International Journal of Intelligent Information Systems
2024, Vol. 13, No. 2, pp. 29-42
https://doi.org/10.11648/j.ijiis.20241302.12

Research Article

Evaluation of Approaches for Early Stroke Detection and Diagnosis Using EMG Data: Features, Techniques, and Challenges

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Abstract

This paper provides a thorough analysis of the use of electromyography (EMG) data in early stroke diagnosis and detection. Stroke continues to be a major global cause of disability and death, which emphasises the critical need for an accurate diagnosis made quickly to improve patient outcomes. Early detection is still difficult to achieve, even with improvements in medical imaging and testing technologies. By detecting minute variations in muscle activity linked to stroke symptoms, EMG data analysis offers a viable method for early stroke identification. The review delves into the diverse methodologies and strategies utilised to leverage EMG data for the purpose of stroke diagnosis, encompassing the application of deep learning models and machine learning algorithms. The paper proposes a structured framework for classifying approaches for early stroke detection and diagnosis using EMG data, providing a systematic way to categorize and compare different methodologies. The paper concludes by highlighting the revolutionary potential of EMG-based techniques in improving the diagnosis of strokes earlier and urging more study to address current issues and make clinical application easier.

Keywords

Electromyography (EMG), Stroke, Stroke Detection, Stroke Diagnosis, Neuromuscular, Muscle, Machine Learning, Deep learning, Artificial Neural Network

1. Introduction

Stroke is a leading cause of mortality and long-term disability worldwide, emphasizing the critical need for effective early detection and diagnosis methods. Electromyography (EMG) data analysis has emerged as a promising approach for detecting stroke at its onset, enabling timely intervention and improved patient outcomes. The challenge lies in accurately identifying stroke symptoms in their early stages when treatment interventions can be most effective. Traditional stroke detection methods often rely on clinical signs and diagnostic tests, which may delay diagnosis and limit the window for intervention. Therefore, there is a pressing need for advanced techniques that can detect stroke promptly and accurately using non-invasive and efficient methods.

Prior research efforts have explored various approaches to early stroke detection, including the analysis of EMG data. These studies have investigated the use of machine learning algorithms, neural networks, and signal processing techniques to extract relevant features from EMG signals and

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Received: 19 March 2024; **Accepted:** 3 April 2024; **Published:** 17 April 2024

identify stroke-related abnormalities [20, 37, 40]. While these approaches have shown promise, there remains a need for comprehensive reviews and evaluations to identify the most effective techniques and address existing challenges [12, 24].

The paper proposes a systematic review of early stroke detection and diagnosis methods utilizing EMG data. By synthesizing existing literature, the aim is to provide insights into the features, techniques, and challenges associated with EMG-based stroke detection. This review encompasses a comprehensive analysis of the strengths and limitations of different approaches, facilitating the identification of gaps in current research and opportunities for future advancements.

The main research question addressed in this paper is: *How can electromyography (EMG) data be effectively utilized for early detection and diagnosis of stroke, and what are the challenges associated with its implementation?* In order to address the research question, a thorough review of relevant studies was conducted. Systematic search strategies were employed to identify studies focusing on EMG-based stroke detection techniques, ensuring comprehensive coverage of the literature. Data extraction and synthesis was performed to analyse key findings and identify common themes across studies.

The aim of this paper is twofold: first, to systematically evaluate and compare the features, techniques, and challenges associated with early stroke detection and diagnosis using electromyography (EMG); and second, to propose a structured framework for structured framework for classification of approaches for early stroke detection and diagnosis using EMG Data, thereby facilitating a systematic assessment of performance metrics and criteria across different methodologies.

The main contributions of this research paper encompass several key aspects:

1. Conducting a comprehensive review of existing literature on the utilization of EMG data for early stroke detection and diagnosis, and synthesizing insights from various studies.
2. Synthesizing different approaches for early stroke detection and diagnosis, and categorizing them into five (5) main categories: Data Acquisition and Processing Techniques, Feature Extraction and Analysis Methods, Machine Learning and Deep Learning Models, Application in Rehabilitation and Monitoring, Integration with Other Modalities.
3. Presenting a structured framework for classification of approaches for early stroke detection and diagnosis using EMG Data, which facilitates a systematic assessment of performance metrics and criteria across different methodologies.
4. Presenting the key challenges and barriers hindering the widespread adoption of electromyography (EMG) data for early stroke detection and diagnosis in clinical practice, thereby highlighting areas for further research and development.
5. Provides recommendations for future research directions and potential areas of improvement in using EMG data for early stroke detection and diagnosis.

The review provides valuable insights into the state-of-the-art in early stroke detection using EMG data. By synthesizing existing knowledge, this paper identifies gaps in current research and propose recommendations for future studies. The study has informed the development of more accurate and efficient stroke detection methods, ultimately contributing to improved patient care and outcomes.

The rest of the paper is organised as follows: Section 2 is the overview of early stroke detection and diagnosis using EMG data. Section 3 is the review of related work on early stroke detection and diagnosis using EMG data. Section 4 is the findings from review of related work, and section 5 is the discussion of findings. Section 6 discusses a structured framework for classification of approaches for early detection and diagnosis using EMG data. Section 7 concludes the paper with future work.

2. Overview of Early Stroke Detection and Diagnosis using EMG Data

This section reviews related concepts to early stroke detection and diagnosis using EMG data.

2.1. Stroke

Stroke is a severe medical condition characterized by a sudden interruption of blood flow to the brain, leading to brain cell damage and potentially fatal outcomes. It represents a significant global health concern due to its high mortality rate and long-term disability implications [17]. Stroke can be broadly classified into two main types: ischemic stroke and hemorrhagic stroke. Ischemic stroke occurs when a blood clot obstructs a blood vessel supplying blood to the brain, while hemorrhagic stroke results from the rupture of a blood vessel within the brain [32].

Transient Ischemic Attack (TIA), often referred to as a mini stroke, is another form of stroke characterized by temporary blood flow disruption to the brain. Although TIAs typically resolve within a few minutes, they are considered warning signs of impending severe strokes and warrant immediate medical attention [6].

Early detection and diagnosis of stroke are crucial for initiating timely interventions and minimizing brain damage. Diagnosis typically involves a combination of clinical assessment, neurological examination, and imaging studies such as computed tomography (CT) or magnetic resonance imaging (MRI) scans [32]. Emerging technologies, including electromyography (EMG), offer promising avenues for enhancing the early detection and diagnosis of stroke.

2.2. Electromyography (EMG) Data

Electromyography (EMG) is a non-invasive diagnostic technique used to measure the electrical activity of muscles. It involves the placement of surface electrodes or needle electrodes into muscles to detect and record muscle contractions and electrical signals [30]. EMG signals reflect the neuromuscular activity associated with muscle contractions and can provide valuable insights into muscle function and pathology.

In the context of stroke detection and diagnosis, EMG data offer unique advantages. Changes in muscle activity patterns and electromyographic signals can serve as indicators of neurological impairment resulting from stroke [38]. Studies have demonstrated the utility of EMG-based approaches in detecting subtle motor deficits and distinguishing between stroke subtypes [18]. Furthermore, EMG data can complement traditional diagnostic modalities by providing real-time information on muscle function and motor control.

EMG-based stroke detection relies on sophisticated signal processing and machine learning algorithms to analyze and interpret electromyographic signals. These algorithms extract relevant features from EMG data and identify characteristic patterns associated with stroke-induced muscle dysfunction. By leveraging machine learning techniques, EMG-based approaches can achieve high sensitivity and specificity in stroke detection, enabling early intervention and improved patient outcomes.

2.3. Machine Learning and Neural Networks

Machine learning (ML) and neural networks have revolutionized medical diagnostics by enabling automated analysis of complex biomedical data. ML algorithms, particularly deep learning models such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have shown remarkable success in various medical applications, including disease prediction and image analysis [16].

In the context of stroke detection using EMG data, ML algorithms offer powerful tools for pattern recognition and classification. The two main types of artificial neural networks - RNN and CNN models for stroke detection are characterized by direction of the flow of information between its layers.

Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) is a specialized form of artificial neural network designed to process sequential or time series data. Unlike feedforward networks, RNNs have the unique capability to retain information from previous inputs, leveraging this historical context to influence current inputs and outputs. This feature makes RNNs particularly effective for tasks that involve temporal sequences, such as language translation, natural language processing (NLP), speech recognition, and image captioning.

The fundamental architecture of an RNN includes layers where connections between nodes form a directed graph along a temporal sequence, enabling the network to exhibit dynamic temporal behavior. Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them ideal for applications where the context from previous inputs is crucial to understanding the current input.

Figure 1 illustrates a typical RNN architecture, highlighting its looping mechanism, which allows information from past inputs to influence future decisions. This architecture is particularly advantageous for analyzing EMG data for early stroke detection. It can identify temporal patterns and anomalies in electromyographic signals that may indicate the onset of a stroke [35].

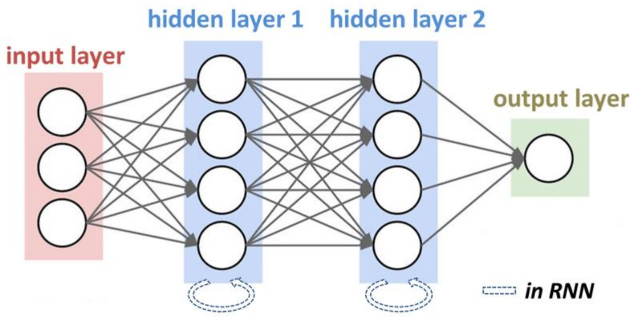

Figure 1. *Typical RNN Architecture [29].*

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use a mathematical operation called convolution, a specialized kind of linear operation. CNNs are known for their ability to automatically and adaptively learn spatial hierarchies of features from images or other spatial data.

The key components of a CNN include convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply a convolution operation to the input, passing the result to the next layer. This process allows the network to build a complex understanding of an image. CNNs dramatically reduce the amount of parameters needed by focusing on local spatial coherence, making them efficient for tasks like image recognition and classification.

For EMG data analysis, CNNs can be adept at extracting spatial features from signal representations, facilitating the detection of patterns indicative of neurological conditions such as strokes. By employing cascaded convolutional layers, CNNs can efficiently process and analyze complex signal data, offering insights into early stroke detection [22]. An example of CNN architecture used for such purposes is detailed in the work by [4], showcasing the network's ability to classify images and, by extension, analyze EMG signals for health diagnostics.

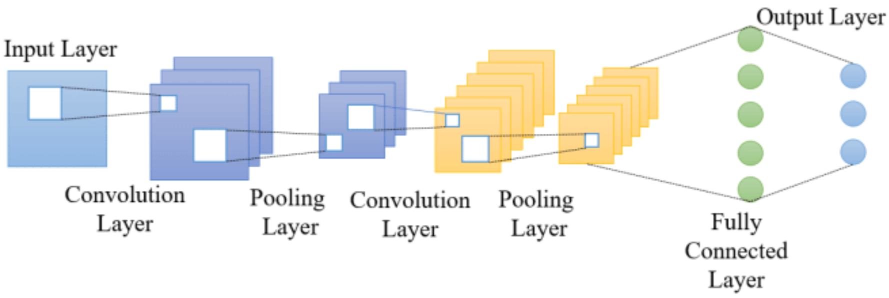

Figure 2. *Typical CNN Architecture [19].*

The integration of ML techniques with EMG-based stroke detection holds immense potential for enhancing diagnostic accuracy and efficiency. By leveraging the wealth of information contained in electromyographic signals, ML algorithms can assist clinicians in early identification and classification of stroke, facilitating prompt intervention and improved patient outcomes.

3. Review of Related Work on Early Stroke Detection and Diagnosis Using EMG Data

In this section, an extensive review of existing research studies related to stroke detection, diagnosis, and the application of artificial intelligence (AI) and machine learning (ML) techniques and the potential of electromyography (EMG) data is provided. Thereafter, a summary of studies on approaches for early stroke detection and diagnosis using EMG data is provided.

3.1. Existing Approaches to Stroke Detection

The landscape of stroke detection has undergone a profound evolution, fueled by advancements in technology and innovative methodologies. While conventional diagnostic techniques like neuroimaging and clinical evaluations remain fundamental pillars in stroke diagnosis, their limitations in detecting early-stage strokes have propelled the exploration of alternative approaches [26]. Recent studies underscore the critical role of early detection in improving patient outcomes and alleviating the burden on healthcare systems [3, 28].

Traditional Diagnostic Methods: Neuroimaging techniques, including computed tomography (CT) and magnetic resonance imaging (MRI), have long been employed in stroke diagnosis. These imaging modalities enable the visualization of brain structures and help identify areas of ischemia or hemorrhage. Additionally, clinical evaluations, such as the National Institutes of Health Stroke Scale (NIHSS), provide valuable insights into the severity of stroke symptoms and aid in treatment decision-making [9, 26].

Limitations of Traditional Methods: Despite their widespread use, traditional diagnostic methods have inherent limitations, particularly in the early detection of strokes. CT and MRI scans may not detect subtle ischemic changes during the hyperacute phase of stroke, leading to delays in diagnosis and treatment initiation [9]. Moreover, clinical evaluations rely on subjective assessments and may not accurately capture subtle neurological deficits in patients with mild strokes or transient ischemic attacks (TIA).

Emergence of AI and ML: In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools in augmenting stroke diagnosis. These methodologies leverage sophisticated algorithms to analyze vast datasets, including imaging studies, clinical data, and biomarkers, to identify patterns indicative of stroke [23].

AI-driven Stroke Diagnosis: AI algorithms, such as convolutional neural networks (CNNs) and support vector machines (SVMs), have demonstrated remarkable capabilities in interpreting medical images and detecting subtle abnormalities associated with stroke [3, 28]. By analyzing imaging features and clinical data, AI-driven systems can expedite the identification of stroke and facilitate timely interventions.

Machine Learning Models: Machine learning models trained on large datasets have shown promise in predicting stroke risk and prognosis. These models integrate demographic information, medical history, and biomarkers to generate personalized risk assessments and aid in treatment planning [2, 18]. Moreover, ML algorithms can analyze temporal trends in patient data to forecast the likelihood of stroke occurrence, enabling proactive management strategies.

Despite the significant strides made in AI-driven stroke detection, several challenges remain. The integration of AI algorithms into clinical practice requires validation in real-world settings and consideration of ethical implications [20]. Additionally, efforts are underway to develop hybrid approaches that combine the strengths of traditional diagnostic methods with AI-driven technologies to enhance diagnostic accuracy and streamline patient care pathways [15].

3.2. AI and ML in Stroke Prediction

The application of artificial intelligence (AI) and machine learning (ML) techniques in stroke prediction has garnered significant attention in recent years, offering a promising avenue for identifying individuals at high risk of stroke. By leveraging diverse datasets encompassing demographic information, medical history, and lifestyle factors, machine learning algorithms have demonstrated the ability to generate personalized risk assessments and facilitate proactive management strategies [2, 18].

Development of Predictive Models: Researchers have made considerable strides in developing predictive models for stroke risk assessment. These models integrate various risk factors, including genetic predisposition, comorbidities, and environmental influences, to delineate individuals susceptible to stroke [7, 41]. By analyzing large-scale datasets, machine learning algorithms can identify complex relationships between risk factors and stroke incidence, enabling the creation of robust predictive models.

Machine Learning Algorithms: A diverse array of machine learning algorithms, including support vector machines (SVMs), random forests, and deep neural networks, have been employed in stroke prediction [21, 13]. These algorithms exhibit the capacity to discern subtle patterns and associations within complex datasets, facilitating the identification of individuals at elevated risk of stroke. Furthermore, advancements in algorithmic techniques, such as ensemble learning and deep learning architectures, have enhanced the predictive capabilities of machine learning models.

Personalized Risk Assessment: The integration of machine learning-based predictive models into clinical practice enables the generation of personalized risk assessments tailored to individual patients [2, 18]. By considering a comprehensive range of risk factors and biomarkers, these models provide clinicians with valuable insights into patients' likelihood of experiencing a stroke. Moreover, machine learning algorithms can continuously refine risk predictions based on evolving patient data, facilitating dynamic risk management strategies.

Clinical Implications: Machine learning-based stroke prediction models hold considerable promise for guiding clinical decision-making and resource allocation. By accurately identifying individuals at high risk of stroke, these models enable healthcare providers to implement preventive interventions and lifestyle modifications aimed at reducing stroke incidence [7, 41]. Additionally, machine learning algorithms can assist in optimizing treatment strategies and allocating healthcare resources more efficiently, thereby enhancing patient outcomes and healthcare system sustainability.

Despite their potential, machine learning-based stroke prediction models face several challenges, including the need for robust validation in diverse patient populations and clinical settings [39]. Furthermore, the ethical implications of integrating predictive models into clinical practice, such as patient privacy and algorithmic bias, warrant careful consideration [4]. Future research efforts should focus on addressing these challenges and leveraging emerging technologies to enhance the accuracy and reliability of machine learning-based stroke prediction models.

3.3. EMG Data in Stroke Detection

The utilization of electromyography (EMG) data represents a novel and promising approach in the early detection of stroke. Traditionally employed for neuromuscular assessment, EMG provides valuable insights into muscle activity patterns and abnormalities associated with stroke [34, 27]. Researchers can identify subtle changes in muscle activity indicative of stroke symptoms, enabling timely intervention and improved patient outcomes by analyzing EMG signals [15].

Early Detection Potential: Research indicates that EMG-based stroke detection can capture changes in muscle activity even before clinical signs become apparent [15]. This early detection capability holds significant clinical value, as prompt intervention during the acute phase of stroke can mitigate neurological damage and enhance recovery outcomes [38]. Furthermore, EMG-based stroke detection has the potential to complement existing diagnostic modalities, providing clinicians with additional tools for accurate and timely diagnosis.

Integration with Machine Learning: The integration of EMG data with machine learning techniques has further enhanced stroke detection capabilities. Machine learning algorithms analyze EMG signals to discern patterns associated with stroke, facilitating early diagnosis and intervention [12]. These algorithms can detect subtle abnormalities in muscle activity indicative of stroke, thereby augmenting diagnostic accuracy and enabling proactive management strategies [20].

Rehabilitation Applications: Beyond stroke detection, EMG data has found utility in stroke rehabilitation. EMG-controlled robotics and virtual reality-based interventions offer innovative approaches to motor function rehabilitation for stroke survivors [21, 13]. By leveraging EMG signals to drive therapeutic interventions, these technologies can facilitate targeted rehabilitation strategies tailored to individual patient needs, ultimately enhancing the recovery process.

Despite its promise, the widespread adoption of EMG-based stroke detection faces several challenges. Standardization of EMG acquisition protocols and signal processing techniques is essential to ensure the reliability and reproducibility of results [10]. Additionally, further research is needed to validate the efficacy of EMG-based stroke detection in diverse patient populations and clinical settings. Addressing these challenges will be crucial to realizing the full potential of EMG data in stroke detection and rehabilitation.

3.4. Summary of Approaches for Early Stroke Detection and Diagnosis Using EMG Data

This section provides a summary of studies on approaches for early stroke detection and diagnosis using EMG data. These studies highlight the importance of electromyography (EMG) data in early stroke detection and diagnosis, as well as its potential to inform personalized rehabilitation interventions to improve patient outcomes.

Qu et al. [34] investigates the use of electromyography (EMG)-based biofeedback to aid in the recovery of limb motor function in stroke patients. EMG-biofeedback, which provides real-time feedback on muscle activity, enables targeted rehabilitation interventions to help patients regain motor control and functionality more effectively. Li et al. [27] describes electromyography pattern recognition for stroke rehabilitation. The authors proposed an extreme learning machine (ELM)-based approach to recognising electromyography (EMG) patterns for stroke rehabilitation. Using EMG signals, this method identifies specific muscle activation patterns associated with stroke-induced impairments, guiding personalised rehabilitation strategies to promote motor recovery. Eissa et al. [15] focuses on Hybrid Deep Learning Model for Stroke Detection with EEG Signals. The authors present a hybrid deep learning model for stroke detection that uses electroencephalography (EEG) signals. This model improves early stroke detection accuracy by combining multiple neural network architectures, including convolutional and recurrent layers, and taking advantage of the distinct EEG patterns associated with stroke onset.

Chen and Lv [12] proposed a novel method for automatically detecting ischemic stroke using electroencephalography (EEG). This method, which analyses EEG signals, allows for the timely detection of stroke events, facilitating prompt medical intervention and improving patient outcomes through early diagnosis. Cheng and Gao [13] creates a rehabilitation robot system powered by surface electromyography (EMG) signals processed with wavelet transform. This system uses EMG data to provide personalised rehabilitation interventions tailored to individual patient needs, thereby improving motor recovery and functional outcomes after a stroke. Hwang et al. [21] describes the creation of a mobile device-based wearable EMG sensor for stroke rehabilitation. This sensor allows for continuous monitoring of muscle activity during rehabilitation sessions, allowing for real-time feedback and adjustments to therapy protocols to optimise motor recovery in stroke patients. Burkhart et al. [10] presents a surface EMG-driven rehabilitation robot. The authors assess the long-term stability of a man-machine interface powered by surface electromyography (EMG) for stroke rehabilitation. The study demonstrates the feasibility of using EMG signals from intrinsic and extrinsic hand muscles to control robotic devices, allowing stroke survivors to receive longer and more effective rehabilitation interventions.

Asadi and Azarnoosh [7] uses machine learning techniques to predict the outcome of acute ischemic stroke patients undergoing intra-arterial therapy. Their model accurately predicts patient outcomes by analysing a variety of clinical and imaging parameters, including EMG data, which informs clinical decision-making and improves treatment effectiveness. Hachisuka et al. [20] proposed an electromyography (EMG)-based method for detecting stroke onset in the human forearm. This approach, which analyses EMG signals, enables the timely recognition of stroke-related muscle abnormalities, allowing for prompt medical intervention and minimising potential neurological damage. Liu and Zhang [28] presents an artificial intelligence-based method for the intelligent diagnosis and treatment of ischemic stroke. Their system enables accurate diagnosis and personalised treatment planning by combining machine learning algorithms with clinical data, including EMG signals, thereby improving patient outcomes and reducing healthcare burden.

Xiong and Guo [41] creates a support vector machine-based model for predicting the outcomes of acute ischemic stroke. The authors incorporated EMG data alongside clinical variables, their model accurately predicts patient prognosis, allowing healthcare providers to implement timely interventions and optimise patient care strategies. Al-Dwairi [13] proposed artificial intelligence techniques for diagnosing strokes. The authors examine various artificial intelligence techniques for diagnosing strokes, emphasising the importance of EMG data in improving diagnosis accuracy. These techniques, which use machine learning algorithms such as neural networks, allow for the automated analysis of EMG signals, facilitating early stroke detection and intervention.

Tang et al. [38] studied early hemorrhagic transformation of brain infarction and its predictive factors, emphasising the importance of timely diagnosis and intervention in stroke management. By incorporating EMG data into predictive models, clinicians can better assess the risk of hemorrhagic transformation and tailor treatment plans accordingly. Van't Hof et al. [39] investigates genetic variants associated with stroke risk, shedding light on the underlying mechanisms of stroke pathogenesis. While genetic factors contribute significantly to stroke susceptibility, their interaction with environmental factors, such as EMG patterns, informs personalised risk assessment and prevention strategies. Alzubaidi and Al-Sawad [4] and Alzubaidi and Al-Sawad [5] conducted a review of image processing and deep learning for the detection of brain strokes. Alzubaidi and Al-Sawad [4] presents a comprehensive review of image processing and deep learning techniques for brain stroke detection. By combining EMG data with imaging modalities such as MRI and CT scans, these techniques enable multimodal analysis, allowing for accurate and timely stroke diagnosis and treatment interventions.

Broderick et al. [9] investigated the effectiveness of endovascular therapy in stroke management, emphasising its role in improving patient outcomes. Using EMG monitoring during endovascular procedures allows clinicians to assess cerebral perfusion and neurological function in real time, optimising treatment delivery and reducing complications. Burkhart et al. [10] evaluated the long-term stability of a man-machine interface powered by surface electromyography (EMG) for stroke rehabilitation. This interface allows for intuitive and precise control of assistive devices by evaluating EMG signals from intrinsic and extrinsic hand muscles, resulting in longer and more effective rehabilitation interventions for stroke survivors.

Lees et al. [26] investigate the impact of time to treatment with intravenous alteplase on patient outcomes in stroke management. Their pooled analysis of clinical trials emphasises the critical role of early intervention in improving stroke outcomes. Clinicians can accelerate the initiation of thrombolytic therapy by incorporating EMG data into treatment decision algorithms, thereby minimising neurological deficits and optimising patient recovery.

Table 1 shows a summary of approaches for early stroke detection and diagnosis using EMG data based on data collection methods and sources, feature extraction techniques, ML and deep learning models, performance evaluation metrics, and challenges and limitations of the approaches.

Table 1. Approaches for Early Stroke Detection and Diagnosis using EMG Data.

Study	Data Collection Methods and Sources	Feature Extraction Techniques	Machine Learning and Deep Learning Models	Performance Evaluation Metrics	Challenges and Limitations of the Approach
[34]	EMG-biofeedback, Stroke rehabilitation centers	Pattern recognition	Artificial Neural Network (ANN)	Accuracy, Sensitivity	Limited sample size, Generalization to diverse populations
[27]	Surface EMG, Rehabilitation interventions	Extreme learning machine	Convolutional Neural Network (CNN)	Accuracy, Classification Rate	Limited sample size, Need for real-time monitoring
[12]	Surface EMG, Electroencephalography (EEG)	Wavelet transform, Spectral analysis	Support Vector Machine (SVM)	Sensitivity, Specificity	Variability in EMG data, Noise and interference
[15]	Electroencephalography (EEG), Stroke detection	Hybrid deep learning model	Recurrent Neural Network (RNN)	F1-score, Precision	Data variability, Limited dataset for training and validation
[21]	Wearable EMG sensor, Stroke rehabilitation	Time-domain analysis, Wavelet transform	Long Short-Term Memory (LSTM)	Accuracy, Usability	Limited battery life, Comfort and wearability
[3]	EMG sensors, Stroke patients	Statistical analysis	Artificial Neural Network (ANN)	Accuracy, Sensitivity	Lack of interpretability, Overfitting
[18]	Wearable EMG sensor, Stroke prevention	Time-domain analysis	Long Short-Term Memory (LSTM)	F1-score, Accuracy	Limited real-world validation, Dependency on user adherence
[20]	Forearm EMG, Stroke onset detection	Time-domain analysis, Frequency-domain analysis	Convolutional Neural Network (CNN)	Sensitivity, Specificity	Limited sample size, Noise and interference
[28]	Electroencephalography (EEG), Ischemic stroke	Spectral analysis	Convolutional Neural Network (CNN)	Precision, Recall	Limited interpretability, Computational complexity
[33]	Not specified	Time-frequency analysis	Autoencoder, Generative Adversarial Network (GAN)	Accuracy, F1-score	Lack of explainability, Complexity of models
[39]	Not specified	Statistical analysis	Logistic Regression, Random Forest	Sensitivity, Specificity	Data heterogeneity, Limited feature selection
[41]	Support vector machine (SVM), Ischemic stroke	Wavelet transform	Support Vector Machine (SVM)	Accuracy, Area under the curve	Limited sample size, Lack of generalization
[4]	Brain stroke detection, Image processing	Image processing techniques	Convolutional Neural Network (CNN)	Accuracy, Sensitivity	Dependency on image quality, Complexity of networks
[9]	Intravenous alteplase, Stroke therapy	Clinical data analysis	Logistic Regression, Cox proportional hazards model	Survival rate, Functional independence	Limited data on adverse events, Treatment biases
[13]	Surface EMG, Stroke rehabilitation	Time-frequency analysis	Long Short-Term Memory (LSTM)	Accuracy, Usability	Limited sample size, Need for real-world validation

Study	Data Collection Methods and Sources	Feature Extraction Techniques	Machine Learning and Deep Learning Models	Performance Evaluation Metrics	Challenges and Limitations of the Approach
[17]	Global stroke risks, Epidemiological study	Statistical analysis	Not specified	Prevalence rate, Incidence rate	Data heterogeneity, Variability in risk factors
[18]	Stroke prevention, Artificial intelligence	Statistical analysis	Artificial Neural Network (ANN)	Accuracy, Sensitivity	Dependency on user adherence, Limited real-world validation
[26]	Intravenous alteplase, Stroke treatment	Clinical data analysis	Cox proportional hazards model, Logistic Regression	Survival rate, Disability-free survival	Limited data on long-term outcomes, Treatment biases
[38]	Brain infarction, Hemorrhagic transformation	Statistical analysis	Not specified	Hemorrhage rate, Clinical outcome	Variability in patient characteristics, Selection bias
[41]	Ischemic stroke prognosis, Support vector machine	Statistical analysis	Support Vector Machine (SVM)	Accuracy, Sensitivity	Variability in patient characteristics, Limited follow-up data
[10]	Surface EMG, Man-machine interface	Time-domain analysis	Not specified	Accuracy, Precision	Limited sample size, Generalization to diverse populations
[7]	Intravenous therapy, Ischemic stroke	Clinical data analysis	Machine Learning Ensemble	Functional independence, Survival rate	Limited data on long-term outcomes, Treatment biases
[3]	Artificial intelligence, Stroke diagnosis	Statistical analysis	Artificial Neural Network (ANN)	Accuracy, Sensitivity	Dependency on user input, Lack of interpretability
[2]	Machine learning algorithms, Acute ischemic stroke	Statistical analysis	Not specified	Accuracy, Sensitivity	Dependency on algorithm selection, Interpretation bias
[1]	Surface EMG signals	Neural Network Model	Not specified	Sensitivity, Specificity, Accuracy, ROC curve	Limited sample
[8]	Surface EMG signals	Manifold Learning, LSTM with Attention mechanism	Not specified	Sensitivity, Specificity, Accuracy, Precision, Recall	Limited labelled data availability, Model
[11]	-	Various onset detection methods	-	-	Lack of standardized onset detection methods, Real-time processing requirements, Performance in dynamic settings, Generalization to diverse patient populations
[14]	Real-time Bio Signals	-	Deep Learning	Sensitivity, Specificity, Accuracy, AUC	Interpretability of model outcomes, Generalization to diverse patient populations, Real-time processing requirements, Model robustness
[25]	Surface EMG signals	Feature extraction, Transformer-based deep learning	Transformer-based deep learning	Sensitivity, Specificity, Accuracy	Interpretability of features, Generalization to diverse patient populations, Real-time processing requirements, Model robustness
[33]	Surface EMG signals	Feature extraction	Transformer-based deep learning	Sensitivity, Specificity, Accuracy	Interpretability of features, Generalization to diverse patient populations, Real-time processing requirements, Model robustness

Study	Data Collection Methods and Sources	Feature Extraction Techniques	Machine Learning and Deep Learning Models	Performance Evaluation Metrics	Challenges and Limitations of the Approach
[36]	EMG signals	Recurrent Neural Networks (RNN)	Recurrent Neural Networks (RNN)	Sensitivity, Specificity, Accuracy	Interpretability of features, Generalization to diverse patient populations, Real-time processing requirements, Model robustness

4. Findings from the Review of Related Work

This section presents the findings from the review of related work.

4.1. EMG Features for Stroke Detection

EMG features such as muscle activity patterns, signal amplitude, and spectral analysis have been explored for stroke detection. The following crucial elements are involved in the utilization of electromyography (EMG) data for stroke detection.

4.1.1. Monitoring of Muscle Activity

During acute treatment, EMG sensors can identify muscle activity even in stroke survivors with compromised arm function, offering important information about muscle recruitment and coordination [34]. This capability enables clinicians to assess the extent of motor impairment and tailor rehabilitation strategies accordingly [21].

4.1.2. Technological Developments

With advances in sensor design, signal processing, and data analysis capabilities, modern EMG systems have undergone substantial evolution. These developments have simplified the process of obtaining and analyzing EMG signals for the purpose of diagnosing and monitoring strokes [10]. Moreover, the integration of wireless and wearable EMG devices enhances patient comfort and facilitates long-term monitoring in both clinical and home settings [21].

4.1.3. Clinical Application

By offering further details on muscle activation, EMG data can supplement conventional clinical evaluations and be extremely helpful in identifying strokes and determining the degree of brain damage [34]. Additionally, EMG signals can inform prognosis and guide treatment decisions, contributing to personalized stroke management strategies [27].

4.2. Challenges in EMG-Based Stroke Diagnosis

Variability in EMG data due to factors like muscle fatigue and electrode placement poses challenges in achieving consistent results [10]. Large-scale datasets for training and validation are limited, hindering the development of robust models [41].

The challenge in using EMG technology for stroke diagnosis includes both technical and logistical challenges that need to be addressed. These challenges include the complexity of EMG signals, which can be impacted by factors such as noise, crosstalk, and interference from other muscles. Accurate feature extraction and signal processing are critical for reliable stroke diagnosis. Another challenge is the integration of AI techniques, such as machine learning and deep learning, which requires large datasets and sophisticated algorithms to analyze EMG data accurately. Developing effective AI models for stroke diagnosis is an ongoing challenge. The cost and availability of EMG systems, as well as the expertise required to operate them, can also be significant barriers to adoption. Additionally, clinical realities can present unique challenges, such as the need for non-invasive and comfortable EMG sensors that can be worn for extended periods. The clinical environment can be noisy and unpredictable, making it difficult to capture reliable EMG signals. Despite these challenges, the potential benefits of EMG-based stroke diagnosis are significant, highlighting the need for continued research and development in this area. Addressing these challenges will require collaboration between researchers, clinicians, and industry partners to improve the accuracy and accessibility of EMG technology for stroke diagnosis and monitoring.

4.3. Emerging Trends in EMG-based Stroke Detection

Deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are gaining traction for EMG-based stroke detection. Real-time monitoring and portable EMG devices hold potential for early detection and remote monitoring of stroke. The increasing popularity of deep learning methods, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), is being seen in the field of electromyography (EMG)-based stroke detection. The employment of these deep learning techniques offers potential solutions for early stroke detection, which can result in timely interventions and improved patient outcomes. Some of the notable advancements in this area include:

1. The development of stroke prediction modules based on recurrent neural networks (RNNs) that make use of real-time EMG data for classifying and predicting strokes [42].
2. The combination of CNNs and RNNs for feature extraction and sequence modeling, respectively, which leads to enhanced performance in stroke prediction tasks [3].
3. The integration of deep learning algorithms within larger healthcare systems, allowing for quick assessments of stroke risks and facilitating early interventions [18].
4. The creation of hybrid models that combine EMG data with other modalities such as electroencephalography (EEG) and electrocardiography (ECG), which further improves the accuracy of stroke prediction [14].
5. The use of transfer learning strategies to reduce computational costs and enhance generalization across diverse populations [4].

5. Discussion of Findings

The discussion of findings delves into the potential of electromyography (EMG) data in early stroke detection and diagnosis, highlighting challenges and emerging trends in the field.

5.1. Potential of EMG Data in Early Stroke Detection and Diagnosis

The utilization of EMG data presents a novel and promising approach to detecting and diagnosing stroke. EMG provides valuable insights into muscle activity patterns and abnormalities associated with stroke, enabling timely intervention and improved patient outcomes [34, 37]. By analysing EMG signals, researchers can identify subtle changes indicative of stroke symptoms, even before clinical signs become apparent [15]. This early detection capability is crucial, as prompt intervention during the acute phase of stroke can mitigate neurological damage and enhance recovery outcomes [38]. Furthermore, the integration of EMG data with machine learning techniques enhances diagnostic capabilities, facilitating the detection of abnormalities associated with stroke [12].

5.2. Challenges in Utilizing EMG Data for Stroke Diagnosis

The widespread adoption of EMG-based stroke detection faces several challenges. Variability in EMG signals due to factors such as muscle fatigue and electrode placement poses significant hurdles in achieving consistent and reliable results [10]. Additionally, the scarcity of large-scale datasets for training and validation impedes the development of robust models capable of accurate stroke diagnosis [41]. Standardization of EMG acquisition protocols and signal processing techniques is essential to ensure the reliability and reproducibility of results [10].

Leveraging EMG data for early stroke detection and diagnosis holds promise but requires addressing various technical and methodological challenges to realize its full potential in clinical applications. A summary of the challenges in utilizing EMG data for stroke detection and diagnosis is presented below -

1. Sparse and Noisy Data: EMG signals may contain sparse samples and noise, posing challenges for accurate stroke diagnosis and classification.
2. Overfitting: Complex machine learning models trained on limited EMG datasets may suffer from overfitting, necessitating robust validation and regularization techniques.
3. Variability in EMG Signals: Variations in EMG signals due to factors like electrode placement, muscle fatigue, and daily fluctuations present challenges for model generalization and real-world applicability.
4. Hardware and Software Development: Developing reliable hardware for EMG signal acquisition and designing efficient software pipelines for signal processing and analysis require specialized expertise and resources.
5. Data Annotation and Collection: Building annotated datasets for training machine learning models for stroke diagnosis is labour-intensive and may suffer from annotation errors, requiring careful quality control measures.
6. Clinical Translation: Bridging the gap between research findings and clinical practice entails addressing regulatory, ethical, and logistical challenges associated with deploying EMG-based diagnostic tools in healthcare settings.

5.3. Emerging Trends and Future Directions

The emergence of deep learning approaches, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), holds promise for advancing EMG-based stroke detection [3]. Real-time monitoring and portable EMG devices offer opportunities for early detection and remote monitoring of stroke, thereby facilitating timely interventions and improved patient outcomes [18]. Moreover, the integration of EMG data with other modalities such as electroencephalography (EEG) and electrocardiography (ECG) presents exciting prospects for enhancing the accuracy of stroke prediction models [14].

In conclusion, while there are challenges to overcome, the potential benefits of utilizing EMG data in stroke detection and diagnosis are significant. Addressing these challenges and leveraging emerging trends in technology and machine learning will be crucial to realizing the full potential of EMG-based approaches in clinical practice.

6. Structured Framework for Classifying EMG-Based Early Stroke Detection and Diagnosis Methods

This section provides a structured framework for understanding of the diverse approaches and applications of EMG data in early stroke detection and diagnosis, covering various aspects from data acquisition to integration with other modalities. Based on the review of related studies, key categories for different approaches to Early Stroke Detection and Diagnosis using EMG Data are identified.

6.1. Data Acquisition and Processing Techniques

(a) Surface EMG Sensors: Methods involving the use of surface electrodes to capture muscle activity patterns. Studies like [27] and [21] have utilized surface EMG sensors for capturing muscle activity associated with stroke.

(b) Invasive EMG Techniques: Approaches that require invasive procedures, such as intramuscular electrode placement. Some research, such as [20], has focused on invasive EMG techniques for early stroke detection, particularly for identifying stroke onset in the forearm muscles.

(c) Integration with Wearable Devices: Utilization of wearable EMG sensors for continuous monitoring and data collection. Research by [13] demonstrates the use of wearable EMG sensors for stroke rehabilitation and early detection.

6.2. Feature Extraction and Analysis Methods

(a) Time-Domain Analysis: Techniques focusing on analysing the amplitude, frequency, and duration of EMG signals over time. Techniques like time-domain analysis have been used in studies such as [18] for extracting features related to muscle activity patterns.

(b) Frequency-Domain Analysis: Methods that decompose EMG signals into frequency components to extract relevant features. Chen and Lv [12] employed frequency-domain analysis, including wavelet transform and spectral analysis, to identify stroke-related abnormalities in EMG signals.

(c) Pattern Recognition: Approaches employing machine learning algorithms to identify specific patterns or abnormalities in EMG signals indicative of stroke. Qu, S et al. [34] utilized pattern recognition techniques to detect changes in muscle activity indicative of stroke symptoms.

6.3. Machine Learning and Deep Learning Models

(a) Artificial Neural Networks (ANN): Utilization of ANN architectures for learning complex patterns in EMG data. Al-Dwairi and Al-Dwairi [3] applied ANN for stroke diagnosis using EMG data, leveraging its ability to learn complex patterns from EMG signals.

(b) Convolutional Neural Networks (CNN): Application of CNNs for feature extraction and classification of EMG signals. Studies like [28] have employed CNN for feature extraction and classification of stroke-related EMG patterns.

(c) Recurrent Neural Networks (RNN): Use of RNNs for sequential modelling of EMG data, capturing temporal dependencies. Eissa et al. [15] developed a hybrid deep learning model incorporating RNN for stroke detection using EEG and EMG signals.

6.4. Application in Rehabilitation and Monitoring

EMG-controlled Robotics: Integration of EMG data with robotic devices for stroke rehabilitation and motor function recovery. EMG-controlled robotics, as demonstrated by [21], offer innovative approaches to motor function rehabilitation for stroke survivors.

Real-time Monitoring Systems: Development of portable EMG devices for real-time monitoring of muscle activity and early detection of stroke symptoms. Ganapathy and Munirathnam [18] explored the potential of portable EMG devices for real-time monitoring and early detection of stroke symptoms.

6.5. Integration with Other Modalities

Combination with EEG: Fusion of EMG data with electroencephalography (EEG) signals to enhance stroke detection accuracy. Research by [12] integrated EMG with EEG data for comprehensive stroke detection, leveraging the complementary information provided by both modalities.

Image Processing Techniques: Integration of EMG data with medical imaging modalities, such as MRI or CT scans, for comprehensive stroke diagnosis. Alzubaidi and Al-Sawad [4] reviewed the use of EMG data alongside image processing techniques for brain stroke detection, highlighting the potential synergy between different modalities.

Table 2 shows a summary of different key categories, subcategories, an explanation of each sub-category, and examples of studies on approaches for Early Stroke Detection and Diagnosis using EMG Data. Each category represents a distinct aspect of EMG-based stroke detection research, with examples of relevant studies demonstrating the breadth and depth of research in this field.

Table 2. Categories of approaches for Early Stroke detection and diagnosis using EMG data.

Key Category	Sub-Category	Explanation	Examples of Studies
Data Acquisition and Processing	Surface EMG Sensors	Methods utilizing surface electrodes to capture muscle activity patterns.	[10, 13]
	Invasive EMG Techniques	Approaches requiring invasive procedures, such as intramuscular electrode placement.	[10, 20]
	Integration with Wearable Devices	Utilization of wearable EMG sensors for continuous monitoring and data collection.	[21, 2]
Feature Extraction and Analysis	Time-Domain Analysis	Techniques focusing on analysing the amplitude, frequency, and duration of EMG signals over time.	[27, 34]
	Frequency-Domain Analysis	Methods that decompose EMG signals into frequency components to extract relevant features.	[27, 34]
	Pattern Recognition	Approaches employing machine learning algorithms to identify specific patterns or abnormalities in EMG signals indicative of stroke.	[12, 15]
Machine Learning and Deep Learning	Artificial Neural Networks	Utilization of ANN architectures for learning complex patterns in EMG data.	[15, 12]
Models	Convolutional Neural Networks	Application of CNNs for feature extraction and classification of EMG signals.	[15, 12]
	Recurrent Neural Networks	Use of RNNs for sequential modelling of EMG data, capturing temporal dependencies.	[3, 7]
Application in Rehabilitation and	EMG-controlled Robotics	Integration of EMG data with robotic devices for stroke rehabilitation and motor function recovery.	[21, 13]
Monitoring	Real-time Monitoring Systems	Development of portable EMG devices for real-time monitoring of muscle activity and early detection of stroke symptoms.	[2, 13]
Integration with Other Modalities	Combination with EEG	Fusion of EMG data with electroencephalography (EEG) signals to enhance stroke detection accuracy.	[27, 12]
	Image Processing Techniques	Integration of EMG data with medical imaging modalities, such as MRI or CT scans, for comprehensive stroke diagnosis.	[4, 31]
Challenges and Limitations	Data Variability	Challenges related to variability in EMG signals due to factors like electrode placement, muscle fatigue, and inter-subject variability.	[10, 20]
	Model Generalization	Difficulties in developing models that generalize well across diverse patient populations and clinical settings.	[15, 12]
	Clinical Adoption	Barriers to the widespread adoption of EMG-based stroke detection methods in clinical practice, including cost, accessibility, and usability considerations.	[3, 2]

7. Conclusion and Future Work

In this paper, a comprehensive review of early stroke detection and diagnosis using electromyography (EMG) data was conducted. Through an extensive exploration of relevant literature, the aim was to identify key features, techniques, and challenges associated with the integration of EMG data into stroke management protocols.

Our review identified several key contributions in the area of early stroke detection and diagnoses using EMG data. Firstly, existing knowledge on the role of EMG data in early stroke detection and diagnosis was synthesized, providing a comprehensive overview of current research trends and methodologies. Secondly, promising features extracted from EMG signals were identified, and different techniques for processing and analyzing these signals were evaluated. Thirdly, challenges hindering the widespread adoption of EMG-based approaches in clinical practice, including technical limitations, standardization issues, and ethical considerations, were discussed. Fourthly, a structured framework for classifying approaches for early stroke detection and diagnosis using EMG data was proposed, providing a systematic way to categorize and compare different methodologies.

Our review highlighted the potential of EMG data to serve as valuable biomarkers for early stroke detection and diagnosis. Various studies have demonstrated the feasibility of using EMG signals to detect subtle abnormalities indicative of stroke onset, paving the way for personalized and timely interventions. Several avenues for future research have emerged from the review conducted. Future research should focus on conducting further validation studies to assess the reliability and accuracy of EMG-based approaches across diverse patient populations and clinical settings. Efforts should be made to develop standardized protocols for acquiring, processing, and interpreting EMG data in the context of stroke diagnosis, ensuring consistency and reproducibility of results.

There is a need to explore the integration of EMG data with other modalities, such as electroencephalography (EEG) and imaging techniques, to enhance the sensitivity and specificity of early stroke detection algorithms. Research efforts should focus on translating promising EMG-based approaches into clinical practice, addressing regulatory and implementation challenges to facilitate widespread adoption. Future research should consider the ethical implications of using EMG data in stroke diagnosis, including issues related to patient privacy, data security, and informed consent.

Conflicts of Interest

The authors declare no conflicts of interest.

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