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Ergonomic Posture Classification of Bench Work Utilizing Muscle Data: A Case Study In Educational Workshop

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Abstract

Occupational musculoskeletal disorders (MSDs) often result from prolonged non-ergonomic postures, especially in educational and industrial bench work activities. This study presents an approach to classify ergonomic and non-ergonomic working postures using surface electromyography (sEMG) signals and machine learning. sEMG data were recorded from four upper limb muscles during simulated bench work conditions. Time-domain and frequency-domain features were extracted from segmented EMG signals using sliding windows. Dimensionality reduction was performed using Principal Component Analysis (PCA), and classification was carried out using logistic regression. The proposed system achieved an overall classification accuracy of 75% in distinguishing ergonomic and non-ergonomic postures. Visualization using PCA and Linear Discriminant Analysis (LDA) showed clear class separation, validating the discriminatory power of the extracted features. While the small sample size and class imbalance were identified as limitations, the study demonstrates that a simple and interpretable model like Logistic Regression, when combined with proper feature engineering, can yield promising results.This work contributes to the development of low-cost, efficient, and interpretable ergonomic assessment tools. It is particularly relevant for vocational and educational environments where real-time posture monitoring and early prevention of MSDs are essential. Future research should focus on expanding the dataset, exploring deep learning methods, and implementing real-time wearable systems.

Keywords: *Ergonomics; surface electromyography (sEMG); logistic regression; posture classification; occupational health*

1. Introduction

Occupational health has become a critical concern in various industries, including educational settings where students perform practical activities. Improper ergonomic postures can lead to musculoskeletal disorders (MSDs), which can impact workers’s health over time [1-2]. In educational settings, particularly in mechanical engineering workshops, students may unknowingly perform repetitive tasks in poor working postures, leading to long-term health risks. Early ergonomic detection deviations is essential for preventing chronic conditions. Occupational health risks associated with musculoskeletal strain have received increasing attention in recent years. As an example a study examined dental students in the UAE and found that poor ergonomic posture was a primary contributor to neck and shoulder MSDs during practical activities [1]. This underscore the necessity of ergonomic monitoring in educational settings. Another research [3] reported that medical students experienced a significant rise in musculoskeletal discomfort during distance learning, which they correlated to improper posture and workstations setups. This research highlighted the direct relationship between posture habits and the developmnets of MSDs. Similar study related to ergonomical posture [4], found that nearly

72% of occupational therapy students developed MSDs due to prolonged laboratory work and poor body alignment. This findings can be stated as proof that even in controlled educational environment, ergonomic related risks are substantial.

Recent developments in artificial intelligence (AI) and its integration with waearable sensors have paved the way for intelligent systems to worker's postures monitoring. A study [5] demonstrated that wearable sensor data (Accelerometers) processed using machine learning models could succesfully classify some postures i.e. sleeping, standing, sitting, running, forward bending and backward bending. This study supports the integration of intelligent posture recognition system in routine safety practices. Wearable sensor such as accelerometers are widely used in ergonomic monitoring due to their lightweight nature and its ability to detect body segment orientations. Another wearable sensors study to monitor, detect and classify ergonomic postures are inertial measurement unit (IMU) [6-7] and surface electromyography (sEMG) [8-9]. IMUs which combined accelerometers and gyroscope offer more comprehensive motion tracking, especially for multi-joint analysis. Meanwhile, sEMG provides insights into muscle activation patterns which can be affected by ergonomic strain. Table 1 shows the summary between wearable sensor and its unique benefits.

Table 1. Wearable sensor modality for ergonomic monitoring [5-9]

Sensor Type	Strengths	Example Use Case
Accelerometer	Low cost, can be used to measure posture angles and static pose detection	Sitting or standing monitoring posture
IMU	Can be used to measure joint angles and dynamic movement tracking	Construction, manufacturing and long task analysis
sEMG	Can be used to measure muscle activation, effort and fatigue estimation	Repetitive motion and heavy load posture detection

Among all wearable sensors, sEMG has shown promise in measuring muscel activity associated with different body postures. Wearable sEMG and MU sensors enable real-time ergonomic risk assessments during physical tasks [10]. Recent study demonstrated that AI models can be used to segment human activity and evaluate ergonomics risk from video-based data.

However, despite significant progress in using wearable sensors and AI for posture analysis, most studies have focused on industrial workers or office environment. There is a lack of targeted research evaluating the ergonomic risks faced by students and technician in vocational or engineering education settings, particularly during bench work activities. Furthermore, few studies integrate real-time sEMG signal analysis with modern classification techniques to differentiate between ergonomic and non-ergonomic postures specific to tool-based tasks. This research aims to fill that gap by developing and evaluating a machine learning model to classify posture conditions using EMG data collected from students engaged in bench work in a Politeknik Negeri Semarang workshop setting.

2. Methodology

This study adopted an experimental design, in order to simulate ergonomic and non-ergonomic working conditions and analyze muscle activity using wearable EMG sensors. The experiments were conducted in a controlled workshop environment that represents typical mechanical bench work. The design was structure to compare muscle signals during two posture conditions: Ergonomically correct and ergonomically incorrect. Figure 1 illustrates the research methodology, which consists of experimental setup, data acquisition, feature extraction, feature selection and reduction, classification, and interpretation of the classification results.

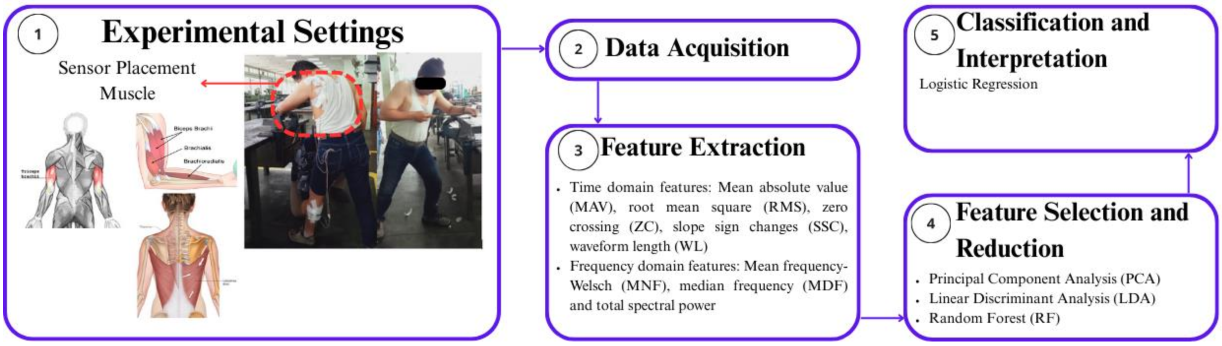

Figure 1. Research method flow diagram

2.1. Experimental settings

Research participants were students from Mechanical Engineering Department, Politeknik Negeri Semarang. Politeknik Negeri Semarang is a vocational institution that implements a bench work curriculum for first and third semester students, with sessions held twice a week, each lasting 8 hours per meeting. A total of 96 students were instructed to perform bench work activities such as rough filing and fine filing in both ergonomic and non-ergonomic position. The ergonomic working position is represented by a vise height adjusted to the subject's body height, while the non-ergonomic position is represented by a vise that is either too high or too low relative to the subject. This illustration is shown in Figure 2. The ergonomic position (Figure 2(a)) shows working surface positioned at elbow height, upright spine, arms at 90 degrees. Meanwhile, the non-ergonomic position (Figure 2 (b) and (c)) where working surface either too high or too low, requiring excessive arm lifting or forward leaning. This posture setting followed Occupational Safety and Health Administration (OSHA) and ISO 11226:2000 standard [11-12]. Each trial lasted 5 minutes with 3 repetitions per condition, and 1 minute break for muscle fatigue.

(a) (b) (c)

Figure 2. Ergonomic and non-ergonomic position in bench work: (a) Vise right at height, (b) Vise too high and (c) Vise too low

2.2. Sensor Placement and Data Acquisition

This study used a custom sEMG called Myomes which was developed with 50-150 Hz frequency [13]. Myomes system was designed for portability, low power and real-time data streaming. Electrodes were placed according to SENIAM guidelines and a neurologist professional opinion, dr. Elta Diah Pasmanasari, Sp. N. Electrodes were placed on specific muscle that are commonly active in bench work activity, i.e. *Biceps brachii*, *brachioradialis*, *triceps brachii*, *trapezius* and *latissimus dorsi*. Data from sEMG channels were streamed using serial communication to a PC running python. A high-pass filter (20 Hz) and notch filter (50 hz), were applied to remove motion artifacts and power-line noise.

2.3. Feature Extraction

Filtered sEMG signal extracted using twelve features to represent both temporal and spectral characteristic of muscle activity. These features, which consist of time-domain features and frequency-domain features, are widely utilized in biomedical signal processing especially muscle signal processing [14-15]. The time-domain features are mean absolute value (MAV), root mean square (RMS), zero crossing (ZC), slope sign changes (SSC), and waveform length (WL). Meanwhile, frequency-domain features are mean frequency (MNF), median frequency (MDF), and total power (TP).

2.4. Feature Selection and Reduction

Three statistical and machine learning-based approaches were employed for feature selection and dimentionality reduction in this study. The feature selection and reduction aim to enhancing classification performance and interpretability improvement. Principal component analysis (PCA), linear discriminant analysis (LDA) and random forest feature importance are used for feature selection and reduction. PCA is a method for data dimensionality reduction [16]. PCA selects components that explain the greatest amount of variance in the data, making it effective in reducing redundancy among correlated features [17].

LDA is a supervised technique designed to maximize class separability by projecting the data onto a lower-dimensional space where the ratio of between-class variance to within-class variance is maximized. In ergonomics and biomedical applications, LDA has proven effective in enhancing class separability for EMG and IMU signals by aligning features with meaningful physiological distinctions.

Random Forests are ensemble learning models that build multiple decision trees and aggregate their predictions. Feature importance scores help identify which EMG features most significantly influence the classification outcome. In this study, features such as Root Mean Square (RMS) and Median Frequency (MDF) consistently ranked high, indicating their strong discriminative power between ergonomic and non-ergonomic conditions.

2.5. Classification and Performance Evaluation

In this study, ergonomic and non-ergonomic working postures classification is performed using logistic regression algorithm method. logistic regression is a supervised learning method commonly used for binary classification problem like the case in this research. The output represented as either class 0 or 1. This algorithm is chosen due to its simplicity, interpretability, and efficiency, especially in problems involving a limited number of features that have already undergone dimensionality reduction using PCA.

The classification performance is evaluated using standard metrics: accuracy, precision, recall, and F1-score. Additionally, a confusion matrix is used to provide a visual overview of prediction performance between the two posture classes, i.e. ergonomic and non-ergonomic.

3. Result and discussion

3.1. Logistic Regression Classification Performance

Logistic Regression model classification performance is illustrated in Figure 3, which presents confusion matrix based on test data. Out of the four test samples, the model correctly classified three: One non-ergonomic, and two ergonomic instances. One ergonomic instance was misclassified as non-ergonomic, resulting in a model accuracy of 75%. Despite the small test sample size due to limited data availability, the LR model showed potential to differentiate between the two posture classes. This outcome aligns with the nature of Logistic Regression, which performs well in linearly separable problems, particularly when combined with dimensionality reduction such as PCA.

However, the small sample size may have contributed to instability in classification metrics, making it difficult to generalize. This highlights the importance of expanding the dataset in future studies to validate performance consistency.

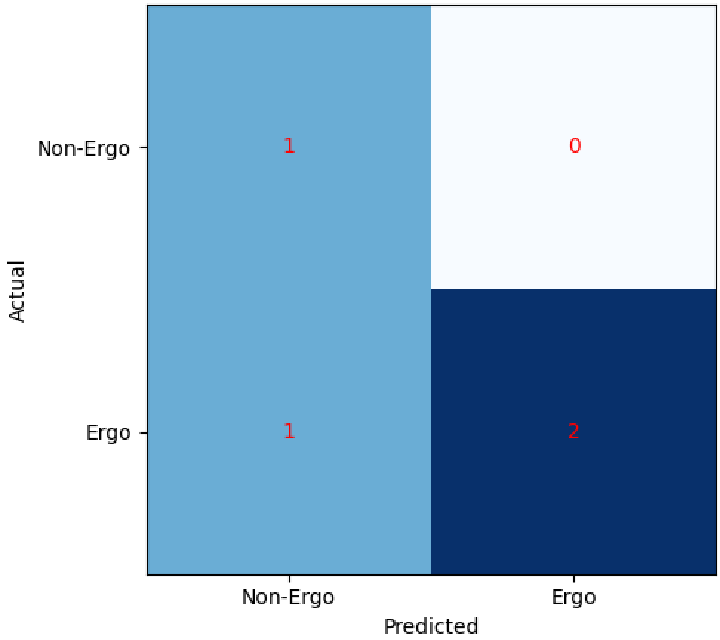

Figure 3. Logistic regression confusion matrix

3.2. Feature Separability with PCA and LDA

PCA scatter plot using the first two principal components is displayed in Figure 4 where zero ("0") is non-ergonomic label and one ("1") is ergonomic label. The ergonomic and non-ergonomic clusters show a clear separation along the principal component axes, which confirms PCA effectiveness in capturing underlying patterns in the EMG features. The model's decision boundary in the transformed feature space allowed Logistic Regression to distinguish between classes with relatively low computational complexity.

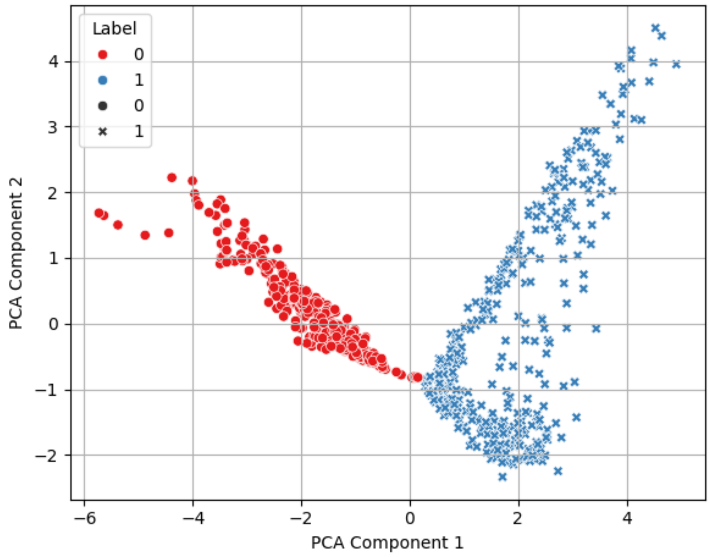

Figure 4. PCA scatter plot

LDA projection result is shown in Figure 5 where zero (“0”) is non-ergonomic label and one (“1”) is ergonomic label. Figure 5 shows that bot classes are tightly grouped and well separated along a single LDA axis. his supports the hypothesis that the extracted EMG features contain strong discriminatory information, which is essential for posture classification. The LDA visualization further confirms that the dataset is well-suited for linear classification methods.

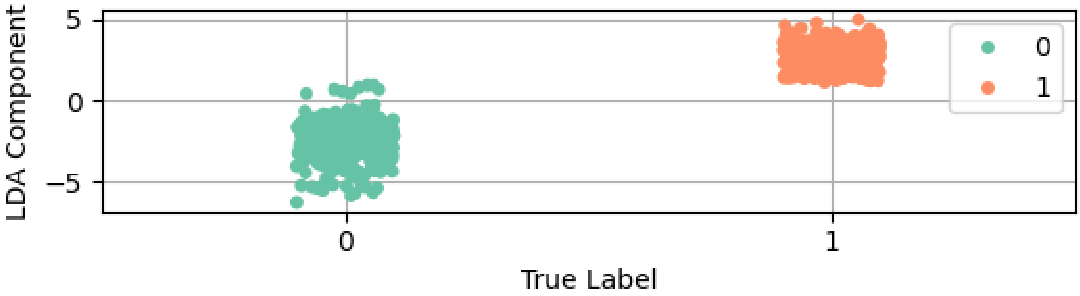

Figure 5. LDA projection result

3.3. Logistic Regression Performance Analysis

Table 2 shows summary of the logistic regression classification performance. The classification overall accuracy result is 75%, which corresponds to correct predictions in 3 out of 4 test cases. The model achieved 1.00 precision and F1-score pf 0.80 in identifying ergonomic postures (Class 1), while obtaining a recall of 1.00 and precision of 0.50 for the non-ergonomic class (Class 0).

This suggest that the model is highly effective in identifying ergonomic postures but is prone to misclassifying non-ergonomic ones. Such an imbalance can be explained by the unequal distribution of data in the test set, where ergonomic samples outnumber non-ergonomic samples by a factor of 3:1. Athough the non-ergonomic class had only one sample, it was corrctly identified, resulting in perfect recall but lower precision due to a false positive.

Table 2. Logistic Regression Classification Metrics

Class	Precision	Recall	F1-Score	Support
Non-ergonomic (0)	0.50	1.00	0.67	1
Ergonomic (1)	1.00	0.67	0.80	3
Accuracy	**-**	**-**	**0.75**	**4**

These findings reinforce the utility of logistic regression as baseline model, especially in low-resource settings or scenarios where real-time interpretability is crucial. Compared to more complex method like CNN-LSTM, which yielded accuracies between 96-99% for human activities recognition [18], the logistic regression method in this study remains competitive in terms of simplicity and implementation feasibility. Nevertheless, the limited dataset size constrains statistical generalizability. Future experiments should aim to balance class representation and increase the number of labeled samples to validate the consistency of these results.

4. Conclusion

This study explored the use of sEMG signals and logistic regression classification method to detect ergonomic and non-ergonomic postures during bench work activities in a education laboratory setting. The combination of feature extraction techniques (time-domain and frequency-domain), dimensionality reduction using PCA, LDA and random forest, and linear classifier (logistic regression), resulting an overall accuracy 75% in a small-scale test set. The use of

PCA enabled effective feature separation, as shown in the PCA and LDA visualization results, improved model interpretability and computational efficiency.

However, this research has several limitations, i.e. The dataset was limited in size and lacked cclass balance, with significantly fewer non-ergonomic samples. This imbalance may have skewed classification performance and reduced the generalizability of the model. In addition, only one type of machine learning algorithm which is logistic regression was evaluated in-depth, without comparative analysis against more complex models such as random forest (RF), support vector machines (SVM), or deep learning approaches like convolutional neural networks (CNN).

To improve the robustness of future studies, a larger dataset with more balanced class representation should be collected across a broader range of postural variations. It is also recommended to implement cross-validation strategies, integrate additional sensor modalities such as IMUs or accelerometers, and evaluate ensemble or deep learning models for better performance. Future research may also focus on real-time implementation of EMG-based ergonomic posture monitoring systems, allowing dynamic feedback and posture correction during industrial or educational tasks. Integration into wearable IoT devices could extend the application to occupational health, rehabilitation, or sports ergonomics.

This study contributes to the growing field of ergonomic posture detection using biosignals by demonstrating that even simple and interpretable models like logistic regression—when combined with effective feature engineering—can yield meaningful results. It provides a foundation for low-cost, efficient ergonomic assessment tools that are especially valuable in educational settings such as vocational schools, where early identification of non-ergonomic behavior is essential for long-term musculoskeletal health.

Acknowledgement

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