Integration and validation of pattern recognition-based myoelectric control system for enhanced human-robot interaction of wearable robots

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***Abstract*—The demand for upper limb exoskeletons has been growing over the last couple of years. While there are many approaches and viable products on the market, they rarely use the newest Artificial Intelligence (AI) Algorithms, such as Random Convolutional Kernel Transformation (ROCKET), to perform EMG Classification tasks. The general problem lies in the detection and implementation of EMG signals and then transforming the signal in real-time to an upper limb exosuit.**

During our research, we used the NinaPro dataset and included measurements of our own EMG sensors. The dataset includes 52 different hand gestures, whereas the recorded data consists of 14 movements including the flexion of the upper arm. The proposed neural network is based on the derived version of ROCKET called Mini-ROCKET.

The network is designed to detect distinctive features in the upper limb and forearm. The achieved accuracy is 91% for the NinaPro 4 dataset and 82% for the NinaPro 5 dataset. The classification time of the EMG signal is $130\,\mathrm{ms}$. Comparison to other models shows a superior outcome of the approach with the ROCKET model. Implementing this network to existing exosuits can achieve a more comfortable and active work experience. Rehabilitation devices could benefit in general from this proposed approach.

***Index Terms*—Electromyography, time-series classification, machine-learning, ROCKET**

I. Introduction

In recent years, the convergence of electromyography (EMG) technology and wearable robots has improved significantly. Both in the field of human augmentation and rehabilitation EMG technology has improved disease diagnosis and recovery of patients [1]. Wearable robots can be divided into active and passive actuation mechanisms. Later, uses elastic components to activate the assistive force. Elastic components can vary from mechanical springs to elastic bands depending on their applications. Since they depend on the elastic characteristics there is a limit on how much external force can be assisted during dynamic tasks. Furthermore, passive exosuits generate the resistive force counteracting the trunk flexion. In theory, a passive exosuit can assist even with heavy loads by increasing the device's stiffness. However, this can result in decreased mobility and comfort for the user. Simple tasks requiring higher mobility and flexibility can be tedious with a higher resistive force [2]. On the other hand, active exos use electrical motors to assist the user. Sensors can be implemented to achieve a more accurate power output. While this increases adaptability during more dynamic tasks, active exosuits are limited in other ways. Active exosuits are built with electrical motors, sensors, and data transfer to assist tasks. These components are prone to errors and need proper maintenance. The power supply needs to be built in, adding additional complexity (i.e., charging and weight) [3]. Even though exosuits have limitations, they are already widely used and have shown great purpose in the industry and medical field. Over the past decade, people have improved and developed systems that can help people in their daily activities [4], [5].

From the inspiration of previous works and literature, this paper proposes a machine learning detection algorithm for EMG signals to classify and assess the characteristics of EMG signals. EMG is the measurable muscle activation in milli voltage (mV). The EMG signal of movements can be derived and classified to actuate an exosuit. This paper aims to classify EMG signal with a Random Kernel Convolutional Transform (ROCKET) [6] and the derived Mini-ROCKET (Minimally RandOm Convolutional KErnel Transform) [7]. The proposed network architecture shows excellent promise in time series classifications. The upside of ROCKET is the low computation time of the network. This reduces the classification process time of a movement, hence reducing the latency between the muscle and the actuator. Additionally, in the NinaPro database, EMG data was recorded from 10 subjects performing 14 different movements. The machine learning algorithm was then trained to classify the recorded dataset.

II. Methodology

A dataset is needed to implement a pattern recognition-based myoelectric control system in the future. The NinaPro dataset is a publicly available database aimed at improving EMG signal classification and advancing research on prosthetics for the forearm. In this work, the NinaPro datasets 4 and 5 were used to train a machine-learning algorithm for classification [8]. The proposed method for signal extraction of EMG signals is based on a neural network with a Mini-ROCKET architecture. Additionally, the Mini-ROCKET model is trained and tested on the recorded dataset.

A. NinaPro Dataset

The NinaPro dataset is a publicly available resource supporting research on advanced myoelectric hand prosthetics. Since its first introduction in 2014, additional datasets with different EMG sensors have been released, all with the aim of making EMG data more freely and easily accessible. The NinaPro dataset has multiple versions, each tailored for specific research needs. The datasets include different recording hardware and variations in experimental conditions, including different gestures, postures, and muscle contraction levels. However, classified movements stay mostly the same throughout the various datasets [8].

In this experiment, the Ninapro datasets 4 and 5 were used. EMG signals in the NinaPro datasets were recorded using a standardized protocol to ensure consistency and reliability across sessions and subjects. They have the same 52 different movements, starting from standard finger extensions to more sophisticated grasping and flexion movements. The dataset's difference lies in the hardware used to record the EMG signal. The NinaPro 4 used 12 Cometa electrodes, and the Nina Pro 5 relied on two Thalmic Myo Armbands, adding up to 16 electrodes to measure the EMG signals from ten subjects [8].
Subjects performed the movements while seated, with arms resting on a table, to minimize movement artifacts. The subjects had to follow a video displaying the movements consecutively, repeating each movement 6 times. The raw EMG signals underwent several preprocessing steps before being converted to Matlab files. These steps typically include filtering to remove noise, normalization to account for inter-subject variability, and segmentation to isolate individual movements. After the recordings, the signals were processed and converted to Matlab files, which were publicly accessible and downloaded from the NinaPro website. The dataset includes variables such as restimulus, which indicate the period of an active movement. Repetition, labeling the repetition period of each movement. Besides the restimulus and repetition variables, the dataset also includes detailed metadata about the experimental setup, such as electrode placement and signal acquisition parameters. Moreover, characteristics such as age, gender, and height of the subjects are also included. The variables are needed to later divide the data into training and test sets to train and evaluate the Mini-ROCKET model [8].

B. Collected Data

For the data collection phase of this study, we employed the Noraxon USA Inc. telemyo DTS system, a sophisticated surface electromyography (sEMG) recording system known for its reliability and precision in capturing muscle activity data. The electrodes from this system were strategically placed on the subjects' forearms and upper arms to ensure accurate measurements of muscle dynamics during various hand movements. The subject pool consisted of ten healthy volunteers thoroughly briefed on the study's aims and procedures. Before data collection, each subject gave informed consent. The electrodes were positioned over major muscle groups: on the Biceps Brachii and Triceps Brachii at their peak contraction points for upper arm recordings and around the circumference of the upper forearm for capturing the complex interactions of the approximately 20 muscles located there, mirroring the electrode placement used in the NinaPro dataset [**?**]. The following Figure 1 shows the acquisition setup with the Noraxon system [9].

Fig. 1. Eight sEMG electrodes were placed in total on the arm. Two of which are placed on the upper arm and the other six around the forearm. The white batches in the picture are the electrodes capturing the signal, whereas the little grey-blue boxes record the data and are used in the Noraxon system as the reference electrode.

During the data collection sessions, subjects were instructed to perform a series of 14 distinct hand movements, each repeated six times to maximize data consistency and reliability. These movements were demonstrated to the subjects via both video displays and printed guides to ensure a clear understanding and accurate performance of each gesture. The resultant dataset provides a foundation for training and evaluating machine learning models for precise hand movement classification with the Noraxon system.

C. Random Convolutional Kernel Transformation

ROCKET (Random Convolutional Kernel Transform) is a time series classification method that uses thousands of random convolutional kernels to extract features. These kernels, which vary in length, weight, dilation, and padding, are applied to the input data to transform it into a high-dimensional feature space. The feature extraction process involves two primary outputs for each kernel: the maximum value and the proportion of positive values (PPV) in the convolutional output. This transformation effectively captures diverse patterns in time series data, leading to a robust feature set for classification tasks. Consider a time series vector $X(t)$ of length n, a convolution kernel ω, and a bias vector b. The process of global max pooling (GMP) can be defined as follows:

$$GMP = \max_{i} \left(X * \omega\right)(i) \tag{1}$$

where the convolution operation ($(X * \omega)(i)$) is given by:

$$(X * \omega)(i) = \sum_{j=0}^{l_{\text{kernel}}-1} X(i+j) \cdot \omega(j) \tag{2}$$

Additionally, define the Proportion of Positive Values (PPV) as:

$$PPV = \frac{1}{n} \sum_{i} \left[\left(X * \omega - b\right)(i) > 0\right] \tag{3}$$

This formulation enables each kernel ω to generate two features for a given time series $X(t)$ [6].

Building on the foundations of ROCKET, Mini-ROCKET is an optimized variant designed to reduce computational complexity and resource usage. Mini-ROCKET achieves this by employing a significantly reduced number of convolutional kernels, which are smaller and more standardized than those used in ROCKET, without compromising on the classification accuracy. Mini-ROCKET kernels are specifically designed with a fixed length of 9 units. Moreover, the weight of each kernel is restricted to one of two possible values. This makes Mini-ROCKET particularly advantageous for deployment in embedded systems or devices with limited processing capabilities, such as modern prosthetic limbs [7]. The high accuracy and efficiency of Mini-ROCKET suggest it is a superior choice for real-time EMG signal classification in prosthetic control. Its reduced computational demand enables the integration into lower-powered wearable devices, potentially increasing the responsiveness and functionality of prosthetic technology. Furthermore, the adaptability of Mini-ROCKET allows for its application across a broader range of biomedical signal processing tasks, where real-time analysis is crucial [7], [10].

III. Model for Datasets

A. NinaPro

To benchmark our machine learning model, the NinaPro datasets NP4 and NP5 were utilized, which consist of electromyography (EMG) recordings from ten subjects performing 52 distinct hand movements. These datasets differ primarily in their hardware configurations: NP4 employs 12 Cometa electrodes with a sampling rate of $2\,\mathrm{kHz}$, whereas NP5 utilizes two Thalmic Myo Armbands with a sampling rate of $200\,\mathrm{Hz}$.

The NinaPro dataset is well-structured and labeled, requiring minimal preprocessing. Key columns include 'repetition' and 'restimulus,' which denote the start and end of each hand movement repetition. To create a balanced dataset, the resting label is excluded due to its disproportionate representation. The data is segmented using the repetition column to form training and validation subsets: repetitions 1, 3, 4, and 6 for training and repetitions 2 and 5 for validation.

Signal processing involved applying a $20\,\mathrm{Hz}$ lowpass filter to eliminate unwanted frequencies, followed by the *StandardScaler* function to normalize the signal. This process normalizes the data to have a zero mean and a variance of one, ensuring uniform contribution from each feature. Data segmentation was achieved through a sliding window technique, with each window spanning $400\,\mathrm{ms}$ and overlapping subsequent windows by $20\,\mathrm{ms}$, resulting in a three-dimensional array with dimensions $19009 \times 400 \times 14$, representing the number of samples, window size, and number of channels, respectively.

For feature extraction, the Mini-ROCKET model was implemented. It was initialized with 10,000 kernels to capture the diverse features of the EMG data adequately. The extracted features were fed into a ridge regression classifier to determine the optimal regularization parameters and assess the model's classification accuracy.

In addition to the standard Mini-ROCKET model, an ensemble learning approach was employed to enhance classification accuracy and robustness further. This involved training five distinct Mini-ROCKET models on the same data, with a voting mechanism aggregating their predictions. The final classification outcome was determined by a majority hard vote, leveraging the diverse perspectives of multiple models to achieve higher accuracy and better generalization, making the system more resilient to overfitting and varied data characteristics.

B. Collected Data

The preprocessing of the EMG data collected via the Noraxon system began with manual labeling to ensure accurate identification of muscle activity during specific hand movements. This process involved reviewing the raw EMG recordings to assign labels to segments where muscle activation was evident, corresponding to the initiation of each hand movement. Artifacts that exceeded a threshold of $1000\,\mu\mathrm{V}$ were identified and removed to reduce noise and potential biases in the subsequent analysis. Gaps between activations, indicating rest periods or transitions, were also labeled to facilitate accurate segmentation and to aid in the removal of non-movement data. The Labels were further segmented into Repetitions to allow a similar training process as for the NinaPro dataset. The segmentation was done by detecting a change in the EMG signal after a two-second waiting period between each repetition. The following two figures 2 and 3 showcase the labeling process for movements and the repetitions, respectively.

Each distinct movement captured in the dataset was assigned a unique label and repetition, which was crucial for training the machine learning models to recognize and differentiate between the various hand gestures. After labeling, the signals underwent further preprocessing. They were passed through a bandpass filter with cutoff frequencies set between $20\,\mathrm{Hz}$ and $500\,\mathrm{Hz}$. This filtering isolated the muscle frequency components most relevant to the hand movements while eliminating irrelevant frequencies. To handle the high sampling rate of $2000\,\mathrm{Hz}$ the data was downsampled to

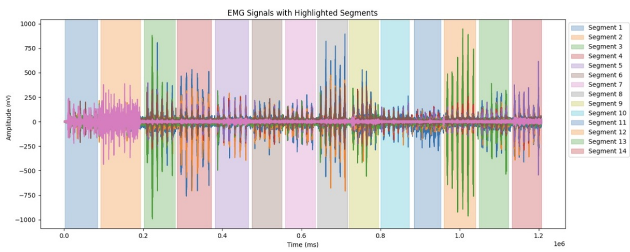

Fig. 2. Visualization of the finished manual label segmentation per movement. The different segments are the movements for the collected data process.

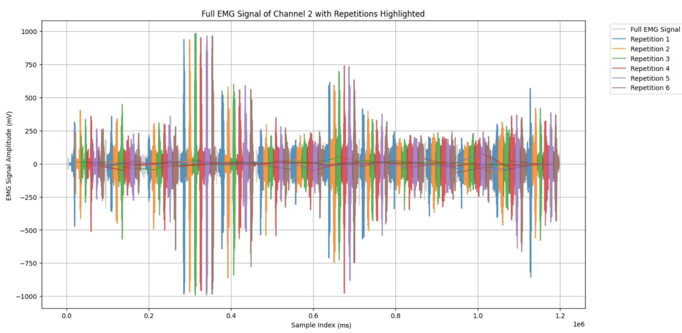

Fig. 3. This figure highlights the data segmentation of the movement repetitions across the movement-labeled data. The linear graphs across the EMG signal are an error in the graphical illustration of the Python environment.

400 Hz. An anti-aliasing filter was applied concurrently with downsampling to prevent distortion.
Normalization is followed by normalizing features by removing the mean and scaling to unit variance, helping to standardize data across a dataset for optimal performance in machine learning algorithms, also known as the StandardScaler. This step standardized the data, ensuring that variations in signal strength due to individual differences in muscle power or electrode placement did not bias the analysis. Finally, a sliding window technique was implemented, where the data was segmented into 1200 ms windows with a 50 ms overlap. This segmentation was designed to capture the EMG signals for analysis. The resultant segments were then systematically divided into training and testing sets, following a structured protocol similar to that used in preprocessing the NinaPro dataset to ensure robust model training and evaluation.

The data was divided into training and test data with the same approach as the NinaPro dataset. Repetitions 1, 3, 4, and 6 for training and repetitions 2 and 5 for the test data set. The Mini-ROCKET model, implemented via the Python 'tsai' library [11], was employed to classify various hand movements. Mini-ROCKET extracts features from the EMG data for accurate classification. For classification, we used the RidgeClassifierCV, which is a ridge regression. A cross-validation was also applied to optimally select the regularization parameter and alpha and boost the model's performance. This cross-validation method allows the model to tune alpha over a specified range, enhancing its generalization capabilities on new, unseen data.

IV. Results

The Mini-ROCKET model achieved high classification accuracies and Area Under the Receiver Operating Characteristic (AUROC) values on two NinaPro datasets (NP4 and NP5). The Mini-ROCKET model attained an accuracy of 91.34% with an AUROC of 0.99 on NP4 and 82.4% accuracy with an AUROC of 0.98 on NP5. The weighted F1-Score was also determined to be 0.811 for the Mini-ROCKET model and 0.834 for the Voting model. These results highlight the model's effectiveness in classifying EMG signals for hand movement recognition. The following table I shows the Results of the Mini-ROCKET model and also the results of the ensemble model.

TABLE I
The AUROC for the Mini-ROCKET Voting model could not be calculated due to the different models involved.

Model	Accuracy	time (training set)	time (test set)
Mini-Rocket	0.824	12 min 34 s	1.44 s
Mini-Rocket Voting	0.853	14 min 21 s	2 min 30 s

Efficiency was a highlight, with the Mini-ROCKET model requiring only about 13 minutes for training on NP4 and slightly less on NP5. Testing times were notably rapid, supporting the model's applicability in real-time scenarios, with response times on the whole test dataset being as low as 1.44 seconds. Compared to other models applied to the same datasets, such as Random Forest and SVM, which showed accuracies of 65% and 74% respectively, Mini-ROCKET clearly outperformed these approaches, showcasing its efficiency in multi-class classification tasks. This table II summarizes the results for the NinaPro dataset 4. A confusion Matrix 4 for both datasets was also calculated so a visual presentation of the model‘s performance can be given. All 52 labels are compared to the predicted labels and the results can be seen across the diagonal. Furthermore, the confusion matrix was also printed for the NinaPro 4 dataset and can be seen in Figure 5.

TABLE II
This Table summarizes the results for the NinaPro dataset 4.

Model	Accuracy	time (training set)	time (test set)
Mini-Rocket	0.913	13 min 6 s	2 min 1 s

The evaluation and processing methods applied to the collected data mirrored those used for the NinaPro dataset. Preprocessing involved various strategies such as adjusting filter frequencies, normalization, and scaling techniques. Optimal results were obtained with a bandpass filter set from 20 Hz to 1200 Hz, aligning with literature recommendations [9]. Data normalization involved the StandardScaler method. Additionally, the size and overlap of the sliding window significantly influenced model outcomes, with the best

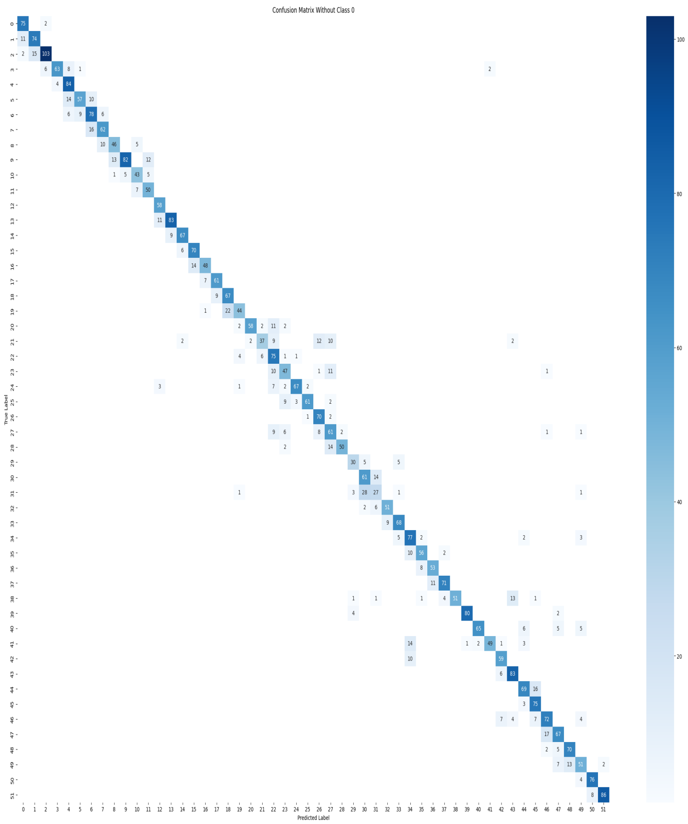

Fig. 4. Confusion Matrix of the Mini-ROCKET Voting model for the NP5 dataset. The true labels axis states the actual movements, and the predicted labels refer to the classified labels from the model. The blank space across the matrix is zero and, for visualization purposes, made white.

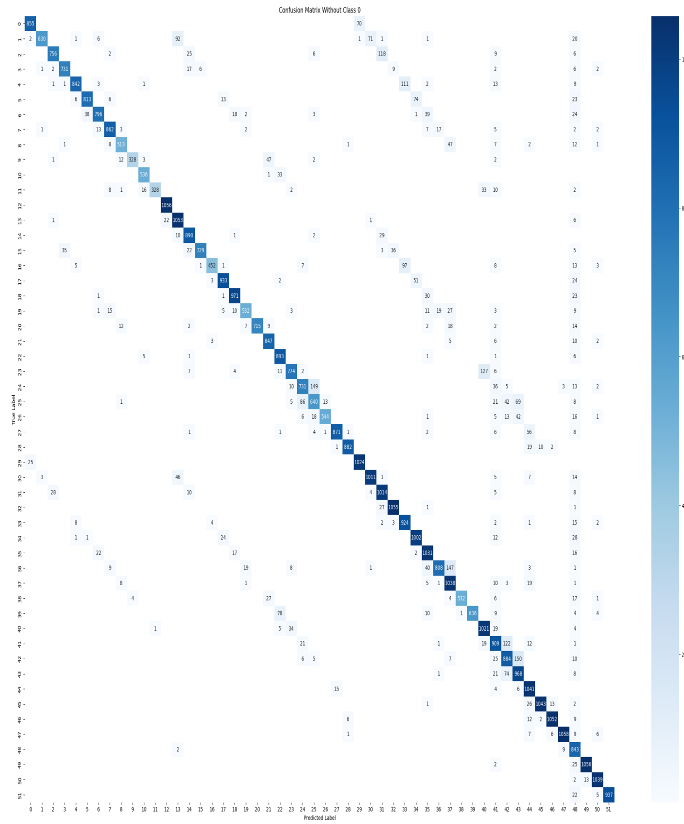

Fig. 5. Confusion Matrix of the Mini-ROCKET Voting model for the NP4 dataset. The true labels axis states the actual movements, and the predicted labels refer to the classified labels from the model. Also, the actual zeros are replaced with blank spaces for a better overview.

performance noted at a window size of 400 ms and an overlap of 20 ms.

The Mini-ROCKET model utilized 10,000 kernels for feature extraction from the EMG signals. Due to the dataset's extensive size, computational challenges were addressed by employing memory mapping (mmap) to reduce load on the system's memory and converting data into tensors to enhance GPU compatibility. These adjustments facilitated efficient computation and feature extraction, critical for training the linear classifier. The RidgeClassifier, equipped with cross-validation, was then used to ensure the robustness and accuracy of the model in mapping features to corresponding hand movements.
Upon training the Mini-ROCKET model with 8 gigabytes of training data, it achieved an accuracy of 69.89%, effectively classifying approximately 70% of the 14 distinct hand movements. The performance metrics are detailed in the results table. Notably, the confusion matrix depicted in Figure 6 illustrates the model's precision in classifying the initial two movements—the BP and TB contraction. The superior accuracy for these movements is attributed to the isolated electrodes that focused exclusively on the upper arm, as indicated in Table III, which further outlines the metrics used to evaluate the model's performance.

TABLE III
THIS TABLE SUMMARIZES THE RESULTS OF THE COLLECTED DATA.

Model	Accuracy	time (training set)	time (test set)
Mini-Rocket	0.69	$16\,\mathrm{min}\ 36\,\mathrm{s}$	$1\,\mathrm{min}\ 50\,\mathrm{s}$

V. DISCUSSION

The Mini-ROCKET model demonstrated high classification accuracies on the NinaPro datasets, with 82% and 91% accuracy for NP4 and NP5, respectively. These results were supported by AUROC values of 0.98 and 0.99, indicating excellent model discrimination between different classes. The model's robustness was evident from its high predictive performance across various hand movements, which are critical for prosthetic applications. The comparison with existing models highlights the Mini-ROCKET's superior performance. Prior models achieved accuracies around $65\%$to 74%, making Mini-ROCKET's outcomes particularly notable. The model showed improved accuracy and managed rapid processing times, with NP5 testing completed in $14\,\mathrm{s}$ for the entire set, translating to approximately $135\,\mathrm{ms}$ per movement—well within the desirable range for real-time prosthetic control. A paper with similar but different Mini-ROCKET model strategy included cosine similarity and dimensionality reduction methods to push the accuracy of

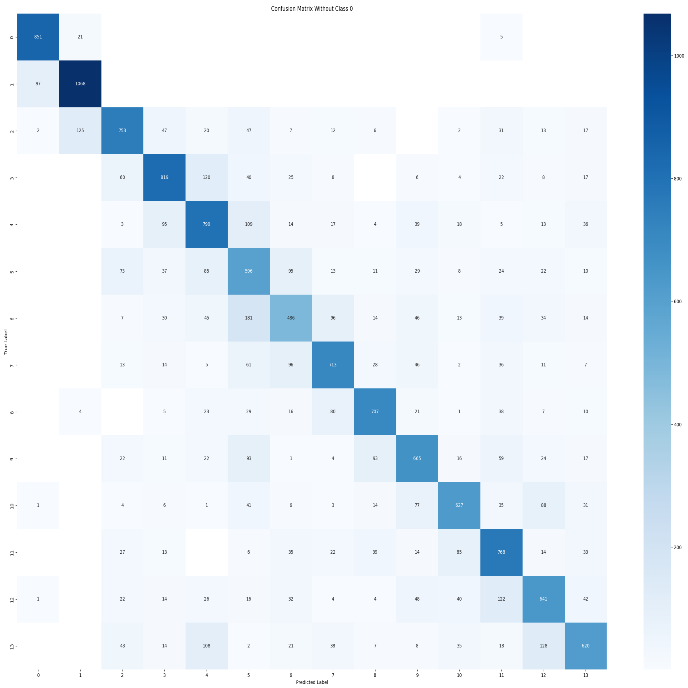

Fig. 6. Confusion Matrix of the Mini-ROCKET model for the created dataset. The true labels axis states the actual movements, and the predicted labels refer to the classified labels from the model. Also, the actual zeros are replaced with blank spaces for a better overview.

the Mini-ROCKET model even further. Their results were above 94% and are depicted in [12]. Further, the test times and AUROC values suggest that Mini-ROCKET effectively handles multi-class classification problems, even in complex settings like hand movement classification from EMG data, which involves distinct motion types.

The Mini-ROCKET model yielded an accuracy of 69% and an AUROC of 0.92 on the collected data, indicating a solid capability to differentiate between class features despite some challenges in accurately assigning these features to specific hand movement labels. The model excelled at classifying upper arm movements, particularly contractions of the Biceps Brachii and Triceps Brachii, with minimal misclassification due to targeted electrode placement. However, the model's performance was less effective for other hand movements, with widespread misclassification suggesting areas for model refinement. Several factors contributed to the lower performance compared to the NinaPro datasets:

- Electrode Configuration: The setup involved fewer electrodes (eight in total, with only six dedicated to hand movements) than the twelve and sixteen used in the NinaPro datasets. This reduced the coverage and resolution of the EMG signals. The different subjects' forearms' radii differed greatly, so the same area covered by the electrodes differed.
- Skin Preparation: Unlike the preparation in NinaPro studies, the electrode sites in this study were not uniformly prepared, potentially affecting signal clarity and consistency.
- The data was initially sampled at 2000 Hz but had to be downsampled to 400 Hz due to hardware constraints, compromising data quality. Additionally, the data was tested on external servers with more computational resources. However, after multiple tests, it crashed multiple times due to an integer overflow in LAPACK (Linear Algebra Package), meaning the dataset was too large for the algorithm's underlying libraries to handle.

These factors probably contribute to the reduced classification outcome, which results in lower overall accuracy. Future work should focus on standardizing skin preparation and electrode placement, considering enough electrodes to cover the forearm and reduce noise in the signal.

VI. Conclusion

This paper successfully achieved its goals of training and evaluating a machine learning model on EMG data from the NinaPro dataset and ten subjects using Noraxon Inc. electrodes. Utilizing the Mini-ROCKET architecture, the study demonstrated effective classification of hand movements, showcasing the potential of machine learning to enhance prosthetic control and human-machine interaction.

Future directions include improving model accuracy, enhancing real-time processing, and expanding applications beyond hand movement classification to other biomechanical signals. Additionally, the model can be embedded in a microcontroller and improve classification processes for wearable robots and prostheses alike. These advancements could further leverage EMG technology in medical and rehabilitation devices.

Acknowledgment

The Author would like to thank his supervisor and guide for this work MFH-Prof. Yeongmi Kim, PhD. Further thanks also to Dott. Mag. Yunus Schmirander, BSc, for his assistance in machine learning and time-series data classification.

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