Electromyography Signal-Based Hand Gesture Recognition for Human-Robot Interface

Dr.Lakshmi
Computer Science and Engineering
Panimalar Engineering College
Chennai, India

Viknesh K.S
Computer Science and Engineering
Panimalar Institute of Technology
Chennai, India

Yogul Kishore.S *Computer Science and Engineering Panimalar Institute of Technology*
Chennai, India

Sanjay.B
Computer Science and Engineering
Panimalar Institute of Technology
Chennai, India

Veniyan.U
Computer Science and Engineering
Panimalar Institute of Technology
Chennai, India

Dr.Malathi Velu
Computer Science and Engineering
Panimalar Engineering College
Chennai, India

Abstract—**The development of hand gesture recognition in numerous scientific fields has proven to offer major advantages in enhancing the need for Robotics and human contact. The change of big data and machine learning as intelligent statistical knowledge techniques has transformed data science and brought about a new era. simpler to reliably categorize Electromyography (EMG) signals are used to measure hand movements. Unfortunately, the labor-intensive process of gathering and labeling the enormous dataset demands a lengthy implementation period. As a result, a special method Electromyography (EMG) signals are used to animate the hands the detection of hand gestures based on EMG was created. Without taking into account the hand motion sequence, it is possible to automatically categorize Employing ensemble learning, determine the type of obtained EMG data. The growing requirement for human-robot interaction has been significantly increased by the development of hand gesture recognition in several scientific domains. A new era of data science has begun with the emergence of big data and machine learning as sophisticated statistical knowledge approaches, making it easier than ever to categorize hand motions using electromyography (EMG) signals. Unfortunately, a lengthy implementation period is necessary due to the time- consuming procedure of gathering and labeling the massive dataset. In order to combine the benefits of depth perception training using the detection of hand gestures based on EMG, a unique technique was developed. It is feasible to automatically classify the collected EMG data using ensemble learning without considering the hand motion sequence.**

Keywords—Human-Robot interaction, Electromyography, Ensemble learning, Hand motion.

I. INTRODUCTION

Important hand advancements is known as hand motion acknowledgment. Motion association is a noteworthy technique that can be used for a variety of purposes [1, 2], including Human-robot interaction (HRI) [5, 6], sports [4, 3], signing interpretation [3, 3], and even more thoroughly when people and machines interact. Moreover, hand motion recognition systems are applied in therapeutic settings, where bioelectrical signals are used to detect motions rather than visual cues. The most often used biological sign for identifying handmotion and designing prosthetic hand regulators is electromyography [7, 8]. EMG calculates the electrical signal generated by solid withdrawal. The engine's potential for producing brain excitability a wide range of physiological processes are active. Support their works by differentiating between different hand motions using EMG is a challenging task. One way to get over these restrictions is to use a multimodal methodology, which combines EMG data with data from various sensors Hand gestures are seen as a significant coherence channel for data stream in daily life. The process of acknowledging, multi sensor information combining is motivated by the widely accepted theory that some regular cycles and idiosyncrasies are communicated under radically various actual pretenses [9]. Nevertheless, multi sensor frameworks increase accuracy by combining multiple sensors that assess the same indication in various but connected roadways. A clear repetitiveness gain reduces the amount of vulnerability in the generated data, leading to better precision. Recent research reveals a growing interest in multi tactile combination in a variety of fields,such as formative advanced mechanics [10, 11], general media signal processing, spatial discernment, and more. is referred to as the guessing period. We are comparing electromyography (EMG) readings,which use transducers to collect electrical activity from muscles. SVM is used to process the signals' classification utilizing Best hyper parameter RBF kernel, RandomForest, and Cat boost. The following is a breakdown of how this work is organized. Section 2 provides more information about the inspiration and related works. Section 3 presents the framework and methods. The created system is described in Section 4. The experimental demonstration is shown in Section 5 in the context of a lab setup. Section 6 also includes conclusions and suggestions for additional research. general media signal processing, spatial discernment, and more. is referred to as the guessing period. We are comparing electromyography (EMG) readings,which use transducers to collect electrical activity from muscles. SVM is used to process the signals' classification utilizing Best hyper parameter RBF kernel, RandomForest, and Cat boost. The following is a breakdown of how this work is organized. Section 2 provides more information about the inspiration and related works. Section 3 presents the framework and methods. The created system is described in Section 4. The experimental demonstration is shown in Section 5 in the context of a lab setup. Section 6 also includes conclusions and suggestions for additional research.

II. METHODS AND MATERIALS

A. *Data Acquisition*

Data gathering. The database comprises around 11,000 occurrences, which each is a measurement obtained using the electromyography (EMG) technique, a medical diagnostic technique that uses transducers to gather muscle electrical activity. The present database includes measures for four classes, where 0 represents a rock, 1 represents scissors, 2 represents paper, and 3 represents other objects. alright. There are four files with 65 columns each, the last of which contains the instance's class and the first 64 of which measure eight EMG transducers. Although there are many situations, the proportions are balanced. The dataset was available in the Kaggle repository (https://www.kaggle.com /georgesaavedra/hand- gestures-prediction/data).

B. *Modeling*

Radial Basis Function parts are a nonexclusive sort of kernelization and quite perhaps the most widely used part because of their resemblance to the Gaussian appropriation. The Radial Basis Function portion work recognizes the similarity, or if they are so close to one another of the two focuses Y1 and Y2 [29]. The component can be expressed quantitatively as follows. A kernel that is frequently employed in SVC is the radial basis function:

$$K(Y, Y') = \exp\left(\frac{||Y - Y1"}{2\sigma^2}\right)$$

|Y - Y1"| is the distance in Euclid between two the Y and Y1 points, and represents the variable. Gamma and C are the two parameters found in Radial Basis Function.

(1) Gamma:

The Radial Basis Function kernel parameter called gamma determines how low the curve of choice border is, which causes a relatively wide decision zone. The decision boundary's curve is steep when gamma is high [30].

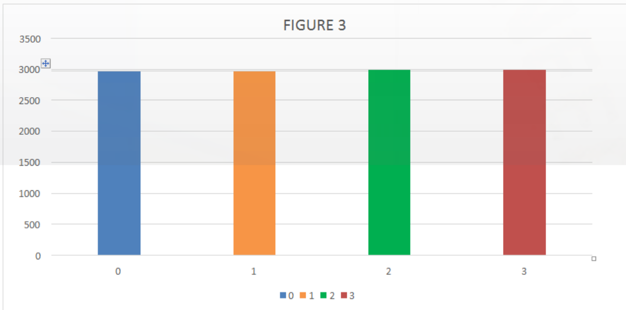
FIGURE 1: Myo armband: (a) Myo and EMG signal, (b) muscle activities on the forearm, and (c) gesture.

	0	1	2	3	4	5	6	7	8	9	...	55	56	57	58	59	60
0	26.0	4.0	5.0	8.0	−1.0	−13.0	−109.0	−66.0	−9.0	2.0	...	−28.0	61.0	4.0	8.0	5.0	4.0
1	−47.0	−6.0	−5.0	−7.0	13.0	−1.0	35.0	−10.0	10.0	−4.0	...	−25.0	47.0	6.0	6.0	5.0	13.0
2	−19.0	−8.0	−8.0	−8.0	−21.0	−6.0	−79.0	12.0	0.0	5.0	...	−83.0	7.0	7.0	1.0	−8.0	7.0
3	2.0	3.0	0.0	2.0	0.0	22.0	106.0	−14.0	−16.0	−2.0	...	−38.0	−11.0	4.0	7.0	11.0	33.0
4	6.0	0.0	0.0	−2.0	−14.0	10.0	−51.0	5.0	7.0	0.0	...	38.0	−35.0	−8.0	2.0	6.0	−13.0

FIGURE 2: Sample input.

The classifier does not mind if data points are incorrectly labeled, i.e., have a large bias and low variance, when C is small.

The classifier goes out of its way to avoid any misclassified data points, i.e., low variance and bias as a result of misclassified data has serious consequences once C is large [30].because misclassified data has serious consequences when C is large [30].



Reference	Data set	Complete instance
[20]	Kinect gesture	6244
[21]	CGD	50,0000
[22]	Microsoft Kinect and leap motion	1400
[23]	Creative senz3D	1320
[24]	MSR Gesture3D	336

(3) Apply the same Support Vector Machine-Radial Basis Function classifier, keeping C constant, to the identical data in the four graphs below.

The gamma value will always be raised, which is the only change between each graphic. The Decision boundary exhibits the gamma effect [30–32]. Selecting an appropriate kernel function in the Support Vector Machine method is significantly trickier. It requires a lot of time if the dataset is large.

III. RANDOM FOREST

During training, Random Forests (RFs) create numerous unique decision trees.. The word "ensemble approaches" refers to the fact that they draw a conclusion from a set of results. When the number of base learners (k) rises, the variance falls. Ask is decreased, variance increases. Yet, bias does not change during the process. Finding k can be done via cross- validation [33]. The main limitation of Random Forest is the number of trees that can be used without the calculation being unreasonably slow and prediction-impaired. These calculations often take little time to train, but take a long time to produce expectations after training. Low bias and large variance should characterize the fundamental learner. DT should be taught to the full depth length as a result. The following steps are an illustration of how Random Forest is implemented:

Step 1: Examine the N perceptions and M items in the training informative collection. Starting off, a random sample is picked with substitution from the training information collection.

Step 2: The best parted inclusion is used to recursively split the hub from a randomly chosen subset of M characteristics.

Step 3: The tree has arrived at its customary spot.

Step 4: After recapitulating the previous processes, a guess is formed in light of the number of expectations from n trees.

Reference	Dataset	Count of the gesture data	Techniques utilized	Resultant analysis
[25]	Own dataset	60	Block scaling	84%
[26]	American sign language (ASL)	208	Neural networks	92.78%
[27]	Arabic numbers	298	BP neural network	90.45%
[28]	Own dataset	130	Self-growing and self-organizing neural gas	90.45%

TABLE 2: System comparisons for hand gesture recognition

A confusion matrix is a performance evaluation tool used in machine learning and statistics to evaluate the accuracy of a model's classification. It is a table that compares the predicted labels of a model with the true labels of the data to calculate the number of true positive, true negative, false positive, and false negative values. The confusion matrix is often used in binary classification problems where the model predicts one of two possible outcomes. The four values in the confusion matrix are:

True Positive (TP): The model correctly predicted the positive class (actual positive, predicted positive). False Positive (FP): The model incorrectly predicted the positive class (actual negative, predicted positive). True Negative (TN): The model correctly predicted the negative class (actual negative, predicted negative).

False Negative (FN): The model incorrectly predicted the negative class (actual positive, predicted negative).

The confusion matrix is useful for evaluating the performance of a model by providing information about its accuracy, precision, recall, and F1 score. It can also be used to identify areas where a model is making mistakes and to adjust the model's parameters accordingly. Training time is equal to O (log (ND)*L) run time is equal to O (DP* L) and space is equal to O (MT*L).

Classes	Precision	Recall	F1 score	Support
0	0.93	0.97	0.95	417
1	0.92	0.96	0.94	426
2	0.95	0.91	0.93	472
3	0.90	0.86	0.88	437
Accuracy			0.93	1752
Macro avg	0.92	0.93	0.93	1752
Weighted avg	0.93	0.93	0.92	1752

TABLE 3 performance evaluation metrics of SVC with RBF kernel.

The training run time increases as the number of base models increases, hence cross-validation is always utilized to find the optimum hyperparameter.

A. *Cat Boost*

In 2017, the Yandex team developed Cat boost, a free gradient boosting technique. It is a machine learning method that is distinct from XG Boost and Lite GBM in that it makes it easier for users to handle categorical characteristics for a sizable dataset.. Regression,classification, and ranking issues can all be handled with Cat boost. The advantages of the Cat boost approach include faster GPU/CPU training execution, increased model quality, and the avoidance of the overfitting issue. Cat boost can offer lists to unconstrained sections using one-hot max size (use one-hot encoding for any features with a number of various qualities not exactly or equal to the given boundary esteem) [34– 38].

B. Units

C. Results and Discussion

Metrics for Performance Assessment. Accuracy typically refers to classification accuracy. The proportion is the number of correct expectations divided by the total number of information tests. That might work if there are an equal number of tests in each class. 60% of class A examples and 40% of class B tests result in a 60% fall in test accuracy when a similar model is polled on a test set during the discussion. The Major issue only becomes apparent when the cost of misclassifying small class tests is exceedingly high. As a result, a framework that depicts the broad presentation of the model is created via the confusion matrix. The evaluation metrics utilized to evaluate the model's performance as shown in the illustration are precision, recall, and F1 score. Accuracy performance measurements are essential when working with unpredictable data [35, 39–44]. What proportion of all the optimistic predictions is actually positive, according toprecision? accuracy is equal to the product of true positives and false positives.Recall specifies how much of the absolute certainty is anticipated to be favorable:

True positive/True positive plus false positive equals recall.There is a harmonic mean between recall and precision. False positives and false negatives are both received and brought into account. As a result, it works well even with a dataset that is uneven. Precision+Recall/Precision+Recall=2 for the F1 score.We can give recall and precision various weights using the weighted F1 score.Different issues place differing weights on recall and precision, as stated in the part before:

F = 1 + 2 *(Precision Recall) / (2*precision) +Recall.

Beta has a greater priority than accuracy by a certain factor. The value of beta is two, Considering that correctness is just half as crucial as review.Precision, recall, F1 score, and support were the evaluation measures used to determine the SVM with RBF kernel model's performance. It was noted that the class 2 had a better precision value of 0.95, the class 1 had a higher recall value of 0.97, and the class 2 had a higher F1 score of 0.95.

Precision, recall, F1 score, and support were the assessment criteria used to calculate the random forest model's performance. It was noted that the class 1 had higher precision values around 0.96, class 2 had higher recall values around 0.95, and class 1 had higher F1 Scores around 0.95. The outcome value indicates that Random Forest outperforms SVM with kernel in terms of performance.Precision, recall, F1 score, and support were the assessment metrics used to determine how well the cat boost classifier model performed. It was noted that the class 2 had higher precision values around 0.98, the class1 had higher recall values around 0.97, and the class 2 had higher F1 scores around 0.97.The macro average, weighted average, and total accuracy were all close to 0.95. According to the outcome value, the Cat boost algorithm compares favorably to the SVC and Random forest in terms of performance.

D. Conclusion

The proposed work classifies various hand motions using EMG signals. Any human computer focused systems or gadgets can be controlled using the signal. The results of the experiment reveal that the Cat boost classifier–based NN distinguishes the necessary signals quickly and efficiently. The developed model was found to successfully classify EMG signals based on hand gestures with a typical accuracy amount of 9.31 percent. If the network is fed additional evocative EMG inputs, classification efficiency can be improved. The EMG signals, on the other hand, fluctuate and vary depending on the topic. It has been discovered that the cat boost classifier efficiently and computationally inexpensively recognizes the necessary motions. The created model quickly and accurately recognized the gestures. In order to construct a human mainframe interface that disabled individuals may use, the classified EMG signals were used. Future work will concentrate on integrating muCI with applications for human-robot interaction. The muCI is also explained using straight forward teaching technique. To combine hand gesture detection with surgical robot control and training, we intended to use augmented reality. Futuresensor systems may incorporate IoT-based technology. Future studies will make advantage of more complex learning techniques, such deep learning.

IV. REFERENCE

[1] E. Ceolini, C. Frenkel, S. B. Shrestha et al., ―Hand-gesture recognition based on EMG and event-based camera sensor fusion: a benchmark in neuromorphic computing,‖ *Frontiers in Neuroscience*, vol. 14, p. 637, 2020.

[2] M. Yasen and S. Jusoh, ―A systematic review on hand gesture recognition techniques, challenges and applications,‖ *PeerJ Computer Science*, vol. 5, article e218, 2019.

[3] M. J. Cheok, Z. Omar, and M. H. Jaward, ―A review of hand gesture and sign language recognition techniques,‖ *Interna- tional Journal of Machine Learning and Cybernetics*, vol. 10,no. 1, pp. 131–153, 2019.

[4] J. F. Loss, D. Cantergi, F. M. Krumholz, M. La Torre, and
C. T. Candotti, ―Evaluating the electromyographic signal during symmetrical load lifting,‖ in *Applications of EMG in Clinical And Sports Medicine, ed C*, p. 1, Books on Demand, Steele, Nor-derstedt, 2012.

[5] G. Cicirelli, C. Attolico, C. Guaragnella, and T. D'Orazio,
―Kinect-based gesture recognition approach for a natural human robot interface,‖ *International Journal of Advanced Robotic Systems*, vol. 12, no. 3, p. 22, 2015.

[6] H. Liu and L. Wang, ―Gesture recognition for human-robot collaboration: a review,‖ *International Journal of Industrial Ergonomics*, vol. 68, pp. 355–367, 2018.

[7] S. Benatti, F. Casamassima, B. Milosevic et al., ―A versatile embedded platform for EMG acquisition and gesture recogni-tion,‖ *IEEE Transactions on Biomedical Circuits and Systems*, vol. 9, no. 5, pp. 620–630, 2015.

[8] E. Donati, M. Payvand, N. Risi, R. B. Krause, and G. Indiveri,
―Discrimination of EMG signals using a neuromorphic implementation of a spiking neural network,‖ *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 5, pp. 795–803,2019.

[9] D. Lahat, T. Adali, and C. Jutten, ―Multimodal data fusion: an overview of methods, challenges, and prospects,‖ *Proceedings Of the IEEE*, vol. 103, no. 9, pp. 1449–1477, 2015.

[10] A. Droniou, S. Ivaldi, and O. Sigaud, ―Deep unsupervised net- work for multimodal perception, representation and classifica- tion,‖*Robotics and Autonomous Systems*, vol. 71, pp. 83–98,2015.

[11] O. Zahra and D. Navarro-Alarcon, ―A self-organizing network with varying density structure for characterizing sensorimotor transformations in robotic systems,‖ in *Towards AutonomousRobotic Systems*, K. Althoefer, J. Konstantinova, and K. Zhang, Eds., pp. 167–178, Springer International Publishing, Cham, 2019.

[12] S. Braun, D. Neil, J. Anumula, E. Ceolini, and S. Liu,
―Atten-tion driven multi-sensor selection,‖ in *2019 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, Budapest,Hungary, 2019.

[13] M. Markovic, S. Dosen, D. Popovic, B. Graimann, and D. Farina, ―Sensor fusion and computer vision for context- aware control of a multi degree-of-freedom prosthesis,‖ *Jour-nal of Neural Engineering*, vol. 12, no. 6, article 066022, 2015.

[14] V. Malathi and M. P. Gopinath, ―Classification of pest detec- tion in paddy crop based on transfer learning approach,‖ *Science*, vol. 71, no. 7, pp. 552–559, 2021.

[15] V. Malathi and M. P. Gopinath, ―A review on rice crop disease classification using computational approach,‖ *International Journal of Image and Graphics*, vol. 2240007, 2021.

[16] V. Malathi and M. P. Gopinath, ―Noise deduction in novel paddy data repository using filtering techniques,‖ *Scalable Computing: Practice and Experience*, vol. 21, no. 4, pp. 601–610, 2020.

[17] V. Malathi and M. P. Gopinath, ―Classification of diseases in paddy using deep convolutional neural network,‖ *Journal of Physics: Conference Series*, vol. 1964, no. 4, article 042028, 2021.

[18] N. Qiao, H. Mostafa, F. Corradi et al., ―A reconfigurable on- line learning spiking neuromorphic processor comprising 256 neurons

[19] and 128k synapses," *Frontiers in Neuroscience*, vol. 9, p. 141, 2015.

[20] S. Moradi, N. Qiao, F. Stefanini, and G. Indiveri, ―A scalable multicore architecture with heterogeneous memory structures for dynamic neuromorphic asynchronous processors (DYNAPs),‖ *IEEE Transactions on Biomedical Circuits and Systems*, vol. 12, no. 1, pp. 106– 122, 2018."Kinect gesture dataset," 2019, https://www.microsoft.com/en-us/download."ChaLearngesturedataset,"2019,http://gesture.chalearn.org/data.

[21] G. Marin, F. Dominio, and P. Zanuttigh, ―Hand gesture recog-nition with leap motion and kinect devices,‖ in *2014 IEEE International conference on image processing (ICIP)*, pp. 1565–1569, Paris, France, 2014.

[22] A. Memo, L. Minto, and P. Zanuttigh, *Exploiting Silhouette Descriptors and Synthetic Data for Hand Gesture Recognition*, The Eurographics Association, 2015.

[23] A.Kurakin, Z. Zhang, and Z. Liu, ―A real time system for dynamic hand gesture recognition with a depth sensor,‖ 2012 Proceedings of the 20th European signal processing conference (EUSIPCO), pp. 1975–1979, Bucharest, Romania, 2012.

[24] M. M. Hasan and P. K. Misra, ―Brightness factor matching for gesture recognition system using scaled normalization,‖ *AIR-CC's International Journal of Computer Science and Informa-tion Technology*, vol. 3, no. 2, pp. 35–46, 2011.

[25] V. S. Kulkarni and S. D. Lokhande, ―Appearance based recog-nition of American sign language using gesture segmentation,‖ *International Journal on Computer Science and Engineering*,vol. 2, no. 3, pp. 560–565, 2010.

[26] S. Zhao, W. Tan, S. Wen, and Y. Liu, ―An improved algorithm of hand gesture recognition under intricate background,‖ in *International Conference on Intelligent Robotics and Applications*, pp. 786–794, Springer, Berlin, Heidelberg, 2008.

[27] E. Stergiopoulou and N. Papamarkos, ―Hand gesture recogni-tion using a neural network shape fitting technique,‖ *Engineer- ing Applications of Artificial Intelligence*, vol. 22, no. 8,pp. 1141–1158, 2009.

[28] Z. A. A. Hammouri, M. F. Delgado, E. Cernadas, and S. Barro, ―Fast SVC for large-scale classification problems,‖ *IEEE Trans- actions on Pattern Analysis and Machine Intelligence*, vol. PP,p. 1, 2021.

[29] A. Muratyan, W. Cheung, S. V. Dibbo, and S. Vhaduri,―Opportunistic multi-modal user authentication for health- tracking IoT wearables,‖ 2021, http://arxiv.org/abs/2109.13705.

[30] D. Koundal, ―Texture-based image segmentation using neutrosophic clustering,‖ *IET Image Processing*, vol. 11, no. 8, pp. 640–645, 2017.

[31] K. Bhalla, D. Koundal, B. Sharma, Y. C. Hu, and A. Zaguia, ―A fuzzy convolutional neural network for enhancing multi-focus image fusion,‖*Journal of Visual Communication and Image Representation*, vol. 84, article 103485, 2022.

[32] Z. K. Senturk and M. S. Bakay, ―Machine learning based handgesture recognition via EMG data,‖ *Advances in Distributed Computing and Artificial Intelligence Journal*, vol. 10, no. 2, 2021.

[33] N. Nahar, F. Ara, M. Neloy et al., ―Feature selection Based Machine Learning to Improve Prediction of Parkinson Dis- ease,‖ in *International Conference on Brain Informatics*, pp. 496–508, Springer, Cham, 2021.

[34] D. Chicco, N. Tötsch, and G. Jurman, ―The Matthews correla- tion coefficient (MCC) is more reliable than balanced accu- racy, bookmaker informedness, and markedness in two-class confusion matrix evaluation,‖ *BioData Mining*, vol. 14, no. 1,pp. 1–22, 2021.

[35] D. Koundal, S. Gupta, and S. Singh, ―Neutrosophic based Nakagami total variation method for speckle suppression in thyroid ultrasound images,‖ *IRBM*, vol. 39, no. 1, pp. 43– 53, 2018.

[36] N. Salankar, D. Koundal, C. Chakraborty, and L. Garg, ―Auto-mated attention deficit classification system from multimodalphysiological signals,‖ *Multimedia Tools and Applications*, pp. 1–16, 2022.

[37] M. Zakariah, Y. A. Alotaibi, D. Koundal, Y. Guo, and M. Mamun Elahi, ―Sign language recognition for Arabic alpha- bets using transfer learning technique,‖ *Computational Intelli-gence and Neuroscience*, vol. 2022, 15 pages, 2022.

[38] S. Bhat and D. Koundal, ―Multi-focus image fusion using neu-trosophic based wavelet transform,‖ *Applied Soft Computing*,vol. 106, article 107307, 2021.