Journal of Electronics and Informatics (ISSN: 2582-3825)
www.irojournals.com/iroei/

Evaluating Performance of Different Machine Learning Algorithms for the Acute EMG Hand Gesture Datasets

Jeevanshi Sharma[1], Rajat Maheshwari[2], Salman Khan[3], Abid Ali Khan[4]

[1]Department of Electrical Engineering Aligarh Muslim University, Aligarh, India
[2]School of Computer Science Engineering Lovely Professional University, Aligarh, India
[3,4]Department of Mechanical Engineering Aligarh Muslim University, Aligarh, India

E-mail: [1]sharma.jivanshi@gmail.com, [2]rajat.11807504@lpu.in, [3]Salmanmkhan225@gmail.com, [4]abid.khan.me@amu.ac.in

Abstract

In this paper, different machine learning and tabular learning classification algorithms have been studied and compared on the acute hand-gesture Electromyogram dataset. The comparative study between different models such as KNN, RandomForest, TabNet, etc. depicts that small datasets can achieve high-level accuracy along with the intuition of high-performing neural net architectures through tabular learning approaches like TabNet. The performed analysis produced an accuracy of 99.9% through TabNet while other conventional classifiers also gave satisfactory results with KNN being at highest achieving accuracy of 97.8 %.

Keywords: Machine Learning, TabNet, Hand Gestures, EMG Dataset, XG Boost Algorithm

1. Introduction

In recent years, gesture detection for human-computer interaction has garnered a lot of attention. Applications for this particular combination include the recognition of sign language, robotic equipment control, virtual reality games, and prosthetics control. [1] Electromyography (EMG), which is employed to record hand gesture information, is thought to be more suited because it records the electrical activity of the muscle and the physical phenomena that cause hand motions. Recognition of EMG Hand Gestures finds its applications in multiple areas like health, sign language recognition [2], prosthetic limb control [3], robotics, virtual environment, game gestures etc. Convenient with robots using Hand Gestures have proved very convenient as when compared with vocal control, gesture-

DOI: https://doi.org/10.36548/jei.2022.3.007
Received: 02.08.2022, received in revised form: 23 .08.2022, accepted: 05.09.2022, published: 14.09.2022

based robot control system saves troubles of wearing additional devices. [4] EMG measurements can be taken using either invasive or non-invasive techniques. The EMG signals acquired are processed by pattern recognition technique, a common way for sEMG-based gesture recognition. [5] Earlier methods of EMG Gesture Recognition include methods based on Dynamic Time Warping algorithm (DTW - Dynamic Time Warping, DDTW - Derivative Dynamic Time Warping, PDTW - Piecewise Dynamic Time Warping) [6], etc. The pattern recognition includes signal pre-processing, feature extraction, model definition, and inference using ML workflows. [7] The temporal and frequency aspects of the data are captured bythe features used for categorization.

Machine learning methods have improved over time to provide natural myoelectric control. In order to accurately classify data, the extracted features are fed into machine learning (ML) classifiers like k- Nearest Neighbors (kNN), Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), Linear Discriminant Analysis (LDA), and Random Forests (RF). [8] Optimizing feature sets to close the gap between EMG signals and prosthetic control has been the focus of numerous investigations. [9] Previous studies have explored the effect of different EMG features on the performance of Machine learning models. [10] Among multiple feature extraction methods, researchers have pointed out redundancy in time-based and frequency-based features and noted that time-domain-based features are better performance in EMG signal classification. [11] Over the years, there have been significant research carried out related to Hand Gesture based on Electromyography (EMG) [References]. Jia et al [12] presented a robust CAE+CNN scheme for feature extraction and windowing scheme from the EMG dataset containing 10 different hand gestures. They concluded that the implemented deep learning model had minimal improvement compared to the other baseline machine learning models. In another study,

Devaraj et al. [13] compared the performance of the KNN and SVM models used for identifying 8 different time-domain features. The datasets recorded using the Myo Armband were pre-processed to reduce the artifacts and noise. A 5^{th} order Butterworth filter was equipped in a half-wave rectified to obtain a flat frequency response in the available passband. The refined model depicts the accuracy of 93.92%, and 83.71% for KNN, and SVM respectively. Asif et al. examined the impact of hyper-parameters on each hand motion, and a convolutional neural network (CNN) was used to decode the sEMG data collected from 18 participants. 18 subjects were chosen for the experiment, which was conducted in a neutral position. [14] Hyun Lee et al. used machine learning techniques to create EMG-based hand/finger gesture classifiers based on fixed electrode placement. Three channels of EMG signals were obtained, and from each channel, six time-domain (TD) features were derived. A total of 18 features were combined with an artificial neural network (ANN), a support vector machine (SVM), a random forest (RF), and a logistic regression to create customized classifiers for ten gestures (LR), the study was found to be robust enough to reduce the computational burden. [15] M.V.Arteaga et al. presented a strategy for robot-assisted hand motion therapy to recognize and describe healthy people's finger mobility patterns.

Machine learning techniques were utilized to recognize six hand motions using time and frequency features as inputs, and the performance of ANN, SVM, and k-nearest neighbor was compared. [16] Although effective, machine learning (ML) algorithms have two main drawbacks, namely the inability to properly handle big datasets and feature extraction. Both of these restrictions have been solved by the development of deep learning. Deep learning algorithms have demonstrated greater effectiveness with huge datasets and can naturally extract crucial elements for categorization. [17] In recent years, deep learning has been widely adopted in almost every research area ranging from Image Processing to Linguistics. For the problem of hand gesture classification based on EMG data, the majority of the deep learning methods have been applied to large quantities of data. [18] The authors suspect some potential issues with the utilization of real world datasets and small datasets for the classification of hand gestures. The EMG data acquisitions have their own challenges, which ultimately result in the lack of captured data for the researchers for processing. Such acute datasets tend to affect the robustness and the accuracy of deep learning models. Also, aiming towards creating large directories of datasets will not be a solution, as it will require an initial huge investment for data capturing, and also extensive high computational costs for simulations. The aims of this study are to evaluate the performance of machine learning methods on the binary classification of gestures learned through acute EMG dataset and to investigate the impact of tabular learning approaches while keeping low computational complexity.

2. Methodology

2.1 Apparatus

The EMG signals were recorded using 4 differential bipolar EMG sensors placed on 4 forearm muscles. The forearm muscles selected were: Flexor Carpi Ulnaris (FCU), Flexor

Carpi Radialis (FCR), Extensor Carpi Radialis (ECR) and Extensor Carpi Ulnaris (ECU). The positioning of the sensors was decided on the basis of Surface Electromyography for Noninvasive Assessment of Muscles (SENIAM). The reference/ground electrode was placed behind the earlobe. The EMG Data Acquisition System used belonged to Biometrics Data Ltd, with a sampling rate of 1000Hz.

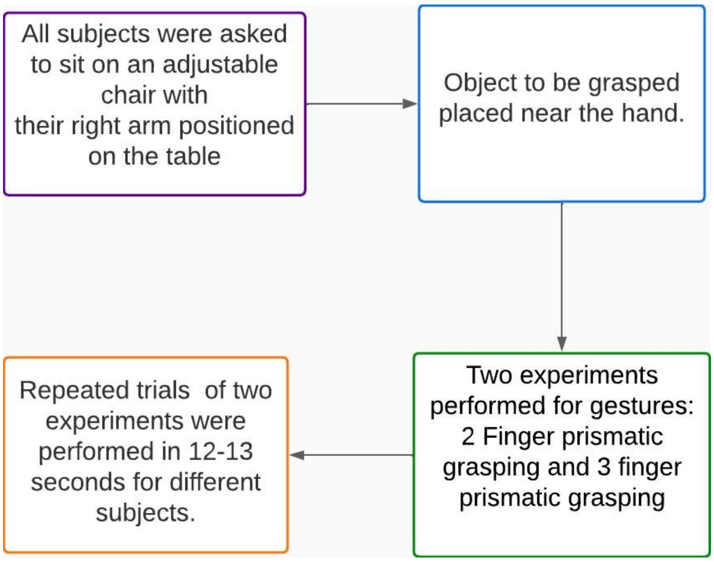

Figure 1. Data Acquisition Method

2.2 Experimentation

All subjects were asked to sit on an adjustable chair with their right arm positioned on the table as shown in Fig 1. The object to be grasped was placed near the hand. The experiment was performed for two gestures: Two fingered prismatic grasping and Three fingered prismatic grasping. Repeated trials of two grasping gestures were performed for different subjects. Each trail was performed in 12-13 seconds. 10 right handed, able bodied subjects (All Males, Age: 21-29 years) were asked to perform an experiment. All the subjects were introduced to the experimental procedure. The study was approved by the Departmental Ethical committee.

2.3 Feature Extraction

The acquired EMG signals from 4 muscles were subjected to data processing. Two important steps performed during data processing were data segmentation and feature extraction. LabVIEW software was used for extracting features from the signals. An overlapped data segmentation was performed with a segment length of 150ms and an overlap of 100ms. For each segment, 7 different features were extracted, which include Entropy, Hjorth Mobility Parameter Parameter, Zero Crossing, Slope Sign Change, Willison Amplitude, Root Mean Square and Waveform Length. Using these features as input, different classifications were applied.

2.4 Classifiers

These classification schemes include Machine Learning classifiers and a Tabular Learning Approach. TabNet is a deep neural network specifically designed to learn from tabular data. Relevant features are selected at each decision step in the encoder of TabNet using sparse learned masks. This ensures the selection of a small subset of features which makes model learning more efficient as model capacity is fully utilized at each decision step. Instead of using a harsh threshold on a feature, TabNet uses these learnable masks to make a soft decision.

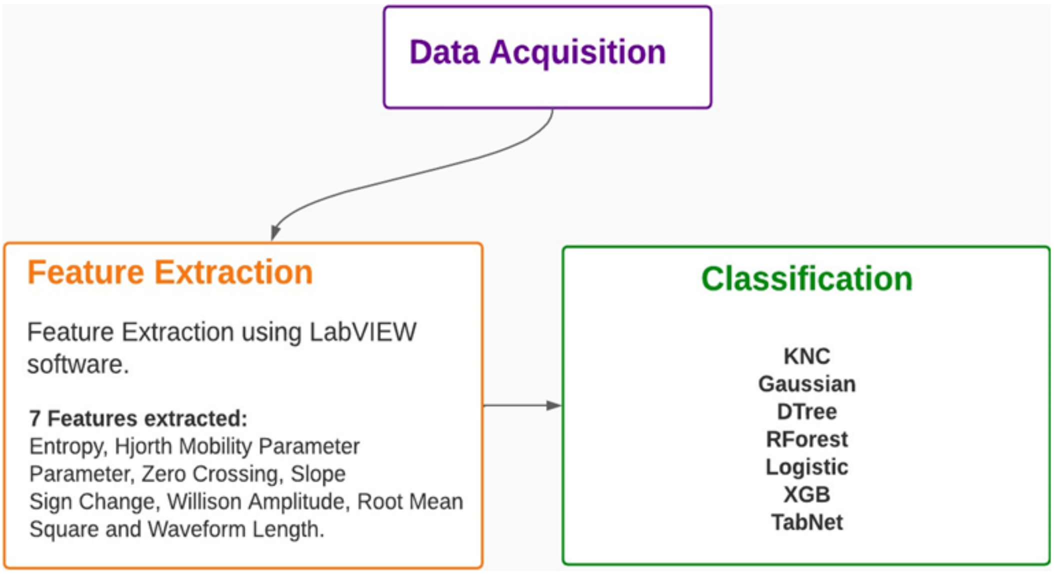

Figure 2. Simulation Steps

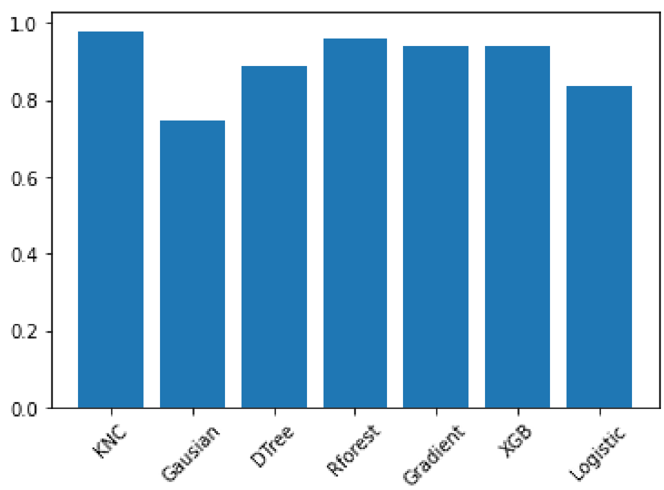

Figure 3. Data Acquisition of the EMG Signals for Different Grasping Gestures

3. Results and Discussion

As described in the previous section, this study focuses on the selection of a best fit machine learning model from the baseline machine learning algorithms, boosting algorithms, and a tabular learning model.

Table 1. Test accuracies of various machine learning models

Table	Test Accuracy
K-Nearest Neighbour Classifier (KNC)	0.9781
Gaussian Classifier (Gaussian)	0.7480
Decision Tree Classifier (DTree)	0.8856
Random Forest Classifier (Rforest)	0.9601
Gradient Boost Classifier (Gradient)	0.9383
XGBoost Classifier (XGB)	0.9408
Logistic Regression (Logistic)	0.8341
TabNet (TabNet)	0.9997

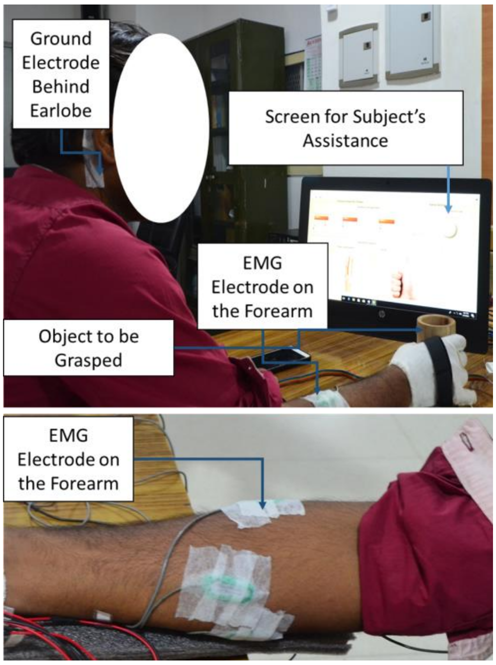

Figure 4. Comparative Test Accuracy of different ML Models

From Table 1, it can be seen that K-Nearest Classifier (KNC) performs best among the classifiers with test accuracy of 0.9781, followed by Random Forest and XGBoost respectively. The KNC model calculates the euclidean distance between the to-be-processed data sample, and the rest of the dataset, during training. The optimal value of k which resulted in this accuracy was k = 3. During hyperparameter optimization for the values of k, other values also showed marginally closed accuracy which started declining after k = 5. Following KNC, Random Forest and XGBoost algorithms have shown quite satisfactory performance, with Random Forest giving a Test Accuracy of 0.9601 at max depth = 5 and XGBoost of 0.9408 respectively. Random Forest is an en semble of multiple decision trees that is able to generalize well on tabular data. XGBoost and Gradient Boosting classifiers are both ensemble tree methods that apply the principle of boost ing weak learners (Decision Trees) using the gradient descent architecture. XGBoost uses a few computational tricks that exploit a computer's hardware to speed up gradient descent and allows robust modeling. Other classifiers which performed comparatively low are Gaussian and Logistic Regression with Test Accuracies of 0.7480 and 0.8341. Previous studies have demonstrated the use of tools such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

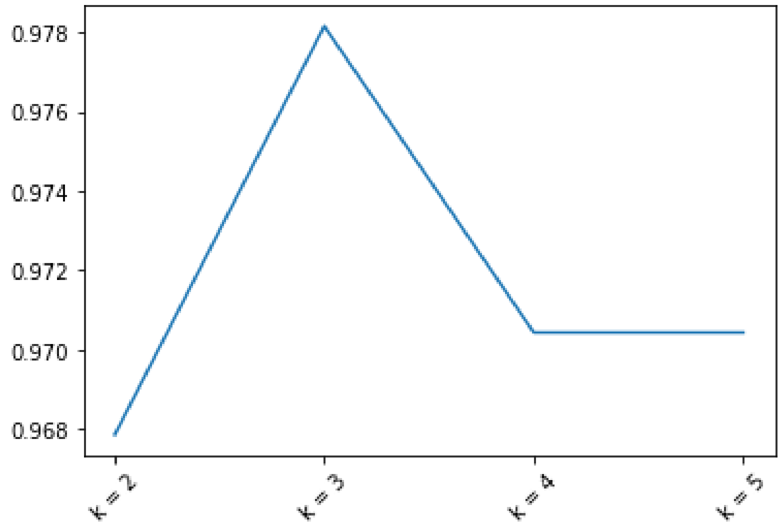

Figure 5. Test Accuracy of KNC on different values of k

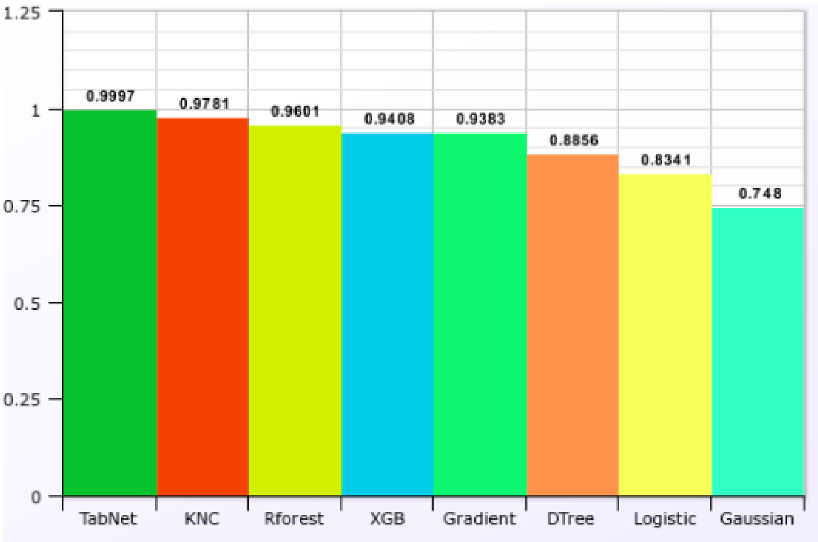

Figure 6. Comparison of TabNet with other classifiers

[19]In this study, a tabular learning neural network i.e. Google's TabNet [20] has also experimented which and was able to achieve a test accuracy of 0.9997. TabNet is surprisingly robust in its hyperparameters, and default hyperparameters often provided good performance TabNet provides benefits from the interpretability and quicker pace of the tree-based approach, while also leveraging the performance boost through deep learning architectures. TabNet uses a machine learning technique called sequential attention, in which two operations, an Attentive Transformer and a Feature Transformer are applied sequentially. The Attentive Transformer performs feature selection to select which model features to reason from at each step in the model and a Feature Transformer processes features into more useful representation and to learn complex data patterns which improve interpretability and help it learn more accurate models.

4. Conclusion

In this study, the traditional machine learning algorithms have proven to given satisfies results on small EMG hand gesture datasets. As the features in this data have been presented in tabular form, gradient boosting models such as XGBoost show the best performance in class for tabular data. Though recently, some tabular learning approaches have been proposed which could outperform the leading tree-based models across a variety of benchmarks. TabNet is one such architecture, which seemed to outperform previous work across tabular datasets from different domains. The key benefit Tabnet has over boosted trees algorithms is its explainability, as it follows the intuition of tree-based algorithms and also benefits from the deep learning aspect of high performing neural networks. Overall, it can be shown that a simple supervised Machine Learning classifier like K-Nearest Neighbour can be a true success at the task of classifying hand gestures. Minor modification to the model parameters can effectively enhance the performance of the model. TabNet enables two kinds of interpretability: local interpretability which visualizes the importance of features and how they are combined, and global interpretability which quantifies the contribution of each feature to the trained model, which will be explored in future work.

References

[1] M. J. Cheok, Z. Omar, and M. H. Jaward, "A review of hand gesture and sign language recognition techniques," International Journal of Machine Learning and Cybernetics, vol. 10, no. 1, pp. 131–153, 2019.

[2] Cheok, Ming Jin, Zaid Omar, and Mohamed Hisham Jaward. "A review of hand gesture and sign language recognition techniques." *International Journal of Machine Learning and Cybernetics* 10, no. 1 (2019): 131-153.

[3] R. Bagherian Azhiri, M. Esmaeili, and M. Nourani, “Emg-based feature extraction and classification for prosthetic hand control,” arXiv e-prints, pp. arXiv–2107, 2021.

[4] Q. Lei, H. Zhang, Y. Yang, Y. He, Y. Bai, and S. Liu, “An investigation of applications of hand gestures recognition in industrial robots,” In ternational Journal of Mechanical Engineering and Robotics Research, vol. 8, no. 5, pp. 729–741, 2019.

[5] E. Scheme and K. Englehart, “Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use.” Journal of Rehabilitation Research & Development, vol. 48, no. 6, 2011.

[6] K. Barczewska and A. Drozd, “Comparison of methods for hand gesture recognition based on dynamic time warping algorithm,” in 2013 Federated Conference on Computer Science and Information Systems. IEEE, 2013, pp. 207–210.

[7] S. Young, B. Stephens Fripp, A. Gillett, H. Zhou, and G. Alici, “Pattern recognition for prosthetic hand user’s intentions using emg data and machine learning techniques,” in 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM). IEEE, 2019, pp. 544–550.

[8] S. Bhushan, M. Alshehri, I. Keshta, A. K. Chakraverti, J. Rajpurohit, and A. Abugabah, “An experimental analysis of various machine learning algorithms for hand gesture recognition,” Electronics, vol. 11, no. 6, p. 968, 2022.

[9] S. M. Qaisar, A. Lo´pez, D. Dallet, and F. J. Ferrero, “semg signal based hand gesture recognition by using selective subbands coefficients and machine learning,” in 2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). IEEE, 2022, pp. 1–6.

[10] D. Tkach, H. Huang, and T. A. Kuiken, “Study of stability of time domain features for electromyographic pattern recognition,” Journal of neuroengineering and rehabilitation, vol. 7, no. 1, pp. 1–13, 2010.

[11] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “Feature reduction and selection for emg signal classification,” Expert systems with applications, vol. 39, no. 8, pp. 7420–7431, 2012.

[12] W. Ren, L. Zhai, J. Jia, L. Wang, and L. Zhang, “Learning selection channels for image steganalysis in spatial domain,” Neurocomputing, vol. 401, pp. 78–90, 2020.

[13] A. Devaraj and A. K. Nair, “Hand gesture signal classification using machine learning,” in 2020 International Conference on Communication and Signal Processing (ICCSP). IEEE, 2020, pp. 0390–0394.

[14] R. Asif, A. Waris, S. O. Gilani, M. Jamil, H. Ashraf, M. Shafique, and K. Niazi, “Performance evaluation of convolutional neural network for hand gesture recognition using emg,” Sensors, vol. 20, no. 6, p. 1642, 2020.

[15] H. Lee, J. Y. Min, and S. Byun, “Electromyogram-based classification of hand and finger gestures using artificial neural networks,” Sensors, vol. 22, no. 1, p. 225, 2021.

[16] M. V. Arteaga, J. C. Castiblanco, I. F. Mondragon, J. D. Colorado, and Alvarado Rojas, “Emg driven hand model based on the classification of individual finger movements,” Biomedical Signal Processing and Control, vol. 58, p. 101834, 2020.

[17] Q. He, N. Li, W.J. Luo, and Z. Shi, “A survey of machine learning algorithms for big data,” Pattern recognition and artificial intelligence, vol. 27, no. 4, pp. 327–336, 2014.

[18] A. Phinyomark and E. Scheme, “Emg pattern recognition in the era of big data and deep learning,” Big Data and Cognitive Computing, vol. 2, no. 3, p. 21, 2018.

[19] S. D. Gupta, S. Kundu, R. Pandey, R. Ghosh, R. Bag, and A. Mallik, “Hand gesture recognition and classification by discriminant and principal component analysis using machine learning techniques,” Hand, vol. 1, no. 9, 2012.

[20] S. O¨ . Arik and T. Pfister, “Tabnet: Attentive interpretable tabular learning,” CoRR, vol. abs/1908.07442, 2019. [Online]. Available: http://arxiv.org/abs/1908.07442