Review of Signal Processing Methods for EEG-Based Wrist Rehabilitation Robots
EEG Tabanlı Bilek Rehabilitasyon Robotları için Sinyal İşleme Yöntemlerinin İncelenmesi

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Abstract—**Rehabilitation is a crucial aspect of recovery for individuals affected by accidents, injuries, or medical conditions. Its objective is to restore functionality and enhance quality of life through a range of therapeutic techniques. This review emphasizes the pivotal role of electroencephalography (EEG) in advancing rehabilitation technologies, particularly through its integration with robotic systems. EEG devices, in conjunction with brain-computer interfaces (BCIs), offer profound insights into patient neural activities, enabling the tailored application of therapeutic exercises. Furthermore, machine learning techniques are employed to interpret EEG data, enhancing the precision and adaptability of rehabilitation interventions. This paper discusses the development and application of advanced machine learning algorithms that classify EEG signals for effective control of rehabilitation robots. These innovations promise to personalize treatment procedures, optimize recovery outcomes, and improve patient autonomy by facilitating direct brain-to-device communication. The continuous evolution of EEG and BCI technologies is set to revolutionize rehabilitation practices, offering new pathways to restore independence and improve the quality of life for patients globally.**

***Keywords*—eeg; brain-computer interface; rehabilitation robots; machine learning; classification**

Özetçe—**Rehabilitasyon, kazalardan, yaralanmalardan veya tıbbi durumlardan etkilenen bireylerin iyileşme sürecinde kritik bir rol oynar. Temel amacı, çeşitli terapötik tekniklerle işlevselliği yeniden sağlamak ve yaşam kalitesini artırmaktır. Bu derleme, özellikle robotik sistemlerle entegrasyonu yoluyla, rehabilitasyon teknolojilerinin geliştirilmesinde elektroensefalografinin (EEG) önemli rolünü vurgulamaktadır. EEG cihazları, beyin-bilgisayar arayüzleri (BCI'ler) ile birlikte, hastaların sinirsel aktivitelerine ilişkin derinlemesine bilgiler sunarak terapötik egzersizlerin hassas bir şekilde uygulanmasına olanak tanır. Ayrıca, EEG verilerini yorumlamak için makine öğrenimi tekniklerinin kullanılması, rehabilitasyon müdahalelerinin doğruluğunu ve uyarlanabilirliğini artırmaktadır. Bu makale, rehabilitasyon robotlarının etkili kontrolü için EEG sinyallerini sınıflandıran gelişmiş makine öğrenme algoritmalarının geliştirilmesini ve uygulanmasını tartışmaktadır. Bu yenilikler, tedavi prosedürlerini kişiselleştirmeyi, iyileşme sonuçlarını optimize etmeyi ve beyinden cihaza doğrudan iletişimi kolaylaştırarak hasta özerkliğini artırmayı vaat etmektedir. EEG ve BCI teknolojilerinin sürekli gelişimi, rehabilitasyon uygulamalarında devrim yaratacak ve dünya çapında hastaların bağımsızlığını yeniden kazanması ve yaşam kalitesini iyileştirmesi için yeni yollar sunacaktır.**

***Anahtar Kelimeler*—eeg; beyin-bilgisayar arayüzü; rehabilitasyon robotları; makine öğrenmesi; sınıflandırma**

I. Introduction

Rehabilitation is a crucial process aimed at helping individuals regain their capacity for daily activities and restore their normal functions. This is often necessary after accidents, injuries, or medical conditions. Through various therapeutic techniques, it seeks to help patients recover and improve their abilities that were impaired due to these adversities. The approach involves multiple strategies and technologies focused on restoring functional abilities and enhancing quality of life. This enables patients to return to their normal routines as efficiently as possible [1].

In the field of rehabilitation, a variety of medical techniques and signals are employed to optimize patient outcomes. One such method involves the use of sensor-based signal-monitoring systems, which have been subjected to critical review concerning their efficacy in rehabilitating physically disabled patients. These systems employ a variety of sensors to monitor physiological signals, thereby enabling the implementation of therapeutic measures that are specifically tailored to the individual's needs [2]. Another noteworthy development is the field of intelligent medical systems, which facilitate lower limb joint rehabilitation through the remote transmission of physiological signals. This methodology allows for precise monitoring and adjustment of rehabilitation protocols, significantly improving patient engagement and recovery outcomes [3].

Electroencephalography (EEG) has been demonstrated to be a fundamental tool in the field of rehabilitation, offering significant insights and therapeutic opportunities, particularly in neurorehabilitation settings. The significance of EEG in rehabilitation is further reinforced by its capacity to provide immediate feedback and facilitate the modulation of neural activities through non-invasive means. Studies conducted by Bartur et al. [4] have demonstrated the feasibility of EEG tools in monitoring patient engagement during stroke rehabilitation. These studies have highlighted how EEG metrics can significantly enhance patient outcomes by tailoring therapies based on the brain's electrical activity. Moreover, EEG hyperscanning, a technique that involves the simultaneous recording of EEG from multiple subjects, has been explored for its potential in motor rehabilitation scenarios. This approach facilitates a more profound comprehension of the dynamics between patients and therapists during therapy sessions, which may ultimately result in more efficacious rehabilitation practices [1].

The field of rehabilitation has witnessed a significant evolution over the past few decades, moving from traditional therapeutic methods to innovative approaches that leverage the potential of modern technology. One of the most significant advancements in this field is the development and integration of robotic systems designed for hand rehabilitation after stroke. Electroencephalography (EEG), a diagnostic tool traditionally employed in the field of neurology, has recently been employed in the field of rehabilitation. This integration is primarily facilitated through the development of brain-computer interfaces (BCIs), which allow direct communication between the brain and external devices. Such technologies not only promise to enhance the effectiveness of rehabilitation practices but also offer new hopes for patient autonomy and recovery [5]. According to Liu et al. [6], robotic-assisted rehabilitation has shown promise in providing functional training for the hand, which is often impaired after a stroke. These robots offer a range of motion exercises and assist with daily activities, addressing the specific needs of patients with hand disorders. Despite these advancements, the review highlights that there are still unmet user needs, particularly in the areas of actuation and control strategies. Future research is likely to focus on improving the adaptability and responsiveness of these robotic systems to enhance patient outcomes [6].

Furthermore, electroencephalogram (EEG)-based brain-computer interfaces (BCIs) have emerged as transformative tools in rehabilitation. They facilitate the restoration of mobility and communication for individuals with severe motor impairments, thereby bridging the gap between patient intent and physical execution through direct brain control of external devices [7]. These interfaces employ sophisticated algorithms to interpret neural signals, enabling patients to control prosthetic limbs, wheelchairs, and even computers, thereby markedly enhancing their quality of life [8].

Furthermore, recent developments have demonstrated the potential of virtual reality (VR) in the field of rehabilitation. The combination of VR and EEG can create immersive environments that enhance motor learning and cognitive rehabilitation, providing engaging and interactive therapeutic experiences. Some studies have demonstrated that VR-based rehabilitation can result in significant improvements in motor function and cognitive abilities in patients who have suffered a stroke [9].

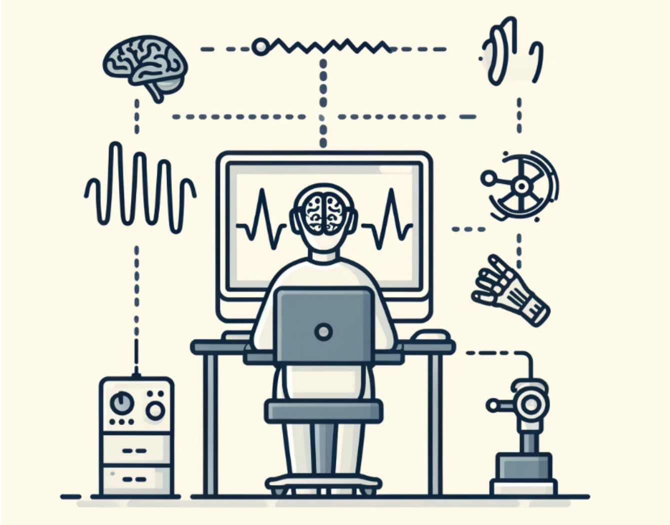

Figure 1: Illustration of a Brain-Computer Interface (BCI) System for Rehabilitation

Moreover, the integration of artificial intelligence (AI) with electroencephalography (EEG) and brain-computer interfaces (BCI) technologies has opened new avenues in the field of personalized medicine. Artificial intelligence (AI) algorithms can analyze large datasets of electroencephalography (EEG) signals to predict patient outcomes and optimize rehabilitation protocols, thereby enhancing the effectiveness and personalization of treatments [10].

These studies collectively illustrate the pivotal role of EEG in enhancing rehabilitation techniques, affirming its value in both clinical and research settings to improve the quality and effectiveness of patient care. The continuous evolution of these technologies promises to bring even more innovative solutions to the field of rehabilitation, with the ultimate goal of restoring independence and improving the quality of life for patients worldwide (Fig.1).

II. EEG-Based Rehabilitation Systems

A. Related Studies

A review of the literature reveals that the use of electroencephalography (EEG) [11]–[20] and electromyography (EMG) [21]–[23] signals in control systems for prosthetic and assistive devices, particularly for hand and wrist rehabilitation, has been extensively studied [24]–[26]. Fernandez-Vargas, Kita, and Yu (2016) investigated a real-time hand motion reconstruction system that integrates EEG and EMG signals to enhance prosthetic control. The authors emphasized the importance of targeting motor cortex regions to improve motor execution and intention understanding [27]. Similarly, Khan, Khan, and Farooq (2019) discussed the processing of EEG signals for feature extraction and classification, furthering the use of these signals in brain-computer interface (BCI) systems for prosthetic applications. These studies emphasize the crucial importance of high-resolution temporal and spatial EEG data in the development of more intuitive and effective rehabilitative and assistive technologies [28].

For instance, Rashid et al. explored the potential of electroencephalography (EEG) signals to classify movements of the fingers and thumbs, which are crucial for controlling upper limb prostheses. The methodology employed sophisticated algorithms capable of capturing subtle changes in brain activity corresponding to different finger movements. This was achieved through the design of an embedded system for multivariate classification of finger and thumb movements using EEG signals for control of upper limb prostheses [29]. A recent study concentrated on EEG data obtained during imagined hand movements, utilizing Common Spatial Patterns (CSP) to extract features that enhance the classification of motor imagery for neuro-rehabilitation purposes [30].

A systematic review of the literature was conducted to assess the effectiveness of the Wrist Rehabilitation Robot System (WRRS) for patients [31]. This study aimed to investigate the integration of electroencephalography (EEG) and near-infrared spectroscopy (NIRS) data to evaluate the effectiveness of a wrist rehabilitation robot system. The EEG data were employed to monitor the motor cortex activity and emotional responses of the patients during the therapy sessions. This provided insights into the patients' motivation and their interaction with the system. The comprehensive data analysis enabled an objective assessment of both the therapeutic outcomes and the overall performance of the rehabilitation system, demonstrating its impact on patient recovery.

The objective of this research was to design an embedded system for multivariate classification of finger and thumb movements using EEG signals for the control of upper limb prostheses. This research project aimed to develop an embedded system that utilizes electroencephalography (EEG) signals to control upper limb prostheses by classifying finger and thumb movements. Advanced signal processing algorithms were employed to analyze EEG data collected from the motor cortex. Time and frequency domain analyses were used to extract detailed features that were necessary for accurate movement classification. The system was designed to be highly responsive and energy-efficient, thereby enhancing the functionality and user-friendliness of prosthetic devices [29].

A recent study describes the development of an affordable, portable wrist exoskeleton designed to facilitate wrist rehabilitation through a hybrid control strategy using both EEG (electroencephalography) and sEMG (surface electromyography) signals. The study involved both healthy participants and patients needing wrist rehabilitation. EEG data were collected using electrodes placed according to the international 10-20 system, while sEMG signals were obtained from sensors on the forearm muscles. Key features such as movement-related cortical potentials (MRCPs), spectral power from EEG, and amplitude and frequency characteristics from sEMG, were extracted and processed using convolutional neural networks (CNNs). These signals were then used to control the wrist exoskeleton, enabling precise, responsive movements tailored to the user's rehabilitation needs. The combined EEG-sEMG strategy significantly improved the accuracy and effectiveness of the exoskeleton, making it a promising tool for home-based wrist rehabilitation [32].

Another study focuses on developing a deep learning-based assistive device that utilizes EEG signals to aid in the rehabilitation of elbow and finger movements. The study involves both healthy participants and patients requiring rehabilitation. EEG data is collected using a 32-channel setup according to the international 10-20 system, capturing electrical activity from various brain regions. Key features such as movement-related cortical potentials (MRCPs) and spectral power are extracted from the EEG signals. Deep learning algorithms, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are employed to classify these signals and detect movement intentions. The EEG-driven assistive device translates these detected intentions into control commands for rehabilitation exercises. The results indicate high accuracy in movement detection and significant improvements in the rehabilitation process, providing a more effective and user-friendly solution for patients with motor impairments [33].

The objective of this research is to develop a Brain-Computer Interface (BCI)-based robotic end effector system for the rehabilitation of wrist and hand function [34]. In this study, electroencephalogram (EEG) data from chronic stroke patients were employed to control a robotic end effector for wrist and hand rehabilitation. The data were processed through a brain-computer interface (BCI), to enhance the personalization of the rehabilitation process. By accurately interpreting the patients' motor intention signals, the system was able to provide tailored therapeutic exercises, significantly improving the rehabilitation outcomes for stroke survivors.

In another study, the potential of EEG signals is examined to predict self-initiated movements in the upper limb, with a focus on both healthy individuals and stroke patients. The study employed electroencephalography (EEG) data collected from 64 channels positioned according to the international 10-20 system, a standard method for capturing brain activity related to motor functions. The data analysis focused on motor-related cortical potentials (MRCPs) and spectral power features to identify movement intentions. Machine learning algorithms, including artificial neural networks (ANN), support vector machines (SVM), and linear discriminant analysis (LDA), were employed to classify the EEG signals, with detection accuracy ranging from 64.3% to 77.0%. The study demonstrated that anticipatory detection could occur between 620 and 1000 milliseconds before movement onset, suggesting significant potential for enhancing neurorehabilitation devices by enabling more responsive and natural control during rehabilitation therapy [35].

This study presents an EEG-based BCI system designed to detect finger movements. This paper presents the development of a brain-computer interface system that utilizes electroencephalography (EEG) data to detect finger movements. The EEG signals, indicative of motor cortex activity, were subjected to processing using sophisticated algorithms and feature extraction techniques. The system was designed with the specific intention of enhancing the precision of movement detection, thereby improving the effectiveness of rehabilitative therapies

[36].

In addition, the EEG data play a pivotal role in the development of a brain-computer interface (BCI) designed to classify imagined wrist movements. The EEG signals are collected from multiple scalp electrodes, which have been strategically placed to capture electrical activities from the motor cortex. This is the region of the brain where neural representations of limb movements are processed. The data are primarily focused on the electroencephalogram (EEG) patterns associated with the imaginary flexion and extension of both the left and right wrists. The EEG data are subjected to a two-stage classification process, the initial stage of which is to distinguish between the types of movement (flexion or extension), and the subsequent stage is to identify the specific wrist (left or right) involved in the imagined movement. This study employs sophisticated signal processing techniques, including band-pass filtering, to isolate the frequency bands most associated with motor imagery. It also utilizes advanced classification algorithms to enhance the accuracy of detecting these imagined movements. The high-resolution temporal and spatial data extracted from the EEG allows for the precise interpretation of subtle differences in brain activity patterns, which is essential for the effective operation of BCIs in prosthetic control and rehabilitation applications. This comprehensive approach to data utilization exemplifies the potential of EEG-based systems to revolutionize assistive technology, offering more intuitive and adaptable user interfaces for individuals with motor impairments [37].

This study introduces an innovative approach to wrist rehabilitation that employs a low-cost EEG sensor to monitor and respond to patient attention levels. This study introduced an innovative approach to wrist rehabilitation, employing a low-cost EEG sensor to monitor and respond to patient attention levels. By adjusting the device's operation based on real-time EEG data reflecting the patient's cognitive engagement, the rehabilitation process became more adaptive and patient-centred. This method not only enhanced patient participation but also demonstrated the potential for cognitive monitoring to enhance the effectiveness of physical rehabilitation [38].

B. Preprocessing Steps

1) Signal Filtering: Signal filtering is a fundamental preprocessing step used to improve the quality of EEG signals. It involves the isolation of relevant frequency bands and the removal of noise. Band-pass filters are frequently employed to concentrate on specific frequency ranges, including the alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-100 Hz) bands. These bands are associated with motor control and cognitive activities. For example, band-pass filtering is employed to enhance the signal-to-noise ratio by eliminating unwanted frequencies and artifacts [29], [31], [36].

2) Artifact Removal: Another crucial preprocessing step is the removal of artifacts from EEG signals. This involves the elimination of unwanted physiological and external artifacts. The most common artifacts include eye blinks, muscle movements, and electrical noise. Techniques such as Independent Component Analysis (ICA) and Principal Component Analysis (PCA) are frequently employed to identify and remove these artifacts. Studies such as [34] and [38] utilize artifact removal methodologies to ensure that the EEG data accurately reflects the user's brain activity, free from interference from external sources.

3) Normalization: Normalization is a technique employed to scale EEG signals to a common range, which is a crucial step in ensuring consistent feature extraction and analysis. This process adjusts the amplitude of the EEG signals to a standardized range, thereby reducing variability and enhancing the comparability of the signals across different sessions and subjects. Normalization techniques are employed in studies such as [33] to guarantee that the input data to machine learning models is consistent and reliable.

4) Baseline Correction: Baseline correction is a preprocessing technique employed to adjust EEG data to a baseline level, thereby correcting for drifts and other slow variations in the signal. This process entails the subtraction of the baseline, which is typically a period of rest or inactivity, from the EEG data. This serves to remove low-frequency noise and enhance the detection of event-related potentials (ERPs) and movement-related cortical potentials (MRCPs). The study, entitled [35], employs baseline correction to ensure the accurate detection of anticipatory brain activity related to self-paced movements.

5) Signal Segmentation: Signal segmentation is the process of dividing continuous EEG signals into smaller, more manageable epochs or segments for subsequent analysis. This is particularly useful for the analysis of time-locked events, such as motor imagery tasks or specific cognitive activities. Segmentation permits the focused analysis of specific time windows in which it is anticipated that relevant brain activity will occur. The study, entitled [37], employs signal segmentation to analyze distinct epochs corresponding to different motor imagery tasks.

6) Attention Level Quantification: Attention level quantification is a specific preprocessing step employed in studies that focus on cognitive engagement, such as [38]. This process entails the extraction of features related to attention and cognitive states from EEG signals, frequently employing metrics such as mean amplitude and frequency. The quantified attention levels are subsequently employed to regulate assistive devices, thereby enabling the rehabilitation process to be responsive to the user's mental state and to adapt accordingly.

7) Multimodal Signal Processing: In studies that combine EEG with other physiological signals, such as [32], the preprocessing stage involves the handling of multiple types of data. In the case of EEG and sEMG signals, preprocessing involves filtering, artifact removal, and normalization for both signal types in order to ensure accurate integration and analysis. This multimodal approach enhances the robustness and effectiveness of the rehabilitation system by leveraging complementary information from different physiological sources.

It is of paramount importance to employ preprocessing methods in order to guarantee the quality of EEG data utilized in rehabilitation studies. This ensures the accurate extraction of features and subsequent analysis. The removal of noise, and artifacts, and the establishment of consistency through these preprocessing steps facilitate the development of more effective and reliable EEG-based rehabilitation technologies.

C. Feature Exctraction

1) Time-Domain and Frequency-Domain Analysis: Time-domain and frequency-domain analysis are crucial for extracting features that capture the dynamics of EEG signals. Time-domain analysis extracts features such as mean, variance, and amplitude to understand the temporal characteristics of motor intentions [29], [33]. Frequency domain analysis, often performed using Fourier transform, converts EEG signals from the time domain to the frequency domain, allowing extraction of the power spectral density (PSD) and dominant frequency components [31], [37].

2) Event-Related Potentials (ERP) and Movement-Related Cortical Potentials (MRCPs): ERP and MRCP analysis are key techniques for identifying brain activity associated with motor tasks. ERPs are used to extract features that reflect the user's motor intentions and cognitive engagement. In [38], ERP analysis helps to quantify the level of attention required to control the movements of the wrist exoskeleton. MRCPs, which indicate motor planning and execution, are extracted [31], [32]. These potentials provide insight into the user's motor-related brain activity and are crucial for the design of responsive rehabilitation systems.

3) Spatial Filtering: Spatial filtering techniques, such as Common Spatial Patterns (CSP), improve the signal-to-noise ratio by identifying spatial filters that maximize the variance between different classes of movement. This method is particularly effective in distinguishing between different motor imagery tasks. CSP is used in several studies [29], [34], [37]. Spatial filtering helps to improve the discrimination of motor intentions, leading to more accurate and reliable control of rehabilitation devices.

4) Machine Learning and Deep Learning Algorithms: Advanced machine learning algorithms, including support vector machines (SVM) and linear discriminant analysis (LDA), are used to classify extracted features into specific movements. These methods are highlighted in studies [29], [36]. In addition, deep learning techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are used to automatically extract complex features from EEG signals. Another study demonstrates the use of CNNs and RNNs to classify EEG patterns corresponding to different movements, thereby improving the control strategy of assistive devices [33].

5) Time-Frequency Analysis: Time-frequency analysis provides a dynamic representation of EEG signals, capturing changes in frequency components over time. Techniques such as Short-Time Fourier Transform (STFT) and Wavelet Transform are used to perform time-frequency analysis. This method is used in studies [33], [34]. Time-frequency analysis allows the extraction of both temporal and spectral features, providing a comprehensive understanding of brain activity associated with motor tasks.

6) Feature Reduction: Feature reduction techniques, such as Principal Component Analysis (PCA), are used to reduce the dimensionality of the extracted features, retaining the most informative components while minimizing redundancy. This helps to improve the computational efficiency and performance of the classification algorithms. PCA is used to ensure that the system processes only the most critical information necessary for accurate prosthesis control [29].

7) Multimodal Signal Processing: In [32], EEG is combined with other physiological signals, and feature extraction involves handling multiple types of data. For EEG and sEMG signals, features such as movement-related cortical potentials (MRCPs), spectral power from EEG, and amplitude and frequency characteristics from sEMG are extracted and integrated. Convolutional Neural Networks (CNNs) are used to process these multimodal signals, enabling precise and responsive control of the rehabilitation device.

8) Attention and Cognitive Engagement Metrics: In studies focusing on cognitive engagement, feature extraction involves quantifying attention and cognitive states from EEG signals [38]. Metrics such as mean amplitude, frequency, and level of attention are extracted to control assistive devices, making the rehabilitation process adaptive and responsive to the user's mental state.

D. Classification

1) Support Vector Machines: Support Vector Machines (SVM) is a widely employed classification method. SVM is a novel classification method developed by Vapnik that has shown remarkable effectiveness in solving various practical problems, including those of the Brain-Computer Interface (BCI) [39]. The method is employed to differentiate data into distinct classes by identifying the optimal hyperplane that maximizes the margin between the classes. Support Vector Machines (SVM) utilize hyperplanes to effectively distinguish between data from multiple classes. This classification technique is categorized based on the nature of the dataset it handles: whether it is linearly separable or not. For linearly separable datasets, the decision boundary must be positioned as far as possible from the nearest data points of each class, which are known as support vectors. These support vectors are critical as they define the margin of the classifier and enhance its robustness to new data. In scenarios where the dataset is not linearly separable, SVMs adapt by employing the *kernel trick*. This method involves the transformation of data into a higher-dimensional space using a kernel function, denoted as K(x, y), allowing for the linear separation of data in this new feature space. The kernel function facilitates this transformation implicitly, bypassing the need for explicit computation in the high-dimensional space. Within the realm of EEG-based Brain-Computer Interface (BCI) research, kernels such as the Gaussian and radial basis function (RBF) are predominantly utilized. These kernels are adept at handling the complex nature of EEG data, which often involves intricate patterns that are not linearly separable in their original form. By using these kernels, SVM can effectively classify EEG signals, thus enhancing the interpretative capabilities of BCI systems [40], [41]. This technique has been employed in several studies to classify electroencephalogram (EEG) signals associated with different motor tasks. SVM is employed to categorize the EEG signals into distinct finger and thumb movements, thereby enhancing the system's capacity to accurately discern motor intentions [29]. Similarly, SVM is also employed to achieve high accuracy in the detection of motor intentions from EEG patterns [36]. Furthermore, SVM is employed to categorize motor imagery tasks, thereby enhancing the system's capacity to comprehend user intentions [34].

2) Linear Discriminant Analysis: Linear Discriminant Analysis (LDA) is a statistical method used for finding a linear combination of features that best separates two or more classes of objects or events. This technique, introduced by R. A. Fisher in 1936, aims to maximize the ratio of between-class variance to the within-class variance in any particular dataset, thus guaranteeing maximal separability [42]. LDA works by projecting the data onto a lower-dimensional space with good class separability to avoid overfitting and reduce computational costs. It is particularly useful in scenarios involving more than two classes, making it a generalization of Fisher's linear discriminant [43].

LDA is employed to categorize EEG signals into distinct motor tasks, while simultaneously reducing the dimensionality of the data and preserving the discriminatory features [29]. Similarly, LDA is also used in the initial classification stage to differentiate between flexion and extension movements, followed by the identification of the specific wrist involved in the subsequent stage [37].

3) Mathematical Formulation:

a) Mean Vectors: For a given dataset with k classes, compute the mean vector for each class μ_k and the overall mean μ:

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i \tag{1}$$

where N_k is the number of samples in class k and x_i is a sample vector in class k [42].

b) Scatter Matrices: Compute the within-class scatter matrix S_W and the between-class scatter matrix S_B:

$$S_W = \sum_{k=1}^{K} \sum_{i=1}^{N_k} (x_i - \mu_k)(x_i - \mu_k)^T \tag{2}$$

$$S_B = \sum_{k=1}^{K} N_k (\mu_k - \mu)(\mu_k - \mu)^T \tag{3}$$

[43].

c) Eigenvalue Problem: Solve the generalized eigenvalue problem for the matrix $S_W^{-1} S_B$:

$$S_W^{-1} S_B w = \lambda w \tag{4}$$

Here, w are the eigenvectors and λ are the corresponding eigenvalues. The eigenvectors corresponding to the largest eigenvalues form the columns of the transformation matrix [46].

d) Transformation: Project the original dataset X onto the new subspace using the transformation matrix W:

$$Y = XW \tag{5}$$

where Y is the transformed dataset [46].

By maximizing the between-class scatter while minimizing the within-class scatter, LDA effectively separates the classes in a lower-dimensional space. These steps help in transforming the data in such a way that the clusters become more distinct. This dimensionality reduction not only improves computational efficiency but also aids in avoiding overfitting, thus optimizing the performance of machine learning models [42], [44], [46].

4) Common Spatial Patterns (CSP): Common Spatial Patterns (CSP) is a spatial filtering technique that enhances the discriminative power of electroencephalogram (EEG) signals by maximizing the variance between different classes. CSP is particularly effective in motor imagery tasks and has been employed in several studies. For instance, CSP is employed to enhance the signal-to-noise ratio, thereby improving the system's ability to differentiate between motor tasks [29]. CSP facilitates the differentiation of motor imagery tasks, thereby enhancing the accuracy of classification [34]. Similarly, CSP is also employed to enhance feature extraction, thereby aiding the classification of motor imagery tasks [37].

The CSP algorithm works by finding spatial filters that maximize the variance for one class while minimizing it for the other. This method is particularly effective for analyzing EEG signals associated with different mental states or motor imagery tasks. CSP can optimally filter spatial components of EEG data to enhance the detection of specific mental tasks [47].

5) Mathematical Formulation: The mathematical formulation of CSP involves several key steps:

a) Data Preparation: Consider two sets of multivariate signals X_1 and X_2, corresponding to two different classes. Each signal is represented as a matrix of size $N \times T$, where N is the number of channels (sensors) and T is the number of time points.

b) Covariance Matrices: Compute the spatial covariance matrices for each class. For a given signal matrix X, the covariance matrix C is computed as follows:

$$C_i = \frac{X_i X_i^T}{\text{trace}(X_i X_i^T)} \tag{6}$$

where i denotes the class (1 or 2), and trace denotes the sum of the diagonal elements of the matrix [47].

c) Composite Covariance Matrix: Calculate the composite covariance matrix C_c by adding the covariance matrices of both classes:

$$C_c = C_1 + C_2 \tag{7}$$

d) Eigenvalue Decomposition: Perform an eigenvalue decomposition on the composite covariance matrix C_c:

$$C_c = U \Lambda U^T \tag{8}$$

Here, U is the matrix of eigenvectors, and Λ is the diagonal matrix of eigenvalues [48].

e) Whitening Transformation: Compute the whitening transformation matrix P:

$$P = \Lambda^{-\frac{1}{2}} U^T \tag{9}$$

This transformation ensures that the covariance matrix of the transformed data is the identity matrix [48].

f) Transformation of Covariance Matrices: Apply the whitening transformation to the covariance matrices C_1 and C_2:

$$S_1 = PC_1P^T \tag{10}$$

$$S_2 = PC_2P^T \tag{11}$$

g) Generalized Eigenvalue Problem: Solve the generalized eigenvalue problem for the matrices S_1 and S_2:

$$S_1 w = \lambda S_2 w \tag{12}$$

Here, w are the generalized eigenvectors, and λ are the corresponding eigenvalues [49].

h) Selection of Filters: The eigenvectors w corresponding to the largest and smallest eigenvalues form the spatial filters. These filters maximize the variance for one class while minimizing it for the other.

i) Feature Extraction: Project the original signals X onto the spatial filters to obtain the CSP features:

$$Z = W^T X \tag{13}$$

Here, W is the matrix of selected eigenvectors (spatial filters), and Z represents the transformed signals in the new feature space [50].

6) Convolutional Neural Networks (CNNs): Convolutional Neural Networks (CNNs) are deep learning models that automatically extract complex features from input data by applying convolutional layers. These networks are particularly effective in analyzing visual data but have also been adapted for other types of data, such as time series and signal processing. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, each of which plays a crucial role in feature extraction and classification. A convolutional neural network can have tens or hundreds of layers that each learn to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer [51].

In a study, convolutional neural networks (CNNs) are employed to extract and classify features from electroencephalography (EEG) signals, to enhance the control strategy of the assistive device [33]. CNNs are capable of capturing complex patterns in EEG data related to different movements, thereby enhancing the accuracy of the system. Furthermore, CNN is also employed to process multimodal signals (EEG and sEMG), thereby enabling precise and responsive control of the wrist exoskeleton [32].

The foundational work by Yann LeCun and colleagues demonstrated the effectiveness of CNNs in document recognition, paving the way for their application in various fields [52]. The introduction of AlexNet by Krizhevsky et al. [53] marked a significant milestone in image classification, showcasing the power of deep CNNs in handling large-scale image datasets. Further advancements, such as the VGG network [54] and ResNet [55], have continued to push the boundaries of what CNNs can achieve.

7) Recurrent Neural Networks (RNNs): Recurrent Neural Networks (RNNs) are deep learning models designed to handle sequential data, effectively capturing temporal dependencies in time-series data such as electroencephalogram (EEG) signals. Unlike feedforward neural networks, RNNs have connections that form directed cycles, allowing them to maintain a 'memory' of previous inputs through internal states, which makes them particularly suited for sequential data processing. RNNs process sequential data by passing the input through hidden layers one step at a time while retaining information about previous inputs. This recurrent structure allows the network to maintain short-term memory, enabling it to predict future data points based on past inputs. Specifically, RNNs work by incorporating loops within their architecture that allow information to persist.

Each unit of an RNN can be mathematically described as follows: At each time step t, the input x_t is combined with the hidden state from the previous time step h_{t-1}. The hidden state h_t at time step t is computed as

$$h_t = \tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{14}$$

where W_{xh} is the weight matrix for the input to hidden state, W_{hh} is the weight matrix for the hidden state to hidden state transition, and b_h is the bias vector. The output y_t at each time step t is computed as

$$y_t = W_{hy}h_t + b_y \tag{15}$$

where W_{hy} is the weight matrix from hidden state to output, and b_y is the bias vector.

RNNs are widely used in various applications, including natural language processing (NLP), speech recognition, and time-series forecasting. They excel at tasks where context and sequential information are crucial for accurate predictions. In NLP, RNNs can be used for tasks such as language modeling, machine translation, and text generation. Their ability to handle sequences makes them ideal for understanding and generating human language. In speech recognition, RNNs are used to convert spoken language into text by processing the sequential audio signals. For time-series forecasting, RNNs can predict future values in a time series by learning patterns from historical data.

RNNs are used to capture the temporal dynamics of EEG signals, thereby improving the accuracy of the assistive device's control strategy by modeling the sequential nature of the data [33]. Hochreiter and Schmidhuber introduced Long Short-Term Memory (LSTM) networks, a variant of RNNs that addresses the vanishing gradient problem, making them more effective for long-term dependencies [56]. Bahdanau and colleagues demonstrated the effectiveness of RNNs in machine translation tasks, showing how they can maintain context through sequences to translate languages accurately [57]. These advancements have significantly contributed to the widespread adoption and success of RNNs in various fields.

8) Artificial Neural Networks (ANNs): Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural networks. They consist of interconnected layers of nodes, or neurons, that process information by responding to external inputs, passing information between each other, and learning from data. The connections between nodes, known as weights, are adjusted during the training process, allowing the network to learn specific tasks from input-output pairs. This learning process is typically performed using the back-propagation algorithm, which updates the weights to minimize the error in predictions [56].

ANNs have been successfully applied in various domains, such as document recognition [52] and pattern recognition [55]. ANNs are also used to classify EEG signals and predict self-initiated movements, achieving high detection accuracy by learning complex patterns in the EEG data related to anticipatory brain activity [35]. Advances in deep learning, such as the development of deep belief networks [56] and convolutional neural networks [53], have further enhanced the capabilities of ANNs, enabling them to tackle complex tasks in image and speech recognition. These developments highlight the versatility and effectiveness of ANNs in handling diverse and challenging problems in artificial intelligence.

III. Results

In a study, although several signal processing methods such as band-pass filtering, event-related potential (ERP) analysis, power spectral density (PSD) analysis, and near-infrared spectroscopy (NIRS) analysis were employed, the accuracy rate was not specified [31]. In another study, a variety of methods were employed, including band-pass filtering, time-domain analysis, frequency-domain analysis, Common Spatial Patterns (CSP), and Principal Component Analysis (PCA). These methods were used to achieve an accuracy rate of 92% [29]. Another study employed band-pass filtering, Event-Related Desynchronization/Synchronization (ERD/ERS), Common Spatial Patterns (CSP), and Short-Time Fourier Transform (STFT) methodologies, resulting in an accuracy rate of 85% [34]. A study employed band-pass filtering, time-domain analysis, frequency-domain analysis, and Common Spatial Patterns (CSP) methods, resulting in an accuracy rate of 90% [36]. Another study employed band-pass filtering, Event-Related Potential (ERP) analysis, and attention level quantification methods, resulting in a 25% reduction in rehabilitation time. However, the accuracy rate was not specified [38]. In another study, a variety of analytical techniques were employed including band-pass filtering, time-domain analysis, frequency-domain analysis, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). This approach yielded an accuracy rate of 88% [33]. Another study also employed a range of analytical techniques, including band-pass filtering, extraction of Movement-Related Cortical Potentials (MRCPs), the use of Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA). This approach resulted in an accuracy rate of 77% [35]. Another study employed band-pass filtering, Common Spatial Patterns (CSP), Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA) methods, achieving an accuracy rate of 80% [37]. In another study, some methods were employed, including band-pass filtering, the extraction of Movement-Related Cortical Potentials (MRCPs), the analysis of amplitude and frequency characteristics from sEMG, the use of Convolutional Neural Networks (CNNs), and the application of Multimodal Integration Techniques. These methods were used in conjunction with one another, and the resulting accuracy rate was 87% [32].

IV. Conclusion

This review emphasizes the pivotal role of electroencephalography (EEG) technology and machine learning algorithms in the rehabilitation of individuals who have lost functional abilities as a result of accidents, injuries, or medical conditions. EEG devices and brain-computer interfaces (BCI) provide comprehensive information about patients' neural activities, allowing for the personalization of rehabilitation processes. By interpreting EEG data, machine learning techniques enable rehabilitation robots to adapt to the patient's needs, thus making treatment processes more effective.

The continued development of EEG and BCI technologies has the potential to advance rehabilitation practices further, improving independence and quality of life for patients around the world. These technologies have improved the accuracy of therapeutic applications and recovery processes of patients, especially in areas such as neurorehabilitation and post-stroke hand rehabilitation. In the coming period, EEG-based rehabilitation systems are expected to be further personalized and widespread.

Consequently, EEG-based rehabilitation technologies can transform patients' lives by occupying a unique position at the intersection of health sciences and engineering disciplines. The evolution of these technologies will continue to shape rehabilitation practice and revolutionize global health. These developments will not only be limited to technological innovations but will also require redefining ethical, social, and legal frameworks.

References

[1] Short MR, Hernandez-Pavon JC, Jones A, Pons JL. EEG hyperscanning in motor rehabilitation: a position paper. Journal of NeuroEngineering and Rehabilitation 2021; 18: 98.

[2] Ahamed NU, Hasan S, Majid FH, Afroz F, Chowdhury SA, Laskar FI. Rehabilitation systems for physically disabled patients: A brief review of sensor-based computerised signal-monitoring systems. Journal of Rehabilitation Research 2013; 24(3): 150-160.

[3] Wang J, Zhang X, Huang Y. Design on intelligent perception system for lower limb rehabilitation robot. In 2016 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 1907-1912, 2016.

[4] Bartur G, Joubran K, Peleg-Shani S, Vatine JJ, Shahaf G. An EEG Tool for Monitoring Patient Engagement during Stroke Rehabilitation: A Feasibility Study. Biomedical Research International 2017; 2017: 9071568.

[5] Pichiorri F, Mattia D. Brain-computer interfaces in neurologic rehabilitation practice. Handbook of Clinical Neurology 2020; 168: 101-116.

[6] Liu C, Lu J, Yang H, Guo K. Current state of robotics in hand rehabilitation after stroke: A systematic review. Applied Sciences 2022; 12(9): 4540.

[7] Lazarou I, Nikolopoulos S, Petrantonakis PC, Kompatsiaris IK, Tsolaki M. EEG-based brain-computer interfaces for communication and rehabilitation of people with motor impairment: A novel approach of the 21st century. Frontiers in Human Neuroscience 2018; 12: 0014.

[8] Brantley JA, Paek AY, Steele AG, Contreras-Vidal JL. Brain-Machine Interfaces for Upper and Lower Limb Prostheses. In: Thakor, N.V. (eds) Handbook of Neuroengineering. Springer, Singapore, 2022.

[9] Laver KE, Lange B, George S, Deutsch JE, Saposnik G, Crotty M. Virtual reality for stroke rehabilitation. The Cochrane Database of Systematic Reviews 2017; 11(11): CD008349.

[10] Zhang X, Ma Z, Zheng H, Li T, Chen K, Wang X, Liu C, Xu L, Wu X, Lin D, Lin H. The combination of brain-computer interfaces and artificial intelligence: Applications and challenges. Annals of Translational Medicine 2019; 8: 11.

[11] Sayilgan E, Yuce YK, Isler Y. Evaluation of mother wavelets on steady-state visually-evoked potentials for triple-command brain-computer interfaces. Turkish Journal of Electrical Engineering & Computer Sciences 2021; 29(5): 2263-2279.

[12] Sayilgan E, Yuce YK, Isler Y. Evaluation of wavelet features selected via statistical evidence from steady-state visually-evoked potentials to predict the stimulating frequency. Journal of the Faculty of Engineering and Architecture of Gazi University 2021; 36(2): 593-605.

[13] Sayilgan E, Yuce YK, Isler Y. Investigating the effect of flickering frequency pair and mother wavelet selection in steady-state visually-evoked potentials on two-command brain-computer interfaces. Innovation and Research in BioMedical Engineering 2022; 43(6): 594-603.

[14] Yesilkaya B, Sayilgan E, Yuce YK, Perc M, Isler Y. Principal component analysis and manifold learning techniques for the design of brain-computer interfaces based on steady-state visually evoked potentials. Journal of Computational Science 2023; 68: 102000.

[15] Sayilgan E, Yuce YK, Isler Y. Frequency recognition from temporal and frequency depth of the brain-computer interface based on steady-state visual evoked potentials. Journal of Intelligent Systems with Applications 2021; 4(1): 68-73

[16] Degirmenci M, Sayilgan E, Isler Y. Evaluation of Wigner-Ville distribution features to estimate steady-state visual evoked potentials' stimulation frequency. Journal of Intelligent Systems with Applications 2021; 4(2): 133-136.

[17] Avci MB, Hamurcu R, Bozbas OA, Gurman E, Cetin AE, Sayilgan E. Design of steady-state visually-evoked potential based brain-computer interface system. Journal of Intelligent Systems with Applications 2022; 5(2): 86-89.

[18] Degirmenci M, Yuce YK, Perc M, Isler Y. Statistically significant features improve binary and multiple motor imagery tasks predictions from EEGs. Frontiers in Human Neuroscience 2023; 17: 1223307.

[19] Degirmenci M, Yuce YK, Isler Y. Classification of finger movements from statistically-significant time-domain EEG features. Journal of the Faculty of Engineering and Architecture of Gazi University, vol. 39(3), 1597-1609, 2024.

[20] Degirmenci M, Yuce YK, Perc M, Isler Y. EEG-based finger movement classification with intrinsic time-scale decomposition. Frontiers in Human Neuroscience 2024; 18: 1362135.

[21] Isler Y, Isler O. Design of expert systems using surface EMG signal for movements of multi-function prosthetic hand. Karaelmas Science and Engineering Journal 2019; 9(2): 237-243.

[22] Isler Y, Isler O. EMG controlled 3D printed bionic hand. Natural and Engineering Sciences 2019; 4(3): 59-64.

[23] Karakul MS, Gokcen A. Wavelet transform based finger movement recognition. Journal of Intelligent Systems with Applications 2023; 6(2): 21-26.

[24] Sayilgan E, Isler Y. Review of rehabilitation technologies based on brain-computer interfaces. In Book of Abstracts, 18, 3rd International Conference of Applied Sciences, Engineering and Mathematics (IBU-ICASEM 2021), June 3-5, Skopje/North Macedonia, 2021.

[25] Arslan O, Isler Y. Development of personal trainer device for exercise and rehabilitation tracking. In 5th International Conference on Medical Devices (ICMD'2022), Abstract Book, Gaziantep / Turkey, 06-07 June 2022.

[26] Ciklacandir S, Isler Y. System design for entertainment based rehabilitation of the upper extremity. Tıp Teknolojileri Kongresi 2017 (TIPTEKNO-2017), October 12-14, Trabzon/Turkey, Bildiriler Kitabi, 364-367, 2017.

[27] Fernandez-Vargas J, Kita K, Yu W. Real-time hand motion reconstruction system for trans-humeral amputees using EEG and EMG. Frontiers in Robotics and AI 2016; 3: 0050.

[28] Khan SM, Khan AA, Farooq O. Selection of features and classifiers for EMG-EEG-based upper limb assistive devices-A review. IEEE Reviews in Biomedical Engineering 2020; 13: 248-260.

[29] Rashid N, Iqbal J, Javed A, Tiwana MI, Khan US. Design of embedded system for multivariate classification of finger and thumb movements using EEG signals for control of upper limb prosthesis. Biomed Research International 2018; 2018: 2695106.

[30] Ma Z, Wang K, Xu M, Yi W, Xu F, Ming D. Transformed common spa-tial pattern for motor imagery-based brain-computer interfaces. Frontiers in Neuroscience 2023; 17: 1116721.

[31] Yamamoto I, Matsui M, Higashi T, Iso N, Hachisuka K, Hachisuka A. Wrist Rehabilitation Robot System and its Effectiveness for Patients. Sensors and Materials 2018; 30(8-2): 1825-1830.

[32] Yang S, Li M, Wang J, Shi Z, He B, Xie J, Xu G. A low-cost and portable wrist exoskeleton using EEG-sEMG combined strategy for prolonged active rehabilitation. Frontiers in Neurorobotics 2023; 17: 1161187.

[33] Mukherjee P, Roy AH. EEG sensor driven assistive device for elbow and finger rehabilitation using deep learning. Expert Systems with Applications 2024; 244: 122954.

[34] Ang KK, Guan C, Phua KS, Wang C, Zhou L, Tang KY, Ephraim Joseph GJ, Kuah CW, Chua KS. Brain-computer interface-based robotic end effector system for wrist and hand rehabilitation: results of a three-armed randomized controlled trial for chronic stroke. Frontiers in Neuroengineering 2014; 7: 30.

[35] Hernandez-Rojas LG, Montoya OM, Antelis JM. Anticipatory detection of self-paced rehabilitative movements in the same upper limb from EEG signals. IEEE Access 2020; 8: 119728-119743.

[36] Belwafi K, Gannouni S. EEG-based BCI system to detect fingers movements. Brain Sciences 2020; 10(12): 965.

[37] Vuckovic A, Sepulveda F. A two-stage four-class BCI based on imaginary movements of the left and the right wrist. Medical Engineering & Physics 2012; 34(7): 964-971.

[38] Li M, Liang Z, He B, Zhao CG, Yao W, Xu G, Xie J, Cui L. Attention-controlled assistive wrist rehabilitation using a low-cost EEG sensor. IEEE Sensors Journal 2019; 19(15): 6497-6507.

[39] Kousarrizi MRN, Ghanbari ARA, Teshnehlab M, Shorehdeli MA, Gharaviri A. Feature extraction and classification of EEG signals using wavelet transform, SVM and artificial neural networks for brain computer interfaces. In 2009 International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing, pp. 352-355, 2009.

[40] Zhang Y, Zhou G, Jin J, Wang X, Cichocki A. Evaluation of wavelet features selected via statistical evidence from steady-state visually-evoked potentials to predict the stimulating frequency. Journal of Neural Engineering 2014; 11(4): 046014.

[41] Lotte L, Bougrain L, Clerc F. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of Neural Engineering 2018; 15(3): 031005.

[42] Fisher RA. The use of multiple measurements in taxonomic problems. Annals of Eugenics 1936; 7: 179-188.

[43] Rao CR. Linear Statistical Inference and Its Applications, 2nd ed. New York: Wiley, 1973.

[44] Rao CR. The utilization of multiple measurements in problems of biological classification. Journal of the Royal Statistical Society: Series B (Methodological) 1948; 10(2): 159-203.

[45] Hastie T, Tibshirani R, Friedman J. The Elements of Statistical Learning, New York, NY: Springer, 2001.

[46] Ramoser H, Muller-Gerking J, Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. IEEE Transactions on Rehabilitation Engineering 2000; 8(4): 441-446.

[47] Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller KR. Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal Processing Magazine 2008; 25(1): 41-56.

[48] Koles ZJ, Lazar MS, Zhou SZ. Spatial patterns underlying population differences in the background EEG. Brain Topography 1990; 2(4): 275-284.

[49] Lotte F, Congedo M, Lecuyer A, Lamarche F, Arnaldi B. A review of classification algorithms for EEG-based brain–computer interfaces. Journal of Neural Engineering 2007; 4(2): R1-R13.

[50] MathWorks. What Is a Convolutional Neural Network? 2024. [Online]. Available at https://www.mathworks.com/discovery/convolutional-neural-network.html

[51] LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proceedings of the IEEE 1998; 86(11): 2278-2324.

[52] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classification with deep convolutional neural networks. In Advances in Neural Information Processing Systems 2012; 25.

[53] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. In 3rd International Conference on Learning Representations (ICLR 2015), 2015, pp. 1–14.

[54] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770-778.

[55] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Computation 1997; 9(8): 1735-1780.

[56] Bahdanau D, Cho K, Bengio Y. Neural machine translation by jointly learning to align and translate. In Proceedings of the 3rd International Conference on Learning Representations (ICLR 2015), 2015.

[57] Hinton GE, Osindero S, Teh Y. A fast learning algorithm for deep belief nets. Neural Computation 2006; 18(7): 1527-1554.