engineering proceedings

MDPI

Proceeding Paper

An Internet of Medical Things-Based Smart Electromyogram Device for Monitoring of Musculoskeletal Disorders †

Vijayalakshmi Sankaran [1], Paramasivam Alagumariappan [2,*], Malathy Sathyamoorthy [3], Rajesh Kumar Dhanaraj [4], Kamalanand Krishnamurthy [5] and Emmanuel Cyril [6]

1 Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai 600062, India; drvijayalakshmis@veltech.edu.in
2 Department of Biomedical Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai 600062, India
3 Department of Information Technology, KPR Institute of Engineering and Technology, Coimbatore 641407, India; malathy.s@kpriet.ac.in
4 Symbiosis Institute of Computer Studies and Research (SICSR), Symbiosis International (Deemed University), Pune 411016, India; rajesh.dhanaraj@sicsr.ac.in
5 Department of Instrumentation Engineering, MIT Campus, Anna University, Chennai 600044, India; kamalanand@mitindia.edu
6 Academics & Research, Gleneagles Hospital (Health City), Chennai 600100, India; drcemmanuel@globalhospitalsindia.com
* Correspondence: draparamasivam@veltech.edu.in ; Tel.: +91-9843780801
† Presented at the 11th International Electronic Conference on Sensors and Applications (ECSA-11), 26–28 November 2024; Available online: https://sciforum.net/event/ecsa-11.

Abstract: Electromyography (EMG) is a technique that measures the electrical activity of the muscles and it has been used extensively in the field of physiotherapy to assess the muscle function and activity. Grading muscle power is an important aspect of assessing muscle function, as it provides information about the strength and endurance of muscles. Presently, the physiotherapist uses Manual Muscle Testing (MMT) for grading muscle power however it requires the therapist with good expertise. In this work, an Internet of Medical Things (IoMT) based Smart EMG device is designed and developed for monitoring the patients suffering from abnormal musculoskeletal health conditions. Further, the EMG signals are acquired from normal individuals and the patients with abnormal health conditions. Also, the muscle power grading is used to grade the EMG signals and the Convolutional Neural Network (CNN) based deep learning algorithm is utilized to visualize the progress of course of treatment provided to the patients with musculoskeletal problems such as stroke, spinal cord injuries etc. The entire analysis is carried out Google Co-Laboratory based IoT cloud platform and the algorithms are coded using Python programming language. Results demonstrate that the proposed smart IoMT based smart device can predict the different muscle power with an average accuracy of 97.5% which proves the effectiveness of the device. This work appears to be of high clinical relevance since the proposed device is capable of providing valuable information about muscle function and enable the physiotherapists to design personalized treatment plans for patients with musculoskeletal disorders.

Keywords: bio-signals; Electromyography; Internet of Things; muscle power grading; physiotherapy; remote healthcare monitoring

Citation: Sankaran, V.; Alagumariappan, P.; Sathyamoorthy, M.; Dhanaraj, R.K.; Krishnamurthy, K.; Cyril, E. An Internet of Medical Things-Based Smart Electromyogram Device for Monitoring of Musculoskeletal Disorders. *Eng. Proc.* **2024**, *6*, x. https://doi.org/10.3390/xxxxx

Academic Editor(s): Name

Published: 26 November 2024

1. Introduction

Physiotherapy is the one of the treatment procedures for various musculoskeletal disorders and it helps the patients to retain their muscular ability. Also, the physiotherapy process helps in improvising mobility of the muscle function and it helps to reduce muscle pains. Furthermore, the assessment of muscle function is very tedious by Manual Muscle

Testing (MMT) which affects the effectiveness of the physiotherapy process [1]. The MMT is a traditional and commonly followed method for grading power of the muscle in therapy process and these muscle power grading totally depends on the skillset of the therapist. However, the lack of expertise and variability between different physiotherapist leads to inaccurate assessment of the patient progress [2,3].

Electromyography is a technique that measures the electrical activity of the muscles. Further, the electrical signals acquired using Electromyography technique are called as Electromyogram (EMG) signals [4]. Furthermore, the EMG gains more significance in various fields such as, precision medicine, tele-surgeries, rehabilitation medicine etc. [4–9]. In general, the two different methods are commonly followed namely invasive and non-invasive EMG signal acquisition, an invasive-methods for acquiring EMG require invasive procedures such as needle electrodes or catheters which produces discomfort to the patients whereas non-invasive methods are less expensive and highly reliable.

Industrial Internet of Things (IIoT) has made footprint on various fields such as smart cities, telemedicine, product industries etc. Several core technologies are involved and remarkable growth has been achieved in the healthcare applications [10–12]. Also, the huge volumes of IIoT data are used to train various Artificial Intelligence (AI) models to predicts various events. Furthermore, the hardware Graphical Processing Unit (GPU) from various vendors such as Neural Stick from Intel, Jetson Nano/Xavier from Nvidia, Google etc. which enables the GPU capability to the edge devices. Also, the Google and Amazon Web Service enables the GPU capability over cloud platform whereas without owning any hardware one can deploy deep learning/machine learning algorithms with the help of cloud platform [10].

Recent development in the field of Artificial Intelligence enables diagnosis of various musculoskeletal problems such as spinal cord injuries, stroke etc. Several researchers have proposed various deep learning and machine learning techniques for disease diagnosis [13–21]. Lee et al. (2022) [13] have developed a hand/finger gesture classifiers based on EMG signals using Artificial Neural Networks (ANN). Also, the authors have made various personalized classifiers other than CNN namely Support Vector Machine (SVM), random forest (RF), Logistic Regression (LR). Also, the authors have concluded that the CNN exhibits more accuracy than SVM, RF and LR. Najumnissa et al. (2022) [20] have proposed real time system for the identification of plant disease using various deep learning algorithms namely CNN, Polynomial Deep Belief Network (PDBN) and Linear Deep Belief Network (LDPN). Also, the authors have concluded that the CNN exhibited higher accuracy when compared to other two DBN based classifiers. Basak et al. (2021) [21] have utilized SVM and ANN for the classification EMG signals using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). While seeing various literatures, it is seen that the CNN is good at classifying bio-images & signals especially EMG.

The objective of this work is to devise an IoMT based smart EMG device which assists the physiotherapists to adjust treatment plans in real-time and provide immediate feedback to patients. This work is prearranged as follows; Section 2 presents the materials and methods; Section 3 demonstrates the results and conclusions and Section 4 concludes with the conclusion.

2. Methodology

In this proposed work, IoMT based EMG wearable device is designed and developed for the monitoring of motor recovery function. In the hospitals, the proposed IoMT based EMG wearable device can be attached to patients who is undergoing physiotherapy for musculoskeletal problems. Further, the EMG signals from different patient is collected and computed using IoT cloud platform which satisfies the functionality of IIoT. For this, the proposed system can be categorized into two different parts namely IoMT based EMG acquisition device and IoT cloud computing platform.

An IoMT based EMG acquisition device is a wearable hardware which acquires the EMG signals from the normal or patients subjected to physiotherapy treatment and uploads the EMG signal to IoT cloud platform. Furthermore, the IoT cloud platform performs EMG signal processing, classification of EMG signals according to muscle power grading, stores the classification output day wise for future reference and sends the recovery progress of the patient through Mail/Short Messaging Service (SMS) to the physician and patient.

2.1. IoMT Based EMG Acquisition Device

Figure 1 show the overall block diagram of the proposed IoMT based EMG device. Further, the proposed device consists of EMG sensor module, IoT controller and power supply especially battery unit. Also, the proposed device is a wearable IoMT based EMG acquisition device. Additionally, the components of the proposed device such as EMG sensor module, IoT controller and battery unit are enclosed with the help of acrylic box to ensure physical protection. The three electrodes of the EMG sensor module shall be placed to the brachioradialis which is the forearm muscles and the box shall be tied to the arm with the help of Velcro strap. Since, the proposed device is connected to WiFi connection and is powered by battery unit, the device records the EMG of normal/abnormal individuals and the in-built WiFi module of the proposed device helps to transmit the recorded EMG signal to Google spreadsheet via Hypertext Transfer Protocol Secure (HTTPS).

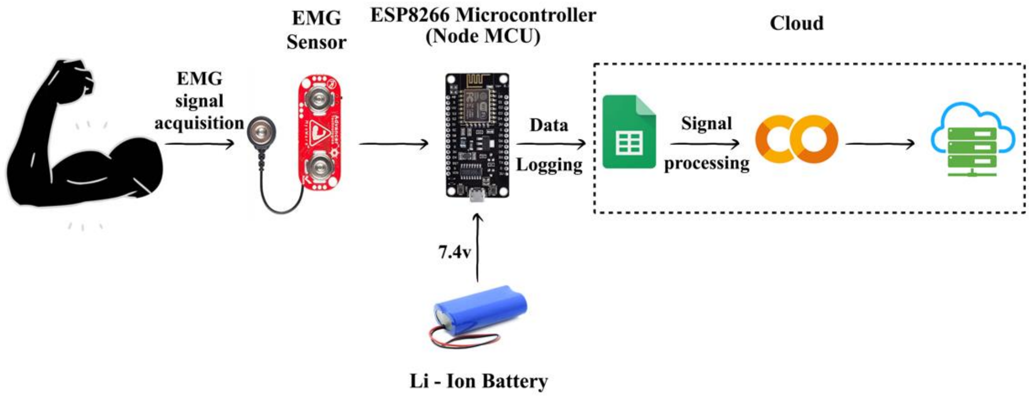

Figure 1. Overall block diagram of the proposed IoMT based EMG device.

2.1.1. EMG Sensor Module

In general, the muscle activity can be monitored using surface EMG sensor namely Electromyography sensor. In this work, a Myoware brand sensor with the product number (SEN-13723) is utilized which is manufactured by Advancer Technologies. Further, the sensor is very compact which operates on the supply voltage ranges from +2.9 V to +5.7 V. The sensor provides output in two different modes namely Raw EMG and EMG envelope. Also, the sensor module has polarity reversal protection, adjustable gain and is compatible with various market microcontrollers.

The Ag/AgCl non-invasive electrodes can be fixed directly to the sensor module and the module can be directly placed to the outer skin of the humans. Furthermore, the sensor module has an inbuilt instrumentation amplifier module and the filter to remove unwanted noise present in the acquired EMG signal. The instrumentation amplifier amplifies the acquired analog EMG signals which can be given to the analog pins of the advanced microcontrollers.

2.1.2. IIoT Controller

Node Microcontroller Unit (MCU) based ESP8266 WiFi module with 802.11 b/g/n is utilized in this work which is versatile, highly affordable and flexible.

The Node MCU has a wide range of built-in libraries such as MQTT, Wi-Fi, HTTP etc. and it acts as an easy platform which supports various development frameworks namely Node-Red, Platform IO etc. for connected devices. Figure 2 shows the function of Node MCU microcontroller in the proposed IoMT based EMG device. In this work, the amplified analog EMG signals from the EMG sensor module is fed to the Node MCU microcontroller. Initially, the microcontroller set up a WiFi connection and it starts acquiring the EMG signal. Further, the acquired EMG signal is converted from analog to digital using in-built Analog to Digital Converter (ADC). Also, the digitally converted EMG signal is stored in a buffer and once the buffer reaches a certain size or a specified time interval elapse, the microcontroller transmits the acquired EMG signal in a secured way to the Google spreadsheet via Hypertext Transfer Protocol Secure (HTTPS).

Figure 2. Function of Node MCU microcontroller.

2.2. *IoT Cloud Platform*

Figure 3 shows the architectural overview of the proposed IoT cloud platform for the monitoring of motor recovery function. Firstly, the EMG signals acquired from different patients are stored in individual Google spreadsheets in the Google drive. Also, the computation is performed with the help of Google Co-Laboratory which acts as a IoT/IIoT cloud platform. Once the EMG signal values are stored in the Google sheets, the signal processing algorithm process the raw EMG signal values.

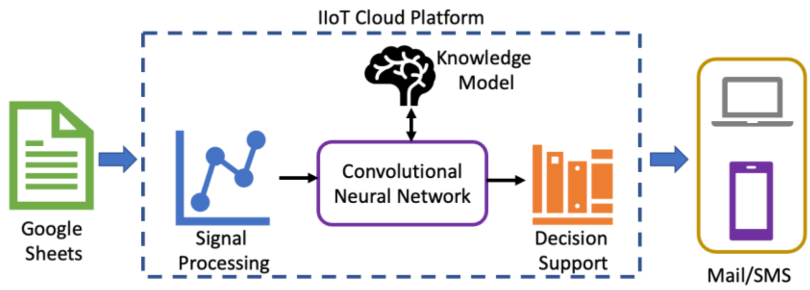

Figure 3. Architectural overview of the proposed IoT cloud platform.

2.2.1. EMG Signal Processing

In this work, a pre-processing of EMG signal is done by two different methods namely Hilbert-Huang transform (HHT) and Scalogram. Furthermore, the HHT is adopted along with Fast Fourier Transform (FFT) for the removal noises from acquired raw EMG signals [14] and the Scalogram is used to convert 1D EMG signals into two-dimensional time frequency signals which is given as an input to the CNN classifier. HHT is the combination of Empirical Mode Decomposition (EMD) and Hilbert Transform (HT). Further, the EMD preserves the characteristics of the varying frequency by decomposing the EMG signal into different mono component signals called as Intrinsic Mode Functions (IMFs). i.e., it is composed of narrow band of frequencies. Also, the EMD can be used for any complicated dataset by decomposing it into a finite small number of components. The EMD algorithm applied on the EMG signal y[n] is represented as [16,17]

$$y[n] = \sum_{i=1}^{k} \mathrm{IMF}_i[n] + z_k[n] \quad (1)$$

where, $\mathrm{IMF}_i[n]$ is the i^{th} IMF, $z_k[n]$ is the residue and the k represents the total number of IMFs. The HT method is used to demodulate IMFs into amplitude and frequency modulation signals. Once the different IMFs is obtained, the frequency of each IMFs can be calculated using Fast Fourier Transform (FFT). In general, the signals from any domain can be represented in frequency domain using FFT analysis and the FFT extracts the various frequency components present in the given signal over a period of time by sampling process [15]. By identifying noises in terms of IMFs helps to remove appropriate IMFs and to concatenate the remaining IMFs results in suppression of noises. The continuous Wavelet Transform (WT) of an EMG signal is depicted as 2D time frequency plot called as scalogram [18,19]. Further, the time parameter is denoted in x-axis and the scale parameter which is inversely proportional to the frequency of the signal is denoted in y-axis. Also, the absolute value of the WT is proportional to the color intensity of the pixel of the scalogram plot.

2.2.2. Deep Learning Algorithm

In the proposed work, the Convolutional Neural Network (CNN) is adopted to classify the muscle power using EMG signals. In the physiotherapy treatment, the muscle power is always graded using Manual Muscle Testing (MMT).

The therapy is done by subjecting patients to various exercises. In the MMT process, the resistance is applied to the muscle of the patient and the grading is done while the muscle is contracted by the patient. Similarly, the grading is derived for various actions which is shown in the Figure 4. An architecture of CNN consists of one input/output layer, one or more pooling and convolution layers and several fully connected layers [18–21]. In general, the training process of the CNN is performed with the help of two different stages namely forward and backward propagation stage. Further, the spatial information is extracted from the given 2D image using CNN in forward propagation stage whereas the internal parameters are updated throughout the network to optimize the objective function. Also, there is no constrain in setting number of layers in CNN. So, the total number of layers can be selected according to the train-test approach and the architecture of CNN is shown in the Figure 5.

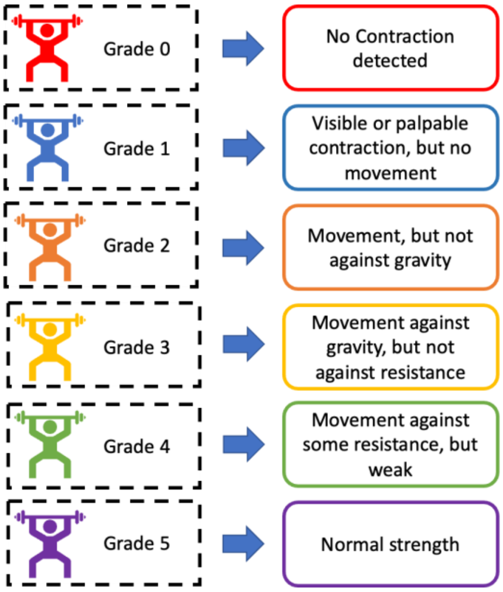

Figure 4. Muscle Power Grading Index.

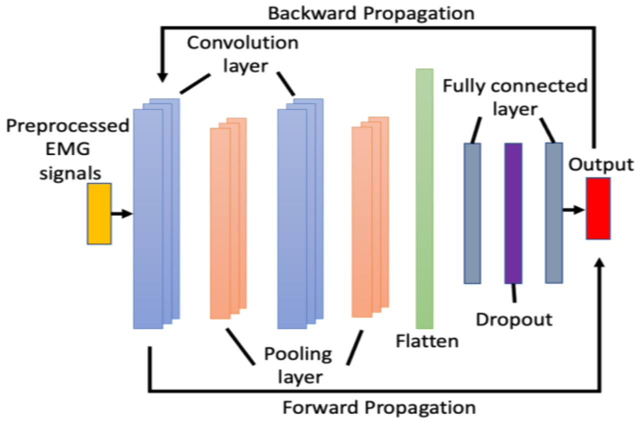

Figure 5. General architecture of the CNN.

The three different layers are present in forward propagation namely convolution layer, pooling layer and fully connected layer. Firstly, the possible features from the given input image are learned to recollect the bonding between the pixels of the input image using convolution layer. Also, the biases and an activation function are used to enhance the learning process and the process is given by the following equation [18]:

$$y_k^j = f\left(\sum_{i \in S_n} y_i^{j-1} * w_{in}^j + b_k^j\right) \tag{2}$$

where y_k^j is the ith component of the layer k, S_n is the nth region of the convolution layer with feature map of j − 1 layer, w_{in}^j and b_k^j are the weight matrix and the added bias respectively. After the Convolution Layers (CLs), the pooling layer is present which is used to eliminate or reduce the redundant features which is extracted by CLs. Further, the max pooling concept is utilized in this work as a polling layer whose output y_k^j is given as [18]:

$$y_k^j = f\left(w_k^j * \max\left(y_k^{j-1}\right) + b_k^j\right) \tag{3}$$

where, the down sampling is done for the output y_k^j of the convolution layer, w_k^j represents the weight matrix and b_k^j denotes bias matrix whereas the max pooling function is represented by $\max\left(y_k^{j-1}\right)$ which is used to reduce the dimensions of the feature maps sourced by the convolution layer. Several convolution and pooling layers are combined together which increases the network depth of the CNN architecture. In general, final output of the Fully Connected Layers (FCLs) is achieved by organizing it layer by layer. Finally, the final FCL gives the output feature which is expressed as follows [18]:

$$x^z = f\left(w^a y^{a-1} + b^a\right) \tag{4}$$

where, the order of CNN network architecture is denoted as a, the output of the FCL is represented by x^z and the activation function is denoted as f.

3. Results and Discussion

According to the standard electrode placement protocol, the Myoware EMG sensor was placed at the brachioradialis which is the forearm muscles [13] and the EMG signals were acquired from various normal and abnormal individuals suffering from musculoskeletal disorders with the supervision of physiotherapist. Also, the proper consent was received from the both normal and abnormal individuals and the EMG signals were acquired. Generally, the two different phases are involved in classification process namely training phase and testing phase. For the training phase, the 80% of acquired normal and abnormal EMG signals were utilized and the knowledge model was created. Also, for the testing phase, the 20% of acquired normal and abnormal EMG signals were used. Furthermore, the four different performance metrics namely accuracy, precision, recall and F1-

score were performed [22] to evaluate the performance of the adopted CNN classifier which is presented in the Table 1. Furthermore, it is seen that the performance metrics for all the six classes were evaluated. Also, it is observed that the average accuracy of the multiclass CNN classifier is 97.5% which indicates that the proposed device is more effective on identifying the course of physiotherapy treatment process. The average precision, recall and F1-score of the adopted multiclass CNN classifier is 92.6%, 92.6% and 92.3% respectively.

Table 1. Performance Metrics of Multiclass CNN Classifier.

Class	Accuracy %	Precision	Recall	F1-Score
Grade 0	97.6	0.94	0.92	0.93
Grade 1	97.1	0.92	0.91	0.91
Grade 2	97.8	0.92	0.95	0.93
Grade 3	98.3	0.94	0.96	0.95
Grade 4	97.1	0.92	0.91	0.91
Grade 5	97.1	0.92	0.91	0.91

For the data transmission over internet, two different library packages were utilized namely smtplib and mime which can be installed to the Python software version 3.9.13 using commands such as pip install smtplib and pip install mime. The purpose of using Multipurpose Internet Mail Extensions (MIME) and Simple Mail Transport Protocol (SMTP) is shown in the Figure 6. Further, it is observed that the MIME allows the user to exchange data files such as images, audio, video etc. over mail whereas SMTP helps the user to send mail to any machine which is connected to internet.

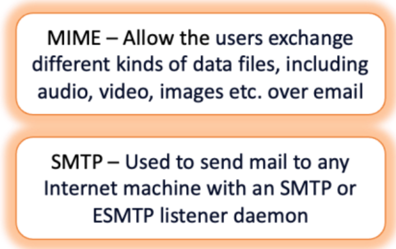

Figure 6. Python commands for data transmission over internet.

Figure 7 shows the decision support of IoT cloud platform for physician which was sent through mail. Further, it is observed that the suspicion about the patient health condition along with patient ID, EMG signal and graph of day wise muscle power grade was sent to the physician. Generally, the Google Co-Laboratory requires user account to perform computation and it is seen that the sender mail ID is same as the mail ID of the user account of the Google Co Laboratory. Also, it is clearly stated that the subject and content "Status of patient (ID:001)" and "The patient (ID:001) has a progressive improvement, and the patient's current power grade is Grade 2—Poor|Active movement but not against gravity. The EMG and day-wise muscle power grade are attached here for your reference" respectively was sent to physician's mail which enables him/her to ensure the progress of physiotherapy process.

Figure 8 shows the day wise muscle power grade values was plotted in the form of graph for 30 days duration which helps the physician to identify the progress of the course of therapy in an easy manner. Also, the duration of the day wise plot can be changed to desired number of days and it is demonstrated that the proposed work can store the grade values for maximum of 40 days. The x-axis denotes the number of days and the y-axis denotes the frequency which in turn grade was predicted using CNN. So, it is evident that the proposed IoMT based smart EMD device helps the physician/therapist to track the course of therapy process and improves patient's quality of life.

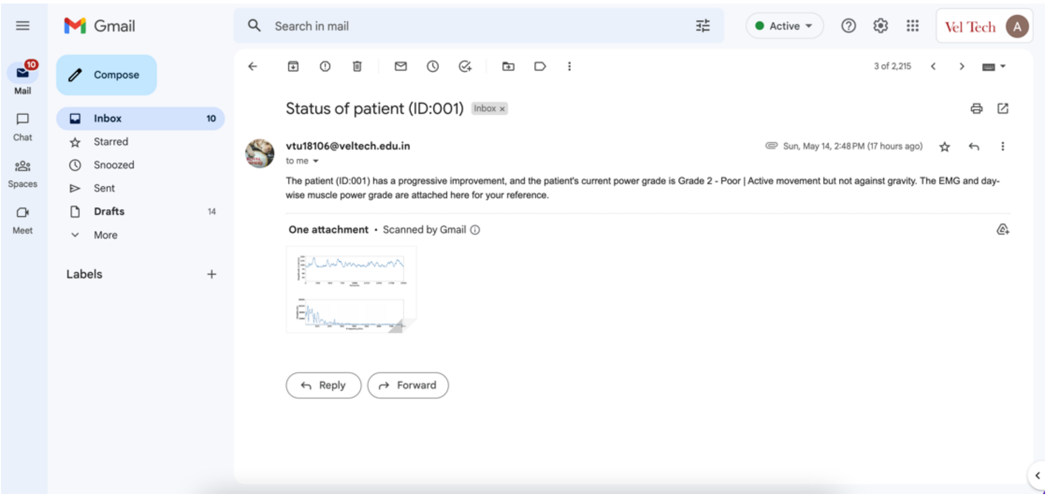

Figure 7. Decision support of IoT cloud platform for physician.

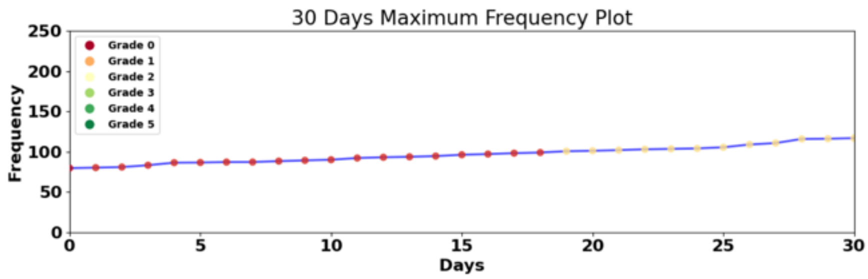

Figure 8. Day wise muscle power grade.

4. Conclusions

Physiotherapy requires continuous monitoring of muscle activity to track progress and adjust treatment plans accordingly. Many patients across globe have limited access to physiotherapy services due to geographical or financial constraints. Traditional methods for monitoring muscle activity are very expensive and requires specialized equipment. In this research work, a cost effective IoMT-based smart EMG device was devised which can be easily deployed in a clinical setting or in a patient's residence. Furthermore, the various performance metrics such as accuracy, precision, recall and F1-score for utilized multiclass CNN classifier was evaluated. Results demonstrate that the proposed device enables the physiotherapists to provide services to patients who may not have access to traditional physiotherapy services. Also, it was observed that the accuracy, precision, recall and F1-score of the utilized CNN classifier is 97.5%, 92.6%, 92.6% and 92.3% respectively. Furthermore, it is demonstrated that any deviations in the treatment process was identified and notified to the physician with the help of IoT cloud platform. Overall, the proposed IoMT based smart EMG device for physiotherapy applications is highly suitable for real-time and remote monitoring of muscle activity, which leads to improved patient outcomes and better access to physiotherapy services.

Author Contributions: P.A., V.S., M.S. and E.C. conceptualized the idea for this manuscript. R.K.D. provided the resources. P.A. designed and developed the hardware for data acquisition. V.S. and M.S. carried out the investigation and data curation of the acquired data. M.S. and R.K.D. validated the data and results acquired. P.A. and V.S. prepared the original draft. E.C. and K.K. reviewed and edited the original draft. E.C. and K.K. supervised the work, and R.K.D. administered the work. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Gleneagles Global Health City, Chennai, India. (Reference number: BMHR/2023/0054).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ethical restrictions.

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

References

1. Latronico, N.; Gosselink, R. A guided approach to diagnose severe muscle weakness in the intensive care unit. *Rev. Bras. Ter. Intensiv.* **2015**, *27*, 199–201.
2. John, J.; John, J. Grading of muscle power: Comparison of MRC and analogue scales by physiotherapists. *Int. J. Rehabil. Res.* **1984**, *7*, 173–182.
3. Demura, S.; Yamaji, S.; Goshi, F.; Nagasawa, Y. Lateral Dominance of Legs in Maximal Muscle Power, Muscular Endurance, and Grading Ability. *Percept. Mot. Ski.* **2001**, *93*, 11–23.
4. McManus, L.; De Vito, G.; Lowery, M.M. Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With Rehabilitation Engineers. *Front. Neurol.* **2020**, *11*, 576729.
5. Kim, E.; Shin, J.; Kwon, Y.; Park, B. EMG-Based Dynamic Hand Gesture Recognition Using Edge AI for Human–Robot Interaction. *Electronics* **2023**, *12*, 1541.
6. Wang, B.; McDaid, A.; Biglari-Abhari, M.; Aw, K.C. Design and development of a glove for post-stroke hand rehabilitation. In Proceedings of the 2017 IEEE International Conference on Advanced Intelligent Mechatronics (AIM), Munich, Germany, 3–7 July 2017; pp. 1047–1051.
7. Tedesco, S.; Belcastro, M.; Torre, O.M.; Torchia, P.; Alfieri, D.; Khokhlova, L.; O'Flynn, B. A Multi-Sensors Wearable System for Remote Assessment of Physiotherapy Exercises during ACL Rehabilitation. In Proceedings of the 2019 26th IEEE International Conference on Electronics, Circuits and Systems (ICECS), Genoa, Italy, 27–29 November 2019; pp. 237–240.
8. Sridar, S.; Qiao, Z.; Muthukrishnan, N.; Zhang, W.; Polygerinos, P. A Soft-Inflatable Exosuit for Knee Rehabilitation: Assisting Swing Phase During Walking. *Front. Robot. AI* **2018**, *5*, 44.
9. Liu, M.; Pu, X.; Jiang, C.; Liu, T.; Huang, X.; Chen, L.; Du, C.; Sun, J.; Hu, W.; Wang, Z.L. Large-area all-textile pressure sensors for monitoring human motion and physiological signals. *Adv. Mater.* **2017**, *29*, 1703700.
10. Rahman, M.A.; Hossain, M.S.; Showail, A.J.; Alrajeh, N.A.; Ghoneim, A. AI-enabled IIoT for live smart city event monitoring. *IEEE Internet Things J.* **2021**, *10*, 2872–2880.
11. Rodić, B.; Stevanović, V.; Labus, A.; Kljajić, D.; Trajkov, M. Adoption Intention of an IoT Based Healthcare Technologies in Rehabilitation Process. *Int. J. Hum.–Comput. Interact.* **2023**, *40*, 2873–2886.
12. Saleem, A.A.; Zafar, K.; Raza, M.A.; Kareem, Z.; Mui-zzud-din; Siddiqui, H.U.R.; Dudley, S. IOT Based Smart Physiotherapy System: A Review. *J. Eng. Res. Sci.* **2022**, *1*, 45–55.
13. Lee, K.H.; Min, J.Y.; Byun, S. Electromyogram-Based Classification of Hand and Finger Gestures Using Artificial Neural Networks. *Sensors* **2021**, *22*, 225.
14. Yang, G.; Deng, J.; Pang, G.; Zhang, H.; Li, J.; Deng, B.; Pang, Z.; Xu, J.; Jiang, M.; Liljeberg, P.; et al. An IoT-Enabled Stroke Rehabilitation System Based on Smart Wearable Armband and Machine Learning. *IEEE J. Transl. Eng. Heal. Med.* **2018**, *6*, 2100510.
15. Understanding the FFT Algorithm. 2013. Available online: https://jakevdp.github.io/blog/2013/08/28/understanding-the-fft/ (accessed on 28 August 2013).
16. Jain, S.; Bajaj, V.; Kumar, A. Riemann Liouvelle Fractional Integral Based Empirical Mode Decomposition for ECG Denoising. *IEEE J. Biomed. Health Inform.* **2017**, *22*, 1133–1139.
17. Krupa, N.; Ma, M.A.; Zahedi, E.; Ahmed, S.; Hassan, F.M. Antepartum fetal heart rate feature extraction and classification using empirical mode decomposition and support vector machine. *Biomed. Eng. Online* **2011**, *10*, 6.
18. Hasan, M.J.; Rai, A.; Ahmad, Z.; Kim, J.-M. A fault diagnosis framework for centrifugal pumps by scalogram-based imaging and deep learning. *IEEE Access* **2017**, *9*, 58052–58066.
19. Neupane, D.; Kim, Y.; Seok, J. Bearing Fault Detection Using Scalogram and Switchable Normalization-Based CNN (SN-CNN). *IEEE Access* **2021**, *9*, 88151–88166.
20. Najumnissa, D.; Vijayalakshmi, S.; Paramasivam, A.; Karthikha, R.; Shuaib, Y.M. Analysis of Deep Learning Algorithms for Intelligent Plant Disease Identification. In Proceedings of the 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 23–25 February 2022; pp. 377–381.

21. Basak, H.; Roy, A.; Lahiri, J.B.; Bose, S.; Patra, S. SVM and ANN based Classification of EMG signals by using PCA and LDA. *arXiv* **2021**, arXiv:2110.15279.
22. Grandini, M.; Bagli, E.; Visani, G. Metrics for multi-class classification: An overview. *arXiv* **2020**, arXiv:2008.05756.