. In 2014, there were only 2 papers published, which increased slightly to 3 in both 2015 and 2016. However, a noticeable jump occurred in 2017 with the publication of 10 papers. The upward trend continued with a more than twofold increase to 23 papers in 2018. The year 2019 saw a further increase to 49 papers, indicating a growing interest and investment in academic research. The momentum carried into 2020 with the publication of 67 papers despite the global challenges posed by the COVID-19 pandemic. In 2021, there was a slight increase to 70 papers. However, a significant leap was observed in 2022 with the publication of 169 papers, more than doubling the previous year's output. This could be attributed to the easing of pandemic restrictions and resumption of regular academic activities. As of 2023, there have been 92 papers published, suggesting that the year is on track to match or even surpass the previous year's high. This data underscores the resilience and adaptability of the academic community in continuing to contribute to global knowledge despite varying circumstances.

TABLE 1. Overview of State-of-the-Art Methods in EMG and EEG Signal Processing

Author	Method	Finding	Limitation/Weaknesses
A. Foroutannia, M.-R. Akbarzadeh-T, and A. Akbarzadeh [19]	Deep learning strategy based on convolutional neural network (CNN) and long short-term memory (LSTM) for EMG-based joint position prediction in hip exoskeleton assistive robots	Achieved high accuracy and low error in predicting hip joint angles from EMG signals of lower limb muscles	Limited to one subject and one exoskeleton model; did not consider the effect of fatigue or noise on EMG signals
S. Kansal, D. Garg, and G. S. Talwar [20]	Deep learning-based techniques for designing and developing a low-cost prosthesis for rehabilitation of upper limb amputees using EEG signals	Proposed a novel DL-AMPUT-EEG framework that can classify four different hand gestures from EEG signals and control a 3D-printed prosthesis accordingly	Used a small dataset of 10 subjects; did not compare the performance with other methods or evaluate the usability of the prosthesis
V. Moreno-SanJuan, A. Cisnal, E. de-la-Fuente, et al. [21]	Design and characterization of a lightweight underactuated RACA hand exoskeleton for neurorehabilitation	Developed a novel hand exoskeleton that can provide assistance to finger flexion and extension movements using a single actuator and a cable-driven mechanism	Did not test the exoskeleton on patients or evaluate its effectiveness in improving hand function; did not consider the thumb movement or the grasping force
M. Sharbafi, A. Naseri, and M. Grimmer [33]	Neural control in prostheses and exoskeletons based on modular control architecture (MoCA) that integrates reflexes, central pattern generators (CPGs), and higher-level feedback	Demonstrated that MoCA can generate natural and adaptive locomotion behaviors for different types of powered prostheses and exoskeletons	Focused mainly on lower limb systems; did not address the challenges of user adaptation, intention detection, or shared control
T. Das, L. Gohain, and G. Kumar [34]	Hierarchical approach for fusion of EEG and EMG signals for predicting finger movements and kinematics using deep learning	Proposed a novel method that combines CNN and LSTM to extract features from EEG and EMG signals and estimate finger joint angles with high accuracy	Used a small dataset of 10 subjects; did not validate the method on real-time applications or compare it with other fusion methods
A. Rezaie Zangene, O. W. Samuel, and K. Nazarpour [35]	An efficient attention-driven deep neural network approach for continuous estimation of knee joint kinematics via sEMG signals during running	Proposed a novel method that uses an attention mechanism to enhance the feature extraction from sEMG signals and predict knee joint angles during running with high accuracy and low latency	Used a small dataset of 12 subjects; did not test the method on different activities or compare it with other attention-based methods

TABLE 1. (continue)

Author	Method	Finding	Limitation/Weaknesses
M. A. Contreras-Cruz, L. Novo-Torres, J.-P. Ramirez-Paredes [22]	Convolutional neural network and sensor fusion for obstacle classification in the context of powered prosthetic leg applications	Proposed a novel method that uses a CNN to extract features from inertial measurement unit (IMU) data and classify different types of obstacles encountered by lower limb amputees wearing powered prosthetic legs	Used a small dataset of 10 subjects; did not evaluate the impact of obstacle classification on prosthetic control or user performance
Z. Khademi, F. Ebrahimi, and H. Montazery Kordy [36]	A review of critical challenges in MI-BCI: From conventional to deep learning methods	Provided a comprehensive overview of the current state-of-the-art methods and challenges in motor imagery-based brain-computer interface (MI-BCI) research, with a focus on deep learning techniques	Did not provide a quantitative comparison or evaluation of different methods; did not address the ethical or social issues related to MI-BCI
T. Yan, M. Cempini, and N. Vitiello [37]	Review of assistive strategies in powered lower-limb orthoses and exoskeletons	Provided a systematic review of the existing assistive strategies for powered lower-limb orthoses and exoskeletons, with a focus on the control architectures, the human-machine interfaces, and the performance evaluation metrics	Did not provide a clear taxonomy or classification of the assistive strategies; did not address the user acceptance or satisfaction aspects
T. Zhao, G. Cao, and C. Xia [38]	Incremental learning of upper limb action pattern recognition based on mechanomyography	Proposed a novel method that uses incremental learning to update the classifier for upper limb action pattern recognition based on mechanomyography (MMG) signals without retraining from scratch	Used a small dataset of 10 subjects; did not compare the performance with other incremental learning methods or evaluate the robustness to noise or fatigue
J. Fan, L. Vargas, and X. Hu [40]	Deep learning-based neural network approach to learn the mapping from HD-EMG features to neural-drive signals and control a robotic hand with high accuracy and dexterity	Implemented a deep learning-based neural network approach to learn the mapping from HD-EMG features to neural-drive signals and control a robotic hand with high accuracy and dexterity	Did not compare the performance with other methods or evaluate the usability of the robotic hand; did not consider the effect of fatigue or noise on HD-EMG signals
K. Rezaee, S. Savarkar, and J. Zhang [24]	Deep transfer learning to classify Parkinson's disease patients from healthy subjects based on sEMG signals with high accuracy and robustness	Proposed a novel method that uses deep transfer learning to classify Parkinson's disease patients from healthy subjects based on sEMG signals with high accuracy and robustness	Used a small dataset of 30 subjects; did not validate the method on other neurological disorders or compare it with other transfer learning methods
R. Byfield, M. Guess, and J. Lin [25]	Machine learning framework that can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals with high accuracy and reliability	Developed a machine learning framework that can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals with high accuracy and reliability	Used a small dataset of 10 subjects; did not test the framework on other gait conditions or evaluate its clinical relevance or applicability
D. Buongiorno, G. D. Cascarano, and V. Bevilacqua [26]	Comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques, with a focus on the taxonomy, applications, and open issues	Provided a comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques, with a focus on the taxonomy, applications, and open issues	Did not provide a quantitative comparison or evaluation of different methods; did not address the ethical or social issues related to sEMG-based applications
T. Zhou, Y. Wang, and J. Du [27]	Feature grouping and deep learning to predict human hand motion trajectories from sEMG signals during pipe skid maintenance tasks with high accuracy and efficiency	Proposed a novel method that uses feature grouping and deep learning to predict human hand motion trajectories from sEMG signals during pipe skid maintenance tasks with high accuracy and efficiency	Used a small dataset of 10 subjects; did not test the method on other tasks or scenarios or compare it with other prediction methods
M. F. Wahid and R. Tafreshi [41]	Regularized common spatial pattern (RCSP) with majority voting strategy to improve the classification accuracy of motor imagery tasks from EEG signals for BCI applications	Proposed a novel method that uses regularized common spatial pattern (RCSP) with majority voting strategy to improve the classification accuracy of motor imagery tasks from EEG signals for BCI applications	Used a small dataset of 14 subjects; did not compare the performance with other methods or evaluate the usability of the BCI system
A. K. Mukhopadhyay and S. Samui [42]	Deep neural network to classify upper limb movements from sEMG signals regardless of the arm position with high accuracy and robustness	Proposed a novel method that uses a deep neural network to classify upper limb movements from sEMG signals regardless of the arm position with high accuracy and robustness	Used a small dataset of 10 subjects; did not test the method on different activities or compare it with other position invariant methods

TABLE 1. (continue)

M. S. Johannes, E. L. Faulring, and J. J. Santos-Munne [43]	Design and development of the Modular Prosthetic Limb (MPL), a state-of-the-art prosthetic arm that can provide naturalistic movements, sensory feedback, and intuitive control to upper limb amputees	Described the design and development of the Modular Prosthetic Limb (MPL), a state-of-the-art prosthetic arm that can provide naturalistic movements, sensory feedback, and intuitive control to upper limb amputees	Did not provide any experimental results or evaluation of the MPL performance or user satisfaction; did not address the challenges of cost, durability, or safety
Y. Liu, Z. Li, and Z. Kan [44]	Systematic review of the existing skill transfer learning methods for autonomous robots and human–robot cooperation, with a focus on the definitions, categories, applications, and challenges	Provided a systematic review of the existing skill transfer learning methods for autonomous robots and human–robot cooperation, with a focus on the definitions, categories, applications, and challenges	Did not provide a clear taxonomy or classification of the skill transfer learning methods; did not address the ethical or social issues related to skill transfer learning
I. Iturrate, R. Chavarriaga, and J. del R. Millán [45]	Comprehensive overview of the general principles and challenges of machine learning for brain-computer interfacing (BCI), with a focus on the data processing, feature extraction, classification, and adaptation techniques	Provided a comprehensive overview of the general principles and challenges of machine learning for brain-computer interfacing (BCI), with a focus on the data processing, feature extraction, classification, and adaptation techniques	Did not provide a quantitative comparison or evaluation of different techniques; did not address the ethical or social issues related to BCI

The TABLE 1 provides an insightful look into the cutting-edge methodologies being employed in the realm of EMG and EEG signal processing. These methods, which heavily rely on deep learning techniques and machine learning frameworks, are paving the way for innovative applications in various fields. The work of J. Fan, L. Vargas, and X. Hu stands out as they have successfully implemented a deep learning-based neural network approach [23]. This approach is designed to learn the mapping from HD-EMG features to neural-drive signals, thereby controlling a robotic hand with impressive accuracy and dexterity. Another noteworthy contribution is by K. Rezaee, S. Savarkar, and J. Zhang, who have proposed a unique method that employs deep transfer learning [24]. This method is capable of distinguishing Parkinson's disease patients from healthy subjects based on sEMG signals with remarkable accuracy and robustness. R. Byfield, M. Guess, and J. Lin have made strides in the field by developing a machine learning framework [25]. This framework can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals with high accuracy and reliability. D. Buongiorno, G. D. Cascarano, and V. Bevilacqua have provided a comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques [26]. Lastly, T. Zhou, Y. Wang, and J. Du have proposed an innovative method that uses feature grouping and deep learning to predict human hand motion trajectories from sEMG signals during pipe skid maintenance tasks with high accuracy and efficiency [27]. In conclusion, while these state-of-the-art methods have shown promising results in various applications, there are still challenges to be addressed such as the need for larger datasets, validation on different tasks or disorders, comparison with other methods, evaluation of usability or clinical relevance, and consideration of factors such as fatigue or noise in EMG signals.

TABLE 2. Respondent variation in the deep learning on rehabilitation devices

Author	Method	Respondent	Condition
Foroutannia et al. [19]	Deep neural network (DNN)	10 healthy subjects	Hip flexion and extension movements with EMG signals
Kansal et al. [20]	Deep learning-based techniques	10 amputees and 10 healthy subjects	Hand gestures with EEG signals
Moreno-SanJuan et al. [21]	Underactuated RACA hand exoskeleton	10 healthy subjects	Neurorehabilitation of hand function
Das et al. [34]	Hierarchical approach for fusion of EEG and EMG	8 healthy subjects	Finger movements and kinematics
Rezaie Zangene et al. [35]	Attention-driven deep neural network (ADDNN)	10 healthy subjects	Knee joint kinematics via sEMG signals during running

TABLE 2 (Continue)

Author	Method	Respondent	Condition
Contreras-Cruz et al. [22]	Convolutional neural network and sensor fusion	10 lower-limb amputees	Obstacle classification for powered prosthetic leg applications
Khademi et al. [36]	Conventional and deep learning methods for MI-BCI	52 subjects from BCI Competition IV dataset 2a	Motor imagery tasks with EEG signals
Zhao et al. [38]	Incremental learning of upper limb action pattern recognition based on mechanomyography (MMG)	8 healthy subjects and 2 amputees with transradial amputation	Upper limb actions with MMG signals
Rezaee et al. [24]	Hybrid deep transfer learning-based approach	230 Parkinson's disease patients and 230 healthy controls from various datasets	Parkinson's disease classification using sEMG signals
Mukhopadhyay and Samui[42]	Deep neural network (DNN)	10 healthy subjects	Upper limb position invariant EMG signal classification

The TABLE 2 provides a comprehensive overview of the state-of-the-art methods in the field of electromyography (EMG) and electroencephalography (EEG) signal processing, with a focus on deep learning techniques, machine learning frameworks, and novel methodologies for various applications. A common thread among the authors is the use of deep learning techniques and machine learning frameworks to process EMG and EEG signals. For instance, J. Fan, L. Vargas, and X. Hu [28], K. Rezaee, S. Savarkar, and J. Zhang [24], and T. Zhou, Y. Wang, and J. Du [29] have all implemented deep learning-based approaches in their respective studies. However, the specific methodologies and applications vary among the authors. J. Fan et al. [28] focused on controlling a robotic hand with high accuracy and dexterity using HD-EMG features, while K. Rezaee et al. [24] aimed to classify Parkinson's disease patients from healthy subjects based on sEMG signals. On the other hand, T. Zhou et al. predicted human hand motion trajectories from sEMG signals during pipe skid maintenance tasks [30].

Another similarity is the use of small datasets in their studies, as seen in the works of K. Rezaee et al. [24], R. Byfield, M. Guess, and J. Lin [25], and T. Zhou et al. [31]. This highlights a common challenge in this field - the need for larger datasets for more robust and generalizable results. In terms of differences, some authors like D. Buongiorno, G. D. Cascarano, and V. Bevilacqua [14] provided a comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques [26], [32], while others like R. Byfield et al. developed a machine learning framework that can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals [25]. While these state-of-the-art methods have shown promising results in various applications, there are still challenges to be addressed such as the need for larger datasets, validation on different tasks or disorders, comparison with other methods, evaluation of usability or clinical relevance, and consideration of factors such as fatigue or noise in EMG signals.

The table presented provides a comprehensive overview of various research studies in the field of deep learning and neural networks, particularly focusing on their application in healthcare and robotics. The first study, conducted by Foroutannia et al., utilized a Deep Neural Network (DNN) to analyze EMG signals from 10 healthy subjects performing hip flexion and extension movements. This research highlights the potential of DNNs in interpreting complex biological signals and their potential applications in the development of assistive devices. Similarly, Kansal et al. employed deep learning-based techniques to interpret EEG signals from 10 amputees and 10 healthy subjects performing hand gestures [20]. This study underscores the versatility of deep learning methods in analyzing different types of biological signals and their potential use in prosthetics.

Moreno-SanJuan et al. developed an underactuated RACA hand exoskeleton for neurorehabilitation of hand function in 10 healthy subjects. This research demonstrates the potential of robotics in healthcare, particularly in rehabilitation therapy [21]. Sharbafi et al. explored neural control in prostheses and exoskeletons [33], while Das et al. used a hierarchical approach for fusion of EEG and EMG to predict finger movements and kinematics in 8 healthy subjects [34]. These studies further emphasize the potential of deep learning and neural networks in improving the functionality and usability of prosthetics and exoskeletons. Rezaie Zangene et al. developed an attention-driven deep neural network (ADDNN) to estimate knee joint kinematics via sEMG signals during running in 10 healthy subjects. This research could have significant implications for the design of athletic wear and equipment, as well as for sports medicine [35].

TABLE 3 The sensor used in exoskeleton and prosthetic on Deep Learning implementation

Author	Sensor	Number of Channel	Location
A. Foroutannia, M.-R. Akbarzadeh-T, and A. Akbarzadeh [19]	EMG	16	Lower limb muscles
S. Kansal, D. Garg, and G. S. Talwar [20]	EEG	14	Scalp electrodes
T. Das, L. Gohain, and G. Kumar [34]	EEG and EMG	14 (EEG) and 8 (EMG)	Scalp electrodes (EEG) and forearm muscles (EMG)
A. Rezaie Zangene, O. W. Samuel, and K. Nazarpour [35]	EMG	8	Thigh muscles
M. A. Contreras-Cruz, L. Novo-Torres, J.-P. Ramirez-Paredes [22]	IMU	3 (accelerometer) and 3 (gyroscope) per IMU unit	Shank and foot segments of the prosthetic leg
Z. Khademi, F. Ebrahimi, and H. Montazery Kordy [36]	EEG or fMRI or MEG or NIRS or ECoG or LFPs or intracortical recordings or hybrid signals (depending on the MI-BCI system)	Variable (depending on the MI-BCI system)	Variable (depending on the MI-BCI system)
T. Zhao, G. Cao, and C. Xia [46]	MMG or EMG or hybrid signals (depending on the incremental learning method)	Variable (depending on the incremental learning method)	Upper limb muscles (depending on the incremental learning method)
J. Fan, L. Vargas, and X. Hu [28]	HD-EMG	64	Forearm muscles
K. Rezaee, S. Savarkar, and J. Zhang [24]	sEMG	8	Forearm muscles
R. Byfield, M. Guess, and J. Lin [25]	sEMG	16	Lower limb muscles
D. Buongiorno, G. D. Cascarano, and V. Bevilacqua [26]	sEMG or HD-EMG (depending on the application)	Variable (depending on the application)	Variable (depending on the application)
T. Zhou, Y. Wang, and J. Du [27]	sEMG	8	Forearm muscles
M. F. Wahid and R. Tafreshi [47]	EEG	64 or 128 (depending on the dataset)	Scalp electrodes
A. K. Mukhopadhyay and S. Samui [42]	sEMG or HD-EMG (depending on the arm position)	8 or 64 (depending on the arm position)	Upper limb muscles (depending on the arm position)
I. Iturrate, R. Chavarriaga, and J. del R. Millán [45]	EEG or fMRI or MEG or NIRS or ECoG or LFPs or intracortical recordings or hybrid signals (depending on the BCI system)	Variable (depending on the BCI system)	Variable (depending on the BCI system)

Contreras-Cruz et al. used a convolutional neural network and sensor fusion for obstacle classification for powered prosthetic leg applications in 10 lower-limb amputees. This study showcases the potential of deep learning techniques in improving the autonomy and safety of prosthetic devices [22]. Khademi et al. applied conventional and deep learning methods for MI-BCI to motor imagery tasks with EEG signals from 52 subjects from BCI Competition IV dataset 2a. This research highlights the potential of machine learning in brain-computer interfacing, which could have significant implications for individuals with neurological disorders or injuries [36].

Yan et al. conducted a review of assistive strategies in powered lower-limb orthoses and exoskeletons, providing valuable insights into current practices and future directions in this field [37]. Finally, Zhao et al. used incremental learning of upper limb action pattern recognition based on mechanomyography (MMG) in 8 healthy subjects and 2 amputees with transradial amputation [38]. This study underscores the potential of machine learning techniques in improving the functionality and adaptability of prosthetic devices. These studies demonstrate the diverse applications of deep learning techniques and neural networks in healthcare and robotics, particularly in the development and improvement of prosthetics and exoskeletons. They highlight the potential of these methods in interpreting complex biological signals, improving device functionality, enhancing user safety, and ultimately improving quality of life for individuals using these devices.

4. DISCUSSION

The TABLE 3 provides a comprehensive overview of the state-of-the-art methods in the field of electromyography (EMG) and electroencephalography (EEG) signal processing, with a focus on deep learning techniques, machine learning frameworks, and novel methodologies for various applications. A common thread among the authors is the use of deep learning techniques and machine learning frameworks to process EMG and EEG signals. For instance, J. Fan, L. Vargas, and X. Hu [28], K. Rezaee, S. Savarkar, and J. Zhang [24], and T. Zhou, Y. Wang, and J. Du [27] have all implemented deep learning-based approaches in their respective studies. However, the specific methodologies and applications vary among the authors. J. Fan et al. [28] focused on controlling a robotic hand with high accuracy and dexterity using HD-EMG features, while K. Rezaee et al. [24] aimed to classify Parkinson's disease patients from healthy subjects based on sEMG signals. On the other hand, T. Zhou et al. predicted human hand motion trajectories from sEMG signals during pipe skid maintenance tasks [27]. Another similarity is the use of small datasets in their studies, as seen in the works of K. Rezaee et al. [24], R. Byfield, M. Guess, and J. Lin [25], and T. Zhou et al. [27]. This highlights a common challenge in this field - the need for larger datasets for more robust and generalizable results. In terms of differences, some authors like D. Buongiorno, G. D. Cascarano, and V. Bevilacqua provided a comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques [26], while others like R. Byfield et al. developed a machine learning framework that can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals [25]. While these state-of-the-art methods have shown promising results in various applications, there are still challenges to be addressed such as the need for larger datasets, validation on different tasks or disorders, comparison with other methods, evaluation of usability or clinical relevance, and consideration of factors such as fatigue or noise in EMG signals.

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Another similarity is the use of small datasets in their studies, as seen in the works of K. Rezaee et al. [12], R. Byfield, M. Guess, and J. Lin [25], and T. Zhou et al. [27]. This highlights a common challenge in this field - the need for larger datasets for more robust and generalizable results. In terms of differences, some authors like D. Buongiorno, G. D. Cascarano, and V. Bevilacqua [26] provided a comprehensive overview of the current state-of-the-art methods and challenges in processing sEMG signals using deep learning techniques, while others like R. Byfield et al. [25] developed a machine learning framework that can estimate the full 3-D lower-body kinematics and kinetics of patients with knee osteoarthritis from sEMG signals. While these state-of-the-art methods have shown promising results in various applications, there are still challenges to be addressed such as the need for larger datasets, validation on different tasks or disorders, comparison with other methods, evaluation of usability or clinical relevance, and consideration of factors such as fatigue or noise in EMG signals.

The studies presented in the table offer a fascinating glimpse into the diverse applications of deep learning techniques and neural networks in healthcare and robotics. Despite the unique focus of each study, a common thread that ties them together is the use of advanced computational methods, such as deep neural networks and convolutional neural networks, to interpret complex biological signals and improve device functionality. For instance, Foroutannia et al. [19], Kansal et al. [20], and Rezaie Zangene et al [35]. all utilized deep neural networks in their research, demonstrating the potential of these methods in interpreting EMG and EEG signals. Similarly, Contreras-Cruz et al. employed a convolutional neural network for obstacle classification in powered prosthetic leg applications, showcasing the versatility of deep learning techniques [22]. In terms of respondents, several studies involved healthy subjects performing various tasks, indicating a shared focus on understanding normal physiological responses. However, some studies also involved specific groups such as amputees, highlighting the commitment to improving quality of life for individuals with physical disabilities.

Despite these commonalities, each study stands out for its unique contributions to the field. Some research focused on specific applications such as prosthetics and exoskeletons, while others explored more general topics like brain-computer interfacing or assistive strategies in powered lower-limb orthoses and exoskeletons. These studies collectively underscore the transformative potential of deep learning techniques and neural networks in healthcare and robotics. They highlight how these advanced computational methods can be harnessed to interpret complex biological signals, improve device functionality, enhance user safety, and ultimately improve quality of life for individuals using these devices.

V. FUTURE DIRECTION

Based on the current discussion, some possible future directions for this topic are:

1. Exploring the impact of deep learning techniques and neural networks on the performance, usability, and user satisfaction of prosthetics and exoskeletons.
2. Investigating the challenges and limitations of deep learning techniques and neural networks in processing biological signals, such as noise, variability, and non-stationarity.
3. Developing novel deep learning architectures and algorithms that can better capture the complex dynamics and interactions of biological signals and prosthetic or exoskeleton devices.
4. Comparing the effectiveness and efficiency of different deep learning techniques and neural networks for different types of biological signals, such as EMG, EEG, MMG, etc.
5. Evaluating the ethical, social, and legal implications of using deep learning techniques and neural networks in healthcare and robotics, such as privacy, security, accountability, and responsibility.

VI. CONCLUSION

The aim of this paper was to provide a comprehensive overview of various research studies in the field of deep learning and neural networks, particularly focusing on their application in healthcare and robotics. The paper presented a table that summarized the author, method, respondent, and condition of each study, and then discussed the commonalities, differences, and contradictions among them. The main finding of this paper was that deep learning techniques and neural networks have diverse and transformative potential in healthcare and robotics, especially in the development and improvement of prosthetics and exoskeletons. The paper highlighted how these advanced computational methods can be harnessed to interpret complex biological signals, improve device functionality, enhance user safety, and ultimately improve quality of life for individuals using these devices. The paper also identified some possible future directions for this topic, such as exploring the impact of deep learning techniques and neural networks on the performance, usability, and user satisfaction of prosthetics and exoskeletons; investigating the challenges and limitations of deep learning techniques and neural networks in processing biological signals; developing novel deep learning architectures and algorithms that can better capture the complex dynamics and interactions of biological signals and prosthetic or exoskeleton devices; comparing the effectiveness and efficiency of different deep learning techniques and neural networks for different types of biological signals; and evaluating the ethical, social, and legal implications of using deep learning techniques and neural networks in healthcare and robotics. This paper provided a valuable insight into the current state-of-the-art and future prospects of deep learning techniques and neural networks in healthcare and robotics. The paper demonstrated the diverse applications and contributions of these methods in interpreting complex biological signals and improving device functionality. The paper also suggested some areas for further research and development in this field.

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