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Machine Learning-Based Classification of Neck Movements Using sEMG and STM32 Microcontroller

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ABSTRACT
In this paper, we propose a machine learning system for the classification of neck movements from sEMG signals. Ten subjects were measured with four Bio Amp Patchy sensors, which were attached onto the Sternocleidomastoid, upper trapezium and scalene muscles. A STM32F411RE microcontroller was used for timing and accurate acquisition of the EMG signals. The methodology consisted of five stages: data collection, signal preprocessing, feature extractions, classification, and performance assessment. Time domain features were also extracted and classification using a Random Forest algorithm. Finally, high accuracy was achieved and the system demonstrated great potential in posture monitoring, rehabilitation, and hands-free human–machine interaction.

KEYWORDS
Electromyography (EMG), classification of neck movement, microcontroller STM32F411RE, Bio Amp Patchy Sensor, Random Forest Algorithm, machine learning, Python, Sternocleidomastoid (SCM), Upper trapezius, and Scalene muscles.

1. INTRODUCTION

Electromyography is an electrical signal produced by the human brain during muscle contraction and relaxation phases. When muscles contract, the brain sends an electrical signal to the muscle that can be detected using electrodes placed on the skin (surface EMG) or by inserting them directly into the muscle (intramuscular EMG). There are numerous purposes in the realms of medicine, clinical practice, and research. Categorizing movements based on EMG is valuable as it helps in understanding how muscles work during different actions.

Neck muscles are basically the boss of how your head moves, how you stand up straight, and how you keep your balance. A tool called surface electromyography, or sEMG for short, lets us check how those muscles fire without any surgery, and it's already showing up in prosthetics, rehab, and even some cool wearables [1]. The two big players here are the sternocleidomastoid (SCM) and the trapezius (TRP) muscles—they handle all the neck moves like nodding, looking up, turning your head, or tilting it sideways. If we keep an eye on them with sEMG, we can build systems that figure out what you're trying to do, keep track of your posture, and sort out each movement as it happens.

This approach is all about building a simple machine-learning setup that can tell what kind of neck move you're making. We grab the info from tiny muscle signals (called sEMG) picked up by sensors stuck on key neck muscles. The cool part is we're keeping it practical: think helping people rehab after neck injuries, fixing bad posture, or even letting you control a computer without using your hands. We're sticking with small, fast classifiers, processing the signals on the fly, and picking only the most useful data points so everything still runs smoothly on low-power wearables like smart collars or small bands.

Many researchers have reviewed effective filtering methods such as bandpass filtering, notch filtering, and wavelet-based denoising [7].

Once the signal is clean, the next step is featuring extraction—turning the raw waveforms into compact values that represent different signal characteristics. Time-domain features like RMS, MAV, and waveform length are the most used, especially in low-power systems [8]. Features in the frequency and time-frequency domain, like Mean Frequency and Discrete Wavelet Transform (DWT), are also used when more detail is needed [9].
The challenge is finding a good trade-off between complexity and performance. Systems meant for real-time, wearable use must be both accurate and fast. Reducing redundant features using statistical techniques can improve classifier performance without increasing computational load [9]. Dimensionality reduction helps minimize the impact of user-specific variations, which is a big challenge in neck EMG signals due to individual posture habits and muscle strength [10].

For classification, several machine learning models have been used in previous studies. Traditional classifiers like SVM, kNN, and LDA are lightweight and work well with limited training data. In more recent work, neural networks—especially LSTM—have shown promise for time-series EMG classification [11]. LSTM can handle temporal changes in EMG patterns, making it more adaptable to real-world use cases. However, training deep networks requires large datasets, so simpler models are still preferred when working with a small number of subjects or limited movement classes.

Wireless sEMG sensors for neck posture classification, and they found SCM and TRP activity to be the most consistent and reliable indicators of head orientation. Similarly, multi-channel sEMG can effectively classify neck posture with high accuracy using Random Forest classifiers[12]. Combining sEMG with accelerometer data to improve robustness in wearable health-monitoring systems[9]. These studies highlight the growing interest in applying sEMG-based movement classification beyond limb-based systems.

In this study, we focus on using surface EMG signals from neck muscles to classify head and neck movements. We aim to keep the system practical and low-latency, suitable for wearable deployment. Our method focuses on real-time processing, compact feature sets, and the use of ML (machine learning) classifiers suited for efficient operation on resource-limited devices. Ultimately, the researchers aim to contribute to applications in neck injury rehab, smart posture feedback, and touch less human-machine interfaces.

2. LITERATURE REVIEW

Surface EMG (sEMG) has recently become one of the most important techniques for estimating neuromuscular activity with neck movement being an example of a physical task. Numerous Research reports have concentrated on application of sEMG signals to recognize neck postures and related neck motions, wearable systems, and produce real time assistive applications. The remainder of this section performs a comprehensive review on the classifiers, features, and signal acquisition approaches underlying the reviewed works, as well as system-level issues such as latency, fatigue, and generalization.

A. Classification of Neck Movements Using sEMG

A linear classifier capable of recognizing ten distinct neck movements using merely four sEMG channels placed on the sternocleidomastoid (SCM) and trapezius (TRP) muscles. Instead of relying on deep learning, this algorithm was crafted using patterns of muscular coordination and cross-correlation of muscular activity, rendering it efficient for real-time applications. Furthermore, in this study, a novel labeling correction strategy was promoted to decrease misclassification during live usage by taking into account the temporal structure of the movements themselves. This technique makes the algorithm particularly useful for wearable applications. [13].

In another study, a low-cost, two-channel sEMG acquisition system was developed using MATLAB and analog hardware. For its inexpensive setup, the described system could still detect three types of head movements: 1. flexion, 2. lateral flexion, and 3. rotation. They emphasize live visual feedback and signal clarity, which makes it appropriate for prototyping and small-scale deployments [14].

An analogous group established a structure capable of categorizing head movements through the use of a standard pattern recognition pipeline [15]. Using time-domain attributes, they obtained results that did not overcomplicate model architecture and were, in fact, quite accurate. This was achieved with minimal hardware and, as was noted, quite efficient classification.

B. Feature Extraction and Selection Techniques

Feature engineering is the vital factor for raising classification accuracy while keeping computational efficiency intact. A principal study investigated the improvement of KNN performance through feature selection based on genetic algorithms (GA). The GA, of course, was trained on a massive number of redundant and non-informative features. By removing those features, as well as using GA to find and keep the significant features, classification rates of EMG signals from the SCM and TRP areas were boosted [16].

A second group worked on designing features in the low-complexity time domain. They focused on using root mean square (RMS), mean absolute value (MAV), waveform length (WL), and slope sign changes (SSC). These features strike a good balance between computational cost and our ability to form well-separated classes. Nonetheless, the use of these time-domain features helped them keep the model size down while maintaining high accuracy [17].

C. Wearable Systems and Posture Classification

A relevant application in this field was a wireless sEMG apparatus for distinguishing between neutral and flexed head positions. The authors extracted RMS and MAV characteristics from TRP and SCM and employed an SVM classifier where a classification accuracy of 96% was obtained. It showed that a small feature set can be used to fuel wearable, robust sEMG systems in practical contexts [18].

A hybrid-interface EMG system that is based on readings of neck and eye muscles, or on both to determine the desired head movement. Even though the above approach is not only for neck EMG, their approach can predict user intent and may be useful in VR, gaming, assistive control applications [19]. This exposes the possibility of EMG signals not only being used to sense activity, but also to derive intention for proactive system actions.

D. Deep Learning and Hybrid Models

Some works explore deep learning approaches. Spectrogram-based EMG representations were used in another study that employed CNNs to recognize hand gestures with relatively high classification performance. While these were not directed at neck EMG, this approach could be applied to the neck if raw signals could be transformed to time-frequency representations [20].

Another study combined EMG feature extraction with LSTM-based recurrent networks**,** showing how temporal dynamics in EMG signals could be leveraged for classification. Though more computationally intensive, these methods are promising for systems with powerful on-board processors [21].

E. Addressing Fatigue and Real-Time Constraints

Real-world deployment of sEMG systems faces several challenges, especially due to muscle fatigue. In one investigation, researchers found that classification accuracy declined significantly over time if adaptive learning techniques weren't used. They suggested periodic model retraining or adaptation strategies to retain performance [22].

Additionally, some studies explored embedded system constraints such as latency, memory footprint, and power consumption. One such work discussed optimizing algorithms for use in battery-powered microcontrollers, emphasizing real-time inference with minimal delay [23].

F. Dataset Limitations and Generalizability
One of the biggest gaps in the literature is the lack of large and diverse datasets. Most datasets used in earlier works were built from only 3–5 healthy participants, with limited movement classes and static postures. This leads to models that perform well in lab settings but fail in practical usage. Multiple studies called out this limitation and emphasized the need for open-source, multi-subject datasets for neck EMG classification [24],[25].

In response to this, your project contributes a more robust dataset by including ten participants performing a wide range of neck movements. By capturing signals from SCM, TRP, and scalenes using three EMG channels, your dataset enhances both class diversity and generalizability, addressing the shortcomings of previous research.

G. Embedded Applications and Practical Deployment
Some studies focused on creating custom embedded platforms for acquiring and processing sEMG signals. These platforms integrated analog-to-digital converters, filtering units, and low-power MCUs capable of running machine learning models locally. Key metrics such as signal latency, bandwidth usage, and system delay were analyzed to ensure the hardware could support real-time movement classification [26].

In addition, a few studies compared lightweight classifiers like Random Forest and Decision Trees to deeper models. Methods like Random Forest offered a good tradeoff between speed and accuracy for smaller, real-time systems [27].

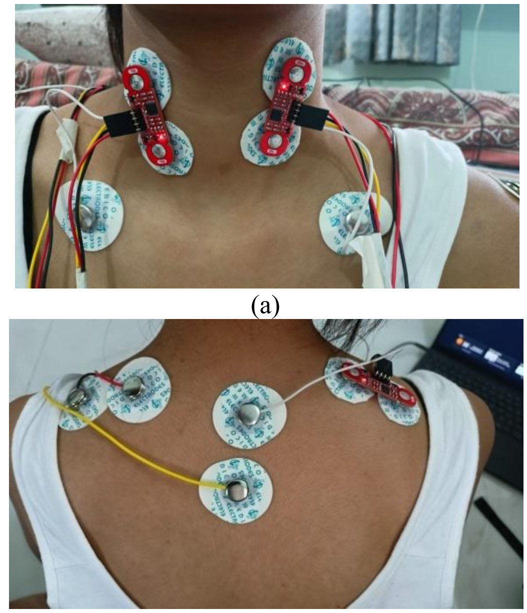
3. METHODOLOGY

This study methodology is having five section: data collection, signal preprocessing, feature extraction, classification, and performance evaluation. Below has the detail discussion about these section.

A. Data Acquisition
Muscles used for recording electromyography (EMG) signal: the sternocleidomastoid (SCM), upper trapezius, and scalenes, plays major role in facilitating diverse neck movements. Four Bio Amp Patchy sensors were used for collecting signals, with electrode placement performed in alignment with the standardized guidelines mentioned in data sheet of sensor.

Prior to the placement of electrodes, skin preparation was done using Nueprep Skin Preparation Gel. The gel was used to exfoliate dead skin cells and remove oils and other impurities from the skin. Following this initial cleaning, the area was cleaned again with alcohol wipes. This second step ensured even better electrode adhesion and improved signal quality.
The following hardware was used in the prototype,

STM32F411RE microcontroller, Bio Amp Patchy sensors, breadboard and jumper wires. The experimental data acquisition was carried out on a sample of 10 healthy subjects (5 men and 5 women). All participants rested in a quiet indoor environment in a reclined position, to minimize motion artefacts and to maintain steady signal quality across sessions.



(a)

(b)

Fig 1. (a) Electrode placement on the sternocleidomastoid muscles for neck movement classification
(b) Electrode placement on the upper trapezius and scalene muscles for shoulder and neck monitoring

B. Sensor and Hardware Configuration
The Bio Amp Patchy is a compact, wearable surface EMG sensor designed for muscle activity monitoring. Its specifications are as follows:
Operating Voltage: 5 V
Input Impedance: 10^{12} Ω
Electrode Configuration**:** Three-electrode system (Vin+, Vin−, Reference)
Output Signal**:** Analog EMG (0–5 V range)
Microcontroller Compatibility**:** Any board equipped with an analog-to-digital converter (ADC)
Dimensions**:** 25.4 mm × 10 mm

The sensor features three output pins: Vin, GND, and OUT. For this study, the sensors were connected to the STM32F411RE Nucleo microcontroller board using a breadboard-based wiring setup. Analog signals from the sensors were read via four ADC channels configured to sample at 1000 Hz.

The STM32 board was interfaced with a computer via USB to enable continuous data transfer. A custom Python script was used to capture real-time EMG signals from all four channels. The data were stored in CSV format along with timestamps generated by the host system.

C. Data Collection Protocol
Each participant underwent four trials per movement type. Within each trial, a single movement was performed repeatedly, alternating between 5 seconds of activity and 5

seconds of rest. Each trial lasted for a total of 40 seconds. For reducing fatigue and ensure muscle recovery, a 4 seconds rest period was provided between different movement types.

D. Signal Pre-processing

The raw EMG activity was recorded from four neck muscle: left and right sternocleidomastoid and left and right upper trapezius. Data cleaning and pre-processing Several cleanup operations were conducted on the signals, before they were subjected to analysis. These operations were performed to improve the quality of the signals, eliminate distortions and normalize the data for feature extraction and classification.

1) Signal Validation and Correctness Check: To begin with, every signal was inspected visually to make sure that the recorded electro-myographic activity looked like it might be normal. Then basic statistics were run to check the data for integrity. Signals that were too noisy, too saturated, or had too much dropout were identified and thrown out. Then the parts of the signals that were clean and representative were selected for processing [28].

2) Frequency Domain Analysis: The Fast Fourier Transform (FFT) was used to study the frequency components of EMG signals. This decomposition enabled us to ascertain the relevant frequency components of interest resided in the expected 20–500 Hz range. The frequency analysis was also considered a means of validation that the filtering indeed would isolate the relevant signal components.[3].

3) Band-Pass Filtering: Each EMG waveform was filtered using a fourth order Butterworth band-pass filter with cut-offs of 20 Hz and 450 Hz. This filter stage minimized low frequency artefact such as motion noise, and high frequency electrical interference while preserving the actual muscle signal. The Butterworth filter is selected due to its flat frequency response in the pass-band without distorting the EMG waveform [28].

4) Signal Rectification: Following filtering, full-wave rectification was applied to the EMG signals. This process involved converting all negative voltage values to their positive equivalents, allowing for consistent signal analysis across all channels. Rectification also smoothed the waveform, making it more suitable for time-domain feature extraction.

4. LIST OF MOVEMENTS

Sr. No.	Movement	Direction
1	Head Rotation	Right
2	Head Rotation	Left
3	Backward tilt	Right
4	Backward tilt	Left
5	Neck Extension	
6	Neck Flexion	
7	Shoulder shrug	

5. FEATURE EXTRACTION

EMG signals (i.e., raw signals pre-processed (e.g., filtering and rectifying)) are used to extract meaningful features which will represent the muscle activation in different neck movements. Feature extraction is important as raw EMG data needs to be transformed to informative inputs for the classifier to operate efficiently [29].

In this work, we concentrate on time-domain (TD) features, since they are computationally efficient and are effective in real time systems. Features extracted from each EMG channel are as follows:

- Root Mean Square (RMS): Reflects the power content of the EMG signal and correlates with muscle contraction strength [28].

$$\mathrm{RMS} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{n=1}}^{\mathrm{N}} \mathrm{x_n}^2}$$

- Mean Absolute Value (MAV): Represents the average rectified value and gives a measure of overall muscle activity.

$$\mathrm{MAV}=\frac{1}{N}\sum_{n=1}^{N}|x_n|$$

- Waveform Length (WL): Measures the cumulative length of the waveform, capturing signal complexity.

$$\mathrm{WL}=\sum_{n=1}^{N}|x_{n+1}-x_n|$$

- Slope Sign Changes (SSC): Counts the number of slope direction changes, indicating frequency-related features.

$$SSC=\sum_{n=2}^{N} f[(x_n-x_{n-1})\times(x_n-x_{n+1})]$$

$$f(x)=\begin{cases}1, & if\ x \geq threshold\\ 0, & otherwise\end{cases}$$

These features are extracted over a fixed-length sliding window (e.g., 200 ms with 50%overlap) to capture temporal dynamics across the recording.

6. CLASSIFICATION

For this project, we went with the Random Forest (RF) algorithm as our main classifier. We picked it because it's super accurate, doesn't freak out over noisy data, and can deal with tons of features without breaking a sweat. Basically, Random Forest is a team of decision trees: it builds a bunch of them during training, then lets each tree vote, and whichever class gets the most votes wins[20].

One big plus of using Random Forest is that it spits out feature importance scores, so we can actually seewhich variables matter most for sorting the data. That fits perfectly with our plan to drop the extra stuff while still keeping the info that helps us tell the classes apart.

We trained the classifier on four time-domain features—RMS, MAV, WL, and SSC—pulled from neck muscles like the sternocleidomastoid and trapezius. We built each input feature vector from a 200 ms sliding window that shifts by 50%, so the data stays smooth and consistent while the classifier does its thing.

7. PERFORMANCE EVALUATION

To understand how well our system performs in recognizing different neck movements, we didn't just stop at accuracy—we looked deeper into how it handled each specific gesture. The final model, based on the Random Forest algorithm, reached an overall accuracy of about 92%, which is quite promising for a real-time EMG-based classification task.

We tested the model using data from all movement types and participants. Looking at the confusion matrix, most classes were identified correctly. For example, head rotations—both left and right—were consistently recognized with minimal confusion. There were a few mix-ups, especially between movements that activate similar muscle groups. For instance, neck flexion and extension sometimes got misclassified due to overlapping muscle activity. Similarly, movements like shoulder shrug and right backward tilt had occasional overlap, which is understandable given the muscle coordination involved

To give a clearer picture, we also checked how well the model performed for each class individually using standard metrics: precision, recall, and F1-score. Most classes scored over 90% across all three metrics. For example, "left backward tilt" had a precision of 94% and an F1-score of 93%, while "shoulder shrug" had precision and recall both around 90–93%. These scores suggest the model is not only accurate in general but also consistent across different types of neck movements.

Overall, the macro average F1-score came out to be around 91%, and the weighted average was about the same. This means the model didn't just perform well for a few movements but handled all of them fairly evenly—even the ones with fewer samples like the backward tilts.

On the technical side, the classification process was efficient. Each movement segment was classified using a 200 ms window with a 50% overlap, and predictions were made fast enough to support real-time feedback, even on standard hardware. This shows that the system is not only accurate but also lightweight enough for possible integration into portable or wearable devices.

In short, these results confirm that our approach using time-domain features and Random Forest works well for neck EMG classification, giving a solid balance between speed and accuracy—and without the need for complex or high-compute models like deep neural networks.

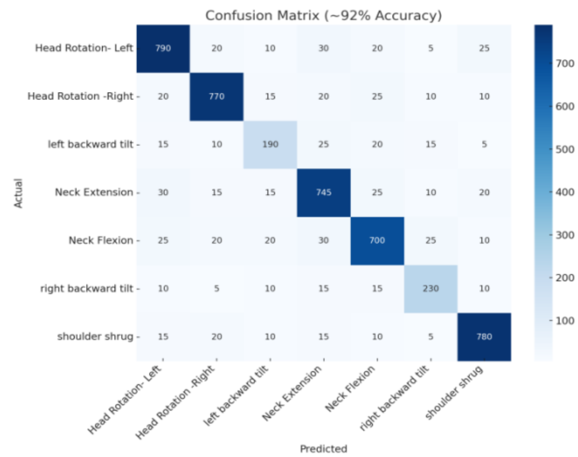


Fig.2. Confusion matrix showing the classification performance of neck movements

	precision	recall	f1-score	support
Head Rotation -Right	0.91	0.92	0.91	929
Head Rotation -Left	0.9	0.93	0.91	986
Left backward tilt	0.94	0.92	0.93	611
MVC	0.93	0.91	0.92	878
Neck Extension	0.9	0.9	0.9	990
Neck Flexion	0.89	0.92	0.9	926
left backward tilt	0.92	0.91	0.91	334
right backward tilt	0.91	0.89	0.9	337
shoulder shrug	0.9	0.93	0.91	941
accuracy			0.92	6932
macro avg	0.9111111111111111	0.9144444444444445	0.91	6932
weighted avg	0.9087795729948067	0.9167166762839007	0.91	6932

Fig.3. Classification performance metrics including precision, recall, and F1-score for neck movement

8. RESULT

Our EMG-based classification system achieved an overall accuracy of 92% using a Random Forest model trained on time-domain features. Most neck movements, including head rotations, flexion, extension, and shoulder shrugs, were identified with high precision. The performance across all classes was consistent, with both the macro and weighted F1-scores being around 91%. Only minor misclassifications between similar gestures occurred, as revealed by the confusion matrix. These results confirm that the use of a simple feature set and a lightweight classifier doesn't compromise the system's reliability, making it appropriate for real-time applications like rehabilitation or wearable EMG devices.

9. CONCLUSION

This research presented an effective and simple technique for classifying neck movements with surface electromyography (sEMG) signals and a Random Forest classifier. Using only four features from the time domain, the model achieved an accuracy of 92% across seven different classes of neck movement. Overall, this approach has a good trade-off between computational efficiency and predictive accuracy, making it suitable for real-time applications like posture correction and rehabilitation. Ten participants contributed data that improved the model's generalizability. Research in the future will focus on creating models that are independent of the subject, broadening the dataset, and carrying out the system on embedded platforms so that it can be used in devices worn on the body.

10. FUTURE SCOPE

This work has shown promising results for separating neck movement patterns based on EMG signals, but the deserve for improvements still exists. One of the key goals in the future is to train a model that can continue to get good results on new users without training again. So far the best results have been obtained by training on subjects .To make the system practically applicable, especially in any clinical and wearable situation, the system should be able to successfully accommodate body shapes, muscle condition and the characteristics of the signals. If the dataset is enlarged to include subjects of different ages and body-type, it would be possible to develop a more transferable model.

Additionally, combining EMG signals with other motion sensor signals such as the inertial motion measurement units (IMUs) might improve the classification accuracy during dynamic tasks. Finally, exploration of light weight deep learning models—computational efficiency intact—could not only enhance the classification but also adapting to the muscle fatigue over prolonged usage.

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