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TOPICAL REVIEW

Surface Electromyography and Artificial Intelligence for Human Activity Recognition–A Systematic Review on Methods, Emerging Trends Applications, Challenges, and Future Implementation

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ABSTRACT Human activity recognition (HAR) has become increasingly popular in recent years due to its potential to meet the growing needs of various industries. Electromyography (EMG) is essential in various clinical and biological settings. It is a metric that helps doctors diagnose conditions that affect muscle activation patterns and monitor patients' progress in rehabilitation, disease diagnosis, motion intention recognition, etc. This review summarizes the various research papers based on HAR with EMG. Over recent years, the integration of Artificial Intelligence (AI) has catalyzed remarkable advancements in the classification of biomedical signals, with a particular focus on EMG data. Firstly, this review meticulously curates a wide array of research papers that have contributed significantly to the evolution of EMG-based activity recognition. By surveying the existing literature, we provide an insightful overview of the key findings and innovations that have propelled this field forward. It explore the various approaches utilized for preprocessing EMG signals, including noise reduction, baseline correction, filtering, and normalization, ensure that the EMG data is suitably prepared for subsequent analysis. In addition, we unravel the multitude of techniques employed to extract meaningful features from raw EMG data, encompassing both time-domain and frequency-domain features. These techniques are fundamental to achieving a comprehensive characterization of muscle activity patterns. Furthermore, we provide an extensive overview of both Machine Learning (ML) and Deep Learning (DL) classification methods, showcasing their respective strengths, limitations, and real-world applications in recognizing diverse human activities from EMG signals. In examining the hardware infrastructure for HAR with EMG, the synergy between hardware and software is underscored as paramount for enabling real-time monitoring. Finally, we also discovered open issues and future research direction that may point to new lines of inquiry for ongoing research toward EMG-based detection.

INDEX TERMS Machine learning (ML), human activity recognition (HAR), deep learning (DL), electromyography (EMG), real-time systems, artificial intelligence (AI).

I. INTRODUCTION

Over the past few years, researchers have taken a greater interest in HAR, primarily as a result of advancements that have been made in computer vision and artificial intelligence. Several elements come into play, including strategies, the availability of wearable sensors, and the Internet of Things [1]. HAR system can distinguish between various human activities. These activities include Walking, sitting, running, standing, sleeping, showering, driving, and cooking.

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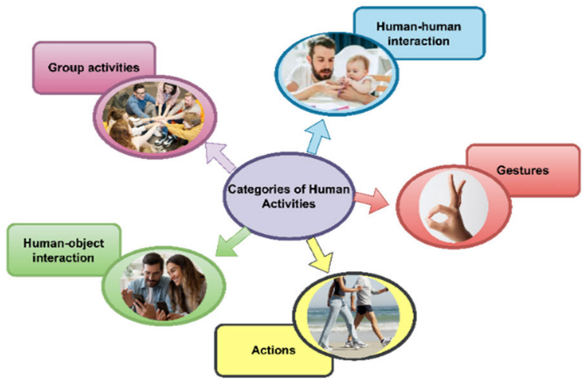

FIGURE 1. Different categories of human activities.

The method of understanding and categorizing behavioral patterns and raw activity data gathered from various sources (so-called gadgets) using AI is known as HAR. Devices with sensors, such as inertial sensors for smartphones [2], camera gadgets, and wearable sensors [3]. HAR is essential in applications like Remote healthcare [4] for elderly [5]people, smart home/office/city, and numerous applications for monitoring, including sports and exercise [6], [7]. Depending on the Application, the objective of recognizing human activity is to identify a specific person's or a group of people's physical work. Some of these jobs could be activities carried out by a particular person, such as running, jumping, walking, and sitting [8], which involve modifications to the complete body. Some actions, like hand gestures [9], are performed through a specific body part movement.

Some situations might be handled by talking to objects, like cooking food in the kitchen. HAR can also refer to any abnormal behaviors, such as unexpected falls [10], Rehabilitation progress [11] of patients. A few of the most popular and practical uses of HAR are in nursing facilities, assisted living environments monitoring one's health, engaging in rehabilitative activities, surveillance, and interacting with computers. It is a complex problem because HAR has several intrinsic difficulties. However, depending on the action under consideration, the difficulty degree connected with these impediments' changes.

As shown in FIGURE 1, HAR can be divided into five different types of activities depending on the difficulty degree and duration [12].

Each form of activity is explained below, with human-object and human-human interactions combined and characterized as interaction.

- A gesture is a straightforward motion made with the hand or other body parts to convey a thought or meaning. Face expressions, hand motions, and head shaking are all examples of gestures. A gesture is the most straightforward activity among the four kinds and is usually performed in a brief amount of time.
- An action is a simple activity performed by people that involves many motions. Knocking, swimming, and running are examples of activities.
- An interaction is defined as a two-agent activity. One of the agents is a human, whereas the other can be an item or another human. The interaction can be divided into two types based on the nature of the agents: human-object interaction and human-human interaction. Human-human interaction examples include wrestling, hugging, and shaking hands, whereas human-object interaction examples include interacting with a mobile phone and laptop.
- A group activity is the most complex type because it requires more than two individuals and may entail interaction with one or more items. It involves several gestures, acts, and interactions. Examples of group activities include a group study and a football game. In recent years, AI Methods have been increasing, including DL methodology, and have demonstrated Superior performance to classical ML methodologies across various HAR challenges. FIGURE 2 illustrates the Basic architecture model for HAR systems using ML/DL [13]. A composite system, the deep learning architecture, is made up of multiple crucial steps for the recognition of human behavior.

As shown in FIGURE 3 main steps involved in HAR. Sensor selection for analysis. The first stage consists in choosing and using sensing equipment. The next step is data collection, where data from input devices is processed by an edge device and sent via various communication systems to the primary server, such as Bluetooth and Wi-Fi. Edge computing, which includes Reliable real-time information processing using edge servers and sensors for data perception, has the establishment of technology and storage devices at the location wherever data is obtained and evaluated. Feature extractions and classification models were used. This paper reviews the recently taken advancements in HAR. The current studies focused on various techniques, including ML & DL.

A. FEATURES OF THE PROPOSED REVIEW

TABLE 1 list some of the surveys and reviews on various HAR methods that have been published. We compare our papers to those already published to determine whether the articles had key components (marked '✔' if discussed in TABLE 1) such as HAR, ML, and DL techniques, dataset discussion, and applications. The TABLE 1 also includes the objectives of the review.

FIGURE 4 illustrates the review's organizational framework. The order of arranging the review paper is mentioned below, and a summary of the review paper is described. Section II describes the research methods, including PRISMA-based paper collection, VOS Viewer-based visualization, and information extraction. Section III will cover the Background of EMG Signal and the literature Survey on HAR. In Section IV, a succinct description of the Data Acquisition, preprocessing, EMG Pattern Recognition flow, and classification, In Section V, Available Datasets are explained. Section VI examines AI for HAR with EMG with various existing works on DL and ML. Section VII discusses Hardware related works with HAR, Section VIII

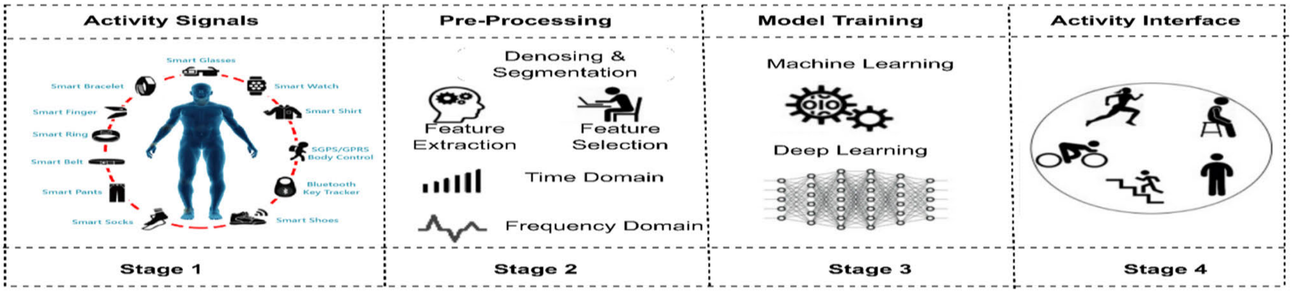

FIGURE 2. Basic architecture model for HAR system using ML/DL.

TABLE 1. Summary of previous surveys and reviews.

Ref	HAR	ML algorithm	DL algorithm	Dataset discussion	Applications	Aim of study/survey
[14]	✓	✗	✓	✓	✓	HAR using CNN, Dataset and Challenges.
[15]	✓	✗	✓	✗	✓	Role of DL in EMG
[16]	✓	✗	✗	✗	✓	Wearable sensors and their applications
[17]	✓	✓	✗	✓	✓	HAR based on Lower Limb
[18]	✓	✗	✗	✗	✓	Recent progress of HAR and motion analysis
[19]	✗	✗	✗	✗	✓	Tele-Rehabilitation Applications
[20]	✗	✗	✗	✗	✗	Lower limb robotic prostheses are controlled myoelectrical.
[21]	✗	✓	✓	✗	✓	Pattern recognition for HMI
[22]	✓	✓	✓	✗	✓	HAR using a smartwatch and smartphone
[23]	✗	✓	✓	✗	✓	HAR for Diverse Applications
Our	✓	✓	✓	✓	✓	AI in HAR using different ML & DL Methods and its Application.

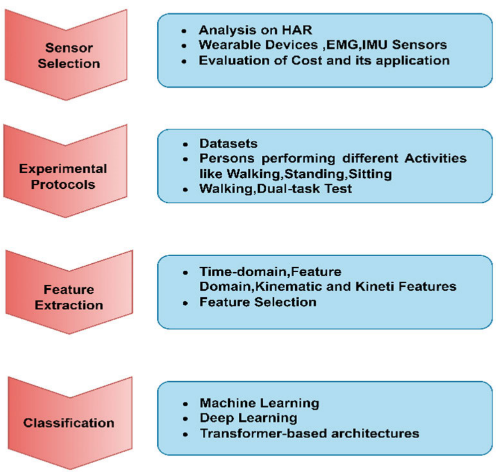

FIGURE 3. Main steps involved in HAR.

with Applications, and Section IX with Open issues, future trends, and Research Direction. Section X, the conclusion of the review paper.

II. RESEARCH METHODOLOGY

In our study, we meticulously followed the structured methodology outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [24]. This approach was instrumental in systematically assessing the extensive landscape of EMG-HAR while ensuring transparency, minimizing bias, and comprehensively covering recent literature in this evolving field. Our journey commenced with an exhaustive search across a multitude of academic databases, encompassing prominent sources like Google Scholar, Web of Science, IEEEXplore, Pub Med, and Dimensions. This comprehensive search yielded a substantial collection of 3507 articles that bore potential relevance to our review. Leveraging keywords such as "Activity Prediction," "Wearable Sensors," "HAR with AI & Applications," "Hardware used in HAR," "Healthcare Application with EMG," and "Hybrid Models used in HAR," we aimed to cast a wide net. To prevent redundancy, we meticulously addressed duplicate entries, leading to the exclusion of 1027 duplicate documents and streamlining the list. With the list of unique articles in hand, we embraced automation tools to conduct an initial eligibility assessment. These tools efficiently identified 289 records that didn't align with our predetermined inclusion criteria, further refining the pool of potential papers. Simultaneously, we identified and pruned 580 records that were unrelated to our study due to various reasons beyond eligibility criteria, such as irrelevance to the research question or misalignment with the scope of the review. Following these initial filtering rounds, a set of 1611 papers remained on our radar.

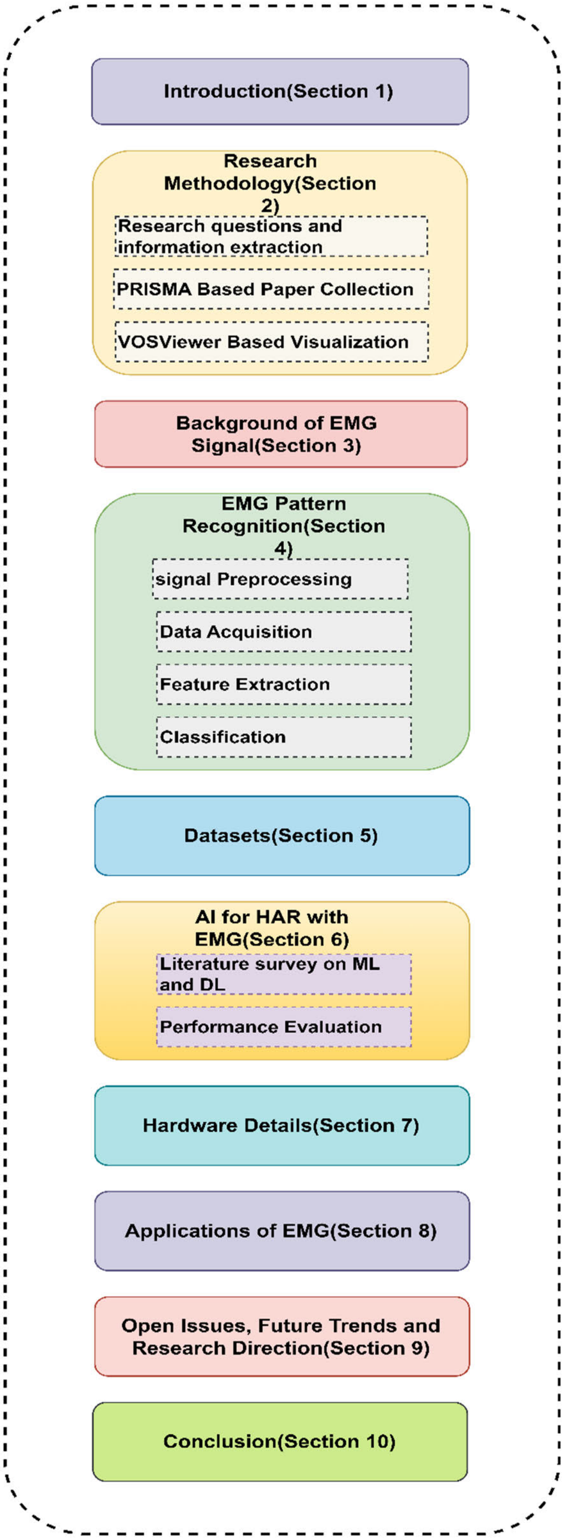

FIGURE 4. Review's organization framework.

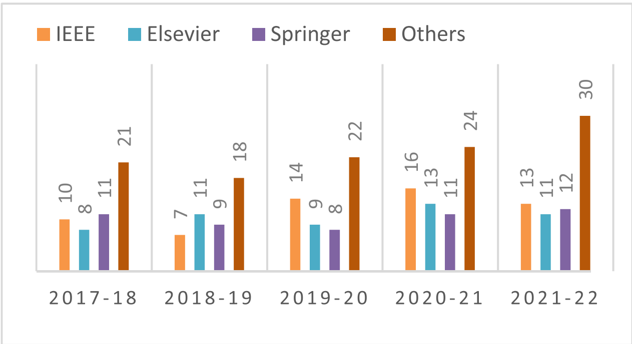

FIGURE 5. Statistical studies in HAR.

To refine our selection further, we subjected these papers to meticulous scrutiny by screening titles and abstracts. This phase allowed us to identify papers that potentially met the inclusion criteria by virtue of their relevance to EMG-based HAR systems. Subsequently, we conducted further refinement based on explicit inclusion and exclusion criteria, ultimately narrowing down the selection. Out of the initial 1611 papers, 1260 were excluded for not involving ML/ DL techniques and for lacking direct relevance to HAR. A more stringent screening process then eliminated an additional 115 papers that either lacked a substantial technical contribution or were deemed irrelevant upon detailed assessment. With a more focused set of 236 papers in our grasp, we proceeded to the next phase—a comprehensive evaluation of the full-text content. During this final phase, we applied the inclusion criteria rigorously, leading to the exclusion of 33 papers for specific reasons such as not providing relevant data, demonstrating non-significant results from experiments, or being in a language other than English. In the culmination of this comprehensive process, 203 papers were meticulously identified and included in our ultimate review list. These papers were thoughtfully chosen to align with our research objective of evaluating EMG-based HAR systems, ensuring they met our predefined criteria for relevance and technical content. FIGURE 7, guided by the PRISMA framework, visually illustrate the systematic process that serves as a robust foundation for our study.

We gathered the following type of documentation from the various publications we read: datasets used, ML/DL methods, feature choice, and extraction analysis.

Statistics of Studies in HAR are provided in FIGURE 5, which gives overall information on HAR related to EMG research publications in the past five years considered in this survey article.

To better identify and display the clusters that influence the subject of the review study, we used VOSviewer, a software tool framework where networks of biometric data are displayed. The network visualization is depicted in Figure 6, where things are represented by their labels and, by default, a circle. Each cluster in the network represents a different color. The titles and the circle's sizes depend on the object's weight. The size of the title and the circle around it increases with an item's weight. In FIGURE 6, for instance, the item labeled "electromyography" has the highest importance and the most prominent label and circle sizes.

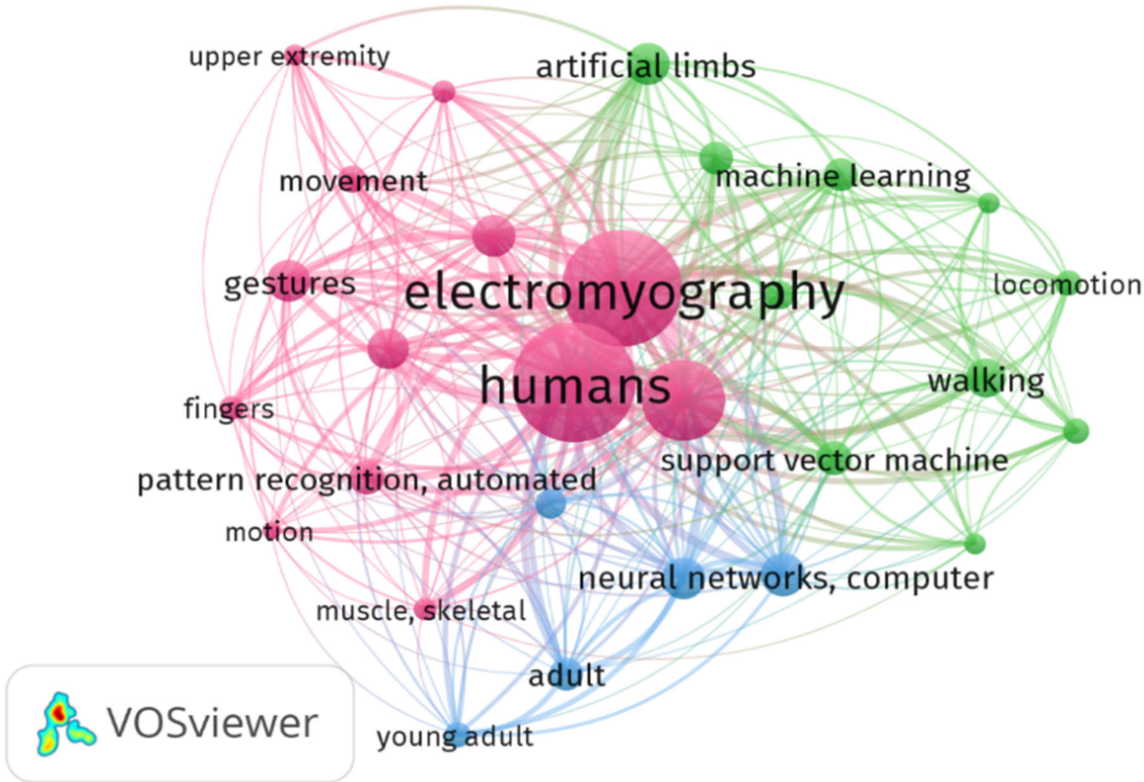

FIGURE 6. Network visualisation using the VOSviewer's term co-occurrence map to display the network of related terms.

A. RESEARCH QUESTIONS AND INFORMATION EXTRACTION

The following research questions served as a guide for both the review analysis and the article selection analysis: "What is the current status in Classification using DL and ML methods for HAR based on EMG ?", "Is there an adequate public dataset for HAR and identification?" "What are Various Application Related to HAR using sEMG?" and "What typical problems remain in contemporary EMG-based HAR systems, and by what methods can they be resolved using AI?"

III. BACKGROUND OF EMG SIGNAL

EMG is an electrical signal that measures electrical potential signals produced by muscle cells to assess muscle activity [25]. This electrical activity, which is referred to as the EMG signal, reveals important information regarding the function of muscles, as well as motor control and neuromuscular diseases [26]. During either voluntary or involuntary muscular contractions, the depolarization of motor neurons in the muscle tissue produces electrical activity that is measured as an EMG signal [27]. These EMG signals can be recorded using Electrodes. EMG Electrodes can be classified into two types (a) Surface Electrode(sEMG)-non-invasively, by placing electrodes on the skin (b)Needle Electrode(iEMG)-invasively, by inserting a needle into the muscle [17].

sEMG most frequently used because of its user-friendliness and absence of invasiveness. FIGURE 8 illustrates EMG Signal Generation in the human body. The motor unit action potentials (MUAPs) that fire within the muscle fibers are detected and recorded by the electrodes, which can pick up on the microscopic electrical potentials they generate [28].

The EMG signal is comprised of several different components, each of which carries its unique information [29]:

1. MUAPs: It represents the electrical impulses produced by individual motor neurons. A compound action potential is produced as a result of the combination of several impulses during a contraction. This potential reflects the coordinated activity of the muscle.

2. The Timing of Activation: The timing and synchronization of MUAP firing provide insights into the patterns of muscle recruitment and the coordination of different muscle groups during various activities.

3. Amplitude: The amplitude of the EMG signal is a measure of how intensely the muscle is being activated. When muscles are relaxed, their amplitudes are smaller, but more muscular contractions result in bigger amplitudes.

4. Frequency: The EMG signal's frequency content can reveal muscle tiredness, tremor, or certain neuromuscular disorders. Frequency is measured in hertz (Hz). A drop in the amount of high-frequency components is frequently caused by fatigue.

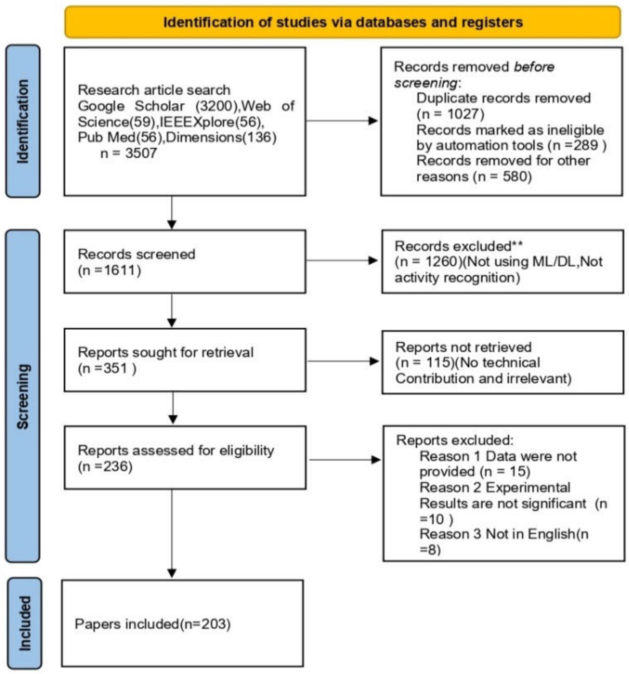

FIGURE 7. The PRISMA chart of the article selection process for this review.

5. EMG Enveloping: The EMG signal can be enveloped to produce the envelope, which represents the total muscle activation pattern across time. This can be accomplished by using the ''enveloping'' technique.

This signal aids in assessing the performance of the muscles [30]. To aid in the diagnosis of the muscle, the indication may take the form of a graph, sound, or numerical value. EMG signals have therefore been utilized in medicine to identify neurodegenerative conditions like Parkinson's [31] and stroke [32] that impact motor functioning. The progress of a patient's rehabilitation after an injury or illness has also been monitored using EMG signals. Recent developments in biomedical technology also enable EMG to be used in new ways, for example, by sending a signal of control to exoskeleton systems to let patients execute tasks [33].

A skeletal muscle is in two different states at rest [34]. An electrochemical potential of about -80 mV can be found in muscle cells (also known as muscle fibers) [35]. Whenever muscles in the skeleton contract, an electrical potential is created in a motor unit (MU) constructed up of muscle fibers and a motor neuron.

Electric potential differences are created when two intracellular action potentials from a motor neuron cause a neuromuscular junction to fire in opposition to one another. They are spread by depolarizing and repolarizing each muscle fiber [36]. The combined intracellular action potential of all the muscle fibers in a motor unit is known as MUAP [17]. Consequently, A linear average of multiple trains of MUAPs makes up the EMG. When a skeletal muscle contracts. Static and dynamic muscle contractions are two different kinds. While the joints are immobile and the muscle fiber [37] lengths do not change during a static contraction, the muscles still tighten, as when a person keeps their peace sign or the hand motionless. The joint movement and the muscle fiber lengths differ during a dynamic contraction.

It is possible to model EMG signals using a stochastic process that depends on the two distinct types of contraction discussed above. First, the EMG is entirely dependent on muscle power, and the mean and covariance of the mathematical model for a static contraction (MMSC) may remain virtually constant across time [34]. Consider:

$$EMG\,(t) = \sum\nolimits_{i=1}^{N} s_i(t) * m_i(t) \tag{1}$$

where N is the total number of active MUs, $s_i(t)$ is the train of impulses representing each MU's active moments, $m_i(t)$is the MUAPs of each MU, and is used to imply convolution. When conditions like physical exhaustion and temperature impact the MMSC, however, it might be seen as a non-stationary process [38].

Second, a dynamic contraction's mathematical model (MMDC) is a non-stationary process and is comparable to amplitude modulation (AM modulation) in that it is a non-stationary process:

$$EMG(t) = a(t)w(t) + n(t) \tag{2}$$

where $a(t)$ is a function that represents the EMG signal's strength (i.e., information signal), $w(t)$ is a unit-variance Gaussian process that represents the EMG signal's stochastic component (i.e., carrier signal), and $n(t)$ is sensor noise and biological signal artifacts [39].

IV. STEPS INVOLVED FOR EMG PATTERN RECOGNITION

Algorithms based on DL and ML Models have been used to interpret the EMG signal [41]. Preprocessing and interpretation, the two critical components of EMG signal processing, are covered in this section. FIGURE 9 displays a flow pattern of the entire processing procedure. Variations in human activity motion patterns can be seen in EMG signals [42]. However, the raw, unclassified EMG data which is obtained is frequently very noisy. Several processing steps are necessary to identify these variances correctly. The following four components can often be used to summarize the HAR process:

1. Data Acquisition
2. Data Preprocessing
3. Feature Extraction and Reduction
4. Classification Method

FIGURE 10 represents the HAR based on sensor and vision. Vision-based HAR uses images, RGB-Cameras. Sensor-based HAR uses EMG, IMU, Accelerometer, etc.

A. DATA ACQUISITION

To achieve a satisfactory level of recognition accuracy, acquiring an EMG signal is significantly sought, making it crucial to develop the front-end EMG acquisition methodologies appropriately. We will contrast the approaches used for front-end EMG acquisition in this section [43].

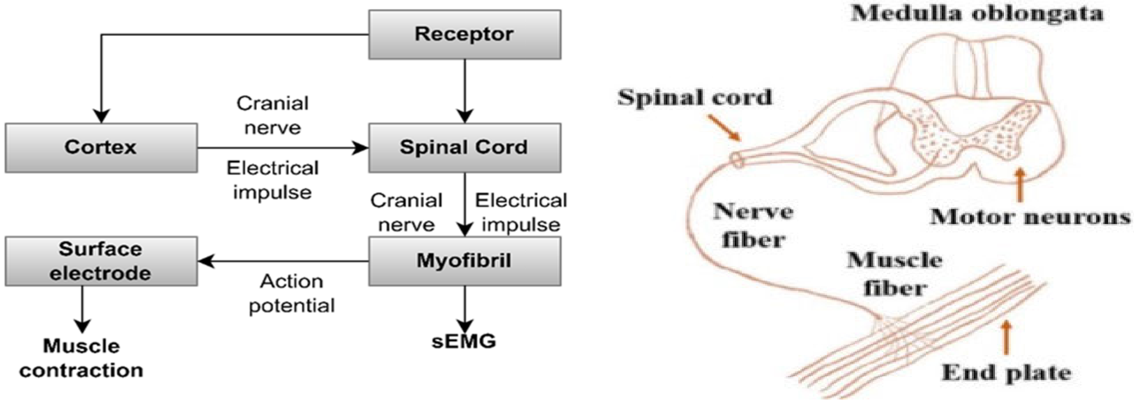

FIGURE 8. EMG Signal Generation in the human body [40] a)Schematic representation of the nerve and muscle system of EMG signal b)neuromuscular system structure.

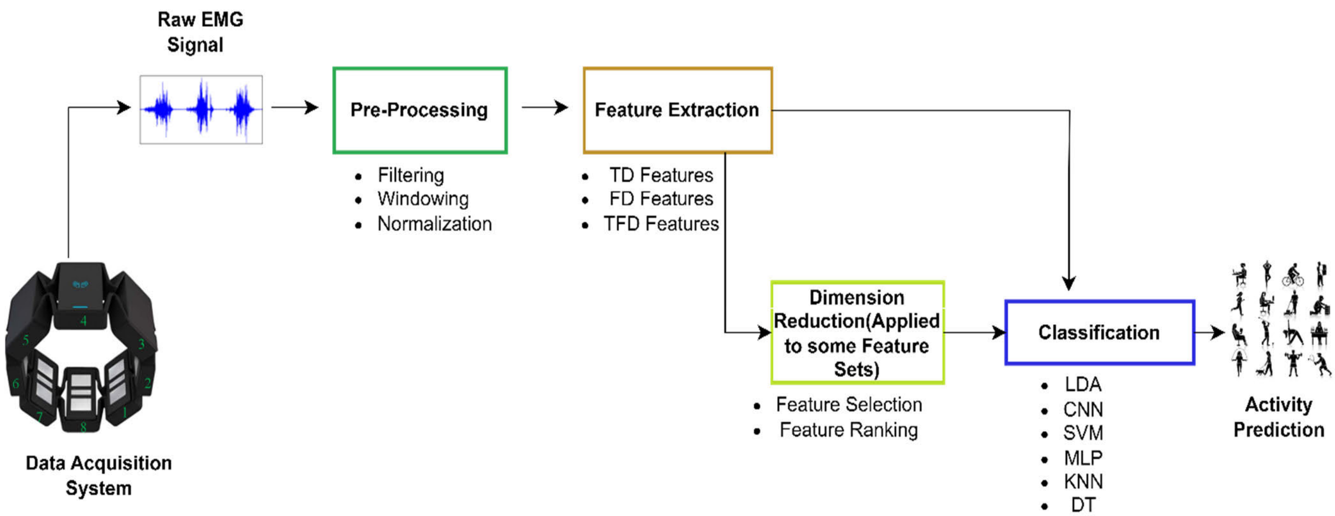

FIGURE 9. Flow pattern for HAR using data acquisition system.

Electrodes, amplifiers, microprocessors, and gearbox devices comprise most of the sensor system used to gather EMG data. The electrodes detect the electrical signal produced by the muscle, the amplification circuit amplifies it, and the transmission device subsequently sends the call to the host computer.

B. SIGNAL PREPROCESSING

Two procedures must be completed to get good performance results, like accuracy and usefulness of the recorded signals, before EMG data is sent to Model-based on classifiers. Preprocessing is the earlier step [21].

It generally consists of three subparts: signal windowing, also known as segmentation; filtering of signal, also known as denoise; and signal rectification. By removing features and reducing the dimensions, windowing (or segmentation) aids in boosting classification precision. Denoising or the removal of various interferences may be aided by filtering. Despite ongoing debate, many experiments still view rectification as essential.

1) WINDOWING

The windowing approach consists of two parts: overlapping and sliding windows. Segmentation can improve classifier accuracy, particularly when acquiring fresh data [43]. The maximum overlapping window length is limited to 300 ms [44]. The approach developed by M. Kunapipat et al. for classifying hand gestures achieved the highest prediction accuracy with a half-overlapping size temporal length [45].Similarly, C. Tepe et al. preprocessed EMG signals for control using 100 milliseconds of 50% overlap. The accuracy of the prosthesis classification was 95.8 percent for five fingers and one rest gesture [46] Most people look out of nearby windows. Using EMG signal preprocessing windows led to an accuracy greater than 98% for identifying gestures [47] used a window size of 128 milliseconds across neighboring segments to address the non-stationarity of the EMG signal and enhance classification accuracy by 98.12%.

2) FILTERING

EMG data from a patient will likely be corrupted by the environment and electrodes. Most noise is baseline wave

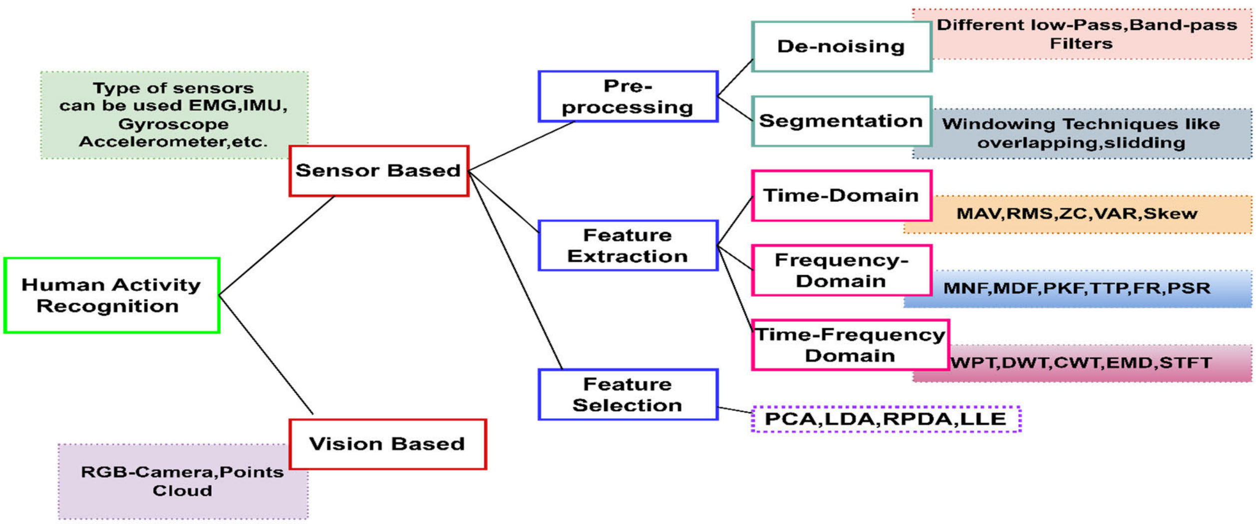

FIGURE 10. HAR classification based on sensor and vision and detail about the sensor-based system.

(BW) or drift, Gaussian white noise (GWN), power line noise, interference (PLI), and artifact noise [204]. The most common filters are software and hardware, including digital filters. Modern EMG electrodes record analog signals that, when fed through an analog-to-digital converter (ADC), create digital signals that personal computers can swiftly interpret. Hence digital filters are employed in more situations. For instance, C. Li and coworkers used a comb filter operating at 50 Hz to filter out disruptive power frequencies [205].To get rid of power line interference, J. R. Torres-Castillo [206] and coworkers employ a rejects-band filter (also called a notch filter) and a third-order Butterworth filter (to dampen the effect of the subject's baseline oscillations on the uncontrollable motion of the signal). ElMohandes and coworkers applied the Kalman filter to decipher kinesthetic signals [207]. Since wavelets and other models have varying responses to various inputs, they are often utilized in signal filtering. Using Wavelet Transform, noise is induced by spectral overlap. However, the main limitation is notions without proof, and the settings chosen will considerably affect the outcome. Modify filtering results. Empirical mode decomposition avoided this restriction by using fewer parameter settings. Its end effect phenomena greatly limit its use (EMD) stands for "empirical mode decomposition." [204] Musical group, Ensemble EMD reducing noise, helped solve the problem of poor performance in complicated spatial and temporal frameworks.S.Ma,coworkers A variable mode decomposition (VMD) filter denoised PLI, BW, and GWN signals with low RMSE and the same SNR [204].

3) RECTIFICATION

Full-wave and half-wave rectification are the EMG signal rectification methods that are used the most [209]. While the full-wave approach polarizes signals below the baseline to a positive value and saves energy, the half-wave process simply ignores them when they are below the baseline. It is recommended to use full-wave rectification, which saves energy. [210] The square value of the incoming signal data can be obtained by a square rectification approach that T. Roland and colleagues developed [212] and [213] Rectified EMG signals can make more accurate predictions of the motor unit (MU) synchronization for frequency components in low-intensity movement, and they have a lower residual partial correlation in the beta frequency region for bidirectional load, according to the findings of a study that was carried out by N. J. Ward and colleagues [212] and [213]. This was discovered as a result of the research that was carried out. EMG rectification represses high-frequency components, making it unsuitable in some situations [211]. The frequency spectrum is distorted by amplitude cancellation [210] EMG rectification is nonlinear and introduces undesirable central frequency filters that distort the power spectrum [212].

C. FEATURE EXTRACTION AND REDUCTION TECHNIQUES

1) FEATURE EXTRACTION

The EMG signal's hidden information can be deduced using feature extraction, which also allows for the analysis of the signal's properties and behavior.

Three categories can be used to group the characteristics of sEMG signals: time domain (TD), frequency domain (FD), and time-frequency domain (TFD).

a: TIME DOMAIN (TD)

Indicators based on statistical approaches make up the TD features of the EMG signal, while the EMG signal itself is treated as a function of time. The EMG signal can be expressed in this way, which is more intuitive. Many early-stage research has concentrated on TD traits because of the comparatively low computational burden involved in doing so. EMG signals were recovered from hand motions by Bhattacharya et al [214], and these signals included root mean absolute value (MAV), mean square (RMS), autoregressive (AR), zero crossing (ZC), waveform length (WL), and slope sign change (SSC). These TD traits can be categorized with the help of LDA, K nearest neighbor (KNN), and other similar methods. The classification accuracy of the mixed multi-feature set with six features is the highest possible, coming in at 83.33%. 11 standard temporal features of 8 different types of hand movements were investigated by Phinyomark et al. [215]. These characteristics were SSC, WL, Willison amplitude (WAMP), variance (VAR), ZC, and MAV.

b: FREQUENCY DOMAIN (FD)

After expressing the TD signal that has been transformed to an FD using Fourier transformation and other techniques, the FD characteristic of the EMG signal analyzes the spectral or power spectrum features of the signal. This analysis takes place after the movement has been represented as an FD. The frequency domain feature is advantageous because it is more stable, easier to extract stable characteristics, and more resistant to noise. The power spectral density (PSD) method is the most essential tool for frequency domain analysis. It is an obvious demonstration of the degree to which the muscles are activated. Comparisons were made between the discrimination power of time domain (TD) features and frequency domain features on EMG data by Too et al. [216] to determine which hand movements were being performed.

c: TIME-FREQUENCY DOMAIN (TFD)

The conventional Fourier transform is only able to describe the frequency characteristics of the signal and does not provide any frequency information about the signal in any TD. The combination of time and frequency characteristics allows for the absorption of the benefits of both approaches. As a result, academics have been interested in time-frequency analysis techniques; short-time Fourier transforms (STFT), Wigner-Ville transforms, Choi-Williams distributions, and wavelet transforms (WT) are examples. Shanmuganathan et al [217] collected the forearm EMG signal and used wavelet packet transform (WPT) for feature extraction after preprocessing and the R-CNN classifier for classification.

2) DIMENSIONALITY REDUCTION

The discriminative features are obscured by the large dimensionality of the feature space occupied by the derived feature set; the patterns may be incorrectly classified. Data dimensionality reduction is effective in enhancing recognition precision, increasing the distance between classes, and decreasing processing costs. Non-negative matrix factorization (NMF), Principle component analysis (PCA), nonlinear projection, and averaging independent components analysis are a few of the algorithms that have been suggested to do this task. We mainly discuss PCA and NMF techniques in this section. Different feature extraction techniques, including LDA for features, LDA for raw EMG, PCA and LDA for raw EMG, and PCA and LDA for features, were compared by Zhang et al. [218]. The findings demonstrate that extracting features from EMG signals can increase classification precision and that dimensionality reduction via PCA is also helpful for classification. The highest categorization success percentage for hand movements is 99.8%. To classify the time-domain properties of the EMG signal, The researchers Negi et al. [219] made a scatter plot. They used principal component analysis (PCA) and uncorrelated linear discriminant analysis (ULDA) to reduce the number of features. The findings indicate that the linear discriminant classifier can produce classification results that are pretty accurate. TABLE 2 summarizes the various Feature extraction technique done using EMG signals.

V. DATASETS

Various emotion databases are openly accessible for anybody to download and analyze without the requirement for permission from anyone or the involvement of an organization in their work. Those available data sets are listed below in the TABLE 3. Among all, UCI-sEMG and WISDM datasets are most employed for research work.

Sanchez et al.'s UCI-sEMG [61] dataset focuses on the three distinct lower limb movements made by 22 male participants, 11 of whom have normal knees and the other 11 have abnormal knees. The subjects were over 18 years old. Walking, sitting, and standing were all used as lower limb activities. The knees of healthy participants had never previously experienced pain or injury. The sciatic nerve, the anterior cruciate ligament (ACL), the meniscus, and six other ligaments were all injured in the atypical patients. The healthy subject's EMG signal was recorded from their left leg, whereas the abnormal subject's signal was recorded from their infected leg. The data was acquired with four surface electrodes. They surround the biceps, rectus, semitendinosus, and vastus medialis. The knee joint angle was measured with a goniometer attached to the exterior to apply a knee prosthetic leg. The resolution was 1000 Hz, and the sample rate was 14 bits.

Used HAR-sEMG dataset Trigno wireless biofeedback sensors collected sEMG data from four lower limb movements—jogging, standing, lunge stretching, walking, and jumping—to form the HAR-sEMG dataset [62]. Forgetting The HAR-sEMG dataset contained nine healthy people, two girls, and seven men, with a mean age of 23.5 years. They each sent 1800 EMG signals for 10 seconds. The experiment used six easily distinguishable lower-limb muscles.

One of the largest gait recognition databases, HuGaDB [63], has two versions: v1 and v2. Study experiments employed HuGaDB v2. HuGaDB v2 comprised 18 people's gaits throughout 10 gait activities, including walking, jogging, climbing, descending, sitting, and more. Six wearable IMUs and two EMG sensors collected data. Each IMU had triaxial accelerometers and gyroscopes. The six IMUs were

TABLE 2. Summary of various feature extraction techniques from sEMG signal.

Ref	Features	Classifier	Accuracy(%)
[48]	ZC, SSC, MAV, WL	naive Bayes	91
[49]	WT	ANN	-
[50]	AR, PSD	EVM (Extreme Value Machine)	91
[51]	RMS, MAV, MAVS, ZC, SSC, WL	DNN(Deep Neural Network)	93.85
[52]	DFT, DWPT	CNN	78.92
[53]	MEAN, VAR, ENT, RMS	ELM (Extreme Learning Machine)	98.9
[54]	WPT,FUZZY C-Means	MLP	99
[55]	SKW , WL, Hjorth Time Domain Parameters (HTD) , ZC AR SSC	LIBSVM (based on SVM))	92
[56]	DWT	FCNN	98
[57]	MI, SFFS, RSFS	SVM	97.6
[58]	WL, MAV, and AR RMS	DT, NB, NB, NB, KNN, and LDA	96.64
[59]	Mean, RMS, WL	Regression Method, Kalman filtering	-
[60]	MV,VAR,SKE,ZC,ARC,WAMP,MMAV	KNN,FR,SVM	97,97,96

on the left and right thighs, calves, and ankles. EMG sensors were on lateral femoral muscles. Data from 38 sensor channels was obtained.36 IMU sensor channels, 2 EMG channels Using 36 channel IMU sensor signals in this experiment. The data was divided into fixed-length frames using a sliding window with a stride of 64 and a window length of 2.3 s (128 points). After segmentation, 17,244 samples existed.

UCI-HAR dataset [64].The UC Irvine, HAR dataset was used. The built-in MEMS IMU of a Samsung Galaxy S2 smartphone recorded triaxial acceleration and gyroscope data. The dataset includes 30 subjects' gait data, including the six gait behaviors of walking, sitting, standing, lying down, moving upstairs, and downstairs. The smartphone was waist-mounted and sampled at 50 Hz. The gait activities were hand-tagged after videoing the data-gathering technique. The data were denoised and gravitational acceleration filtered. The dataset had 10,299 samples. They evaluated 10,299 samples. The publisher split the dataset into 7:3 training and test sets with 7352 and 2947 samples, respectively.

WISDM Dataset [65] is gathered using the integrated triaxial accelerometer of an Android smartphone, such as the Nexus One, HTC Hero, and Motorola Backflip. WISDM collected gait data from 29 people during six different gait activities: walking, jogging, sitting, standing, going upstairs, and going downwards. Data is sampled at a rate of 20 Hz by the accelerometer.

PAMAP [68]-Three-axis MEMS sensors (two accelerometers, a gyroscope, and a magnetometer) are found in IMUs, and they are all captured at 100 Hz. The BM-CS5SR-HR-monitor device for data collecting, a Viliv S5 UMPC with an Intel Atom Z520 1.33GHz CPU and 1GB of RAM was employed. Nine participants in all, eight men and one woman, took part in the data collection. From BM Innovations GmbH was used to record heart rate data.

The OPPORTUNITY dataset [70] was obtained. The OPPORTUNITY dataset examines breakfast-related household duties. A studio apartment with a kitchen, deck chair, and outdoor access is used to recreate a morning routine for 12 subjects, including getting dressed, making and drinking coffee, eating a sandwich, and wiping the Table. The OPPORTUNITY dataset, like CMUMMAC, collects data from accelerometers, gyroscopes, magnetometers, microphones, and video cameras in the environment, objects, and people.

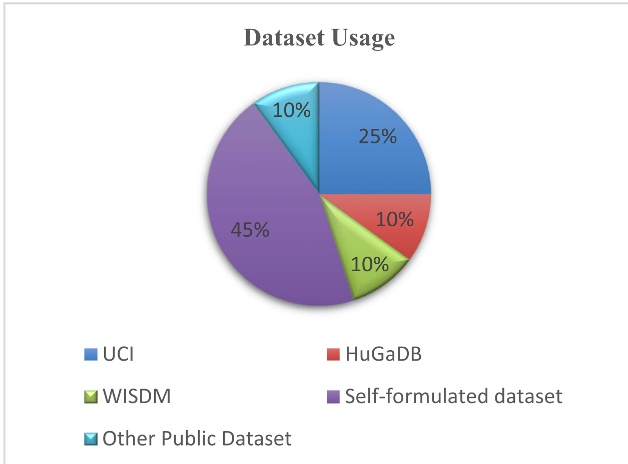

FIGURE 11. Dataset usage in HAR-sEMG.

FIGURE 11 illustrates the Dataset Usage in HAR-sEMG and mainly used dataset, which is available publicly, and most of the work is done by a self-formulated dataset.

VI. ARTIFICIAL INTELLIGENCE FOR HAR WITH EMG SIGNAL

As per the ML subfield of AI, an algorithm on a computer can take in fresh information and adjust itself accordingly. The field of artificial intelligence is complete with ML [71]. In contrast to the purpose of AI, which is to construct an intelligent system or assistant that uses various ML approaches to

TABLE 3. Summary of available sensor-based dataset.

Ref	Dataset	No of Subjects	No of Channels	Equipment	Location	HAR
[61]	UCI-Semg	22 (7 Male, 2 female)	5	MWX8 by Biometrics	Lower Limb	Walking,sitting,standing
[62]	HAR-sEMG	9 (7 Male, 2 female)	4	DELSYS Trigno wireless EMG equipment	Lower Limb	Running, Standing, Lunge Stretching, Jumping, Walking
[63]	HuGaDB	18	6	EMG, MPU9250	calves, ankles ,Thighs	stand, go downstairs, walk ,Sit, go upstairs
[64]	UCI-HAR	30	-	Accelerometer,Gyro scope	Waist	go upstairs , Stand, sit, lie down and go downstairs
[65]	WISDM	29	6	Accelerometer,Gyro scope	Trouser belt	climbing ,stairs Walking, jogging
[66]	WISDM v1.1	29	-	Accelerometer,GPS, Smartphone	Right Thigh or Left Thigh	moving while walking, running, climbing, and descending stairs, as well as while seated and standing.
[67]	USC-HAD	14	-	MotionNode sensing platform	Front Right Hip.	Walking forward, left,right, upstairs, running forward, jumping,sitting, standing,sleeping, elevator up/down
[68]	PAMAP	9	4	IMU, Accelerometers,EMG, gyroscope	Chest, Wrist, Ankle	lie down, sit up, walk, stand up, run, Nordic walk, cycle, iron, hoover, jump rope and go up and down stairs.
[69]	SHO	10	3	four motion sensors	Left Thigh, Right Waist, Right Upper Arm, Right Wrist.	walking, biking, and jogging activities
[70]	OPPORTUNITY	12	-	72 sensors of 10 different modalities	All over the body and environment.	12 patients were active in the morning, producing more than 25 hours of sensor data.

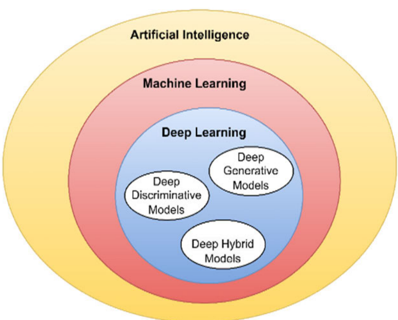

FIGURE 12. Flowchart demonstrates the relation between AI, ML and DL.

solve issues, ML aims to create computer systems that can learn and respond based on prior observation. FIGURE 12 shows how artificial intelligence, ML, and DL are interconnected.

ML methodologies come in two different flavors: supervised and unsupervised. The relationship between unprocessed input and processed output data is the foundation of the supervised approach, which builds a mathematical model. Unsupervised methods seek to identify patterns in raw input data without knowing the final product. On the other hand, it is still necessary to examine the results on a dataset obtained from the real world using a variety of classifiers. Medical databases have been analyzed by ML [72] algorithms.

DL is a comprehensive approach encompassing the entire process from input to output. The procedure commences directly from the initial input data and autonomously performs feature extraction and model learning via a multilayer network. DL offers several advantages over traditional methods in machine learning. Firstly, it eliminates the need for manual feature engineering, which can be a time-consuming and laborious process. Instead, DL algorithms can automatically learn and extract relevant features from the data, resulting in more effective feature representation.

Additionally, DL models can fit complex functions using fewer parameters. This allows for the expression of more intricate and sophisticated models, enabling the

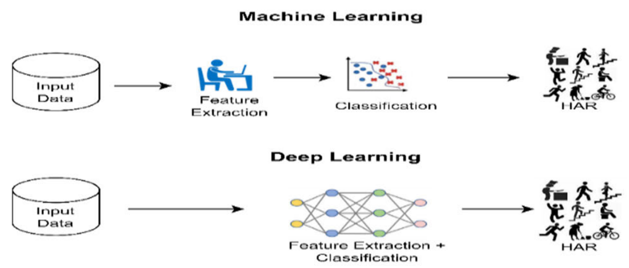

FIGURE 13. Comparison of ML and DL for HAR.

representation of complex relationships within the data. Consequently, DL has the potential to achieve higher levels of performance and accuracy in various tasks and applications. This approach offers significant benefits in terms of feature expression, function modeling, and model generalization. FIGURE 13 illustrates the comparison of DL and ML within the context of HAR.

The rise in popularity of DL techniques can be attributed to their ability to automatically extract key features from vision or image data and time-series data [14]. Accuracy, Precision, Recall, and F1 Score are only a few classification performance criteria where DL methods excel above traditional ML approaches for activity detection [160], [161]. The first step is to choose and set up the necessary sensing equipment. Through wireless connections like Wi-Fi and Bluetooth, data gathered by an edge device is transmitted to a central server. Sensors and edge servers are used in edge computing for real-time data processing [161], [162]. CNN can automatically identify and extract features from unprocessed signals. Here, we make use of the CNN architecture to remember actions. The final step is a notification mechanism for agents. The notification system can alert the appropriate authorities in the event of emergency. TABLE 4 illustrates the various studies carried out with EMG data sets using ML /DL algorithms. Several systematic reviews of the development of activity recognition in humans may be found in this body of work. HAR has been researched using a variety of techniques, including DL [163], ML [164], sensor [165], and vision [166]. Two HARs were conducted [167], and a review of a vision-based HAR was published [168]. Sensor-based HAR radio communication strategies were outlined in [12], while a review of current wearable sensors-based HAR applications and an analysis of twenty-eight HAR systems from varying perspectives were presented in [167]. HAR [169] and research into HAR via vision [166]. The accelerometer, gyroscope, torque, and hybrid sensors, as well as their individual functions, were broken down [170]. In contrast, the preprocessing strategy, data collection methods, and relevant signals were investigated [169]. In addition, DL and other cutting-edge techniques for vision-based HAR have been explored [171]. There was a 2018 roundtable discussion [172] about the latest findings in RGB-depth-based HAR can be seen in FIGURE 10. Using features from both the data streams and the activity recognition, another study characterized vision-based HAR [173].

Montazerin et al. [124] developed a Vision Transformer (ViT) architecture to recognize hand gestures from HD-sEMG data. They leverage the transformer architecture's recent accomplishment in solving complex issues and its attention mechanism's potential for additional input parallelization. The Vision Transformer-based Hand Gesture Recognition (ViTHGR) framework can classify a large number of hand gestures without data augmentation or transfer learning and without training time issues. A 65- isometric hand gesture HD-sEMG dataset is used to evaluate the proposed ViT-HGR system. With only 78,210 learnable parameters, our 64-sample (31.25 ms) window size studies give average test accuracy of 84.62 ± 3.07%.

Zhang et al. [111] worked on Wearable devices that recognize lower limb motions are a major challenge in lower limb-based HCI technologies. Biological and kinematic signals distinguish human mobility. In this research, we suggested a Vision Transformer (ViT)-based architecture for lower limb motion detection from multichannel Mechanomyography (MMG) signals and kinematic data because unimodal signals do not provide enough information. First, we enhanced each input channel signal with self-attention. Then ViT model received data. This paper proposes a Vision Transformer-based Lower Limb Motion Recognition (ViT - LLMR) architecture that avoids model training issues like autonomous feature extraction and feature selection for ML and can recognize eight lower limb motions from six subjects with 94.62% accuracy. We also examined the model's generalization when undersampled and gathering fragment signals.

Rahimian et al. [125] use a vision transformer network to recognize hand gestures using high-density surface EMG (HD-sEMG) signals. The proposed attention mechanism model finds commonalities between data segments for parallel processing.HD-sEMG uses 128 electrodes to record 65 isometric signals. 20 subjects' hand motions. CT-HGR is applied to 31.25, 62.5, 125, 250 ms. Window sizes for 32, 64, and 128 electrode channel datasets. Results are acquired by using the suggested framework to each dataset in 5-fold cross-validation. subject separately and averaging the accuracies. The average accuracy of 86.23% of participants using 32 electrodes and a window size of 31.25 ms climbs to 91.98% for 128 electrodes and 250 ms. CT-HGR achieves 89.13% for immediate recognition from a single HD-sEMG frame.

Rahimian et al. [126]proposed a Transformer-based sEMG signal processing system to overcome these challenges. New idea Vision Transformer-based neural network architecture (TEMGNet) to identify upper limb hand motions from sEMG for control of the prosthesis. Training TEMGNet is planned without pre-training or fine-tuning a limited dataset. Following recent literature, evaluate efficacy.NinaPro DB2's second subset (exercise B) was used, where the suggested TEMGNet

TABLE 4. Various studies carried out with EMG data sets using ML /DL algorithms.

Ref.	Dataset	Algorithm	Application	Performance
[61]	UCI machine learning repository	CNN-LSTM and CNN-GRU,	Lower limb activity recognition	Accuracy 98.69 Precision 98.61
[80]	17 healthy right-handed(9 Females and 8 Males	RNN RCNN	Kinematic and Dynamic Biomechanical Variables	Accuracy 96.9%
[81]	10 healthy volunteers (5 males and 5 females) performed four gestures. movements	QDA, SVM, random Forest, ensemble (subspace KNN)	Hand Movement Classification	Accuracy 83.9%
[82]	6 upper limb amputee subjects performing rest,	RF	Shoulder motion classification	Accuracy 98%
[83]	UCI HAR	1D-CNN	Human Daily Activity Recognition	Accuracy 95.99% F1-score 96.01%
[84]	HuGaDB	SConvLSTM	Gait Pattern Recognition	Accuracy 97.60% F1-score 97.60%
[85]	WISDM	Selective Kernel Convolution	HAR Using Selective Kernel Convolution	Accuracy 98.19%
[86]	13Male(aged 20–30)	LDA, SVM	Control of prostheses	Classification accuracy: Offline: 87.7% Online: 90%
[87]	Privately owned	HMM	Driver's fatigue monitoring	Classification separability: 96%
[88]	Privately owned	KNN, DT, LSVM, SVM-RBF, LDA	Movement examination	Classification accuracy: Valence: 90.35% Arousal: 70.18%
[89]	Privately owned	SVM, RF	Detection of Muscle Fatigue	Accuracy of 85%
[90]	Privately owned	ABC-SVM (artificial bee colony) for support vector machine optimization	Human Gait Recognition	Accuracy 96.77%
[91]	WISDM	AdaB_CNN (Adaptive Boosting with Convolutional Neural Networks)	activity recognition	Accuracy 98%

framework attained recognition accuracy of 82.93% and 82.05% for window sizes 300ms and 200ms.

Zabihi et al. [127] proposed a Transformer for Hand Gesture Recognition (TraHGR) hybrid architecture that uses two parallel processors.pathways followed by a fusion center linear layer integrate module benefits and give robustness distinct situations. We assessed the suggested architecture.TraHGR uses the popular second Ninapro dataset, the DB2. DB2 dataset sEMG signals 40 healthy users' real-life measurements 49 gestures each.TraHGR architecture with each path and showed the hybrid's unique architecture. TraHGR recognition accuracy architecture: 86.18%, 88.91%, 81.44%, and 93.84% are 2.48%, 5.12%, 8.82%, and 4.30% better than the state-of-the-art for DB2 (49 gestures), DB2-B (17 gestures),DB2-C (23) and DB2-D (9 gestures).

Shen et al. [128] propose a stacking ensemble-learning convolutional vision transformer (CviT) with considerable potential in the field.EMG signal fusion with parallel training. NinaPro DB2's approach 80.02% at 200ms. In the Exercise E1 of NinaPro DB2, the recommended approach is 83.47% and 84.09% at 200ms and 300ms. The proposed technique obtains 76.83% in NinaPro DB5 subsets (Exercise

A, Exercise B) and 73.23%. Experimental results show that the proposed CviT outperforms most current methods.

AI-based models for HAR are illustrated in FIGURE 14, and several DL models are used for HAR using EMG signals. Here are some models that were commonly used for HAR.

1. Convolutional Neural Networks (CNNs): CNNs have been applied to EMG-based HAR tasks by treating sequences of EMG signals as images. CNNs can capture spatial patterns in the signal data, which can be indicative of different muscle activations during different activities.

2. Recurrent Neural Networks (RNNs): RNNs, including LSTMs and GRUs, have been used for EMG-based HAR as they can capture temporal dependencies and variations in the EMG signal. They can effectively model the sequential nature of muscle activations during different activities.

3. Hybrid Models: Some approaches combine CNNs and RNNs to leverage both spatial and temporal information in EMG data. CNNs can be used for feature extraction from the raw EMG signals, and the extracted features are then passed to RNNs for sequence modeling and classification.

4. Transformer-based Models: While initially designed for sequential data in natural language processing, transformer-based architectures have been adapted for sequential data like EMG signals [73]. They can capture long-range dependencies in the signal, making them potentially effective for HAR tasks. FIGURE 15 illustrates the basic Transformer model.

5. Attention Mechanisms: Attention mechanisms can be applied to EMG data to focus on specific parts of the signal that are more informative for different activities. These mechanisms can enhance the discriminative power of the model.

6. Graph Neural Networks (GNNs): If the EMG signals come from multiple electrodes placed on different muscles, GNNs can be used to model the relationships between different muscle activations and perform activity recognition.

7. Autoencoders and Variational Autoencoders (VAEs): These models can be used for feature extraction and dimensionality reduction of the EMG signals before feeding them into a classifier. VAEs can also generate synthetic EMG signals for augmentation.

8. Capsule Networks: Capsule networks aim to model hierarchical relationships between features in the data. They have been explored for EMG-based HAR to capture complex patterns in muscle activations during different activities.

Hybrid models in ML and DL refer to approaches that combine the strengths of multiple individual models or techniques to achieve better performance or address specific challenges. These models often leverage the unique characteristics of each constituent model to enhance overall performance.

1) CNN-RNN Hybrid: Combining Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) can be powerful for tasks like video analysis. CNNs extract spatial features from frames, and RNNs capture temporal dependencies between frames, enhancing the model's ability to understand both spatial and sequential information.

2) Autoencoder-GAN Hybrid: Combining autoencoders with Generative Adversarial Networks (GANs) can lead to more realistic and semantically meaningful generated data. Autoencoders can help in learning useful latent representations, which can then be used to guide the GAN's generator for better synthesis.

3) Transformer-Convolutional Hybrid: Transformers are excellent at capturing long-range dependencies in sequences, while convolutional layers are effective at extracting local patterns. Combining these architectures can lead to models that understand both global context and local details, suitable for tasks like image captioning.

4) Ensemble Models: Ensemble models combine the predictions of multiple base models to make final predictions. Techniques like bagging, boosting, and stacking leverage the diversity and expertise of various models to improve overall accuracy and robustness.

Dual-channel LSTM was employed by Hssayeni et al. [74] for hand-crafted features, 1D CNN-LSTM for raw signals, and 2D CNN-LSTM for time-frequency data. In order to investigate the use of DL in recognition of beach volleyball movement, Tora et al. [75] developed a deep convolutional neural network based on sensor-based activity categorization. They then compared the effectiveness of this novel approach with five well-used classification techniques. Deep convolutional neural networks were discovered to be capable of achieving a classification accuracy of 83.2%, which is 16.0% higher than existing classification algorithms. Using CNN and LSTM layers, Mekruksavanch et al. [76] presented a hybrid deep-learning network. The network is suitable for identifying human activity in sensor data from smartphones since it is capable of automatically learning space attributes and time representation.

GRU and LSTM both perform equally well when it comes to identifying human activity, according to Chung et al.'s comparative study [77]. In [78], a Deep Neural Network-based model is proposed as an end-to-end model that does automatic feature extraction and classification of the activities as well. This model makes use of CNN and GRU. A region-convolutional neural network (RCNN) was proposed by Yang et al. [79] to recognize the wearer's gait characteristic TABLE 5 and TABLE 6 summarizes the various ML and DL models used, the Latest DL methods used by various Authors.

An inertial sensor-based HAR method was put forth by Hassan et al. [203]. After extracting usable features from the raw data, linear discriminant analysis (LDA) and kernel PCA (KPCA) were used to increase the robustness of the features.

Deep belief networks (DBN) were then employed to identify a variety of sample actions. This method's prediction accuracy and anti-interference capability are higher than those of conventional SVM and ANN approaches. Two waist-mounted sensors were utilized by Lawal et al. [202] to gather hip joint motion signals, turn them into spectral image signals, and then use deep neural networks to extract features.

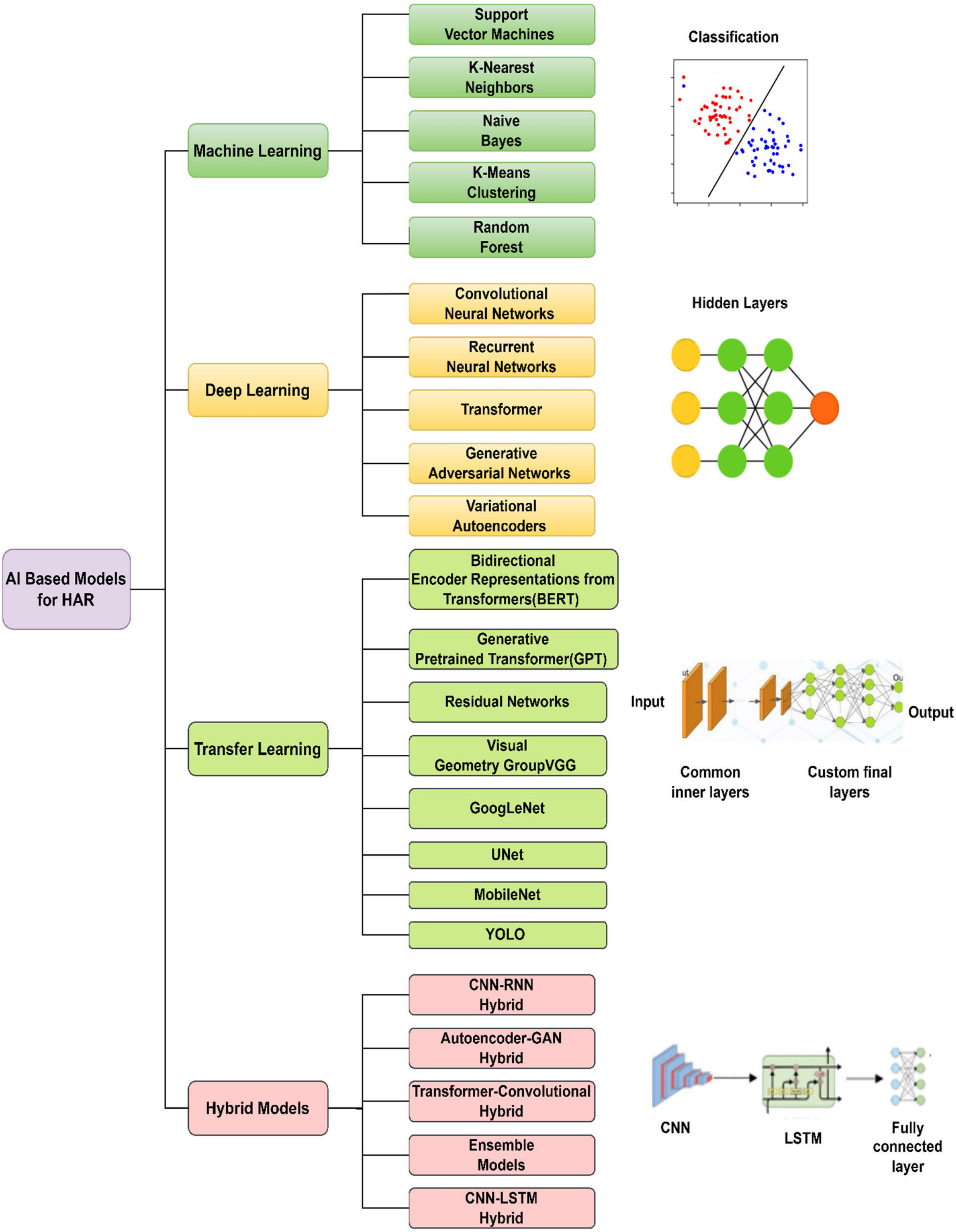

FIGURE 14. AI based models for HAR.

TABLE 5. Summary of HAR using different ML/DL based classifiers.

Reference	Features	Activities	Classifier	Accuracy/Performance
[61]	WD-EEMD	standing , Walking, sitting	LDA	97.45% for healthy
[92]	Mean, Max, Min, SD, MAD	standing, walking on flat ground, ramp climbing and lowering, stair ascending and stair descending	ANN	98.4
[93]	MAV, SSC, WL, ZC, AR Mean, Max, Min, SD, IV, FV	walking on level ground, stairs, and ramps	DBN	95.97
[94]	-	multiple abnormal human actions	CNN (YOLO)	96.8
[95]	-	12 Complex Daily Activities	DCNN	93.89
[96]	-	6 human daily activities	3+3 C-RNN	90.29
[97]	DWT + EMD	Bending, Cycling,Lying,Sitting,Standing,Walking	DT	99.63
[98]	-	multi-resident activity recognition	adaptation algorithm	97
[99]	support vector regression	Wrist motions with online Fitts' law style test	CNN	99
[100]	factorized feature using FFT	53 different hand gestures	CNN	63.86±5.12%63.86±5.12%
[101]	FT	Hand position in 3D space	CNN, RCNN	RCNN: 0.903±0.045 CNN: 0.776±0.056
[102]	STFT	Shoulder and elbow angles	MS-LSTM dueling mode	-
[103]	RMSE,NRMSE	Finger and wrist angle	RNN	-
[104]	-	Elbow flexion force	PCA+DBN	About 0.82–0.92 Baseline: 0.833
[105]	RMSE	Finger force	CNN+RNN	CNN: P < 0.05 CNN-RNN: p < 0.002

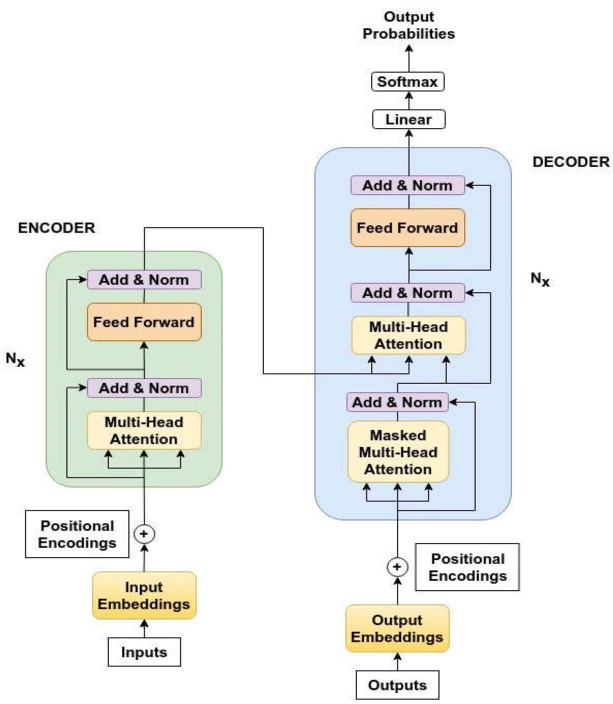

FIGURE 15. Basic architectures of transformer model [73].

A. PERFORMANCE EVALUATION

ML and DL algorithms must be evaluated to be useful. Evaluate a ML classifier by comparing its suggested method to the object's genuine categorization. Evaluation metrics measure and explain a trained classifier's performance versus unseen data. The assessment measure chooses the best training classifier to separate and choose the best answer in the future. Accuracy, Sensitivity, Specificity, Precision, Recall, F1 score, ROC, AUC, ANOVA test, Log-loss, Root Mean Squared Error, Cross Validation, and other metrics are common.

It is often used to evaluate binary or multi-class categorization problems. It is suitable for multi-class and label scenarios because it is easy to understand and compute. Compare the amount of correctly classified points to the total points to compute it [201].

A confusion matrix in TABLE 7 (a),TABLE 7(b)will illustrate the predicted classifier training correct and incorrect points. Accuracy, specificity, Recall (sensitivity), Precision, F-measure, and area under the curve (AUC) are commonly calculated using the confusion matrix in the TABLE 8. The four main metrics of a binary classification result are True Positive (TP) and True Negative (TN), which indicate that the predicted value matches the actual value, and False Positive (FP) and False Negative (FN), which indicate that the predicted value was falsely predicted.

VII. HARDWARE RELATED EXISTING WORKS FOR HAR

This section will give an overview of Existing Hardware works related to HAR, and TABLE 8 illustrates the literature survey on the hardware platform.

TABLE 6. Summary of HAR using advanced DL based models.

Reference	Year	Datasets	Methods	Accuracy
[106]	2023	Self-formulated dataset	hybrid GMDH and LSTM DL model	99%
[107]	2023	OPPO PAMAP2 UniMib-SHAR	RCNN-BiGRU, Marine predator algorithm (MPA),swarm intelligence(SI) optimization algorithms	88.83% 94.06% 86.08%
[108]	2023	HuGaDB	CNN+LSTM,PCA	94%
[109]	2023	Self-formulated dataset	Bi-LSTM, Seq2Seq-LSTM-PE-MA	97.96%
[110]	2023	Self-formulated dataset	CNN-transformer-hybrid-recognition approach	99.02%
[111]	2023	Self-formulated dataset	ViT-LLMR: Vision Transformer-based lower limb motion recognition	94.62%
[112]	2022	OPPO PAMAP2 UniMib-SHAR	Multi-ResAtt (multilevel residual network with attention)	87.83% 93.19% 84.08%
[113]	2022	Self-formulated dataset	LSTM	99.34%
[114]	2022	NinaProDB1 NinaProDB2 NinaProDB4 BioPatRecDB2 UCI Gesture	EMGHandNet: hybrid CNN and Bidirectional LSTM (Bi-LSTM)	95.77% 95.9% 91.65% 98.33%
[61]	2022	UCI	CNN-LSTM CNN-GRU	97.62% 98.69%
[115]	2022	Self-formulated dataset	extreme learning machine (ELM)	98%
[116]	2022	Self-formulated dataset	two streams of CNN called TS-CNN	-
[117]	2022	UCI	MLP	98%
[118]	2021	Self-formulated dataset	HMM+MAP(Hidden Markov Model)	91.88%
[119]	2021	whuGAIT	LSTM	93.14%
[120]	2021	Self-formulated dataset	1D-CNN and GRU Ensemble Model	98.4%
[121]	2021	WISDM UCI-HAR PAMAP2	multibranch CNN-BiLSTM network	96.05% 96.37% 94.29%
[122]	2020	Self-formulated dataset	Convolutional-Neural Network (CNN) based on Residual Networks (ResNet)	99.59%
[123]	2019	NinaPro	MLP AdaBoost-MLP	75.2% 81.5%

FIGURE 16. Knee Bandage [129].

Liu et al. [129] developed a Genutrain knee bandage for patients to measure muscle weakness, as shown in FIGURE 16. They used to outline the offline implementation of HAR models, which cover hardware requirements, software development, data gathering, and biosignal processing, Studying features and modeling human action before concentrating on the switch from offline to real-time models for information on the graphical user interface, sensor/device selection, window length, overlap ratio, and other details(GUI), as well as on-air capabilities.

Kerdjidj et al. [130] proposed a hand gesture recognition hardware architecture for Xilinx's Zynq platform (XC7Z020). This system is intended for robotic prostheses to improve daily life. They create a Vivado HLS architecture to identify hand movements using EMG. The idea architecture requires two intellectual creations to develop, test and validate hardware Ips against software implementation. First performs feature extraction from EMG signals, and the second classifies using the k-NN algorithm with eight-channel biosensor EMG data.

Kundu et al. [131] developed a hand gesture-based omnidirectional wheelchair control employing wearable IMU and myoelectric sensors, as shown in FIGURE 17. Classifying seven typical gestures DSVM classifier with shape-based feature extraction. Animated gestures mapped to wheelchair navigation omnidirectional motion commands. One IMU measures the wrist tilt and three-axis acceleration. EMG waves and Extensor Flexor Carpi Radialis and processed to RMS signal. Autonomous activity starts and stops.

TABLE 7. (a) Confusion matrix. (b) Performance evaluation metrixs.

(a)

True situation	Prediction	
	Positive	**Negative**
Positive	True positive (TP)	False negative (FN)
Negative	False positive (FP)	True negative (TN)

(b)

Metric	Formula	Description
Accuracy	$\frac{(TP+TN)}{(TP+FN+TN+FP)} * 100$	How many cases are accurately classified is measured by this metric. A higher value of accuracy indicates better system Performance.
Sensitivity/ Recall/ TPR	$\frac{TP}{TP+FN} * 100$	It assesses how frequently a classifier correctly classifies a positive result.
Specificity	$\frac{TN}{TN+FP} * 100$	It determines the proportion of times a classifier classifies a correctly identifies negative samples properly.
Precision	$\frac{TP}{TP+FP} * 100$	This measure shows the proportion of accurate classifications. A higher value of PR indicates better system Performance.
F-Measure	$2 * \frac{(Prec * sens)}{(Prec + sens)}$	It gives the harmonic mean of Precision and Sensitivity. A higher value of the F-measure indicates better system Performance.
Cohen's kappa (k)	$\frac{(\text{observed acc} - \text{expected acc})}{(1 - \text{expected acc})}$	The theoretical probability level of a classifier is returned by Cohen's kappa. Even with high accuracy values, the confusion matrix would be meaningless if k were to have a low value.
AUC	--	The area under the ROC (receiver operator characteristic) curve (AUC) indicates how well a classifier differentiates between true positive and true negative data. AUC with a higher value suggests that the system is doing better.

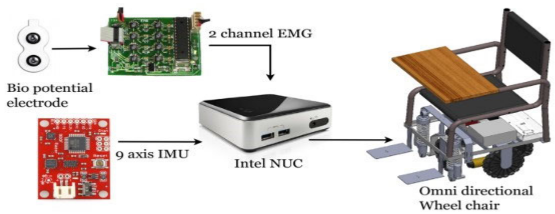

FIGURE 17. Wheelchair navigation omnidirectional motion [131].

Real-world classification with Five healthy participants tested the algorithm for real-time wheelchair navigation. Classification DSVM classifier on 'k' had 94% accuracy fold five-user cross-validation data. Classifier accuracy is 90.5% of wheelchair users.

Bai et al. [132] designed a wearable robotic system for the lower limbs described in this research to provide stroke patients with assistive torque during their rehabilitation. By detecting, the device specifically delivers the helpful torque. The purpose for which sEMG is used. The research was done to gather hamstring and quadriceps EMG readings from 10 healthy volunteers' muscles. The estimated force and torque Results indicate that the assistive technology is a highly implementable device. Online exams using assistive technology were also conducted. Motors are controlled by an EMG signal. The result estimation force, the locations of the hip and knee joints, and the Application in real-time can be seen in FIGURE 18.

Franco et al. [133] implemented an Ageing causes functional decline, which can impair locomotion and require assistance. The NanoStim project intends to build a home electrostimulation system to reduce patient visits. FIGURE 19 illustrates the knee angle helps determine the patient's mobility during treatment. IMU sensors detect knee angles in this wearable system. Low-cost technology, such as an ESP32 microcontroller and an ESP32MPU-6050 sensor, is incorporated into the wearables. This hardware causes

TABLE 8. Summary on hardware used for HAR.

Author	Year	Sensor/Components Used	Used to Analyze(Applied on)	Algorithm Used/ Techniques
[134]	2023	two-channel EMG equipment.	muscle fatigue	Time Warping-K Nearest Neighbour Dynamic (DTW-KNN)
[135]	2023	NVIDIA JETSON NANO, EMG	Dynamic Hand Gesture Recognition	Edge AI
[136]	2022	Semg	lower limb motion detection	CNN-KELM
[137]	2022	EMG, Force Sensor	characterize muscle forces	artificial neural network (ANN)
[138]	2022	inertial measurement unit(IMU)	Gesture recognition	convolutional neural network (CNN)
[139]	2022	MyoWare, ESP32 Devkit	Lower Limb	Extra Tree Classifier
[140]	2022	Microcontroller, IoT Module	Human Activity Monitoring System	Blynk Cloud Platform
[141]	2022	Raspberry Pi 4	human-centered applications in IoT	MultiCNN-FilterLSTM
[142]	2021	EMG,IMU	Understanding and Identifying Human Lower Limb Motions	BP neural network
[143]	2021	IMU Module,Air Pressure Module,Central Node	Personalized HAR	improved pseudo-labels (IPL-JPDA)
[144]	2021	Raspberry Pi 4	Channel state information(CSI-based HAR)	1D-CNN, Long Short-Term Memory (LSTM), and Bi-directional LSTM
[145]	2020	Arduino UNO	robot car for Gesture recognition	SVM based on AdaBoost
[5]	2020	Myo armband, 9 × acvPAL micro, 1 × SmartCardia wearable	Early Supportive Care and Elder Rehabilitation	activity recognition chain (ARC)
[146]	2020	deep Q-network (DQN)	Smart Healthcare	LSTM
[147]	2019	FPGA	HAR system for smart military wearables	MLP models

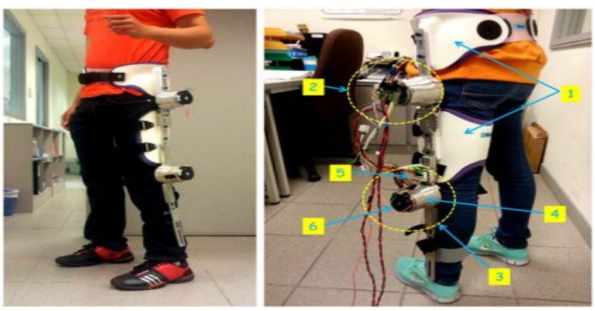

FIGURE 18. Lower extremities rehabilitation device [132].

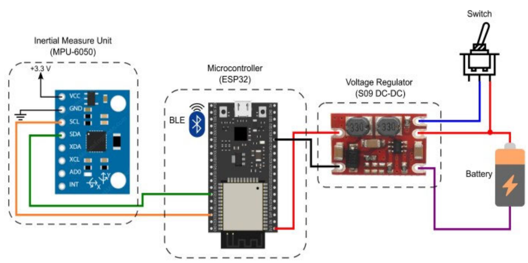

FIGURE 19. IMU acquisition system diagram [133].

a reduction in the Precision of signals when multitasking. The complementary filter had the best performance, with an average error of 0.6 degrees and a 77% improvement in MSE.

Faisal et al. [220] One of the most actively researched areas in the field of HCI is hand gesture recognition. Although several hand gesture detection modalities have been investigated over the past three decades, recent years have seen a resurgence in the field thanks to hardware advancements and DL algorithms. In this article, we assess low-cost dataglove's effectiveness for categorizing hand gestures in the context of deep learning. Additionally, they suggested a brand-new Spatial Projection Image-based method for recognizing dynamic hand gestures, as shown in FIGURE 20.

VIII. APPLICATIONS OF EMG

In the past ten years, there has been a proliferation of sEMG-based solutions, as evidenced by an increase in the number of demonstrations and attempts in three crucial rehabilitation settings. FIGURE 21 illustrate the various Application of EMG; Surface EMG signals huge Application in healthcare, such as the control of prosthetics or exoskeletons, the evaluation of neuromuscular diseases, activity tracking, and other applications [174].

TABLE 9. **Summary of existing important ML/DL models for disease prediction and diagnosis in healthcare domain.**

Reference No.	Disease Type	Algorithm	Dataset	Performance Evaluation
[148]	Heart Diseases Prediction	CNN, RF	Cleveland dataset	CNN-Accuracy—78.688, Recall—79%, Precision—80%,
[149]	Heartbeat recognition method(performance)	SVM	MIT-BIH	Accuracy—97.08%
[150]	Chronic kidney disease	CNN-SVM	Privately own dataset	Accuracy—97.67%, Specificity—97.83% Sensitivity—97.5%,
[151]	Detection and Segmentation of Kidney Disorders	ANN	Data collected own by patients' Ultrasound	Accuracy—99.61%
[152]	Breast Cancer	NB, BN,RF and DT	BCSC	ROC—0.937 (BN)
[153]	CAD tumor	Binary-LR	18 Privately owned Cases	Accuracy—80.39%
[154]	Diabetes and hypertension	DPM	Privately owned	Accuracy—96.74%
[155]	Lung Diseases	VGG19+CNN	Privately owned	Accuracy—96.48% Precision—97.56%
[156]	Chronic kidney disease (CKD)	XGBOOST Model	Privately owned	Accuracy—98.3%, Precision—98.0%, Recall —98.0%
[157]	Degenerative spinal Disease	XGBOOST Model	Data of 49 patients	Accuracy—85.71%
[158]	Skin Cancer	CNN,Resnet50	ISIC2018	CNN-Accuracy—83.2% Resnet50-Accuracy—83.7%
[159]	knee osteoarthritis	ANN	Privately owned	Area under the curve (AUC)of 0.807 (72.3% sensitivity and 80.9% specificity)

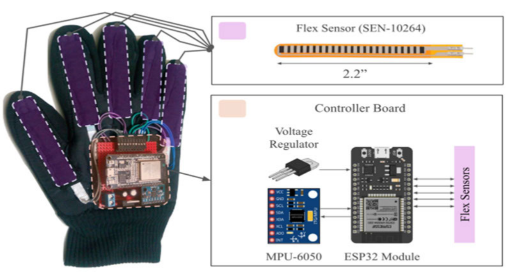

FIGURE 20. **Dataglove architecture [220].**

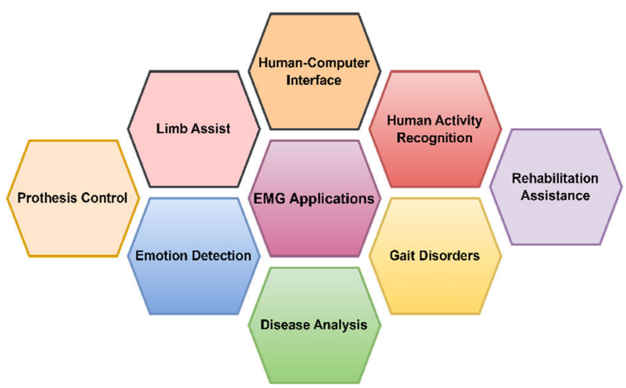

FIGURE 21. **Various applications using EMG.**

A. HEALTHCARE SYSTEM

Systems that analyze and interpret patient behavior are frequently employed in healthcare systems to make it easier for medical personnel and other key staff to monitor, diagnose, and provide treatment for patients [175]. This leads to better patient satisfaction, a reduction in hospital stays, lower medical expenses, and a lower risk of major harm. It also minimizes the stress on healthcare personnel while improving the quality of care provided to patients. Recognition of human activities systems is utilized in a wide

TABLE 10. List of acronyms.

PRISMA	Preferred Reporting Items for Systematic reviews and
ANN	Artificial Neural Network
AI	Artificial Intelligent
HCI	Human-Computer Interface
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
EEMD	Enhanced Empirical Mode Decomposition
HAR	Human Activity Recognition
EMG	Electromyography
EEG	Electroencephalogram
ANOVA	Analysis of Variance
AUC	Area Under Curve
AI	Artificial Intelligence
ESD	Energy Spectral Density
BiLSTM	Bidirectional long short-term memory
CNN	Convolutional neural network
DL	Deep learning
LDA	Linear Discriminant Analysis
KNN	K-Nearest Neighbor
DWT	Discrete wavelet transforms
GRU	Gated Recurrent Unit
HMI	Human Machine Interaction
RMS	Root Mean Square
MAV	Mean absolute value
DNN	Deep Neural Network
FD	Frequency Domain
TD	Time Domain
TFD	Time-Frequency Domain
FFT	Fast Fourier Transform
ML	Machine learning
MLP	Multilayer perceptron
NB	Naïve Bayes
PCA	Principal Component Analysis
PSD	Power spectral density
QDA	Quadratic Discriminant Analysis
ROC	Receiver Characteristic Operator
RACISM	Rational asymmetry index
RF	Random Forest
SVM	Support Vector Machine
VMD	Variable Mode Decomposition
WE	Wavelet Entropy
WPT	Wavelet packet transform
WAMP	Wilson Amplitude
ARC	Auto-Regressive Coefficient
MDF	Median Frequency
MPF	Mean Power Frequency
WT	Wavelet transform
MAV	Mean Absolute Value
VAR	Variance
LSTM	long short-term memory

TABLE 10. *(Continued.)* List of acronyms.

SKW	Skewness
WL	Waveform Length
SSC	Slope Sign Change
ZCR	Zero-crossing rate
MLP	Multilayer perceptron
FPGA	Field Programmable Gate Array

range of health care applications, including automatic fall detection [179], emergency response systems for detecting unintentional falls and offering immediate support, respiratory actions modeling applications for identifying and diagnosing sleep problems [180], cardiovascular diseases, stroke [181], Parkinson's disease [131], Amyotrophic lateral sclerosis (ALS) [176] and prescription drug surveillance systems for ensuring proper medication usage. Automatic wheelchairs, exercise-aid systems that steer suitable postures during everyday activities, hand gesture detection systems for sign language-based interaction, and hand-based monitoring systems for eating disorders are some significant instances of the technologies described [182] and various Applications in Healthcare discussed in TABLE 9.

B. SYSTEMS FOR MONITORING

Surveillance systems, another application category, make extensive use of HAR technologies. Activities detection systems are utilized in monitoring situations to monitor and observe people and gatherings, assisting security personnel in recognizing and identifying threats or suspicious behavior. Drowsiness among drivers detection systems to ensure proper driving behavior [183] and to reduce injuries caused by driver inattention; automatically drowning identifying systems [184] in pool areas to safeguard life; and so on. Identification of human activity systems for monitoring a variety of systems.

C. SYSTEMS FOR ENTERTAINMENT

Recognizing human movement and activities commonly used in the entertainment sector for the track, sports authorities, and participants, as well as to have fun when playing video games. There are various examples of HAR in action. Entertainment systems use activity recognition systems to accurately time swimming and diving, identify and score real-world dance moves, navigate in 3-D spaces, and interact in virtual environments [185], [186], [187]. Tennis games use movement recognition to detect strokes and events.

D. TRAFFIC SAFETY

When driving a car, safety is of the utmost importance. The potential of autonomous vehicles to avoid accidents and promote safety benefits substantially from the assessment of the driver's biological data. The driver data gathering and marking system developed by Seckin et al. [111] makes extensive use of EEG, EMG, and IMU, the vehicle's capacity to distinguish unsafe circumstances in autonomous driving. The

KNN method classifies the data after PCA dimensionality reduction.

E. REHABILITATION AND PROSTHESIS CONTROL
Following some surgeries and diseases, physical rehabilitation therapy is frequently required, and using multimodal measurement systems makes it possible to track the development more precisely [189]. Monge et al. [190] presented an intelligent physical rehabilitation system that used augmented reality, EMG, ECG, and IMU sensors, remote health status monitoring, and supported rehabilitation to engage patients. J. Gallego, others [191].

F. SPORTS ASSESSMENTS
HAR is utilized to collect data like acceleration, which is angular haste, haste, and so on, for numerical analysis of mortal body corridor actions in order to calculate sportsmen and women's performance and assist them with enhancement approaches [192], [193].

IX. OPEN ISSUES, FUTURE TRENDS, AND RESEARCH DIRECTIONS
A. OPEN ISSUES
Although the current HAR-based algorithms excel at identifying atomic and fundamental activities in single-subject settings, they continue to have difficulty with HAR in a variety of complicated real-life scenarios [195]. There are some presented open issues with HAR systems below.

1) SIGNAL INSTABILITY IN THE EMG
The instability problems with the outputted EMG signals (particularly for sEMG technology) show that the reproducibility of EMG signals becomes a challenge. Frequently, even the ability of the same patient to produce EMG signals of varying amplitudes poses significant difficulties for illness analysis and intention/motion interpretation.

2) HIGH-ACCURACY REAL-TIME INTERPRETATION
EMG signals are frequently utilized to control teleoperation and exoskeletons by interpreting the user's intentions. Nevertheless, achieving great interpretation accuracy while exerting less control delay has not yet been attained. In real-time control systems, increased interpretation accuracy typically necessitates longer EMG signal recording times, which causes undesirable a delay [196].

3) CLASS IMBALANCE FOR SPECIFIC ACTIVITIES
Even in specialized datasets, data for other anomalous behaviors like unintentional falls from various positions are quite uncommon, in contrast to the abundance of data for everyday activities like walking, talking, jogging, and swimming. In light of this, data for various sorts of activities frequently show a class imbalance.

4) ISSUES WITH THE UNDERLYING TECHNOLOGY THAT ARE INHERENT
The portability, expensive hardware requirements, and environmental interference of HAR systems relying on radar signals are some of the drawbacks. Similar wearability restrictions apply to HAR systems based on smartphones and wearable sensors. The HAR systems that rely on several sensory modalities are similarly susceptible to data noise, making the data more difficult to understand and extrapolate from.

5) LACK OF STANDARDIZATION
Different research studies employ distinct testing methodologies and benchmarks. While some HAR systems employ many assessment criteria, others only use portions of datasets. Consequently, it is quite challenging to make quantitative comparisons between the systems and carry out an accurate evaluation.

6) OTHER COMMON CHALLENGES
The main challenges are the noisy behavior of EMG signals and data overfitting. In order to eliminate the undesired noise, it is crucial to perform rectification and filtering after the preprocessing stage. Lack of training and testing data represents yet another significant obstacle. The majority of publications split their dataset into training and testing data, which the current study proved was insufficient [194]. As a result, data augmentation techniques that create synthetic data from the obtained data can be utilized to prevent overfitting. Feature selection algorithms may be useful to improve classification accuracy along with the response time.The complexity and limitations of the processing, as well as design problems like electrodes, present difficulties, especially in applications where both recognition accuracy and Real-time efficiency have exacting standards [195].

B. FUTURE TRENDS AND RESEARCH DIRECTIONS
Based on the systematic review of sEMG-based HAR using AI, several research directions can be identified for future studies. These directions aim to address existing challenges and further enhance the capabilities of sEMG-based HAR systems. Some potential research directions include:

1) ROBUSTNESS AND ADAPTABILITY
This investigates methods to improve the robustness and adaptability of sEMG-based HAR systems. This can involve exploring techniques for handling inter-subject and intra-subject variability, electrode placement variation, and different skin conditions. Developing algorithms that can adapt to individual users and accommodate changes over time can improve the reliability and applicability of HAR systems.

2) MULTIMODAL INTEGRATION
This explores the integration of multimodal data sources with sEMG signals to improve activity recognition accuracy

and robustness. This may entail merging sEMG data with accelerometers, gyroscopes, and IMUs. Multiple sensors can be combined to better reflect human behaviors and improve HAR systems.

3) REAL-TIME MONITORING AND FEEDBACK

This system\method focuses on the development of real-time sEMG-based HAR systems that provide immediate feedback and assistance to users. This can be particularly valuable in rehabilitation settings, where real-time feedback can help patients adjust their movements and optimize their rehabilitation exercises. Designing algorithms that can process sEMG signals in real time and provide instantaneous feedback is an important research direction.

4) TRANSFER LEARNING AND DOMAIN ADAPTATION E MONITORING AND FEEDBACK

This method technique investigates transfer learning and domain adaptation techniques for sEMG-based HAR. Transfer learning can leverage knowledge learned from a source domain (e.g., a well-labeled dataset) and apply it to a target domain with limited labeled data. Domain adaptation techniques can help generalize HAR models across different subjects, conditions, or environments. These approaches can reduce the reliance on large labeled datasets and improve the generalization capability of HAR systems.

5) EXPLAINABLE AI IN HAR

This method explores ways to enhance the interpretability and transparency of AI models used in sEMG-based HAR. Explainable AI techniques can provide insights into the decision-making process of AI models and increase the trust and acceptance of HAR systems in real-world applications. Developing explainable AI methods specific to sEMG-based HAR can help users understand the factors influencing activity recognition outcomes and facilitate user interaction and customization.

6) LONG-TERM MONITORING AND CONTEXT AWARENESS

This method investigates approaches for long-term monitoring of activities using sEMG signals. Long-term monitoring can provide valuable data for healthcare professionals, sports scientists, and researchers to analyze activity patterns, detect anomalies, and track progress over extended periods. Additionally, integrating context awareness into HAR systems can enhance their performance by considering contextual information such as environmental conditions, user context, and task-specific factors.

7) PRACTICAL IMPLEMENTATION AND USER ACCEPTANCE

This method looks at the practical implementation of sEMG-based HAR systems in real-world settings. This includes the design and development of user-friendly wearable devices, optimized signal acquisition techniques, and user-centered evaluation studies. Understanding user needs, preferences, and acceptance factors can guide the development of HAR systems that are practical, comfortable to wear, and seamlessly integrated into users' daily lives.

8) GENERATIVE MODELS TO IMBALANCE DATA

Generic models, like GANs [195], are now frequently employed to produce photorealistic fake data. These generative models can be adjusted to produce information on unequal classes.

C. FUTURE ACTIVITY PREDICTION

A development of HAR called future activity prediction makes it possible to forecast the likely course of monitored people's actions. Law enforcement and the identification of driver behavior both use future activity prediction. Due to the sequential nature of human actions, other technologies (such as brain-computer,fMRI, interfaces, and EEG).

1) ESTABLISHING RELIABLE HAR SYSTEMS

The type of surface and environmental factors like clothing and attire selection has a big impact on how people behave. The pertinent sensor data likewise shows these modifications. However, the majority of publicly available datasets on the detection of human activities were gathered in lab test settings that did not take into account these variations. Therefore, future research efforts can concentrate on creating accurate activity datasets for various environments and reliable, environment-resistant human activity identification algorithms.

Technology is helping now. In actuality, commercial low-power MCUs have the computing capacity to conduct near-sensor processing that matches performance, and it will improve in the next years. The capacity to automatically learn features from EMG data is appealing for improving recognition. Natural language computing in linguistics, ML in mech engg, and recently created ECE and EEE networks exist. Additional research into sensing and feature extraction methods for recognizing tiny motions and postures may have implications in a variety of sectors, including HMI. For instance, human finger movements based on UWB Doppler characteristics is one such case for use in portable gadgets.

X. CONCLUSION

In conclusion, this systematic review examined sEMG-based HAR utilizing AI, including methodologies, applications, problems, and future implementation options. The review showed that sEMG signals, which measure muscle electrical activity, are promising for HAR because of their non-invasiveness, ease of acquisition, and potential for real-time monitoring. ML and DL methods have enabled accurate and robust activity detection from sEMG data. Review approaches for sEMG feature extraction and categorization were discussed. Time-domain, frequency-domain, time-frequency analysis, and higher-order statistics extract features. Traditional ML methods like SVM and RF were used for classification, as were DL models like CNN and

RNN. The review showed that HAR systems need the right feature extraction and classification methods to be accurate.

The review also explored a wide range of applications where sEMG-based HAR has been applied, including rehabilitation [197], prosthesis control, human-robot interaction, sports science [193], and virtual reality. The potential benefits of HAR systems in these domains include enhanced rehabilitation outcomes, improved prosthetic control, more natural human-robot interaction, better performance monitoring in sports, and superior immersive virtual reality experiences.

In summary, sEMG-based HAR using AI holds great promise for huge applications in healthcare, robotics, sports, and virtual reality. By addressing the challenges and incorporating advancements in AI techniques, future implementations of sEMG-based HAR systems have the potential to revolutionize human activity monitoring and interaction. Systems for recognizing human activity are vital tools for humanity since they allow for the monitoring, analysis, and aid of general human activities as well as their recording using various sensory modalities through powerful computing systems of daily life. Systems for recognizing human activity in many fields of crucial industries, including healthcare, surveillance, and entertainment [202]. Systems for recognizing human activity are crucial tools for humankind because they make it possible to watch, analyze, and provide assistance while also enabling the recording of common human activities using various sensing modalities. Through powerful computer systems of everyday life. The reviewed systems are given in the context of the importance of AI and details on EMG Signal with various existing systems [201]. Also shown are the systems' available hyperparameters. We also included a quick overview of the publicly accessible datasets that contain information gathered using different types of sensing techniques that are often employed in the systems under examination and the wider field [200]. Finally, we talk about some potential solutions, applications, and open issues. Future studies should be interested in HAR systems that would raise the standard of living for those who have had a stroke or who have lost limbs. EMG signal equality in these patients will be of great help. Consequently, a deep learning-based strategy could aid in the Application of EMG in these circumstances. Future research direction is also discussed in the review [42]. The intended system must be transportable, and these embedded systems must be lightweight. To address the issue of computing cost, techniques including parameter downsizing, embedded GPU, and remote servers should be investigated. Along with the sensing apparatus, mathematical techniques, including feature extraction and classification algorithms, are also covered [199]. In accordance with cutting-edge HAR methodologies, the technical issues targeted included the limitations of sensing methods for convenient applications, reliance on PCs for data processing, challenges in recognizing tiny gestures, specificity in motion analysis, disease prediction [176], and HAR. The direction of future research is thought to be toward finding answers to these problems. HAR and motion analysis may be more important in future IoT-enabled intelligent information systems because they can improve human-information system interaction.

Challenges and limitations in sEMG-based HAR were identified in the review. These include inter-subject and intra-subject variability, sensitivity to electrode placement and skin conditions, limited interpretability of DL models, and the need for large labeled datasets for training. Addressing these challenges requires further research and development in the field [198]. Finally, the review discussed future directions and potential areas for implementation of sEMG-based HAR using AI. These include wearable devices for continuous activity monitoring, multimodal data integration for better recognition, transfer learning, and domain adaptation, and explainable AI methods to improve HAR system interpretability.

REFERENCES

[1] N. Gupta, S. K. Gupta, R. K. Pathak, V. Jain, P. Rashidi, and J. S. Suri, "Human activity recognition in artificial intelligence framework: A narrative review," *Artif. Intell. Rev.*, vol. 55, no. 6, pp. 4755–4808, Aug. 2022, doi: 10.1007/s10462-021-10116-x.

[2] C. Pham, S. Nguyen-Thai, H. Tran-Quang, S. Tran, H. Vu, T.-H. Tran, and T.-L. Le, "SensCapsNet: Deep neural network for non-obtrusive sensing based human activity recognition," *IEEE Access*, vol. 8, pp. 86934–86946, 2020, doi: 10.1109/ACCESS.2020.2991731.

[3] S. Qiu, H. Zhao, N. Jiang, Z. Wang, L. Liu, Y. An, H. Zhao, X. Miao, R. Liu, and G. Fortino, "Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges," *Inf. Fusion*, vol. 80, pp. 241–265, Apr. 2022, doi: 10.1016/j.inffus.2021.11.006.

[4] J. Qi, Z. Wang, X. Lin, and C. Li, "Learning complex spatio-temporal configurations of body joints for online activity recognition," *IEEE Trans. Hum.-Mach. Syst.*, vol. 48, no. 6, pp. 637–647, Dec. 2018, doi: 10.1109/THMS.2018.2850301.

[5] L. Schrader, A. Vargas Toro, S. Konietzny, S. Rüping, B. Schäpers, M. Steinböck, C. Krewer, F. Müller, J. Güttler, and T. Bock, "Advanced sensing and human activity recognition in early intervention and rehabilitation of elderly people," *J. Population Ageing*, vol. 13, no. 2, pp. 139–165, Jun. 2020, doi: 10.1007/s12062-020-09260-z.

[6] C. N. Phyo, T. T. Zin, and P. Tin, "Deep learning for recognizing human activities using motions of skeletal joints," *IEEE Trans. Consum. Electron.*, vol. 65, no. 2, pp. 243–252, May 2019, doi: 10.1109/TCE.2019.2908986.

[7] H. Ding, L. Shangguan, Z. Yang, J. Han, Z. Zhou, P. Yang, W. Xi, and J. Zhao, "FEMO: A platform for free-weight exercise monitoring with RFIDs," in *Proc. 13th ACM Conf. Embedded Networked Sensor Syst.* New York, NY, USA: Association for Computing Machinery, Nov. 2015, pp. 141–154, doi: 10.1145/2809695.2809708.

[8] Y. Liu, Q. Zhang, and W. Chen, "Massive-scale complicated human action recognition: Theory and applications," *Future Gener. Comput. Syst.*, vol. 125, pp. 806–811, Dec. 2021, doi: 10.1016/j.future.2021.06.060.

[9] S. Jiang, P. Kang, X. Song, B. Lo, and P. Shull, "Emerging wearable interfaces and algorithms for hand gesture recognition: A survey," *IEEE Rev. Biomed. Eng.*, vol. 15, pp. 85–102, 2022, doi: 10.1109/RBME.2021.3078190.

[10] O. Kerdjidj, E. Boutellaa, A. Amira, K. Ghanem, and F. Chouireb, "A hardware framework for fall detection using inertial sensors and compressed sensing," *Microprocessors Microsystems*, vol. 91, Jun. 2022, Art. no. 104514, doi: 10.1016/j.micpro.2022.104514.

[11] A. Gautam, M. Panwar, D. Biswas, and A. Acharyya, "MyoNet: A transfer-learning-based LRCN for lower limb movement recognition and knee joint angle prediction for remote monitoring of rehabilitation progress from sEMG," *IEEE J. Translational Eng. Health Med.*, vol. 8, pp. 1–10, 2020, doi: 10.1109/JTEHM.2020.2972523.

[12] L. Minh Dang, K. Min, H. Wang, M. Jalil Piran, C. Hee Lee, and H. Moon, ''Sensor-based and vision-based human activity recognition: A comprehensive survey,'' *Pattern Recognit.*, vol. 108, Dec. 2020, Art. no. 107561, doi: 10.1016/j.patcog.2020.107561.

[13] N. Nazmi, M. A. Abdul Rahman, S.-I. Yamamoto, and S. A. Ahmad, ''Walking gait event detection based on electromyography signals using artificial neural network,'' *Biomed. Signal Process. Control*, vol. 47, pp. 334–343, Jan. 2019, doi: 10.1016/j.bspc.2018.08.030.

[14] M. M. Islam, S. Nooruddin, F. Karray, and G. Muhammad, ''Human activity recognition using tools of convolutional neural networks: A state of the art review, data sets, challenges, and future prospects,'' *Comput. Biol. Med.*, vol. 149, Oct. 2022, Art. no. 106060, doi: 10.1016/j.compbiomed.2022.106060.

[15] D. Xiong, D. Zhang, X. Zhao, and Y. Zhao, ''Deep learning for EMG-based human–machine interaction: A review,'' *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 3, pp. 512–533, Mar. 2021, doi: 10.1109/JAS.2021.1003865.

[16] X. Wang, H. Yu, S. Kold, O. Rahbek, and S. Bai, ''Wearable sensors for activity monitoring and motion control: A review,'' *Biomimetic Intell. Robot.*, vol. 3, no. 1, Mar. 2023, Art. no. 100089, doi: 10.1016/j.birob.2023.100089.

[17] A. Vijayvargiya, B. Singh, R. Kumar, and J. M. R. S. Tavares, ''Human lower limb activity recognition techniques, databases, challenges and its applications using sEMG signal: An overview,'' *Biomed. Eng. Lett.*, vol. 12, no. 4, pp. 343–358, Nov. 2022, doi: 10.1007/s13534-022-00236-w.

[18] Z. Meng, ''Recent progress in sensing and computing techniques for human activity recognition and motion analysis,'' *Electronics*, vol. 9, no. 9, pp. 1–19, Sep. 2020, doi: 10.3390/electronics9091357.

[19] M. Al-Ayyad, H. A. Owida, R. De Fazio, B. Al-Naami, and P. Visconti, ''Electromyography monitoring systems in rehabilitation: A review of clinical applications, wearable devices and signal acquisition methodologies,'' *Electronics*, vol. 12, no. 7, p. 1520, Mar. 2023, doi: 10.3390/electronics12071520.

[20] A. Fleming, N. Stafford, S. Huang, X. Hu, D. P. Ferris, and H. Huang, ''Myoelectric control of robotic lower limb prostheses: A review of electromyography interfaces, control paradigms, challenges and future directions,'' *J. Neural Eng.*, vol. 18, no. 4, Aug. 2021, Art. no. 041004, doi: 10.1088/1741-2552/ac1176.

[21] A. Asghar, S. J. Khan, F. Azim, C. S. Shakeel, A. Hussain, and I. K. Niazi, ''Review on electromyography based intention for upper limb control using pattern recognition for human-machine interaction,'' *Proc. Inst. Mech. Eng., H, J. Eng. Med.*, vol. 236, no. 5, pp. 628–645, May 2022, doi: 10.1177/09544119221074770.

[22] R. A. Lateef and A. R. Abbas, ''Human activity recognition using smartwatch and smartphone: A review on methods, applications, and challenges,'' *Iraqi J. Sci.*, pp. 363–379, Jan. 2022, doi: 10.24996/ijs.2022.63.1.34.

[23] F. Kulsoom, S. Narejo, Z. Mehmood, H. N. Chaudhry, A. Butt, and A. K. Bashir, ''A review of machine learning-based human activity recognition for diverse applications,'' *Neural Comput. Appl.*, vol. 34, no. 21, pp. 18289–18324, Nov. 2022, doi: 10.1007/s00521-022-07665-9.

[24] M. J. Page, ''The PRISMA 2020 statement: An updated guideline for reporting systematic reviews,'' *BMJ*, vol. 372, p. n71, Mar. 2021, doi: 10.1136/bmj.n71.

[25] K. C. McGill, ''Surface electromyogram signal modelling,'' *Med. Biol. Eng. Comput.*, vol. 42, no. 4, pp. 446–454, Jul. 2004, doi: 10.1007/BF02350985.

[26] A. Subasi, ''Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders,'' *Comput. Biol. Med.*, vol. 43, no. 5, pp. 576–586, Jun. 2013, doi: 10.1016/j.compbiomed.2013.01.020.

[27] J. S. Kim and S. B. Pan, ''A study on EMG-based biometrics,'' *J. Internet Services Inf. Secur.*, vol. 7, no. 2, pp. 1–13, 2017.

[28] A. Cimolato, J. J. M. Driessen, L. S. Mattos, E. De Momi, M. Laffranchi, and L. De Michieli, ''EMG-driven control in lower limb prostheses: A topic-based systematic review,'' *J. NeuroEngineering Rehabil.*, vol. 19, no. 1, May 2022, doi: 10.1186/s12984-022-01019-1.

[29] Z. Zheng, Z. Wu, R. Zhao, Y. Ni, X. Jing, and S. Gao, ''A review of EMG-, FMG-, and EIT-based biosensors and relevant human–machine interactivities and biomedical applications,'' *Biosensors*, vol. 12, no. 7, p. 516, Jul. 2022, doi: 10.3390/bios12070516.

[30] C. Fang, B. He, Y. Wang, J. Cao, and S. Gao, ''EMG-centered multisensory based technologies for pattern recognition in rehabilitation: State of the art and challenges,'' *Biosensors*, vol. 10, no. 8, p. 85, Jul. 2020, doi: 10.3390/BIOS10080085.

[31] S. Haufe, I. U. Isaias, F. Pellegrini, and C. Palmisano, ''Gait event prediction using surface electromyography in parkinsonian patients,'' *Bioengineering*, vol. 10, no. 2, p. 212, Feb. 2023, doi: 10.3390/bioengineering10020212.

[32] K. Lee, ''EMG-triggered pedaling training on muscle activation, gait, and motor function for stroke patients,'' *Brain Sci.*, vol. 12, no. 1, p. 76, Jan. 2022, doi: 10.3390/brainsci12010076.

[33] Y. Sun, Y. Tang, J. Zheng, D. Dong, X. Chen, and L. Bai, ''From sensing to control of lower limb exoskeleton: A systematic review,'' *Annu. Rev. Control*, vol. 53, pp. 83–96, 2022, doi: 10.1016/j.arcontrol.2022.04.003.

[34] E. Stålberg, H. van Dijk, B. Falck, J. Kimura, C. Neuwirth, M. Pitt, S. Podnar, D. I. Rubin, S. Rutkove, D. B. Sanders, M. Sonoo, H. Tankisi, and M. Zwarts, ''Standards for quantification of EMG and neurography,'' *Clin. Neurophysiol.*, vol. 130, no. 9, pp. 1688–1729, Sep. 2019, doi: 10.1016/j.clinph.2019.05.008.

[35] C. J. De Luca, ''A model for a motor unit train recorded during constant force isometric contractions,'' *Biol. Cybern.*, vol. 19, no. 3, pp. 159–167, Sep. 1975, doi: 10.1007/BF00337255.

[36] D. Farina and R. Merletti, ''A novel approach for precise simulation of the EMG signal detected by surface electrodes,'' *IEEE Trans. Biomed. Eng.*, vol. 48, no. 6, pp. 637–646, Jun. 2001, doi: 10.1109/10.923782.

[37] N. Foley and C.-H. Yu, ''MusCare+: Muscle monitoring for anomalies,'' in *Proc. IEEE World AI IoT Congr. (AIIoT)*, Jun. 2022, pp. 425–430, doi: 10.1109/AIIoT54504.2022.9817161.

[38] E. Shwedyk, R. Balasubramanian, and R. N. Scott, ''A nonstationary model for the electromyogram,'' *IEEE Trans. Biomed. Eng.*, vol. BME-24, no. 5, pp. 417–424, Sep. 1977, doi: 10.1109/TBME.1977.326175.

[39] Y. Zheng, G. Xu, Y. Li, and W. Qiang, ''Improved online decomposition of non-stationary electromyogram via signal enhancement using a neuron resonance model: A simulation study,'' *J. Neural Eng.*, vol. 19, no. 2, Apr. 2022, Art. no. 026030, doi: 10.1088/1741-2552/ac5f1b.

[40] S. Shan, B. Fang, Y. Zhang, C. Wang, J. Zhou, C. Niu, Y. Gao, D. Zhao, J. He, J. Wang, X. Zhang, and Q. Li, ''Mechanical stretch promotes tumoricidal M1 polarization via the FAK/NF-κB signaling pathway,'' *FASEB J.*, vol. 33, no. 12, pp. 13254–13266, Dec. 2019, doi: 10.1096/fj.201900799RR.

[41] E. L. W. Ting, A. Chai, and L. P. Chin, ''A review on EMG signal classification and applications,'' *Int. J. Signal Process. Syst.*, vol. 9, no. 1, pp. 1–6, Mar. 2022, doi: 10.18178/ijsps.10.1.1-6.

[42] N. Parajuli, N. Sreenivasan, P. Bifulco, M. Cesarelli, S. Savino, V. Niola, D. Esposito, T. J. Hamilton, G. R. Naik, U. Gunawardana, and G. D. Gargiulo, ''Real-time EMG based pattern recognition control for hand prostheses: A review on existing methods, challenges and future implementation,'' *Sensors*, vol. 19, no. 20, p. 4596, Oct. 2019, doi: 10.3390/s19204596.

[43] C. Tepe and M. C. Demir, ''Real-time classification of EMG myo armband data using support vector machine,'' *IRBM*, vol. 43, no. 4, pp. 300–308, Aug. 2022, doi: 10.1016/j.irbm.2022.06.001.

[44] D. D'Accolti, K. Dejanovic, L. Cappello, E. Mastinu, M. Ortiz-Catalan, and C. Cipriani, ''Decoding of multiple wrist and hand movements using a transient EMG classifier,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 31, pp. 208–217, 2023, doi: 10.1109/TNSRE.2022.3218430.

[45] P. S. Palar, V. de Vargas Terres, and A. S. de Oliveira, ''Human–robot interface for embedding sliding adjustable autonomy methods,'' *Sensors*, vol. 20, no. 20, pp. 1–30, Oct. 2020, doi: 10.3390/s20205960.

[46] S. A. Mousavi, F. Moradianpour, F. Heidari, S. M. Yasoubi, S. E. Tahami, and M. Azarnoush, ''Hand movement detection using empirical mode decomposition and higher order spectra,'' in *Proc. Int. Congr. Hum.-Comput. Interact., Optim. Robot. Appl. (HORA)*, Ankara, Turkey, 2020, pp. 1–6, doi: 10.1109/HORA49412.2020.9152901.

[47] J. Chen, S. Bi, G. Zhang, and G. Cao, ''High-density surface EMG-based gesture recognition using a 3D convolutional neural network,'' *Sensors*, vol. 20, no. 4, p. 1201, Feb. 2020, doi: 10.3390/s20041201.

[48] G. Purushothaman and R. Vikas, ''Identification of a feature selection based pattern recognition scheme for finger movement recognition from multichannel EMG signals,'' *Australas. Phys. Eng. Sci. Med.*, vol. 41, no. 2, pp. 549–559, Jun. 2018, doi: 10.1007/s13246-018-0646-7.

[49] J. Maier, A. Naber, and M. Ortiz-Catalan, ''Improved prosthetic control based on myoelectric pattern recognition via wavelet-based de-noising,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 2, pp. 506–514, Feb. 2018, doi: 10.1109/TNSRE.2017.2771273.

[50] R. R. Essa, H. A. Jaber, and A. A. Jasim, "Features selection for estimating hand gestures based on electromyography signals," *Bull. Electr. Eng. Informat.*, vol. 12, no. 4, pp. 2087–2094, Aug. 2023, doi: 10.11591/eei.v12i4.5048.

[51] T. Tuncer, S. Dogan, and A. Subasi, "Novel finger movement classification method based on multi-centered binary pattern using surface electromyogram signals," *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103153, doi: 10.1016/j.bspc.2021.103153.

[52] S. Shen, K. Gu, X.-R. Chen, M. Yang, and R.-C. Wang, "Movements classification of multi-channel sEMG based on CNN and stacking ensemble learning," *IEEE Access*, vol. 7, pp. 137489–137500, 2019, doi: 10.1109/ACCESS.2019.2941977.

[53] N. Sezgin, "A new hand finger movements' classification system based on bicoherence analysis of two-channel surface EMG signals," *Neural Comput. Appl.*, vol. 31, no. 8, pp. 3327–3337, Aug. 2019, doi: 10.1007/s00521-017-3286-z.

[54] N. Nazmi, M. A. A. Rahman, S. A. Mazlan, H. Zamzuri, and M. Mizukawa, "Electromyography (EMG) based signal analysis for physiological device application in lower limb rehabilitation," in *Proc. 2nd Int. Conf. Biomed. Eng. (ICoBE)*, Mar. 2015, pp. 1–5, doi: 10.1109/ICoBE.2015.7235878.

[55] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals," *Expert Syst. Appl.*, vol. 39, no. 12, pp. 10731–10738, Sep. 2012, doi: 10.1016/j.eswa.2012.02.192.

[56] Y. Koçyiğit and M. Korürek, "EMG signal classification using wavelet transform and fuzzy clustering algorithms," in *Proc. ELECO*, 2003, pp. 381–383.

[57] S. Pourmohammadi and A. Maleki, "Stress detection using ECG and EMG signals: A comprehensive study," *Comput. Methods Programs Biomed.*, vol. 193, Sep. 2020, Art. no. 105482, doi: 10.1016/j.cmpb.2020.105482.

[58] M. S. Al-Quraishi, I. Elamvazuthi, T. B. Tang, M. Al-Qurishi, S. Parasuraman, and A. Borboni, "Multimodal fusion approach based on EEG and EMG signals for lower limb movement recognition," *IEEE Sensors J.*, vol. 21, no. 24, pp. 27640–27650, Dec. 2021, doi: 10.1109/JSEN.2021.3119074.

[59] N. E. Krausz, D. Lamotte, I. Batzianoulis, L. J. Hargrove, S. Micera, and A. Billard, "Intent prediction based on biomechanical coordination of EMG and vision-filtered gaze for end-point control of an arm prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 6, pp. 1471–1480, Jun. 2020, doi: 10.1109/TNSRE.2020.2992885.

[60] J. Chen, Y. Sun, and S. Sun, "Improving human activity recognition performance by data fusion and feature engineering," *Sensors*, vol. 21, no. 3, pp. 1–23, 2021, doi: 10.3390/s21030692.

[61] A. Vijayvargiya, B. Singh, R. Kumar, U. Desai, and J. Hemanth, "Hybrid deep learning approaches for sEMG signal-based lower limb activity recognition," *Math. Problems Eng.*, vol. 2022, pp. 1–12, Nov. 2022, doi: 10.1155/2022/3321810.

[62] Y. Luan, Y. Shi, W. Wu, Z. Liu, H. Chang, and J. Cheng, "HAR-sEMG: A dataset for human activity recognition on lower-limb sEMG," *Knowl. Inf. Syst.*, vol. 63, no. 10, pp. 2791–2814, Oct. 2021, doi: 10.1007/s10115-021-01598-w.

[63] K. Xia, J. Huang, and H. Wang, "LSTM-CNN architecture for human activity recognition," *IEEE Access*, vol. 8, pp. 56855–56866, 2020, doi: 10.1109/ACCESS.2020.2982225.

[64] M. Gochoo, S. B. U. D. Tahir, A. Jalal, and K. Kim, "Monitoring real-time personal locomotion behaviors over smart indoor-outdoor environments via body-worn sensors," *IEEE Access*, vol. 9, pp. 70556–70570, 2021, doi: 10.1109/ACCESS.2021.3078513.

[65] Y. Tang, Q. Teng, L. Zhang, F. Min, and J. He, "Layer-wise training convolutional neural networks with smaller filters for human activity recognition using wearable sensors," *IEEE Sensors J.*, vol. 21, no. 1, pp. 581–592, Jan. 2021, doi: 10.1109/JSEN.2020.3015521.

[66] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, "Activity recognition using cell phone accelerometers," *ACM SIGKDD Explorations Newslett.*, vol. 12, no. 2, pp. 74–82, Mar. 2010.

[67] M. Zhang, and A. A. Sawchuk, "USC-HAD: A daily activity dataset for ubiquitous activity recognition using wearable sensors," in *Proc. ACM Conf. Ubiquitous Comput.*, Sep. 2012, pp. 1036–1043.

[68] A. Reiss and D. Stricker, "Introducing a new benchmarked dataset for activity monitoring," in *Proc. 16th Int. Symp. Wearable Comput.*, Jun. 2012, pp. 108–109, doi: 10.1109/ISWC.2012.13.

[69] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, "Fusion of smartphone motion sensors for physical activity recognition," *Sensors*, vol. 14, no. 6, pp. 10146–10176, Jun. 2014, doi: 10.3390/s140610146.

[70] D. Roggen, A. Calatroni, M. Rossi, T. Holleczek, K. Forster, G. Troster, P. Lukowicz, D. Bannach, G. Pirkl, A. Ferscha, J. Doppler, C. Holzmann, M. Kurz, G. Holl, R. Chavarriaga, H. Sagha, H. Bayati, M. Creatura, and J. D. R. Millan, "Collecting complex activity datasets in highly rich networked sensor environments," in *Proc. 7th Int. Conf. Networked Sens. Syst. (INSS)*, Jun. 2010, pp. 233–240, doi: 10.1109/INSS.2010.5573462.

[71] F. Jiang, Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, and Y. Wang, "Artificial intelligence in healthcare: Past, present and future," *Stroke Vascular Neurol.*, vol. 2, no. 4, pp. 230–243, Dec. 2017.

[72] M. M. Ahsan, S. A. Luna, and Z. Siddique, "Machine-learning-based disease diagnosis: A comprehensive review," *Healthcare*, vol. 10, no. 3, p. 541, Mar. 2022, doi: 10.3390/healthcare10030541.

[73] Z. Sun, Q. Ke, H. Rahmani, M. Bennamoun, G. Wang, and J. Liu, "Human action recognition from various data modalities: A review," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 3, pp. 3200–3225, Mar. 2023, doi: 10.1109/TPAMI.2022.3183112.

[74] M. D. Hssayeni, J. Jimenez-Shahed, M. A. Burack, and B. Ghoraani, "Ensemble deep model for continuous estimation of unified Parkinson's disease rating scale III," *Biomed. Eng. OnLine*, vol. 20, no. 1, p. 32, Dec. 2021, doi: 10.1186/s12938-021-00872-w.

[75] M. Roy, T. J. Chen, and J. J. Little, "Classification of puck possession events in ice hockey," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW)*, Jul. 2017, pp. 147–154.

[76] S. Mekruksavanich and A. Jitpattanakul, "LSTM networks using smartphone data for sensor-based human activity recognition in smart homes," *Sensors*, vol. 21, no. 5, pp. 1–25, Mar. 2021, doi: 10.3390/s21051636.

[77] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," 2014, *arXiv:1412.3555*.

[78] N. Dua, S. N. Singh, and V. B. Semwal, "Multi-input CNN-GRU based human activity recognition using wearable sensors," *Computing*, vol. 103, no. 7, pp. 1461–1478, Jul. 2021, doi: 10.1007/s00607-021-00928-8.

[79] S. Yang, L. Xing, W. Liu, W. Qian, W. Qian, H. Xue, and Y. Zhu, "Robust navigation method for wearable human–machine interaction system based on deep learning," *IEEE Sensors J.*, vol. 20, no. 24, pp. 14950–14957, Dec. 2020, doi: 10.1109/JSEN.2020.3010367.

[80] A. Nasr, S. Bell, J. He, R. L. Whittaker, N. Jiang, C. R. Dickerson, and J. McPhee, "MuscleNET: Mapping electromyography to kinematic and dynamic biomechanical variables by machine learning," *J. Neural Eng.*, vol. 18, no. 4, Aug. 2021, Art. no. 0460d3, doi: 10.1088/1741-2552/ac1adc.

[81] H. A. Javaid, M. I. Tiwana, A. Alsanad, J. Iqbal, M. T. Riaz, S. Ahmad, and F. A. Almisned, "Classification of hand movements using MYO armband on an embedded platform," *Electronics*, vol. 10, no. 11, p. 1322, May 2021, doi: 10.3390/electronics10111322.

[82] K. Amanpreet, "Machine learning-based novel approach to classify the shoulder motion of upper limb amputees," *Biocybernetics Biomed. Eng.*, vol. 39, no. 3, pp. 857–867, Jul. 2019, doi: 10.1016/j.bbe.2019.07.007.

[83] N. Tufek, M. Yalcin, M. Altintas, F. Kalaoglu, Y. Li, and S. K. Bahadir, "Human action recognition using deep learning methods on limited sensory data," *IEEE Sensors J.*, vol. 20, no. 6, pp. 3101–3112, Mar. 2020, doi: 10.1109/JSEN.2019.2956901.

[84] L.-F. Shi, Z.-Y. Liu, K.-J. Zhou, Y. Shi, and X. Jing, "Novel deep learning network for gait recognition using multimodal inertial sensors," *Sensors*, vol. 23, no. 2, p. 849, Jan. 2023, doi: 10.3390/s23020849.

[85] W. Gao, L. Zhang, W. Huang, F. Min, J. He, and A. Song, "Deep neural networks for sensor-based human activity recognition using selective kernel convolution," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–13, 2021, doi: 10.1109/TIM.2021.3102735.

[86] W. Guo, X. Sheng, H. Liu, and X. Zhu, "Toward an enhanced human–machine interface for upper-limb prosthesis control with combined EMG and NIRS signals," *IEEE Trans. Hum.-Mach. Syst.*, vol. 47, no. 4, pp. 564–575, Aug. 2017, doi: 10.1109/THMS.2016.2641389.

[87] R. Fu, H. Wang, and W. Zhao, "Dynamic driver fatigue detection using hidden Markov model in real driving condition," *Exp. Syst. Appl.*, vol. 63, pp. 397–411, Nov. 2016, doi: 10.1016/j.eswa.2016.06.042.

[88] T. Althobaiti, S. Katsigiannis, D. West, and N. Ramzan, ''Examining human-horse interaction by means of affect recognition via physiological signals,'' *IEEE Access*, vol. 7, pp. 77857–77867, 2019, doi: 10.1109/ACCESS.2019.2922037.

[89] S. Chen, K. Xu, X. Yao, S. Zhu, B. Zhang, H. Zhou, X. Guo, and B. Zhao, ''Psychophysiological data-driven multi-feature information fusion and recognition of miner fatigue in high-altitude and cold areas,'' *Comput. Biol. Med.*, vol. 133, Jun. 2021, Art. no. 104413, doi: 10.1016/j.compbiomed.2021.104413.

[90] F. Gao, T. Tian, T. Yao, and Q. Zhang, ''Human gait recognition based on multiple feature combination and parameter optimization algorithms,'' *Comput. Intell. Neurosci.*, vol. 2021, pp. 1–14, Feb. 2021, doi: 10.1155/2021/6693206.

[91] M. Diykh, S. Abdulla, R. C. Deo, S. Siuly, and M. Ali, ''Developing a novel hybrid method based on dispersion entropy and adaptive boosting algorithm for human activity recognition,'' *Comput. Methods Programs Biomed.*, vol. 229, Feb. 2023, Art. no. 107305, doi: 10.1016/j.cmpb.2022.107305.

[92] C. Gong, D. Xu, Z. Zhou, N. Vitiello, and Q. Wang, ''BPNN-based real-time recognition of locomotion modes for an active pelvis orthosis with different assistive strategies,'' *Int. J. Humanoid Robot.*, vol. 17, no. 1, Feb. 2020, Art. no. 2050004, doi: 10.1142/S0219843620500048.

[93] J. A. Spanias, A. M. Simon, S. B. Finucane, E. J. Perreault, and L. J. Hargrove, ''Online adaptive neural control of a robotic lower limb prosthesis,'' *J. Neural Eng.*, vol. 15, no. 1, Feb. 2018, Art. no. 016015, doi: 10.1088/1741-2552/aa92a8.

[94] M. A. Gul, M. H. Yousaf, S. Nawaz, Z. U. Rehman, and H. Kim, ''Patient monitoring by abnormal human activity recognition based on CNN architecture,'' *Electronics*, vol. 9, no. 12, p. 1993, Nov. 2020, doi: 10.3390/electronics9121993.

[95] W. Qi, N. Wang, H. Su, and A. Aliverti, ''DCNN based human activity recognition framework with depth vision guiding,'' *Neurocomputing*, vol. 486, pp. 261–271, May 2022, doi: 10.1016/j.neucom.2021.11.044.

[96] B. Xie, B. Li, and A. Harland, ''Movement and gesture recognition using deep learning and wearable-sensor technology,'' in *Proc. Int. Conf. Artif. Intell. Pattern Recognit.* New York, NY, USA: Association for Computing Machinery, Aug. 2018, pp. 26–31, doi: 10.1145/3268866.3268890.

[97] B. Vidya, ''Wearable multi-sensor data fusion approach for human activity recognition using machine learning algorithms,'' *Sens. Actuators A, Phys.*, vol. 341, Jul. 2022, Art. no. 113557, doi: 10.1016/j.sna.2022.113557.

[98] M. Jethanandani, A. Sharma, T. Perumal, and J.-R. Chang, ''Multi-label classification based ensemble learning for human activity recognition in smart home,'' *Internet Things*, vol. 12, Dec. 2020, Art. no. 100324, doi: 10.1016/j.iot.2020.100324.

[99] W. Yang, D. Yang, J. Li, Y. Liu, and H. Liu, ''EMG dataset augmentation approaches for improving the multi-DOF wrist movement regression accuracy and robustness,'' in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2018, doi: 10.1109/ROBIO.2018.8664790.

[100] W. Sun, H. Liu, R. Tang, Y. Lang, J. He, and Q. Huang, ''SEMG-based hand-gesture classification using a generative flow model,'' *Sensors*, vol. 19, no. 8, p. 1952, Apr. 2019, doi: 10.3390/s19081952.

[101] P. Xia, J. Hu, and Y. Peng, ''EMG-based estimation of limb movement using deep learning with recurrent convolutional neural networks,'' *Artif. Organs*, vol. 42, no. 5, pp. E67–E77, May 2018, doi: 10.1111/aor.13004.

[102] J.-L. Ren, Y.-H. Chien, E.-Y. Chia, L.-C. Fu, and J.-S. Lai, ''Deep learning based motion prediction for exoskeleton robot control in upper limb rehabilitation,'' in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 1–12, doi: 10.1109/ICRA.2019.8794187.

[103] I. Sosin, D. Kudenko, and A. Shpilman, ''Continuous gesture recognition from sEMG sensor data with recurrent neural networks and adversarial domain adaptation,'' in *Proc. 15th Int. Conf. Control, Autom., Robot. Vis. (ICARCV)*, Nov. 2018, doi: 10.1109/ICARCV.2018.8581206.

[104] R. Hu, X. Chen, S. Cao, X. Zhang, and X. Chen, ''Investigation on the contributions of different muscles to the generated force based on HD-sEMG and DBN,'' in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2019, pp. 1–12, doi: 10.1109/EMBC.2019.8856690.

[105] Y. Chen, C. Dai, and W. Chen, ''Cross-comparison of EMG-to-force methods for multi-DoF finger force prediction using one-DoF training,'' *IEEE Access*, vol. 8, pp. 13958–13968, 2020, doi: 10.1109/ACCESS.2020.2966007.

[106] B. M. Elbagoury, L. Vladareanu, V. Vlădăreanu, A. B. Salem, A.-M. Travediu, and M. I. Roushdy, ''A hybrid stacked CNN and residual feedback GMDH-LSTM deep learning model for stroke prediction applied on mobile AI smart hospital platform,'' *Sensors*, vol. 23, no. 7, p. 3500, Mar. 2023, doi: 10.3390/s23073500.

[107] A. M. Helmi, M. A. A. Al-Qaness, A. Dahou, and M. A. Elaziz, ''Human activity recognition using marine predators algorithm with deep learning,'' *Future Gener. Comput. Syst.*, vol. 142, pp. 340–350, May 2023, doi: 10.1016/j.future.2023.01.006.

[108] K. Nguyen, V. V. Nguyen, N. T. Mai, A. H. Nguyen, and A. V. Nguyen, ''Human gait analysis using hybrid convolutional neural networks,'' *J. Comput. Sci. Cybern.*, vol. 39, no. 2, pp. 125–142, Jun. 2023, doi: 10.15625/1813-9663/18067.

[109] I. E. Jaramillo, C. Chola, J.-G. Jeong, J.-H. Oh, H. Jung, J.-H. Lee, W. H. Lee, and T.-S. Kim, ''Human activity prediction based on forecasted IMU activity signals by sequence-to-sequence deep neural networks,'' *Sensors*, vol. 23, no. 14, p. 6491, Jul. 2023, doi: 10.3390/s23146491.

[110] Y. Liu, X. Li, L. Yang, G. Bian, and H. Yu, ''A CNN-transformer hybrid recognition approach for sEMG-based dynamic gesture prediction,'' *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–16, 2023, doi: 10.1109/TIM.2023.3273651.

[111] H. Zhang, K. Yang, G. Cao, and C. Xia, ''ViT-LLMR: Vision transformer-based lower limb motion recognition from fusion signals of MMG and IMU,'' *Biomed. Signal Process. Control*, vol. 82, Apr. 2023, Art. no. 104508, doi: 10.1016/j.bspc.2022.104508.

[112] M. A. A. Al-Qaness, A. Dahou, M. A. Elaziz, and A. M. Helmi, ''Multi-ResAtt: Multilevel residual network with attention for human activity recognition using wearable sensors,'' *IEEE Trans. Ind. Informat.*, vol. 19, no. 1, pp. 144–152, Jan. 2023, doi: 10.1109/TII.2022.3165875.

[113] M. Atif Hanif, T. Akram, A. Shahzad, M. Attique Khan, U. Tariq, J.-I. Choi, Y. Nam, and Z. Zulfiqar, ''Smart devices based multisensory approach for complex human activity recognition,'' *Comput., Mater. Continua*, vol. 70, no. 2, pp. 3221–3234, 2022, doi: 10.32604/cmc.2022.019815.

[114] N. K. Karnam, S. R. Dubey, A. C. Turlapaty, and B. Gokaraju, ''EMGHandNet: A hybrid CNN and bi-LSTM architecture for hand activity classification using surface EMG signals,'' *Biocybernetics Biomed. Eng.*, vol. 42, no. 1, pp. 325–340, Jan. 2022, doi: 10.1016/j.bbe.2022.02.005.

[115] W. Wang, R. Li, Y. Chen, Y. Sun, and Y. Jia, ''Predicting human intentions in human–robot hand-over tasks through multimodal learning,'' *IEEE Trans. Autom. Sci. Eng.*, vol. 19, no. 3, pp. 2339–2353, Jul. 2022, doi: 10.1109/TASE.2021.3074873.

[116] G. Hajian and E. Morin, ''Deep multi-scale fusion of convolutional neural networks for EMG-based movement estimation,'' *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 486–495, 2022, doi: 10.1109/TNSRE.2022.3153252.

[117] S. Geravesh and V. Rupapara, ''Artificial neural networks for human activity recognition using sensor based dataset,'' *Multimedia Tools Appl.*, vol. 82, no. 10, pp. 14815–14835, Apr. 2023, doi: 10.1007/s11042-022-13716-z.

[118] L. Liu, ''Ambulatory human gait phase detection using wearable inertial sensors and Hidden Markov model,'' *Sensors*, vol. 21, no. 4, pp. 1–24, Jan. 2021, doi: 10.3390/s21041347.

[119] L. Tran, T. Hoang, T. Nguyen, H. Kim, and D. Choi, ''Multi-model long short-term memory network for gait recognition using window-based data segment,'' *IEEE Access*, vol. 9, pp. 23826–23839, 2021, doi: 10.1109/ACCESS.2021.3056880.

[120] Y.-W. Kim, K.-L. Joa, H.-Y. Jeong, and S. Lee, ''Wearable IMU-based human activity recognition algorithm for clinical balance assessment using 1D-CNN and GRU ensemble model,'' *Sensors*, vol. 21, no. 22, p. 7628, Nov. 2021, doi: 10.3390/s21227628.

[121] S. K. Challa, A. Kumar, and V. B. Semwal, ''A multibranch CNN-BiLSTM model for human activity recognition using wearable sensor data,'' *Vis. Comput.*, vol. 38, no. 12, pp. 4095–4109, Dec. 2022, doi: 10.1007/s00371-021-02283-3.

[122] *Turkey Section. EMB Chapter. and Institute of Electrical and Electronics Engineers*, Tıp, Teknolojileri Kongresi, TIPTEKNO'20, Kasım, Institute of Electrical and Electronics Engineers, Piscataway, NJ, USA, 2020.

[123] S. Zhou, K. Yin, F. Fei, and K. Zhang, "Surface electromyography–based hand movement recognition using the Gaussian mixture model, multilayer perceptron, and AdaBoost method," *Int. J. Distrib. Sensor Netw.*, vol. 15, no. 4, Apr. 2019, Art. no. 155014771984606, doi: 10.1177/1550147719846060.

[124] M. Montazerin, S. Zabihi, E. Rahimian, A. Mohammadi, and F. Naderkhani, "ViT-HGR: Vision transformer-based hand gesture recognition from high density surface EMG signals," in *Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2022, pp. 5115–5119, doi: 10.1109/EMBC48229.2022.9871489.

[125] M. Montazerin, E. Rahimian, F. Naderkhani, S. F. Atashzar, S. Yanushkevich, and A. Mohammadi, "Transformer-based hand gesture recognition from instantaneous to fused neural decomposition of high-density EMG signals," *Sci. Rep.*, vol. 13, no. 1, Jul. 2023, Art. no. 11000, doi: 10.1038/s41598-023-36490-w.

[126] E. Rahimian, S. Zabihi, A. Asif, D. Farina, S. F. Atashzar, and A. Mohammadi, "TEMGNet: Deep transformer-based decoding of upperlimb sEMG for hand gestures recognition," 2021, *arXiv:2109.12379*.

[127] S. Zabihi, E. Rahimian, A. Asif, and A. Mohammadi, "TraHGR: Transformer for hand gesture recognition via ElectroMyography," 2022, *arXiv:2203.16336*.

[128] S. Shen, X. Wang, F. Mao, L. Sun, and M. Gu, "Movements classification through sEMG with convolutional vision transformer and stacking ensemble learning," *IEEE Sensors J.*, vol. 22, no. 13, pp. 13318–13325, Jul. 2022, doi: 10.1109/JSEN.2022.3179535.

[129] H. Liu, T. Xue, and T. Schultz, "On a real real-time wearable human activity recognition system," in *Proc. 16th Int. Joint Conf. Biomed. Eng. Syst. Technol.*, 2023, pp. 711–720, doi: 10.5220/0011927700003414.

[130] O. Kerdjidj, K. Amara, F. Harizi, and H. Boumridja, "Implementing hand gesture recognition using EMG on the Zynq circuit," *IEEE Sensors J.*, vol. 23, no. 9, pp. 10054–10061, May 2023, doi: 10.1109/JSEN.2023.3259150.

[131] A. S. Kundu, O. Mazumder, P. K. Lenka, and S. Bhaumik, "Hand gesture recognition based omnidirectional wheelchair control using IMU and EMG sensors," *J. Intell. Robotic Syst.*, vol. 91, nos. 3–4, pp. 529–541, Sep. 2018, doi: 10.1007/s10846-017-0725-0.

[132] F. Bai, C.-M. Chew, J. Li, B. Shen, and T. M. Lubecki, "Muscle force estimation method with surface EMG for a lower extremities rehabilitation device," in *Proc. IEEE 13th Int. Conf. Rehabil. Robot. (ICORR)*, Jun. 2013, pp. 1–15, doi: 10.1109/ICORR.2013.6650419.

[133] T. Franco, L. Sestrem, P. R. Henriques, P. Alves, M. J. Varanda Pereira, D. Brandão, P. Leitão, and A. Silva, "Motion sensors for knee angle recognition in muscle rehabilitation solutions," *Sensors*, vol. 22, no. 19, p. 7605, Oct. 2022, doi: 10.3390/s22197605.

[134] Y. Dang, Z. Liu, X. Yang, L. Ge, and S. Miao, "A fatigue assessment method based on attention mechanism and surface electromyography," *Internet Things Cyber-Physical Syst.*, vol. 3, pp. 112–120, Jan. 2023, doi: 10.1016/j.iotcps.2023.03.002.

[135] E. Kim, J. Shin, Y. Kwon, and B. Park, "EMG-based dynamic hand gesture recognition using edge AI for human–robot interaction," *Electronics*, vol. 12, no. 7, p. 1541, Mar. 2023, doi: 10.3390/electronics12071541.

[136] J. Tu, Z. Dai, X. Zhao, and Z. Huang, "Lower limb motion recognition based on surface electromyography," *Biomed. Signal Process. Control*, vol. 81, Mar. 2023, Art. no. 104443, doi: 10.1016/j.bspc.2022.104443.

[137] I. Chihi, L. Sidhom, and E. N. Kamavuako, "Hammerstein–Wiener multimodel approach for fast and efficient muscle force estimation from EMG signals," *Biosensors*, vol. 12, no. 2, p. 117, Feb. 2022, doi: 10.3390/bios12020117.

[138] L. Xu, K. Zhang, G. Yang, and J. Chu, "Gesture recognition using dual-stream CNN based on fusion of sEMG energy kernel phase portrait and IMU amplitude image," *Biomed. Signal Process. Control*, vol. 73, Mar. 2022, Art. no. 103364, doi: 10.1016/j.bspc.2021.103364.

[139] A. Vijayvargiya, P. Singh, R. Kumar, and N. Dey, "Hardware implementation for lower limb surface EMG measurement and analysis using explainable AI for activity recognition," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–9, 2022, doi: 10.1109/TIM.2022.3198443.

[140] N. Krishnaraj, "Implementation of a human activity monitoring system through IoT sensor and blynk cloud platform," *J. Inf. Technol. Digit. World*, vol. 4, no. 2, pp. 105–113, Jul. 2022, doi: 10.36548/jitdw.2022.2.005.

[141] H. Park, N. Kim, G. H. Lee, and J. K. Choi, "MultiCNN-FilterLSTM: Resource-efficient sensor-based human activity recognition in IoT applications," *Future Gener. Comput. Syst.*, vol. 139, pp. 196–209, Feb. 2023, doi: 10.1016/j.future.2022.09.024.

[142] J. Wang, Y. Dai, and X. Si, "Analysis and recognition of human lower limb motions based on electromyography (EMG) signals," *Electronics*, vol. 10, no. 20, p. 2473, Oct. 2021, doi: 10.3390/electronics10202473.

[143] Z. Fu, X. He, E. Wang, J. Huo, J. Huang, and D. Wu, "Personalized human activity recognition based on integrated wearable sensor and transfer learning," *Sensors*, vol. 21, no. 3, pp. 1–23, Feb. 2021, doi: 10.3390/s21030885.

[144] P. Fard Moshiri, R. Shahbazian, M. Nabati, and S. A. Ghorashi, "A CSI-based human activity recognition using deep learning," *Sensors*, vol. 21, no. 21, p. 7225, Oct. 2021, doi: 10.3390/s21217225.

[145] C. Wang, S. Wang, X. Zhao, J. Fang, and M. Zhang, "EMG-based gesture recognition system and its hardware implementation," in *Proc. 2nd Int. Conf. Big Data Artif. Intell. Softw. Eng.* Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, 2021, pp. 420–428, doi: 10.1109/ICBASE53849.2021.00084.

[146] X. Zhou, W. Liang, K. I. Wang, H. Wang, L. T. Yang, and Q. Jin, "Deep-learning-enhanced human activity recognition for Internet of Healthcare Things," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6429–6438, Jul. 2020, doi: 10.1109/JIOT.2020.2985082.

[147] N. B. Gaikwad, V. Tiwari, A. Keskar, and N. C. Shivaprakash, "Efficient FPGA implementation of multilayer perceptron for real-time human activity classification," *IEEE Access*, vol. 7, pp. 26696–26706, 2019, doi: 10.1109/ACCESS.2019.2900084.

[148] R. P. R. Kumar and S. Polepaka, "Performance comparison of random forest classifier and convolution neural network in predicting heart diseases," in *Proc. 3rd Int. Conf. Comput. Intell. Inform.*, in Advances in Intelligent Systems and Computing, 2020, pp. 683–691, doi: 10.1007/978-981-15-1480-7_59.

[149] W. Yang, Y. Si, D. Wang, and B. Guo, "Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine," *Comput. Biol. Med.*, vol. 101, pp. 22–32, Oct. 2018, doi: 10.1016/j.compbiomed.2018.08.003.

[150] B. Navaneeth and M. Suchetha, "A dynamic pooling based convolutional neural network approach to detect chronic kidney disease," *Biomed. Signal Process. Control*, vol. 62, Sep. 2020, Art. no. 102068, doi: 10.1016/j.bspc.2020.102068.

[151] A. Nithya, A. Appathurai, N. Venkatadri, D. R. Ramji, and C. A. Palagan, "Kidney disease detection and segmentation using artificial neural network and multi-kernel K-means clustering for ultrasound images," *Measurement*, vol. 149, Jan. 2020, Art. no. 106952, doi: 10.1016/j.measurement.2019.106952.

[152] K. Rajendran, M. Jayabalan, and V. Thiruchelvam, "Predicting breast cancer via supervised machine learning methods on class imbalanced data," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 8, 2020, doi: 10.14569/IJACSA.2020.0110808.

[153] C.-M. Lo, S.-W. Chan, Y.-W. Yang, Y.-C. Chang, C.-S. Huang, Y.-S. Jou, and R.-F. Chang, "Feasibility testing: Three-dimensional tumor mapping in different orientations of automated breast ultrasound," *Ultrasound Med. Biol.*, vol. 42, no. 5, pp. 1201–1210, May 2016, doi: 10.1016/j.ultrasmedbio.2015.12.006.

[154] A. Ali, M. Alrubei, L. F. M. Hassan, M. Al-Ja'afari, and S. Abdulwahed, "Diabetes classification based on KNN," *IIUM Eng. J.*, vol. 21, no. 1, pp. 175–181, 2020, doi: 10.31436/iiumej.v21i1.1206.

[155] G. M. M. Alshmrani, Q. Ni, R. Jiang, H. Pervaiz, and N. M. Elshennawy, "A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images," *Alexandria Eng. J.*, vol. 64, pp. 923–935, Feb. 2023, doi: 10.1016/j.aej.2022.10.053.

[156] G. Nandhini and J. Aravinth, "Chronic kidney disease prediction using machine learning techniques," in *Proc. Int. Conf. Recent Trends Electron., Inf., Commun. Technol. (RTEICT)*, Aug. 2021, pp. 185–190, doi: 10.1109/rteict52294.2021.9573971.

[157] Y. Zhang, D. Wan, M. Chen, Y. Li, H. Ying, G. Yao, Z. Liu, and G. Zhang, "Automated machine learning-based model for the prediction of delirium in patients after surgery for degenerative spinal disease," *CNS Neurosci. Therapeutics*, vol. 29, no. 1, pp. 282–295, Jan. 2023, doi: 10.1111/cns.14002.

[158] W. Gouda, N. U. Sama, G. Al-Waakid, M. Humayun, and N. Z. Jhanjhi, "Detection of skin cancer based on skin lesion images using deep learning," *Healthcare*, vol. 10, no. 7, p. 1183, Jun. 2022, doi: 10.3390/healthcare10071183.

[159] B. Guan, "Deep learning approach to predict pain progression in knee osteoarthritis," *Skeletal Radiol.*, vol. 51, no. 2, pp. 363–373, 2022, doi: 10.1007/s00256-021-03773-0.

[160] A. Maurya, R. K. Yadav, M. Kumar, and Saumya, "Comparative study of human activity recognition on sensory data using machine learning and deep learning," in *Proc. Integr. Intell. Enable Netw. Comput.*, 2021, pp. 63–71, doi: 10.1007/978-981-33-6307-6_8.

[161] F. Alshehri and G. Muhammad, "A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare," *IEEE Access*, vol. 9, pp. 3660–3678, 2021, doi: 10.1109/ACCESS.2020.3047960.

[162] B. Laliberte, "The journey to intent-based networking: Ten key principles for accelerating adoption," 2018.

[163] S. Mekruksavanich, P. Jantawong, and A. Jitpattanakul, "A deep learning-based model for human activity recognition using biosensors embedded into a smart knee bandage," *Proc. Comput. Sci.*, vol. 214, pp. 621–627, Jan. 2022, doi: 10.1016/j.procs.2022.11.220.

[164] S. Ramasamy Ramamurthy and N. Roy, "Recent trends in machine learning for human activity recognition—A survey," *WIREs Data Mining Knowl. Discovery*, vol. 8, no. 4, p. 1254, Jul. 2018, doi: 10.1002/widm.1254.

[165] P. Kumari, L. Mathew, and P. Syal, "Increasing trend of wearables and multimodal interface for human activity monitoring: A review," *Biosensors Bioelectron.*, vol. 90, pp. 298–307, Apr. 2017, doi: 10.1016/j.bios.2016.12.001.

[166] H.-B. Zhang, Y.-X. Zhang, B. Zhong, Q. Lei, L. Yang, J.-X. Du, and D.-S. Chen, "A comprehensive survey of vision-based human action recognition methods," *Sensors*, vol. 19, no. 5, p. 1005, Feb. 2019, doi: 10.3390/s19051005.

[167] Ó. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1192–1209, 4th Quart., 2013, doi: 10.1109/SURV.2012.110112.00192.

[168] S. Wang and G. Zhou, "A review on radio based activity recognition," *Digit. Commun. Netw.*, vol. 1, no. 1, pp. 20–29, Feb. 2015, doi: 10.1016/j.dcan.2015.02.006.

[169] L. Onofri, P. Soda, M. Pechenizkiy, and G. Iannello, "A survey on using domain and contextual knowledge for human activity recognition in video streams," *Exp. Syst. Appl.*, vol. 63, pp. 97–111, Nov. 2016, doi: 10.1016/j.eswa.2016.06.011.

[170] M. Cornacchia, K. Ozcan, Y. Zheng, and S. Velipasalar, "A survey on activity detection and classification using wearable sensors," *IEEE Sensors J.*, vol. 17, no. 2, pp. 386–403, Jan. 2017, doi: 10.1109/JSEN.2016.2628346.

[171] Z. S. Abdallah, M. M. Gaber, B. Srinivasan, and S. Krishnaswamy, "Activity recognition with evolving data streams: A review," *ACM Comput. Surveys*, vol. 51, no. 4, pp. 1–36, Jul. 2019, doi: 10.1145/3158645.

[172] P. Wang, W. Li, P. Ogunbona, J. Wan, and S. Escalera, "RGB-D-based human motion recognition with deep learning: A survey," *Comput. Vis. Image Understand.*, vol. 171, pp. 118–139, Jun. 2018, doi: 10.1016/j.cviu.2018.04.007.

[173] E. E. Cust, A. J. Sweeting, K. Ball, and S. Robertson, "Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance," *J. Sports Sci.*, vol. 37, no. 5, pp. 568–600, Mar. 2019, doi: 10.1080/02640414.2018.1521769.

[174] B. Rodríguez-Tapia, I. Soto, D. M. Martínez, and N. C. Arballo, "Myoelectric interfaces and related applications: Current state of EMG signal processing—A systematic review," *IEEE Access*, vol. 8, pp. 7792–7805, 2020, doi: 10.1109/ACCESS.2019.2963881.

[175] N. Islam, Y. Faheem, I. U. Din, M. Talha, M. Guizani, and M. Khalil, "A blockchain-based fog computing framework for activity recognition as an application to e-healthcare services," *Future Gener. Comput. Syst.*, vol. 100, pp. 569–578, Nov. 2019, doi: 10.1016/j.future.2019.05.059.

[176] H. Zhang, Y. Liu, Z. Qing, J. He, S. Teng, X. Wang, C. Hao, S. Zhang, D. Fan, and G. Su, "Domain contrast network for cross-muscle ALS disease identification with EMG signal," *Biomed. Signal Process. Control*, vol. 82, Apr. 2023, Art. no. 104582, doi: 10.1016/j.bspc.2023.104582.

[177] S. Nooruddin, M. M. Islam, F. A. Sharna, H. Alhetari, and M. N. Kabir, "Sensor-based fall detection systems: A review," *J. Ambient Intell. Humanized Comput.*, vol. 13, no. 5, pp. 2735–2751, May 2022, doi: 10.1007/s12652-021-03248-z.

[178] A. Sathyanarayana, J. Srivastava, and L. Fernandez-Luque, "The science of sweet dreams: Predicting sleep efficiency from wearable device data," *Computer*, vol. 50, no. 3, pp. 30–38, Mar. 2017, doi: 10.1109/MC.2017.91.

[179] M. Panwar, D. Biswas, H. Bajaj, M. Jöbges, R. Turk, K. Maharatna, and A. Acharyya, "Rehab-net: Deep learning framework for arm movement classification using wearable sensors for stroke rehabilitation," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 11, pp. 3026–3037, Nov. 2019, doi: 10.1109/TBME.2019.2899927.

[180] K. Rezaee, S. Savarkar, X. Yu, and J. Zhang, "A hybrid deep transfer learning-based approach for Parkinson's disease classification in surface electromyography signals," *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103161, doi: 10.1016/j.bspc.2021.103161.

[181] F. Sadikoglu, C. Kavalcioglu, and B. Dagman, "Electromyogram (EMG) signal detection, classification of EMG signals and diagnosis of neuropathy muscle disease," *Proc. Comput. Sci.*, vol. 120, pp. 422–429, 2017, doi: 10.1016/j.procs.2017.11.259.

[182] J. Figueiredo, C. P. Santos, and J. C. Moreno, "Automatic recognition of gait patterns in human motor disorders using machine learning: A review," *Med. Eng. Phys.*, vol. 53, pp. 1–12, Mar. 2018, doi: 10.1016/j.medengphy.2017.12.006.

[183] M. Shahverdy, M. Fathy, R. Berangi, and M. Sabokrou, "Driver behavior detection and classification using deep convolutional neural networks," *Exp. Syst. Appl.*, vol. 149, Jul. 2020, Art. no. 113240, doi: 10.1016/j.eswa.2020.113240.

[184] A. I. N. Alshbatat, S. Alhameli, S. Almazrouei, S. Alhameli, and W. Almarar, "Automated vision-based surveillance system to detect drowning incidents in swimming pools," in *Proc. Adv. Sci. Eng. Technol. Int. Conf. (ASET)*, Feb. 2020, pp. 1–5, doi: 10.1109/ASET48392.2020.9118248.

[185] E. Carlson, P. Saari, B. Burger, and P. Toiviainen, "Dance to your own drum: Identification of musical genre and individual dancer from motion capture using machine learning," *J. New Music Res.*, vol. 49, no. 2, pp. 162–177, Mar. 2020, doi: 10.1080/09298215.2020.1711778.

[186] D. C. Luvizon, D. Picard, and H. Tabia, "Multi-task deep learning for real-time 3D human pose estimation and action recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 8, pp. 2752–2764, Aug. 2021, doi: 10.1109/TPAMI.2020.2976014.

[187] K. Kim, A. Jalal, and M. Mahmood, "Vision-based human activity recognition system using depth silhouettes: A smart home system for monitoring the residents," *J. Electr. Eng. Technol.*, vol. 14, no. 6, pp. 2567–2573, Nov. 2019, doi: 10.1007/s42835-019-00278-8.

[188] A. Ç. Seçkin, "Otonom araçların görsel eğitimi için EEG, EMG ve IMU ile etiketleme Sistemi," in *Proc. Bilişim Teknolojileri Dergisi*, Oct. 2019, pp. 299–305, doi: 10.17671/gazibtd.542662.

[189] B. Xie, J. Meng, B. Li, and A. Harland, "Biosignal-based transferable attention bi-ConvGRU deep network for hand-gesture recognition towards online upper-limb prosthesis control," *Comput. Methods Programs Biomed.*, vol. 224, Sep. 2022, Art. no. 106999, doi: 10.1016/j.cmpb.2022.106999.

[190] M. Gaspar, O. Postolache, J. Monge, and J. Mendes, "Augmented reality serious games for smart physical rehabilitation," in *Proc. 13th Int. Symp. Adv. Topics Elect. Eng. (ATEE)*, Mar. 2023, pp. 1–6, doi: 10.1109/ATEE58038.2023.10108178.

[191] J. Á. Gallego, J. Ibanez, J. L. Dideriksen, J. I. Serrano, M. D. del Castillo, D. Farina, and E. Rocon, "A multimodal human–robot interface to drive a neuroprosthesis for tremor management," *IEEE Trans. Syst., Man, Cybern., C Appl. Rev.*, vol. 42, no. 6, pp. 1159–1168, Nov. 2012, doi: 10.1109/TSMCC.2012.2200101.

[192] Z. Wang, J. Wang, H. Zhao, S. Qiu, J. Li, F. Gao, and X. Shi, "Using wearable sensors to capture posture of the human lumbar spine in competitive swimming," *IEEE Trans. Hum.-Mach. Syst.*, vol. 49, no. 2, pp. 194–205, Apr. 2019, doi: 10.1109/THMS.2019.2892318.

[193] Y. J. Kim, K. D. Kim, S. H. Kim, S. Lee, and H. S. Lee, "Golf Swing analysis system with a dual band and motion analysis algorithm," *IEEE Trans. Consum. Electron.*, vol. 63, no. 3, pp. 309–317, Aug. 2017, doi: 10.1109/TCE.2017.014937.

[194] B. Milosevic, S. Benatti, and E. Farella, "Design challenges for wearable EMG applications," in *Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE)*, Mar. 2017, pp. 1432–1437, doi: 10.23919/DATE.2017.7927217.

[195] S. Zhang, Y. Li, S. Zhang, F. Shahabi, S. Xia, Y. Deng, and N. Alshurafa, "Deep learning in human activity recognition with wearable sensors: A review on advances," *Sensors*, vol. 22, no. 4, p. 1476, Feb. 2022, doi: 10.3390/s22041476.

[196] C. L. Toledo-Peral, G. Vega-Martínez, J. A. Mercado-Gutiérrez, G. Rodríguez-Reyes, A. Vera-Hernández, L. Leija-Salas, and J. Gutiérrez-Martínez, "Virtual/augmented reality for rehabilitation applications using electromyography as control/biofeedback: Systematic literature review," *Electronics*, vol. 11, no. 14, p. 2271, Jul. 2022, doi: 10.3390/electronics11142271.

[197] S. Kiani, I. Rezaei, S. Abasi, S. Zakerabasali, and A. Yazdani, ''Technical aspects of virtual augmented reality-based rehabilitation systems for musculoskeletal disorders of the lower limbs: A systematic review,'' *BMC Musculoskeletal Disorders*, vol. 24, no. 1, p. 06062, Jan. 2023, doi: 10.1186/s12891-022-06062-6.

[198] P. Kumar and N. Hamirpur. (2021). *Human Activity Recognition with Deep Learning: Overview, Challenges & Possibilities*. [Online]. Available: http://dx.doi.org/10.20944/preprints202102.0349.v2

[199] A. N. Hussain, S. A. Abboud, B. A. Jumaa, and M. N. Abdullah. (2021). *Gait Classification Using Machine Learning for Foot Disseises Diagnosis*. [Online]. Available: https://www.techniumscience.com

[200] D. Farina, R. Merletti, and R. M. Enoka, ''The extraction of neural strategies from the surface EMG,'' *J. Appl. Physiol.*, vol. 96, no. 4, pp. 1486–1495, Apr. 2004, doi: 10.1152/japplphysiol.01070.2003.

[201] H. Bansal, B. Chinagundi, P. S. Rana, and N. Kumar, ''An ensemble machine learning technique for detection of abnormalities in knee movement sustainability,'' *Sustainability*, vol. 14, no. 20, p. 13464, Oct. 2022, doi: 10.3390/su142013464.

[202] I. A. Lawal and S. Bano, ''Deep human activity recognition using wearable sensors,'' in *Proc. 12th ACM Int. Conf. Pervasive Technol. Rel. Assistive Environments*, pp. 45–48, Jun. 2019, doi: 10.1145/3316782.3321538.

[203] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, ''A robust human activity recognition system using smartphone sensors and deep learning,'' *Future Gener. Comput. Syst.*, vol. 81, pp. 307–313, Apr. 2018, doi: 10.1016/j.future.2017.11.029.

[204] S. Ma, B. Lv, C. Lin, X. Sheng, and X. Zhu, ''EMG signal filtering based on variational mode decomposition and sub-band thresholding,'' *IEEE J. Biomed. Health Inform.*, vol. 25, no. 1, pp. 45–47, 2021.

[205] C. Li, G. Li, G. Jiang, D. Chen, and H. Liu, ''Surface EMG data aggregation processing for intelligent prosthetic action recognition,'' *Neural Comput. Appl.*, vol. 32, pp. 16795–16806, Nov. 2020.

[206] J. R. Torres-Castillo, C. O. López-López, and M. A. Padilla-Castaneda, ''Neuromuscular disorders detection through time-frequency analysis and classification of multi-muscular EMG signals using Hilbert–Huang transform,'' *Biomed. Signal Process. Control*, vol. 71, Jan. 2022, Art. no. 103037.

[207] H. Elmohandes, S. Eldawlatly, J. M. C. Audí, R. Ruff, and K. P. Hoffmann, ''Decoding arm kinematics from EMG signals using Kalman filter,'' in *Proc. 8th Int. Conf. Biomed. Eng. Technol.*, Apr. 2018, pp. 96–102.

[208] S. Bhagwat and P. Mukherji, ''Electromyogram (EMG) based fingers movement recognition using sparse filtering of wavelet packet coefficients,'' *Sādhanā*, vol. 45, p. 3, Dec. 2020.

[209] A. Vijayvargiya, et al., ''Hybrid deep learning approaches for sEMG signal-based lower limb activity recognition,'' *Math. Problems Eng.*, 2022.

[210] T. Roland, S. Amsuess, M. Russold, and W. Baumgartner, ''Ultra-low-power digital filtering for insulated EMG sensing,'' *Sensors*, vol. 19, p. 959, Jan. 2019.

[211] C. J. Dakin et al., ''Rectification is required to extract oscillatory envelope modulation from surface electromyographic signals,'' *J. Neurophysiol.*, vol. 112, no. 7, pp. 1685–1691, 2014.

[212] N. J. Ward et al., ''Rectification of EMG in low force contractions improves detection of motor unit coherence in the beta-frequency band,'' *J. Neurophysiol.*, vol. 110, no. 8, pp. 1744–1750, 2013.

[213] L. Bi and C. Guan, ''A review on EMG-based motor intention prediction of continuous human upper limb motion for human-robot collaboration,'' *Biomed. Signal Process. Control*, vol. 51, pp. 113–127, 2019.

[214] A. Bhattacharya, A. Sarkar, and P. Basak, ''Time domain multi-feature extraction and classification of human hand movements using surface EMG,'' in *Proc. 4th Int. Conf. Adv. Comput. Commun. Syst. (ICACCS)*, Coimbatore, India, 2017, pp. 1–5, doi: 10.1109/ICACCS.2017.8014594.

[215] A. Phinyomark, R. N. Khushaba, and E. Scheme, ''Feature extraction and selection for myoelectric control based on wearable EMG sensors,'' *Sensors*, vol. 18, no. 5, p. 1615, 2018.

[216] J. Too et al., ''Classification of EMG signal based on time domain and frequency domain features,'' *Int. J. Hum. Technol. Interact.*, vol. 1, no. 1, pp. 25–30, 2017.

[217] V. Shanmuganathan, H. R. Yesudhas, M. S. Khan, M. Khari, and A. H. Gandomi, ''R-CNN and wavelet feature extraction for hand gesture recognition with EMG signals,'' *Neural Comput. Appl.*, vol. 32, pp. 16723–16736, 2020.

[218] D. Zhang et al., ''PCA and LDA for EMG-based control of bionic mechanical hand,'' in *Proc. IEEE Int. Conf. Inf. Automat*. IEEE, 2012.

[219] S. Negi, Y. Kumar, and V. M. Mishra, ''Feature extraction and classification for EMG signals using linear discriminant analysis,'' in*Proc. 2nd Int. Conf. Adv. Comput., Commun., Automat. (ICACCA) (Fall)*, Bareilly, India, 2016, pp. 1–6, doi: 10.1109/ICACCAF.2016.7748960.

[220] M. A. A. Faisal et al., ''Exploiting domain transformation and deep learning for hand gesture recognition using a low-cost dataglove,'' *Sci. Rep.*, vol. 12, no. 1, p. 21446, 2022.

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