Article

Predictive Analysis of Damaged Right Arm Muscle State Evolution through Bitalino ECG and EMG Measurements using Artificial Intelligence

[1] Affiliation 1; jmiguyag@myuax.com
[2] Affiliation 2; ddesanto@myuax.com
[†] Current address: UAX
[‡] These authors contributed equally to this work.

Abstract: Muscle damage is a common occurrence in various medical conditions and physical injuries. Monitoring and predicting the evolution of damaged muscle states is crucial for effective treatment and rehabilitation. This study proposes a novel approach utilizing artificial intelligence (AI) techniques in conjunction with Bitalino Electrocardiogram (ECG) and Electromyogram (EMG) measurements to identify and predict the progression of muscle damage. By leveraging AI algorithms trained on a dataset of Bitalino measurements and corresponding muscle states, our system aims to provide early detection of muscle deterioration and forecast its trajectory over time. The integration of ECG and EMG data offers a comprehensive understanding of muscular health and function, enabling clinicians to tailor personalized interventions and optimize patient outcomes. Through this interdisciplinary approach bridging AI, biomedical engineering, and clinical practice, we envision a promising avenue for advancing the management of muscle-related pathologies and enhancing rehabilitation strategies.

Keywords: Muscle damage; Artificial intelligence (AI); Bitalino; Electrocardiogram (ECG); Electromyogram (EMG); Prediction; Rehabilitation; Muscle health; Clinical practice; Biomedical engineering

1. Introduction

Since the 1940s, the concept of artificial intelligence (AI) has been evolving, encompassing various definitions. One key aspect is its ability to mimic human intelligence, including interpreting external data and learning from it to achieve specific goals. In the 1950s, the development of the first perceptron and artificial neural networks (ANNs) laid the groundwork for AI models, aiming to replicate the cognitive processes of the human brain's cortex.

In recent years, there has been remarkable progress in AI, driven by the availability of large datasets and advances in computational power. AI has found diverse applications in areas such as image and voice recognition, text processing, autonomous driving, and medicine. In healthcare, AI has made significant advancements, particularly in radiology diagnostics, electrodiagnostic medicine, genetics, and personalized medicine. Healthcare providers anticipate benefits such as workload reduction, improved diagnostics, treatment predictions, and better patient outcomes. However, concerns persist regarding job security and potential unintended consequences of AI.

This narrative review delves into the fundamentals of AI, highlighting current advancements and its utilization in electrodiagnostic and neuromuscular medicine. Additionally, it briefly explores AI's role in diagnostics using clinical images, prognostication models, and brain-computer interfaces in neuromuscular medicine.[13]

In this paper, we will address Predictive Analysis of Damaged Muscle State Evolution through Bitalino ECG and EMG Measurements using Artificial Intelligence in order to

Citation: . *Journal Not Specified* **2024**, *1*, 0.

Received:
Accepted:
Published:

observe any kind of anomaly in the proper evolution and recovery of damaged muscles. By utilizing predictive analysis, we aim to ensure that the recovery process is on track. This will enable us to enhance the efficiency of the recovery itself, and in the event of any failure, we can swiftly intervene and reduce the recovery times. To embark on this ambitious project, our initial focus will be on developing a system capable of accurately recognizing the current state of the muscle.

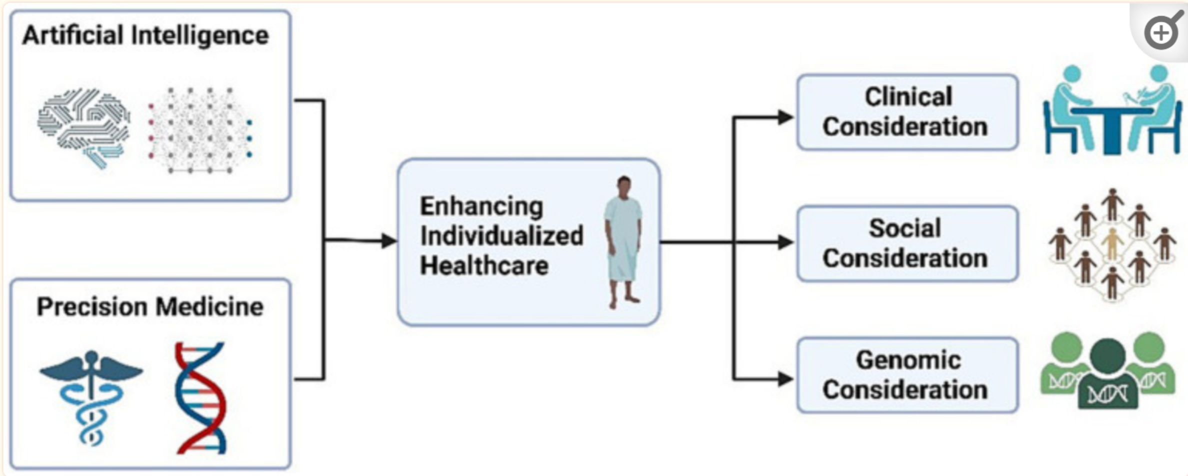


Figure 1

The integration of AI and precision medicine enhances individual healthcare by optimizing therapy planning and diagnostic methods.

[22]

2. State of the Art

Nowdays, significant advancements have been made in the field of artificial intelligence (AI), particularly in the application of AI for medical diagnostics. Current AI systems are capable of distinguishing between various states of muscle health and providing accurate diagnoses based on medical tests. These systems utilize machine learning algorithms, such as convolutional neural networks (CNNs), to analyze medical images and data, demonstrating a high level of precision and reliability in identifying conditions like healthy, exhausted, and sick muscle states.[11][2]

For example, AI models have been successfully trained to analyze electrocardiograms (ECGs) and electromyograms (EMGs) to detect abnormalities and predict potential muscle-related issues. These models are often integrated into diagnostic tools that assist healthcare professionals in making more accurate and faster decisions, improving patient outcomes.[12]

Furthermore, AI-driven diagnostic systems are not only limited to muscle state analysis but are also extensively used in various medical fields, including radiology, pathology, and oncology. They assist in detecting diseases such as cancer, cardiovascular disorders, and neurological conditions, providing critical support in clinical settings.[3][8][1]

Overall, the integration of AI in medical diagnostics and medicine in general represents a significant step forward in healthcare, offering enhanced precision, efficiency, and the potential to revolutionize traditional diagnostic processes.[14][15][20]

3. Materials and Methods

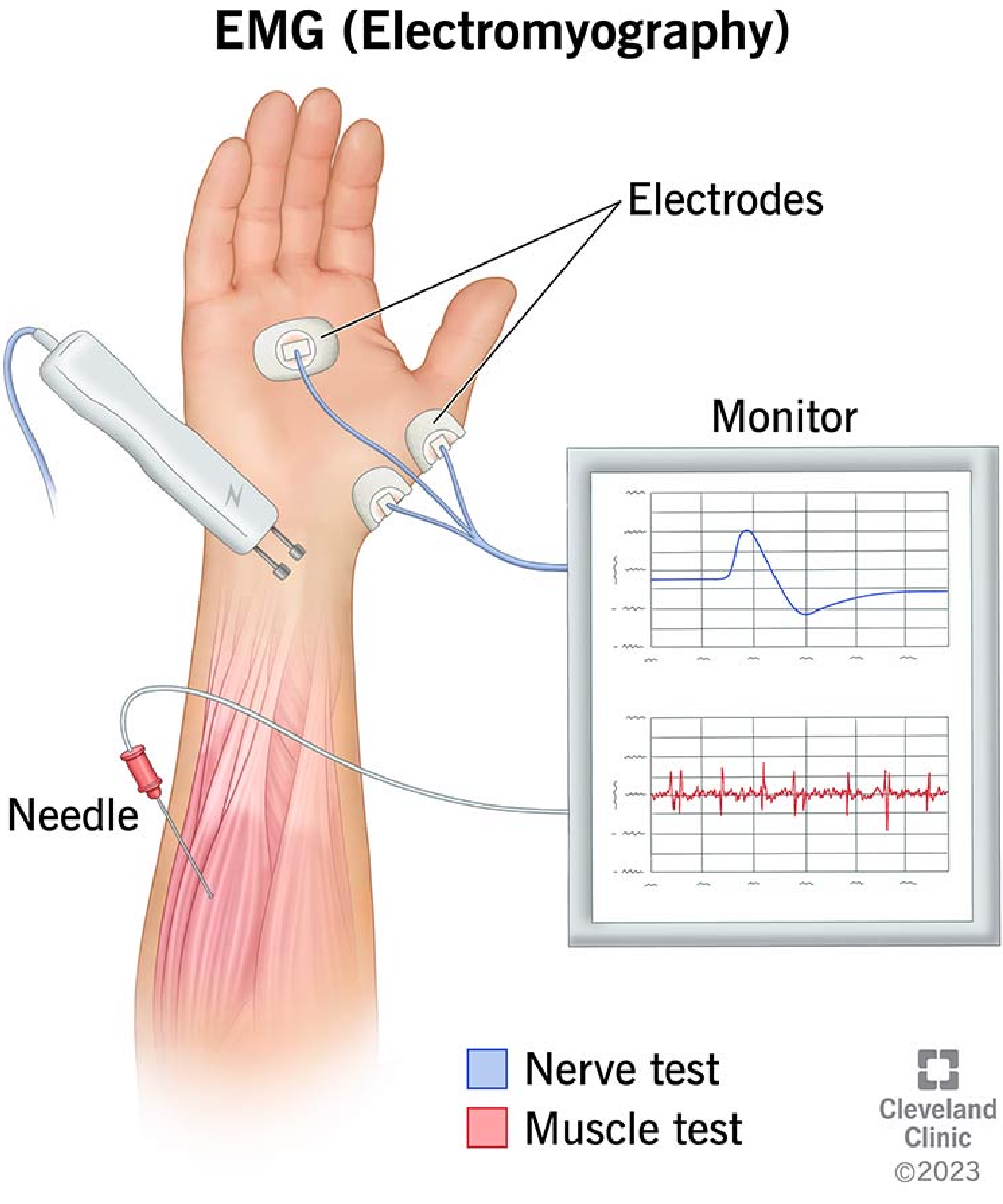
3.1. EMG and ECG Purpose

Electromyography (EMG) and electrocardiography (ECG) tests serve critical roles in medical diagnostics, providing insights into the electrical activity of the heart and muscles, respectively.

3.1.1. Electromyography (EMG)

EMG is a diagnostic technique used to evaluate the electrical activity generated by muscle contractions. By placing electrodes on specific muscles or muscle groups, EMG recordings can detect abnormalities in neuromuscular function, such as nerve damage, muscle disorders, and motor neuron diseases. Medical professionals often employ EMG tests to diagnose conditions such as carpal tunnel syndrome, amyotrophic lateral sclerosis (ALS), and muscular dystrophy.

Moreover, EMG is instrumental in monitoring treatment efficacy and disease progression. Changes in EMG patterns over time can indicate the effectiveness of interventions such as physical therapy, medication, or surgical procedures. Additionally, EMG testing helps clinicians assess muscle function before and after surgeries or injuries, guiding rehabilitation efforts and optimizing recovery outcomes.[7]



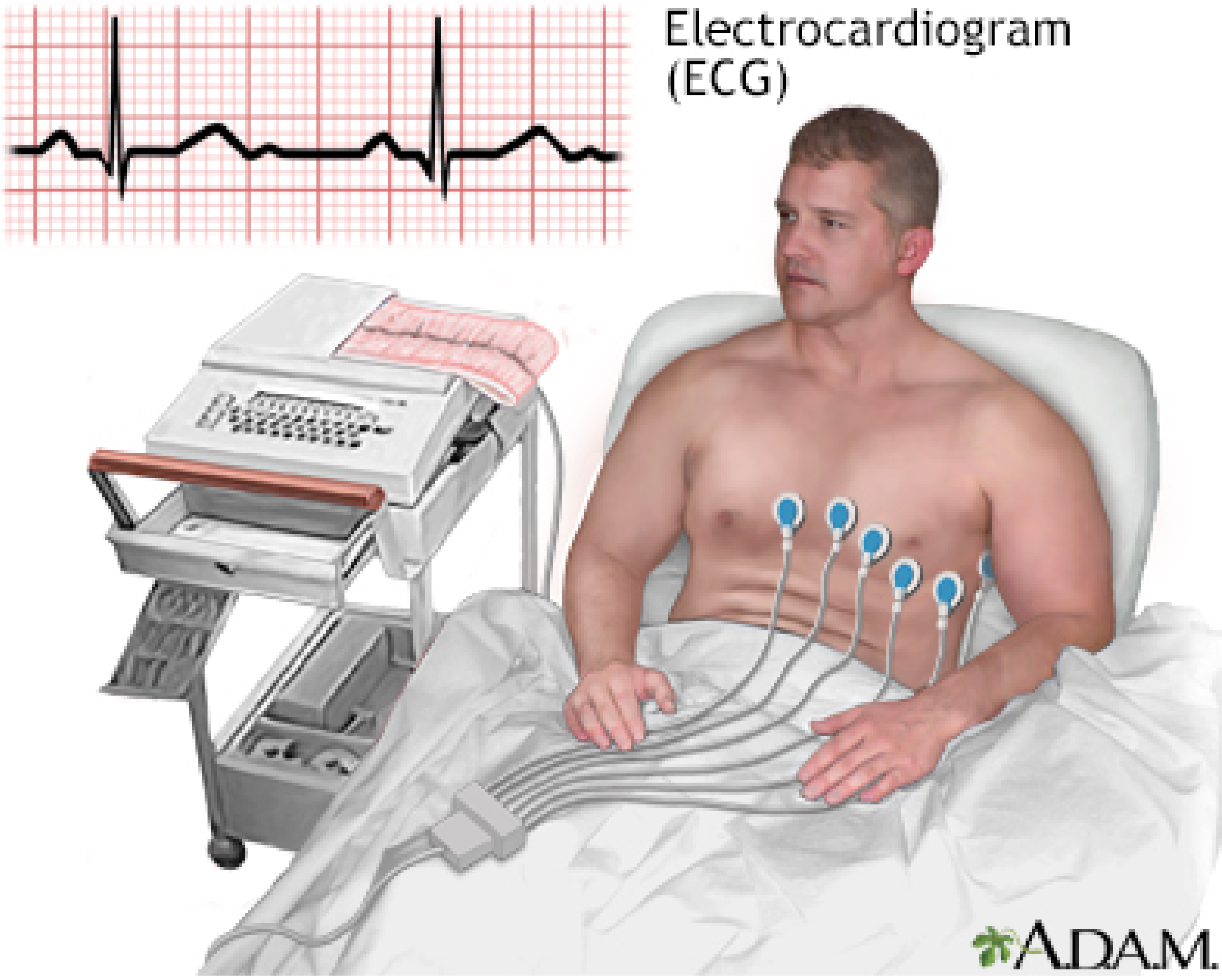
[5]

3.1.2. Electrocardiography (ECG)

ECG, on the other hand, records the electrical activity of the heart, providing essential information about cardiac rhythm, rate, and conduction pathways. This non-invasive test is widely used to diagnose various heart conditions, including arrhythmias, ischemic heart disease, and myocardial infarction (heart attack).

By analyzing ECG waveforms, medical professionals can identify abnormalities in heart function and structure, enabling early detection and intervention for cardiovascular diseases. ECG monitoring plays a crucial role in assessing the risk of cardiac events, guiding treatment decisions, and evaluating the efficacy of cardiac medications or interventions.

Overall, EMG and ECG tests are invaluable tools in clinical practice, offering valuable insights into neuromuscular and cardiac health. Their widespread use by medical professionals underscores their importance in diagnosing disorders, monitoring disease progression, and optimizing patient care.[6]



[21]

3.2. Data Collection

Electromyography (EMG) and electrocardiography (ECG) data were collected using a Bitalino device equipped with three diodes.

For ECG measurements, the positive and negative diodes were positioned on the upper left chest, while the neutral diode was centered below the left chest. This placement allows for the detection of electrical impulses generated by the heart, providing valuable information about cardiac activity. ECG measurements are commonly used to assess heart rate, rhythm, and any abnormalities in cardiac function.

In the case of EMG measurements, two diodes with charge were placed on the biceps, while the neutral diode was positioned on the elbow. This configuration enables the recording of electrical signals produced by muscle contractions.

EMG measurements are essential for evaluating muscle function, detecting abnormalities in neuromuscular activity, and monitoring muscle response to various stimuli.

3.3. Data Analysis

Artificial intelligence techniques, specifically reinforcement learning and machine learning algorithms, were employed for data analysis. Reinforcement learning algorithms were utilized to identify patterns and correlations in the collected data, allowing for the detection of subtle changes indicative of muscle state evolution. Machine learning algorithms were then applied to predict the future evolution of muscle states based on the gathered measurements.[24]

3.4. Ethical Considerations

The study was conducted following ethical guidelines, and ethical approval was obtained from each individual participant prior to their involvement in the research. Participants were fully informed about the purpose and procedures of the study, and their consent was obtained before data collection commenced. Confidentiality and privacy of participant data were strictly maintained throughout the study.

4. Handling EMG data

4.1. Needle EMG Signal Characteristics

Electromyography (EMG) waveform data represent a time series signal characterized by high frequency and periodic fluctuations in amplitudes. Each data point in the signal corresponds to a voltage value generated at a specific time step. For instance, a 1-second recording collected at a sampling rate of 50 kHz encompasses 50,000 data points, typically measured in microvolts. This data is notably rich, stochastic (randomly determined), and high-dimensional, offering detailed insights into the electrical properties of motor units.

Manual interpretation of EMG signals is prone to significant inter-operator variability and does not practically allow for the assessment of every data point before assigning a score or impression. EMG data storage methods vary across recording machines but commonly involve organizing voltage values into columns per unit of time. Additionally, accompanying metadata, such as patient information, study examination details (including facility-specific protocols), and the specific muscle being examined, are also typically stored alongside the EMG waveform data.[27]

4.2. EMG Signal Preprocessing

After EMG signal acquisition, the signal undergoes denoising using lower and upper frequency cutoff filters, with or without a notch filter, to remove contaminant voltage activities, including those from the ambient environment. Machine learning (ML) and other mathematical models have also been developed to reduce or eliminate contaminant signals, such as environmental noise.

Another source of contamination is needle or patient movement artifact, particularly evident during evaluation of EMG activity during muscle contraction and relaxation, respectively. This type of artifact is more variable and challenging to address using simple mathematical formulas, presenting a complex challenge that can be effectively tackled through the application of AI.

Following denoising and application of frequency filters, the resulting EMG signal can be considered as raw EMG data, rich in information and ready for AI processing. There exists a plethora of techniques to extract meaningful features from raw signals, facilitating signal condensation, input optimization, and enhanced processing efficiency for AI models, which is somewhat of what we will use.[27]

4.3. EMG Signal Feature Selection

The conventional process of EMG signal analysis is somewhat subjective, labor-intensive, and prone to inter-rater variability, sometimes necessitating repeated studies. Moreover, the accuracy of this analysis heavily relies on the training, skillset, and experience of the individual conducting it. However, recent advancements in deep learning (DL) algorithms offer promising solutions to overcome these challenges.

Raw EMG data are inherently complex, containing vast amounts of information that demand substantial computational resources and time for analysis. Principal component analysis (PCA) offers a way to simplify the complexity and diversity in EMG data while preserving underlying trends and patterns. The primary objective of PCA is to reduce the high "dimensionality" of these data without sacrificing essential information, with increasing successful implementation observed in ML studies utilizing EMG data.

Alternative strategies to address the complexities of raw data processing include innovative methods of feature extraction tailored to capture specific key attributes. These extraction techniques are typically categorized into time (or temporal) domain (TD), frequency domain (FD), and time-frequency domain (TFD). While the nuances of these techniques exceed the scope of this review, each demonstrates distinct characteristics and has historically been employed with ML approaches limited by computational capabilities.

However, recent strides in DL have significantly facilitated the utilization of raw data as input for EMG analysis. DL models adeptly manage the extensive information present in raw EMG data, resulting in enhanced performance. Subsequent sections will delve into these advancements and underscore the superior capabilities of DL models.

In our endeavor, we aim to harness the power of a convolutional neural network, training it meticulously to discern the unique states of a specific muscle. This endeavor is pivotal as it lays the foundation for leveraging advanced AI techniques in predicting the evolution of muscle conditions, promising profound insights into future applications.[27]

4.4. EMG Signal Databases

Currently, there is a limited availability of publicly accessible databases for the development, testing, and benchmarking of machine learning (ML) and specifically deep learning (DL) algorithms in the field of electrodiagnostic (EDX) medicine.[27]

5. Data Visualization

In this section, we will summarize the visualization of the data collected during our study, which represents a wide variety of states of the right arm, including healthy, fatigued, and diseased individuals. The collection of this data was carried out using a combination of electromyography (EMG) and electrocardiography (ECG) to capture the electrical activity of the muscles and the heart, respectively.

5.1. Description of the Collected Data

Data has been collected from a diverse sample of individuals representing different states of the right arm. This includes:

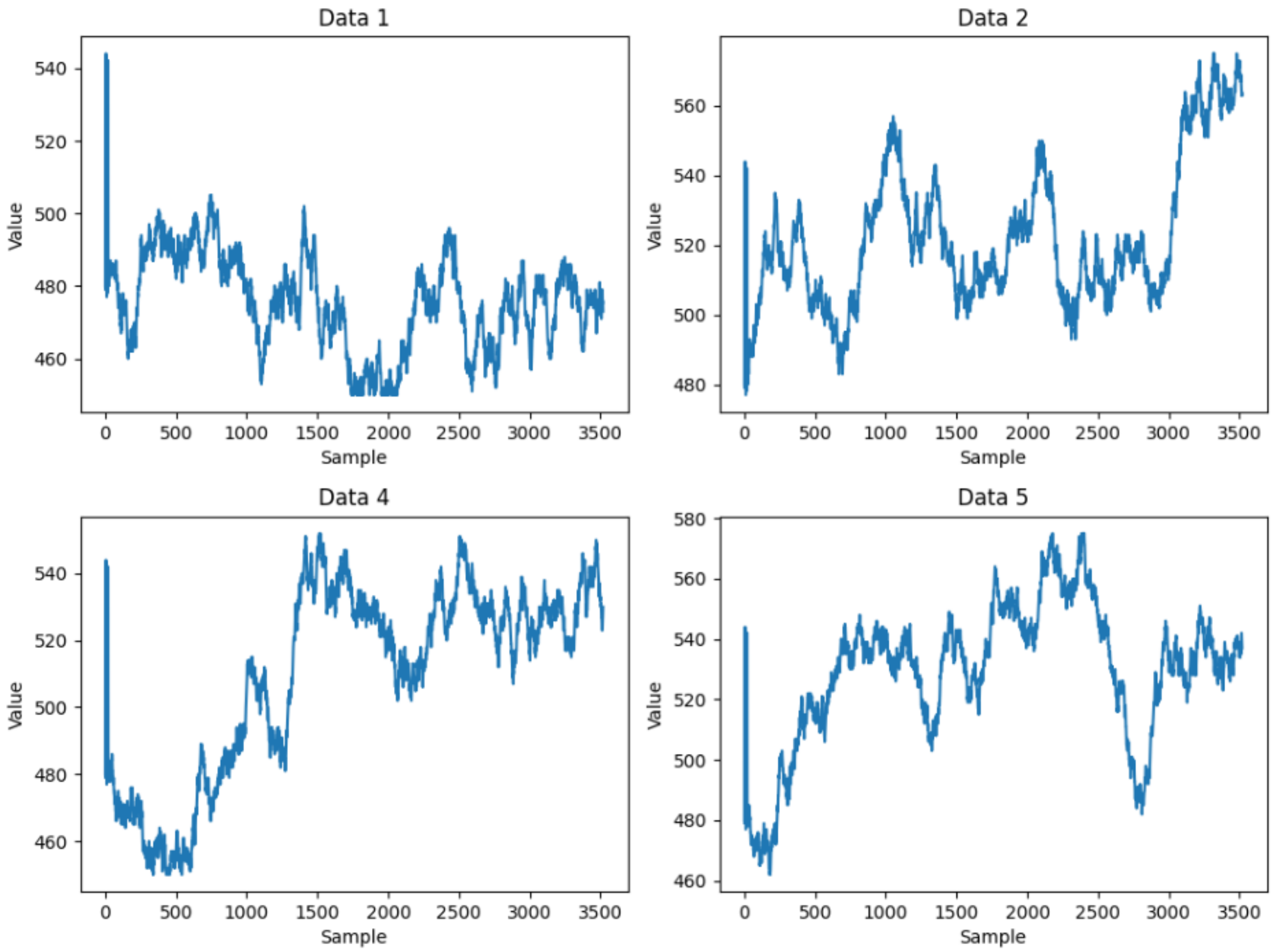
- **Healthy Individuals:** Participants who do not present any relevant medical condition and whose muscular and cardiac activity is in a typical and unaltered state.
- **Fatigued Individuals:** Participants who have experienced muscle fatigue due to physical activity or strenuous work of the right arm. Muscle fatigue may manifest as a decrease in muscle strength or endurance and may affect the electrical activity recorded by the EMG.
- **Diseased Individuals:** Participants who suffer from a variety of medical conditions affecting the muscular and cardiac health of the right arm, such as injuries, neuromuscular disorders, or cardiovascular diseases. These individuals may exhibit anomalous patterns in the electrical activity recorded by the EMG and ECG.

[24]

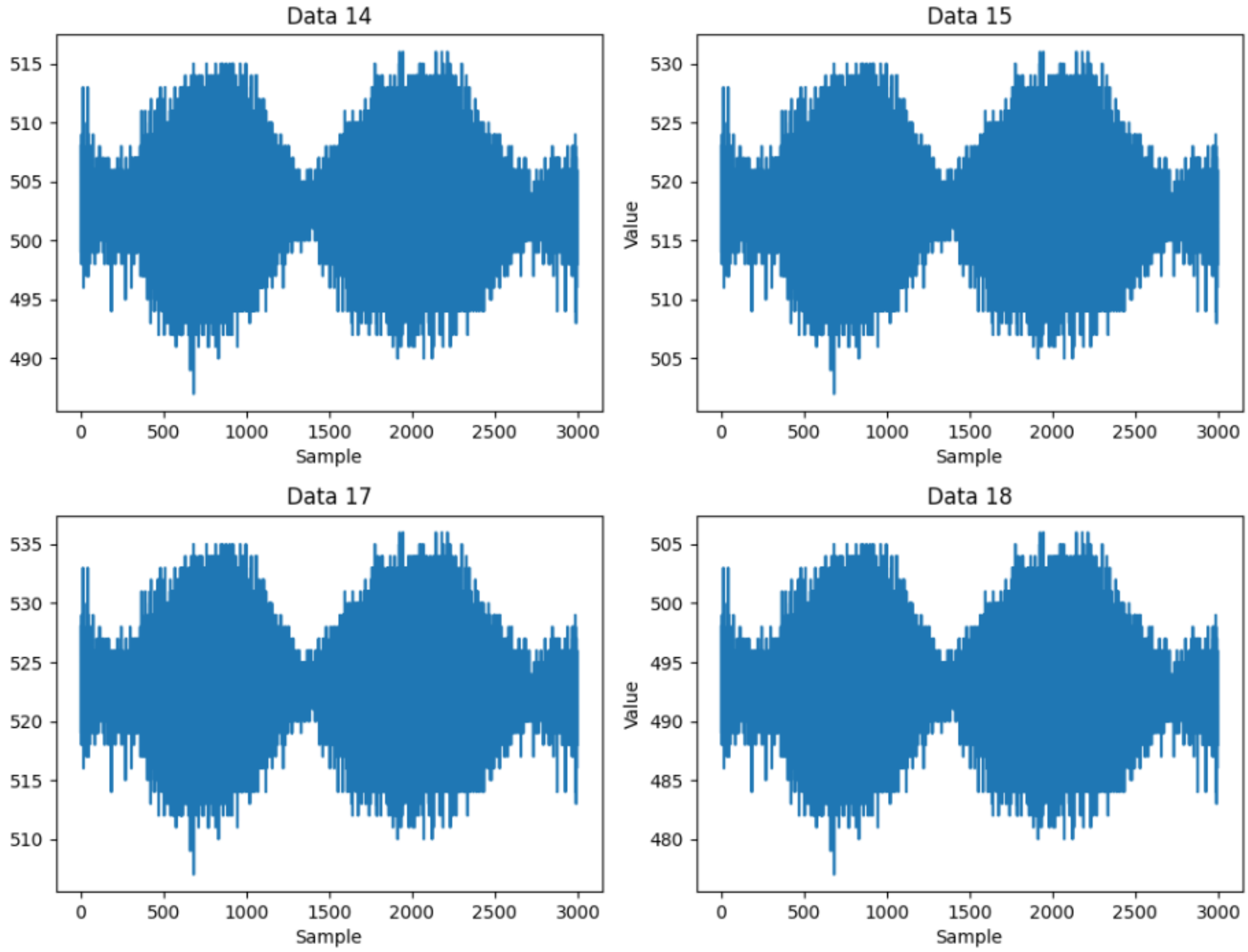
5.2. Examples of Data Visualization

Below, we present some examples of data visualization illustrating the differences in muscular and cardiac activity among different groups of individuals:

1. **Comparison of Resting EMG:** Graphs of muscular electrical activity at rest of healthy, fatigued, and diseased individuals, showing differences in the amplitude and frequency of EMG signals.

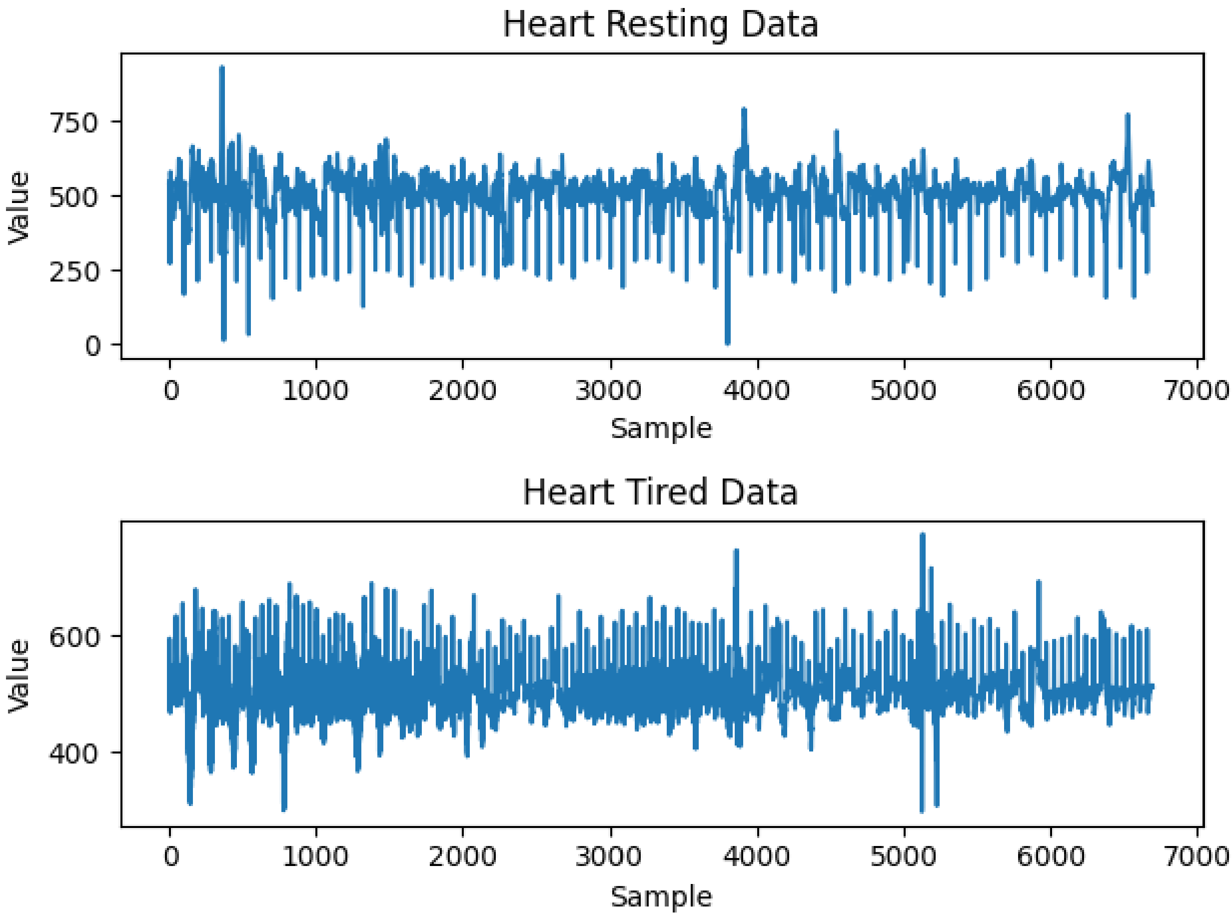


[24]



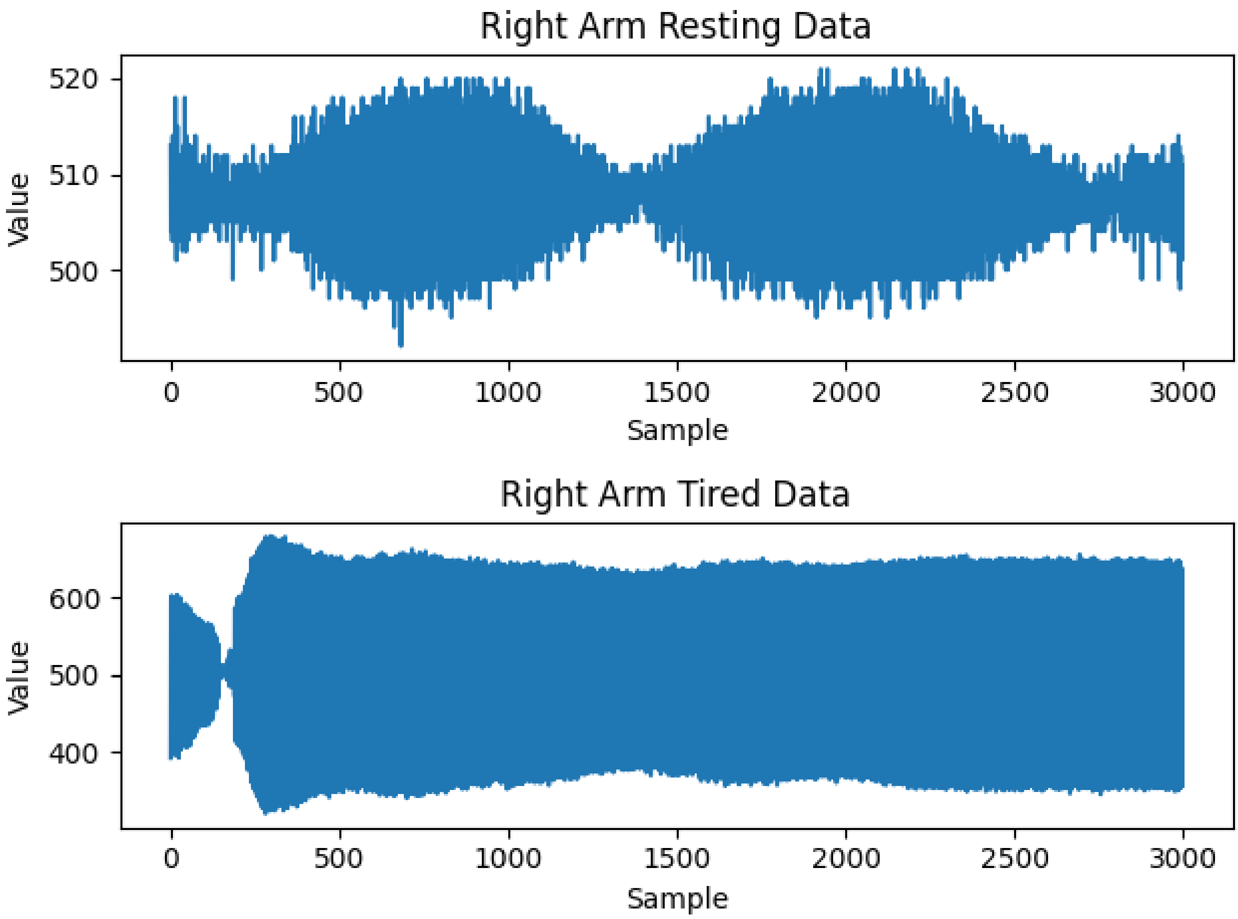
[24]

2. **Analysis of ECG during Exercise:** Graphs showing the heart's response to exercise in healthy and diseased individuals, highlighting changes in heart rate and the waveform of the ECG.

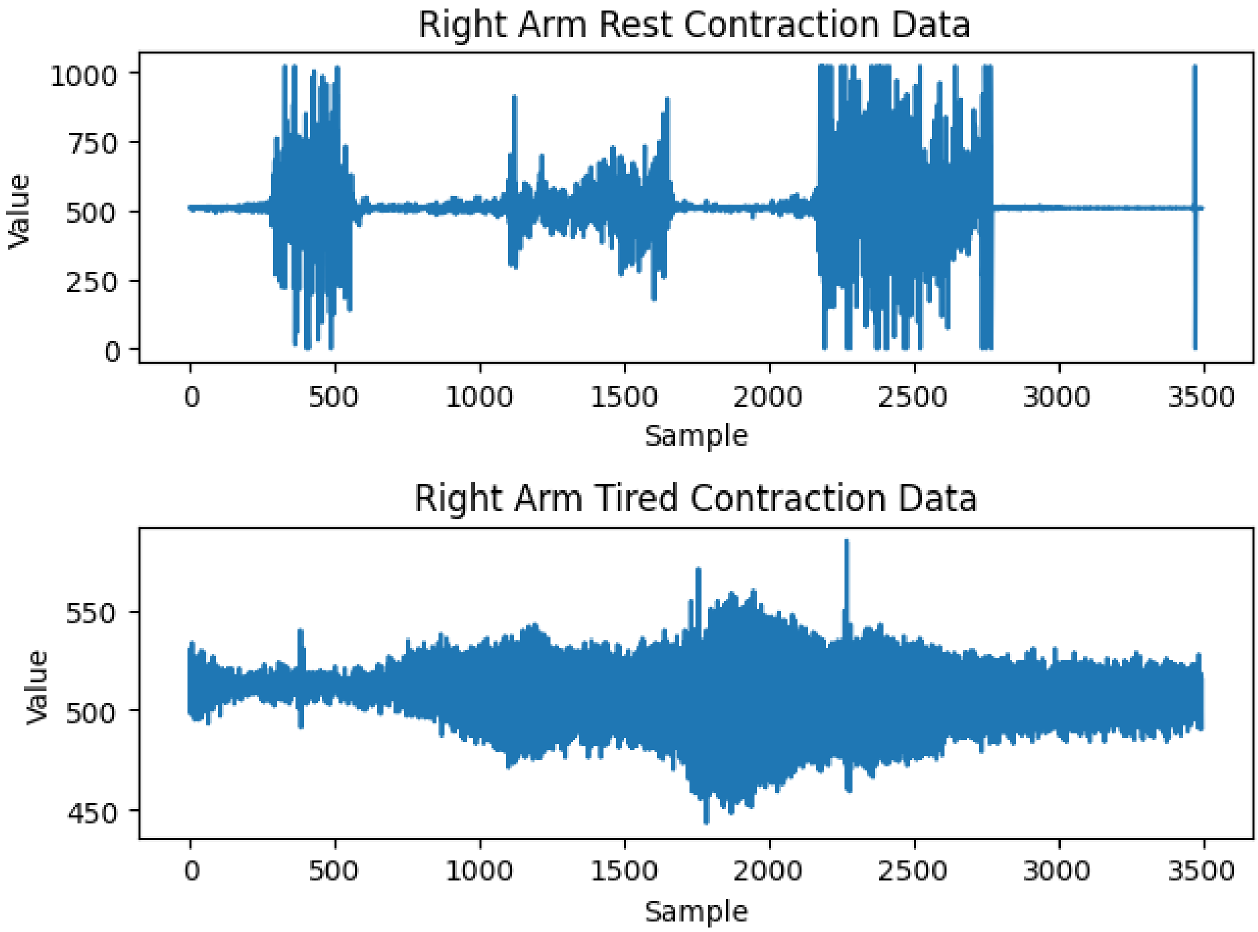


[24]

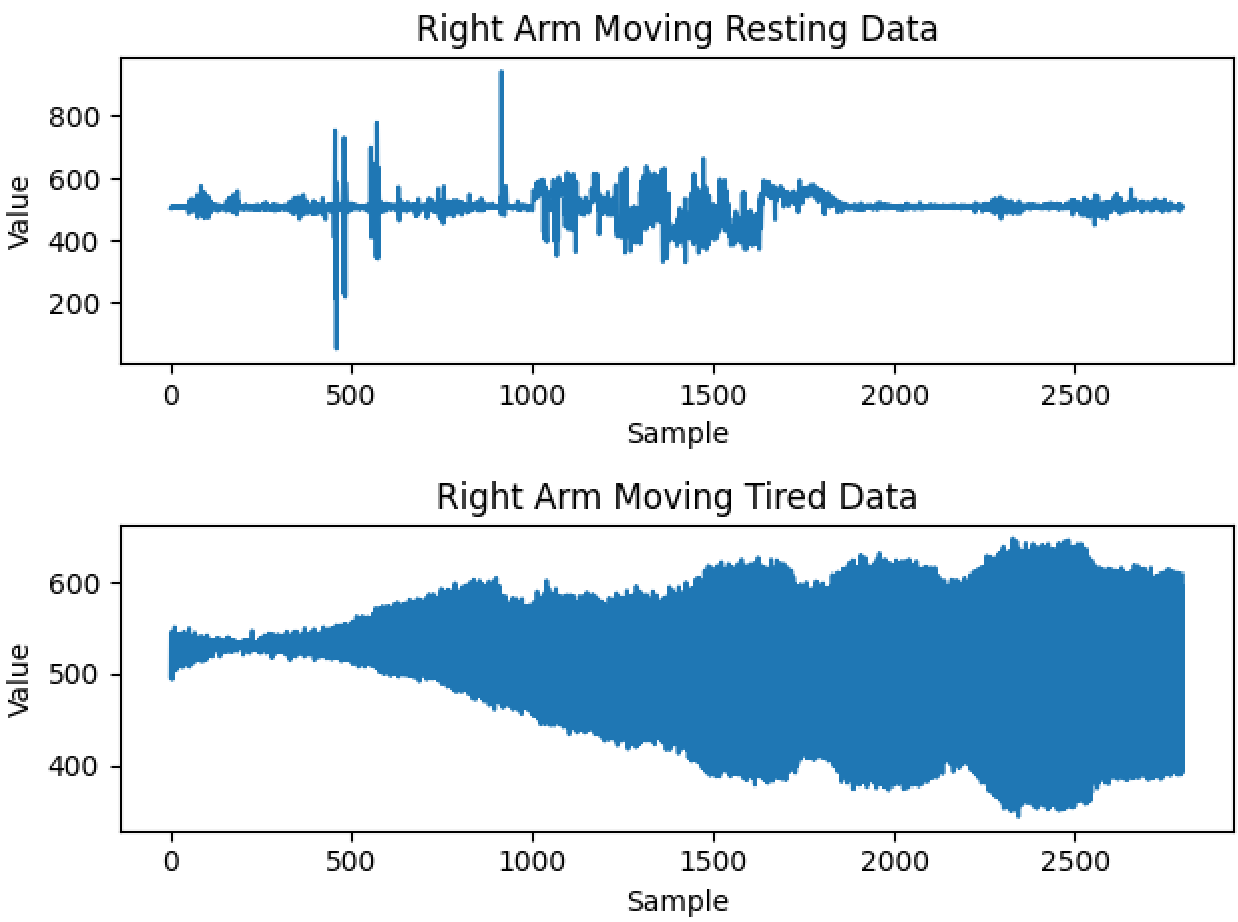
3. **Monitoring Muscle Fatigue:** Graphs of muscular electrical activity during a prolonged period of physical activity, demonstrating the evolution of muscle fatigue in fatigued individuals compared to healthy individuals.


Right Arm Resting Data
Value
520
510
500
0
500
1000
1500
2000
2500
3000
Sample
Right Arm Tired Data
Value
600
500
400
0
500
1000
1500
2000
2500
3000
Sample

[24]


Right Arm Rest Contraction Data
1000
750
500
250
0
Value
0
500
1000
1500
2000
2500
3000
3500
Sample
Right Arm Tired Contraction Data
550
500
450
Value
0
500
1000
1500
2000
2500
3000
3500
Sample

[24]



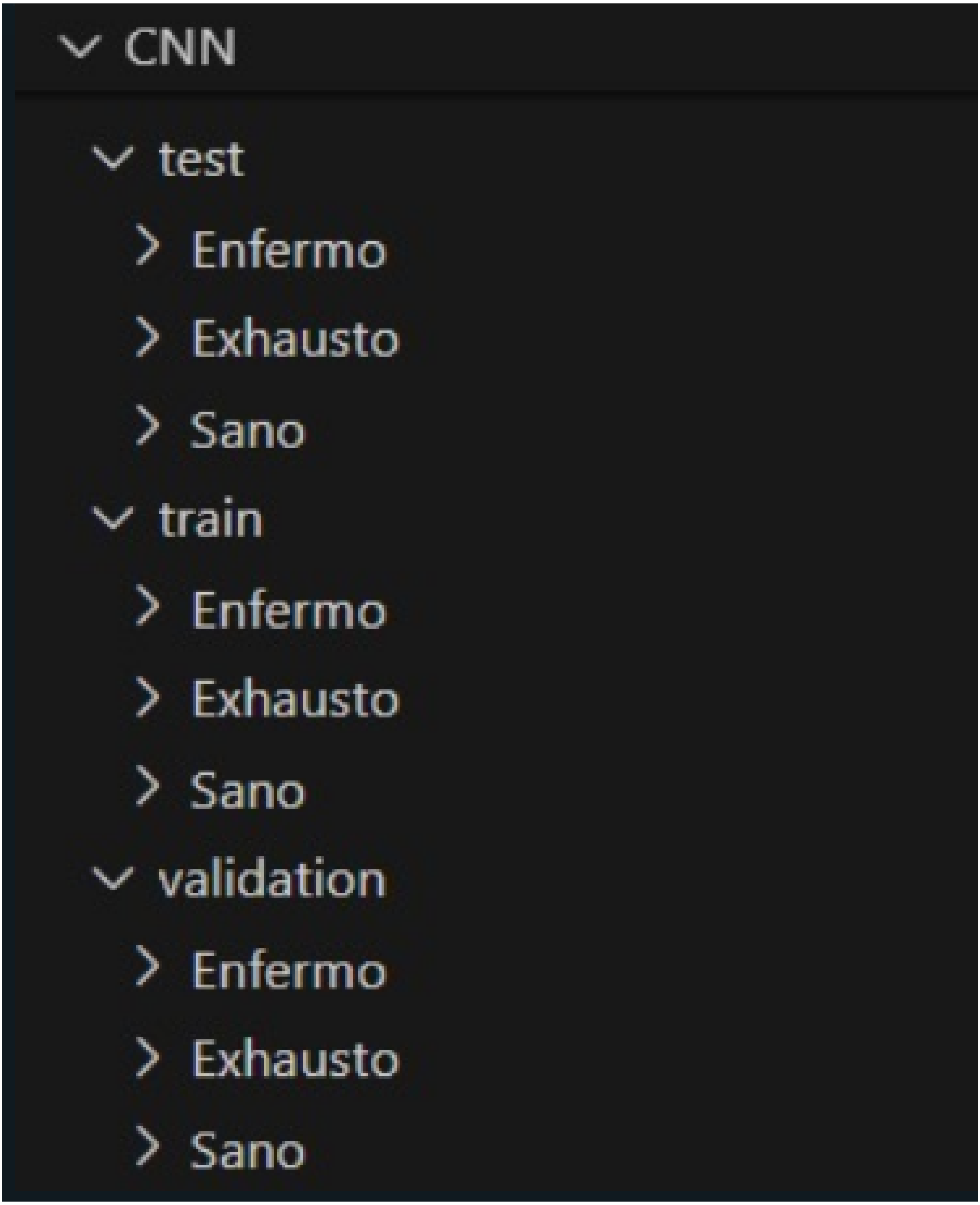
[24]

These examples of data visualization allow us to better understand the differences in electrical activity of the right arm among different groups of individuals and provide valuable information for the analysis and interpretation of our results. They are also indispensable for training our algorithm, ensuring that it can accurately identify and predict the various states of muscle activity.[24]

6. Algorithms

6.1. Data Preparation

The data was organized into three folders: Train, Test, and Validation. Within each folder, there are three subfolders: healthy, exhausted, and sick.



[24]

The images were preprocessed to fit the model input, including resizing and normalization.[24]

6.2. CNN

The choice of a convolutional neural network (CNN) for predicting the evolution of a damaged muscle in the future is based on its inherent ability to capture and learn complex, hierarchical features from visual data, such as medical images in this case.

Damaged muscles or those affected by injuries may exhibit subtle changes in their structure and texture over time, which may be challenging for the human eye to detect but potentially significant for a machine learning model. CNNs are particularly effective in detecting patterns in image data due to their architecture specifically designed for this purpose.

By employing a CNN, one can leverage its convolutional layers to extract relevant features from images of affected muscles, such as texture, shape, and intensity distribution. These features become progressively more abstract as the network deepens, allowing the model to capture detailed and complex information about the muscle's state.

Additionally, pooling layers help reduce the dimensionality of the extracted features, resulting in a more compact and generalizable representation of the information. The final dense layers of the CNN can then combine these features to make predictions about the future evolution of the damaged muscle.

Monitoring metrics such as accuracy and loss during training provides an objective evaluation of the model's performance over time. This enables adjustments to the architecture and parameters of the model as needed to improve its predictive ability and its ability to identify the state of the muscle more accurately.

In summary, the choice of a CNN for this work is justified by its ability to learn complex representations of visual data, its effectiveness in detecting subtle patterns in medical images, and its ability to make accurate predictions about the future evolution of a damaged muscle.[4][29][26][16]

The model architecture included several convolutional layers, pooling layers, and dense layers. The model was trained using the previously organized and normalized images. Metrics for accuracy and loss were monitored throughout the training epochs.

The algorithm used for creating and training the CNN is as follows:

```
batch_size = 12
epochs = 150
input_shape = (150, 150, 3)

train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(150, 150),
    batch_size=batch_size,
    class_mode='categorical'
)

validation_datagen = ImageDataGenerator(rescale=1./255)

validation_generator = validation_datagen.flow_from_directory(
    validation_dir,
    target_size=(150, 150),
    batch_size=batch_size,
    class_mode='categorical'
)

test_generator = validation_datagen.flow_from_directory(
    test_dir,
    target_size=(150, 150),
    batch_size=batch_size,
```

```
    class_mode='categorical',
    shuffle=False
)

model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Flatten(),
    layers.Dropout(0.5),
    layers.Dense(36, activation='relu'),
    layers.Dense(3, activation='softmax')  # 3 output classes: healthy, exhausted, sick
])

model.compile(optimizer=optimizers.RMSprop(learning_rate=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=epochs,
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // batch_size
)

test_loss, test_acc = model.evaluate(test_generator, steps=test_generator.samples // batch_size)
print('Test accuracy:', test_acc)
```

[24]

7. Results

The trained neural network has demonstrated the ability to distinguish the state of a muscle based on ECG and EMG graphs. Through rigorous training and validation processes, the model has achieved a notable, albeit improvable, precision in classification tasks. The precision of the model in determining the muscle state is currently at 80%, highlighting its potential and areas for further enhancement.

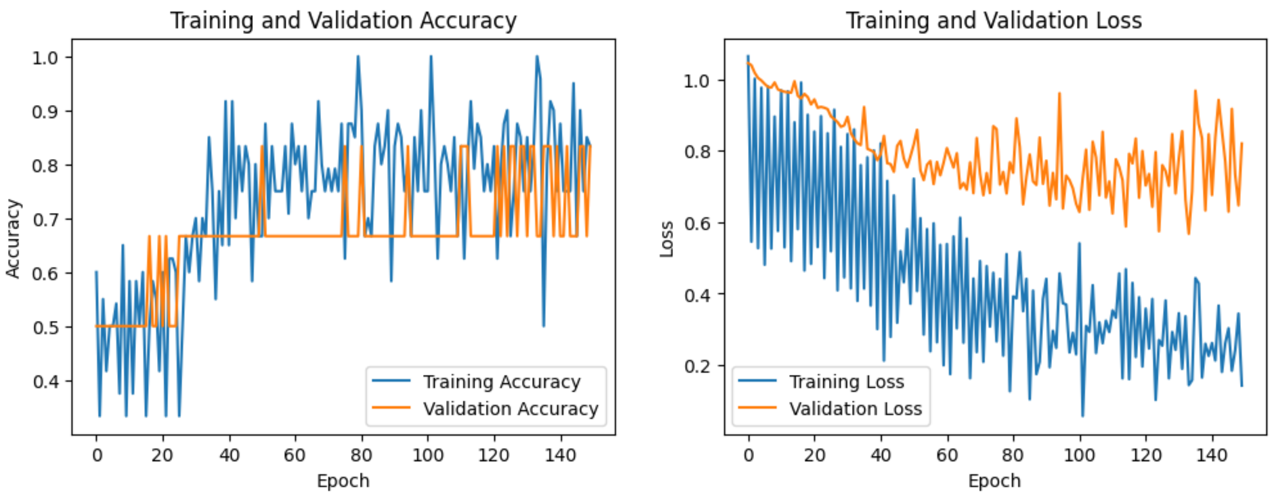
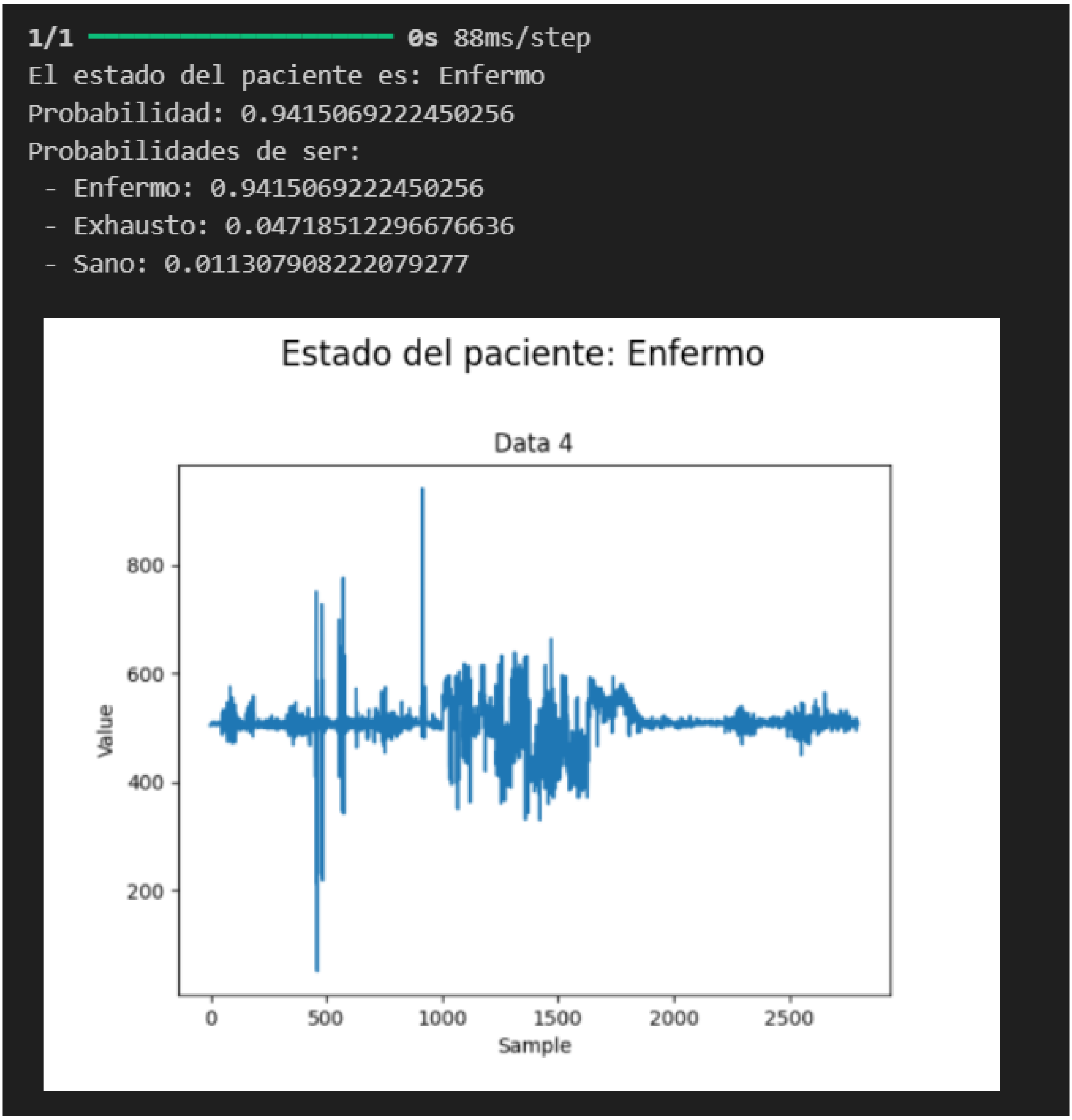


Figure 1

[24]

These results underscore the model's capabilities and point towards future improvements to increase its accuracy. The precision graph, as shown in Figure 1, illustrates the performance metrics of the network, indicating both its strengths and the areas that require further refinement.



[24]

8. Discussion

In this section, we discuss the implications of our findings and the potential impact of our study on the field of muscle state analysis and rehabilitation. Our approach, utilizing EMG and ECG data collected from a diverse sample of individuals, provides a comprehensive understanding of the electrical activity associated with different muscle states. This knowledge is crucial for developing effective diagnostic and therapeutic strategies.[23][18][25]

The data visualizations presented in the previous section highlight significant differences in muscle and cardiac activity among healthy, fatigued, and diseased individuals. These differences underscore the importance of personalized approaches in medical and fitness contexts, where treatments and interventions can be tailored to the specific needs and conditions of each individual.

Moreover, our findings demonstrate the potential of artificial intelligence in enhancing the analysis and interpretation of complex biomedical data. By leveraging machine learning algorithms, we can accurately identify patterns and predict muscle state evolution, which is essential for optimizing recovery processes and improving patient outcomes.[28][19]

8.1. Future Implementations

The current model, which analyzes graphs of muscle and cardiac activity to determine the muscle state, lays the groundwork for more advanced applications. One promising future implementation involves using this trained model to develop an AI system capable of predicting the future evolution of muscle states.

By integrating real-time data from EMG and ECG measurements, the AI could forecast potential changes in muscle condition, such as the onset of fatigue or the progression of recovery from injury. This predictive capability would be invaluable for both clinicians and patients, allowing for timely interventions and adjustments to treatment plans.

However, implementing such a predictive model presents several challenges. One significant issue is ensuring the accuracy and reliability of predictions across diverse populations and varying conditions. To address this, the model would need to be trained on a large and diverse dataset, incorporating a wide range of muscle states and individual characteristics.

Another challenge is the integration of this predictive system into existing clinical workflows. Ensuring that healthcare providers can easily interpret and act upon the AI's predictions is crucial. This might involve developing intuitive user interfaces and providing training for medical staff.

Potential solutions to these challenges include:

- **Expanding the Dataset:** Collecting more extensive and varied data to improve the robustness and generalizability of the AI model.
- **Continuous Learning:** Implementing mechanisms for the AI to learn and adapt from new data over time, enhancing its predictive accuracy.
- **User-Friendly Interfaces:** Designing interfaces that clearly present the AI's predictions and recommendations, making it easier for healthcare providers to utilize the system effectively.
- **Interdisciplinary Collaboration:** Working closely with medical professionals, data scientists, and engineers to ensure the AI system meets clinical needs and standards.

Ultimately, the integration of predictive AI models into muscle state analysis holds great promise for advancing personalized medicine and rehabilitation. By addressing the challenges and implementing effective solutions, we can significantly enhance the accuracy and utility of these models, ultimately leading to better patient care and outcomes.

9. Conclusions

In conclusion, the integration of artificial intelligence (AI) into electromyography (EMG) data analysis has brought about transformative advancements in the field. By leveraging machine learning algorithms, AI enables efficient handling of large and complex datasets, allowing for the detection of intricate patterns that may not be readily discernible by human analysts. This has profound implications across various domains, including:

1. **Neurological Disorder Diagnosis:** AI facilitates early detection and treatment planning for conditions such as epilepsy and Parkinson's disease, enabling continuous monitoring and timely adjustments.
2. **Brain-Computer Interfaces (BCIs):** AI enhances BCIs for assistive technology and gaming, providing mobility-impaired individuals with empowering experiences and immersive gaming interactions.
3. **Personalized Treatment Plans:** AI-driven analysis enables the creation of tailored treatment plans, optimizing rehabilitation protocols and effectively managing conditions such as depression and anxiety.

However, the integration of AI into healthcare data analysis also presents challenges and ethical considerations, including data privacy and security concerns, ethical implications of AI usage, and regulatory compliance issues.[9][10][17] Despite these challenges, the future outlook for AI in EMG data analysis remains promising:

1. Advancements in AI and EEG/EMG technology will lead to more sophisticated algorithms capable of extracting deeper insights from larger datasets.
2. The growing demand for AI-powered EEG and EMG equipment presents market opportunities, although competition and regulatory challenges may impact industry dynamics.
3. Predictions suggest that AI-driven EEG and EMG analysis will become standard practice in diagnosing and monitoring neurological disorders, ultimately leading to personalized treatment plans and improved patient outcomes.

[13]

Author Contributions: Conceptualization, Javier Miguélez; methodology, Javier Miguélez; software, Diego De Santos; validation, Javier Miguélez, Diego De Santos; formal analysis, Diego de Santos; investigation, Javier Miguélez; resources, Diego de Santos;

data curation, Diego de Santos; writing—original draft preparation, Javier Miguélez; writing—review and editing, Javier Miguélez; visualization, Diego De Santos; supervision, Javier Miguélez; project administration, Javier Miguélez. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the patient(s) to publish this paper

Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section "MDPI Research Data Policies" at https://www.mdpi.com/ethics.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
EMG	Electromyography
EMG	Electromyography
CNN	Convolutional neural network

References

[1] Omer Adir et al. "Integrating artificial intelligence and nanotechnology for precision cancer medicine". In: *Advanced Materials* 32.13 (2020), p. 1901989.

[2] Mugahed A Al-Antari. *Artificial intelligence for medical diagnostics—existing and future aI technology!* 2023.

[3] Bhavneet Bhinder et al. "Artificial intelligence in cancer research and precision medicine". In: *Cancer discovery* 11.4 (2021), pp. 900–915.

[4] Zhengping Che et al. "Exploiting convolutional neural network for risk prediction with medical feature embedding". In: *arXiv preprint arXiv:1701.07474* (2017).

[5] Cleveland Clinic. *EMG (Electromyography)*. Accessed: 2024-05-16. 2024. URL: https://my.clevelandclinic.org/health/diagnostics/4825-emg-electromyography.

[6] Wikipedia contributors. *Electrocardiography*. Accessed: 2024-05-16. 2024. URL: https://en.wikipedia.org/wiki/Electrocardiography.

[7] Wikipedia contributors. *Electromyography*. Accessed: 2024-05-16. 2024. URL: https://en.wikipedia.org/wiki/Electromyography.

[8] Zodwa Dlamini et al. "Artificial intelligence (AI) and big data in cancer and precision oncology". In: *Computational and structural biotechnology journal* 18 (2020), pp. 2300–2311.

[9] Chukwuka Elendu et al. "Ethical implications of AI and robotics in healthcare: A review". In: *Medicine* 102.50 (2023), e36671.

[10] Orsolya Friedrich and Sebastian Schleidgen. "The Ethical Implications of Using AI in Medicine". In: *Cambridge Quarterly of Healthcare Ethics* (2024), pp. 1–3.

[11] Hiroshi Fujita. "AI-based computer-aided diagnosis (AI-CAD): the latest review to read first". In: *Radiological physics and technology* 13.1 (2020), pp. 6–19.

[12] Shuo Gao et al. "Use of advanced materials and artificial intelligence in electromyography signal detection and interpretation". In: *Advanced Intelligent Systems* 4.10 (2022), p. 2200063.

[13] J. Gautam. *The Role of Artificial Intelligence in EEG and EMG Data Analysis: Market Implications*. Disponible en: https://www.linkedin.com/pulse/role-artificial-intelligence-eeg-emg-data-analysis-market-gautam-vqsgc/. 2023.

[14] Pavel Hamet and Johanne Tremblay. "Artificial intelligence in medicine". In: *Metabolism* 69 (2017), S36–S40.

[15] J Holmes, L Sacchi, R Bellazzi, et al. "Artificial intelligence in medicine". In: *Ann R Coll Surg Engl* 86 (2004), pp. 334–8.

[16] Walaa N Ismail et al. "CNN-based health model for regular health factors analysis in internet-of-medical things environment". In: *IEEE Access* 8 (2020), pp. 52541–52549.

[17] Balaram Yadav Kasula. "Ethical Implications and Future Prospects of Artificial Intelligence in Healthcare: A Research Synthesis". In: *International Meridian Journal* 6.6 (2024), pp. 1–7.

[18] Farah Magrabi et al. "Artificial intelligence in clinical decision support: challenges for evaluating AI and practical implications". In: *Yearbook of medical informatics* 28.01 (2019), pp. 128–134.

[19] Priyanka Mahajan. "Applications of pattern recognition algorithm in health and medicine". In: *Int. J. Eng. Comput. Sci* 5 (2016), pp. 16580–16583.

[20] Paras Malik, Monika Pathania, Vyas Kumar Rathaur, et al. "Overview of artificial intelligence in medicine". In: *Journal of family medicine and primary care* 8.7 (2019), pp. 2328–2331.

[21] MedlinePlus. *Electromiografía (EMG) - Prueba de la EMG*. Accessed: 2024-05-16. 2024. URL: https://medlineplus.gov/spanish/ency/esp_imagepages/1135.htm.

[22] Y. Qian et al. "Transforming medicine: artificial intelligence integration in the peripheral nervous system". In: *Frontiers in Neurology* 15 (2024), p. 1332048. DOI: 10.3389/fneur.2024.1332048.

[23] Vanessa Rampton, Michael Mittelman, and Jörg Goldhahn. "Implications of artificial intelligence for medical education". In: *The Lancet Digital Health* 2.3 (2020), e111–e112.

[24] Diego de Santos del Río and Javier Miguélez Yagüe. *Bitalino*. https://github.com/Diegodesantos1/Bitalino. Accessed: 2024-05-16. 2024.

[25] Murugan Subramanian et al. "Precision medicine in the era of artificial intelligence: implications in chronic disease management". In: *Journal of translational medicine* 18 (2020), pp. 1–12.

[26] Qiuling Suo et al. "Personalized disease prediction using a CNN-based similarity learning method". In: *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. IEEE. 2017, pp. 811–816.

[27] M. A. Taha and J. A. Morren. "The role of artificial intelligence in electrodiagnostic and neuromuscular medicine: Current state and future directions". In: *Muscle & Nerve* (2023). DOI: 10.1002/mus.28023.

[28] Ying Wei et al. "A review of algorithm & hardware design for AI-based biomedical applications". In: *IEEE transactions on biomedical circuits and systems* 14.2 (2020), pp. 145–163.

[29] Xiaokang Zhou, Yue Li, and Wei Liang. "CNN-RNN based intelligent recommendation for online medical pre-diagnosis support". In: *IEEE/ACM Transactions on Computational Biology and Bioinformatics* 18.3 (2020), pp. 912–921.