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Harnessing the Power of Deep Learning For Hand Gesture Recognition

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Abstract: A lot of attention has been paid to hand gesture detection systems in recent times due to its numerous implications and effective human-computer interaction capabilities. This paper presents an effective Hand Gesture recognition (HGR) system that is based on Deep Learning (DL). The primary goal of proposed work is to improve the classification accuracy rate while identifying different Gestures. Moreover, we have used two dataset in the proposed work, one dataset is taken from UCI machine learning repository and other was collected manually from the real world. Data Normalization technique was implemented on the original datasets in order to make the data balanced and normalized. Soon after this, a total of 20 features were extracted from the normalized data to overcome the dataset dimensionality issues. Finally, for the identification and classification of gestures, we have used an advanced variant of DL namely; Bidirectional Long Short Term Memory (Bi-LSTM) in the proposed work. The simulation of the proposed Bi-LSTM based HGR system is examined and validated by comparing it with few state of art HGR techniques using MATLAB Software. Results revealed that the proposed model achieved an accuracy of 99.876% on standard dataset and 98.366% on real time dataset.

Keywords*: artificial intelligence, machine learning, gesture recognition, human interface, medical application, etc.*

1. Introduction

The ability to recognize hand gestures offers an acceptable, natural means for humans and machines to communicate. Real-time applications have frequently used hand gesture detection [1-3] including remote patient monitoring, fingerprints, cutting-edge HMI displays, sign translation software, and virtual and mixed reality-based online gaming. Computers can identify hand motions visually to ensure a few natural and simple applications. Furthermore, as a result of the difficulty of hand motions, which are rich in diversities because of the extensive degrees of freedom, engaged by the human hand, vision-based hand motion detection was a very difficult task. Additionally, most current gesture recognition systems are ineffective due to the unreliability and lengthy calculation times of computer vision algorithms.

HGR models, which are human-computer systems, are able to recognize the movement as well as the moment it was done. Currently, those technologies are used in a variety of applications, including intelligent prostheses [4, 5, 6], sign language recognition [4,5], rehabilitation equipment [7], and remote monitoring [8]. Gloves, visual detectors, IMUs, surface electromyography sensors, and sensor combos including interface electromyography detectors, are some examples of data collection devices used by HGR models. Despite the variety of options for data acquisition, each one has its drawbacks. For instance, Individuals who have disabilities cannot use gloves or eyesight sensors, and gloves can restrict mobility., particularly when manipulating objects; vision sensors can encounter impediment issues, changes in enlightenment, and changes somewhere far off between the hands and the sensors; and IMUs and surface electromyography sensors produce loud information [9]. Surface electromyography sensors separate the development's goal even though all of these devices gather information about how a hand movement was performed. The ability to employ these sensors with individuals those are unable to do the motions but have the desire to do so [10]. It was noticeable that there are two groups of hand gestures. : static gestures [11] and dynamic ones [12]. The methods for static gesture identification classify gestures based on features extracted from a single frame, whereas the methods for dynamic gesture recognition identify hand routes based on the relationship between movements between successive frames.

Skeletal muscle tissue makes for the structure of an arm muscle in humans. Each motor unit of a skeletal muscle was made up of several fibers (i.e., muscular cells) that are all innervated by a solitary engine neuron. These fibers make up a single motor unit. Associated with the

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spinal cord are component of the nervous system. are connected to fibers at the neuromuscular junction. Whenever a muscle was at rest, there was an electric potential differential of -80 mV between the extracellular and intracellular environments of the fibers. Two intracellular activity possibilities (i.e., waves) spread along every fiber to the ligaments with consistent speed and without retention when a muscle was contracting. The engine neuron initially enacts the neuromuscular intersection. These waves are produced when the fibers are depolarized and re-polarized [13]. The total of all the intracellular action potentials from a motor unit's fibers was known as the motor unit action potential (MUAP). EMG was a measurement of the electrical activity generated by human muscles. Multiple trains of MUAPs are linearly added together to form the EMG signal [14]. Hand motions can also be categorized using EMG signals that surface electrodes collect. Using bodily parts like the face and hand, gestures facilitate and make it simple to communicate with others. In some contexts, such as in-vehicle communication, distinct gestures are used[15] in virtual and augmented reality, prosthetic control, teleoperation, sign language, and augmented reality. Different hand gestures are produced by muscles working together, and after training, machine learning algorithms may learn and anticipate these motions. When compared to single-channel EMG devices, multichannel-based wearable devices (such as the Myo Armband) greatly improve the identification of numerous hand gestures, which gives collected EMG data certain benefits in biomedical applications.

Due to the trouble of boundary assessment in non-fixed processes systems is challenging, HGR does not use the mathematical models of EMG. Despite that, machine learning (ML) approaches are extensively employed as they might suggest a remedy for non-stationary mechanisms. Utilizing a variety of strategies, such as segmentation in brief stationary intervals, class-balance change, and covariate shift techniques. One method of myoelectric control, known as HGR using ML, utilizes EMG signs to remove control signs to order outer gadgets, such as prosthetics, drones, computer input devices, etc. Other methods include classic sufficiency-based control and the immediate extraction of neural code from EMG information. In traditional amplitude-based control, one EMG channel manages a single device function (e.g., hand open was appointed out to one channel, and hand shut to a subsequent channel). This function was engaged when the amplitude of this EMG rises above a predetermined threshold. Some other method was the immediate extraction of neural code from EMGs, which decodes the motor neuron spike trains from either the EMG signals to transform them within the instructions.

Due to the various aspects of hands, it can be challenging to determine the hand shape with accuracy. The settings of light, foreground, complexion, distance and position, and hand orientation all have an impact on how well HGR performs. As a result, the HRG problem has been studied for a long time. Numerous techniques exist, such as sensors, gloves, sensors, lasers, conventional cameras, depth chambers, and 3D cameras, among others. Using a standard camera was the most accessible, affordable method because they are so widely available today. To address such issues, various technologies and methods exist. Utilizing an image-extracted function or straight pixels for the training and testing phases. Functions can be extracted using a variety of techniques, including contours, angles, points of interest, Fourier transformation, PCA, etc. These methods are known as function-based methods. Crosscutting approaches are those that don't use functions. The image was classified using a classification technique. Artificial neural networks (ANN), convolutional neural networks (CNN, 3DCNN), linear discriminant analysis (LDA), support vector machines (SVM), decision trees, and K-nearest neighbors (k-NN), and naive Bayes (NB) are a few examples of classifiers.

2. Literature Survey

This section addresses several task scheduling approaches as well as their advantages and disadvantages. The paper also explains the basic idea of the suggested scheduling strategy after looking at the existing approaches.

In [16], researchers discovered a new technique for integrating the benefits of depth vision learning with EMG-based hand motion recognition. Without taking into account the hand motion sequence, ensemble learning was used to automatically categorize the class of the collected EMG data. Using the SVM with RBF kernel, Random Forest, and Catboost with the optimal hyperparameters, the models were created and interpreted. According to the calculated number, when compared to other models, Catboost produces the best accuracy, which was around 0.95 accurate. This demonstrates how the suggested method may recognize hand motions better. This paper [17] introduces the latest technique to categorize the single-channel sEMG to detect low-level hand movement. Due to its simplicity, low computing cost, and efficiency, single-channel sEMG analysis was preferable to multi-channel. To identify and analyze the sEMG signal more effectively, wavelet transformation and an ANN classifier are used. In study [18], scholars propose the gesture recognition algorithm using support vector machines (SVM) and histogram of oriented gradient (HOG). In addition, they also categorize gestures using the CNN model. The objectives of algorithms are to recognize gestures quickly and accurately in real-time, to limit interference, and to minimize the possibility of accidentally capturing movements. This study makes use of static gesture controls, such as on, off, increasing, and decreasing. The current switch can also be activated and the volume can be increased and decreased using motion gestures. Results indicate that the algorithm was up to 99% accurate and has an industrial application-appropriate execution time of 70 milliseconds per frame. In research [19], the authors suggest that When applying both normalization approaches with comparison to the original EMG characteristics, performance metrics like accuracy, F1-score, Matthew correlation coefficient, and Kappa score were improved. Moreover, normalization to the AUC-RMS value produced noticeably better gesture identification than features extracted from the signal normalized to maximum peak value using kNN, NB, and RF ($p< 0.05$). The new method of categorizing various hand motions will be helpful in operating prosthetics, virtual objects, and wheelchairs, as well as in human-computer interaction. In paper [20], researchers suggested three stages 1. Segmentation 2. Feature extraction 3. Classification. The static hand posture database created by Sebastian Marcel was to be used to train and test the developed system. Rotation and scale invariant key descriptors have been extracted using the discrete wavelet transform (DWT) and a modified version of the Speed Up Robust extraction method. The fixed dimension input vector needed for the support vector machine was therefore created using the Bag of Word method. Classification accuracy for the "No" and "grasp" gestures, which belong to classes 2 and 4, has reached 98%. With a recognition time of 0.024 s, the HGR system's SVM classifier achieves an overall classification accuracy of 96.5%. This system can be used in real-time gesture image recognition systems due to its quick recognition time. Our HGR system solves the challenging background issue and strengthens the reliability of hand gesture recognition. In research [21], Naive Bayes, K-Nearest Neighbor (KNN), Random Forest, XGBoost, Support Vector Classifier (SVC), Logistic Regression, Stochastic Gradient Descent Classifier (SGDC), and Convolution Neural Networks were among the most common classification approaches that were analyzed (CNN). Researchers observed that the sign language MNIST dataset and random forest outperform conventional machine-learning classifiers, such as SVC, SGDC, KNN, Nave Bayes, XG Boost, and logistic regression, predicting more accurate outcomes. . However, the CNN method generated the most favorable outcomes. The authors of study [22] maintain that performance indicators including accuracy, F1-score, Matthew correlation coefficient, and Kappa score were enhanced when both normalization procedures were used in contrast to the original EMG features. Additionally, normalization to the AUC-RMS value resulted in considerably better gesture detection than features derived from signal normalized to maximum peak value using kNN, NB, and RF (p 0.05). The new system for classifying different hand gestures will be useful for interacting with computers, operating wheelchairs, and controlling virtual items and prostheses. In study [23], the authors suggested a hand gesture recognition method based on electromyograms that were adaptable to various arm postures. The suggested method recognizes the proper hand gestures even with different arm postures by simultaneously using the accelerometer and electromyogram signals. Electromyogram signals are statistically modeled using arm postures to recognize hand motions. In the studies, researchers contrasted the situations where the arm postures were considered with the situations where they were not considered in the identification of hand gestures. The identification accuracy for accurate hand gestures was 54.1% in the cases where different arm postures were ignored; however, the cases employing the approach suggested in this study exhibited average recognition accuracy for hand gestures of 85.7%, an improvement of more than 31.6%. In this work, electromyogram and accelerometer signals were employed concurrently, which mitigated the impact of various arm postures on the electromyogram signals and enhanced hand gesture identification accuracy. In paper [24], the researchers evaluate the impact of hyper-parameters on each hand gesture, the convolutional neural network (CNN) was used in this study to decode hand gestures from the sEMG data collected from 18 patients. The results demonstrated that the learning rate set to either 0.0001 or 0.001 with 80–100 epochs considerably exceeded ($p< 0.05$) other factors. Additionally, it was found that during the duration of the investigation, some motions (close hand, flex hand, extend the hand, and fine grip) performed better than others (83.7% 13.5%, 71.2% 20.2%, 82.6% 13.9%, and 74.6% 15%, respectively). As a result, the most effective hand motions may be used to construct a reliable and steady myoelectric control. The deep learning-based technique can be a more reliable alternative to conventional machine learning algorithms due to increased recognition and uniform gains in performance.

In research [25], the authors propose that the output of the first fully connected layer (CNNFeats), when combined with fourth-order vector autoregression parameters, was a good supplementation location based on the most common Hudgins' time domain features, according to this study, which examined CNNs' capacity to learn features (TDAR). Both the support vector machine (SVM) and the linear discriminant analysis (LDA) classifiers saw a gain in performance of >3% by including the automatically learned CNNFeats into the manually created TDAR extracted features. Comparatively, using TDAR as an extra input to the CNN increased accuracy by >1%. Our findings also showed that the CNN technique outperformed conventional approaches when data from numerous participants were available for training, but conventional approaches were better at displaying motion patterns for a single subject. It must be assumed that a pre-trained CNN model would contribute to higher accuracy as well as the reduction of learning burden because it has been determined that substantial "common knowledge/features" can be taught by CNNs from either the raw EMG signals across multiple days and multiple subjects. In paper [26], it was suggested that Hand gesture recognition has been used in several research areas and has demonstrated its significant benefits in expanding the viability of Human-Robot Interaction (HRI). However, the enormous data set's gathering, labeling, and processing require a lot of labor and lead to lengthy implementations. To combine the advantages of depth vision learning and EMG-based hand gesture recognition, a novel method was therefore proposed. Without taking into account the hand motion sequence, it was able to automatically classify the collected EMG data under the guidance of depth perception. Finally, they used a Myo armband to show the suggested technique for identifying the 10 hand movements. The experiment was set up as supervised learning to assess how well the Hk-means algorithm was working. It demonstrates that the suggested approach can recognize hand gestures without labeling the data beforehand. This study [27] focused on a machine learning and image processing method for empirical hand gesture identification. In human society, the most natural and common form of nonverbal communication seems to be hand gestures. To recognize gestures, the article evaluates the effectiveness of the Histogram of Oriented Gradients (HOG) feature descriptor and Support Vector Machine (SVM) classification model. The study's findings demonstrate that the model efficiently and satisfactorily categorizes hand movements for the provided dataset. The results of this work can be applied further in practical contexts of real-world nonverbal communication systems. In study [28], the researchers focused on the aim was to identifying and categorizing these hand gestures as accurately as possible according to their intended meaning. Some other very well-known models have been contrasted to a fresh strategy for the same problem that has been put forth. The many preparation methods include Principal Component Analysis, Local Binary Patterns, and Histogram of Gradients. Utilizing ORB, a bag of words, and clever edge detection, the novel model was created. To provide useful results, the preprocessed data was fed into a variety of classifiers (Random Forests, Support Vector Machines, Naive Bayes, Logistic Regression, K-Nearest Neighbors, Multilayer Perceptron). The new products have been discovered to be considerably more accurate than the old model. Paper [29] suggests that the co-located EMG-FMG may improve hand gesture categorization accuracy compared to sensing methods that use either EMG or FMG alone. To the best of their knowledge, this represents the prototype for hand gesture identification that concurrently monitors EMG and FMG at the same muscle region. This research's implications may be advantageous for a range of muscle activity monitoring applications, such as biomechanics modeling, prosthesis control, and gesture recognition. The purpose of research in [30] was to create a subject-independent algorithm capable of correctly classifying various hand gestures. Some chosen time-domain EMG features are normalized to the averaged area under the root mean square curve to reduce in-between differences (AUC-RMS). Five adult participants, ages 20 to 37, alternated between making fists, waving in, and waving out ten to twelve times each. To categorize the three different hand motions, five machine-learning techniques were employed: ¿-nearest neighbor (KNN), discriminant analysis (DA), Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). The findings demonstrated a moderate to significant correlation between the EMG characteristics and the AUC-RMS values. When utilizing the original EMG characteristics, the SVM produced the highest classification accuracy (97.56%), which was considerably higher when using the normalized EMG features (98.73%) (p 0.05). When compared to utilizing the original EMG features, employing the normalized EMG features caused all learners' accuracy distributions to be closer to mean values. The discovered method of categorizing various hand movements will be helpful in biomedical contexts when a human-computer interface was required, such as when operating exoskeletons.

After analyzing the above literature, it can be concluded that traditionally a number of Hand gesture recognition systems are proposed for identifying various hand gestures. No doubt that these models were generating effective results but there still is a scope of improvement. One of the major limitations of existing HGR systems is that they use Machine learning (ML) classifiers for identifying and classifying various gestures. These ML classifiers undergo through overfitting issues while analyzing huge datasets. Moreover, the majority of the traditional HGR system normalizes data and then passes it directly to classifiers for anticipating gestures, however, this causes dataset dimensionality issues and also results in information loss. Keeping these facts in mind, a new and effective HGR system must be proposed that can overcome above mentioned limitations and also improves accuracy rate.

3. Present Work

In order to overcome the limitations of the existing HGR system, a new and efficient HGR system is proposed in this research that is based on Bi-LSTM model. The key objective of the proposed model is to reduce errors while simultaneously increasing the accuracy of the gesture recognition system. To accomplish this objective, the work has mainly been done on two phases– introduction to feature selection technique and updated classification model. Traditionally, it was seen that after normalizing the data, it was directly passed to the ML classifier, which caused dimensionality issues. However, in the proposed work, we have introduced Feature selection mechanism wherein 20 different features namely as: Enhanced Mean Absolute Value, Average Amplitude Change, Waveform Length, Maximum Fractal Length, Root Mean Square, Zeros Crossing, Slope Sign Change, Variance, Auto Regressive, Difference Absolute Mean Value, Difference Absolute Standard Deviation Value, Difference Variance Value, Mean Value Of The Square Root, Log Detector, Maximum Fractal Length, Simple Square Integral, Integrated EMG, Modified Mean Absolute Value, Skewness and Kurtosis were extracted from given EMG signal. These features aid in enhancing the accuracy of the proposed HGR system. Moreover, to overcome the limitation of overfitting, we have used a Deep Learning variant namely as; Bi-LSTM classifier in the proposed model for identifying and classifying various gestures. The main reason for using the DL classifier in proposed work is that it retains information of past as well as future and can efficiently handle large and complex EMG datasets. Furthermore, instead of using only one dataset, we have utilized two datasets in the proposed work, one standard dataset and other real time dataset to increase system efficiency. However, the data present in both datasets is unbalanced and contains a lot of null and repeated values therefore, it is necessary to implement data normalization technique before extracting features.

a) EMG Datasets

In the proposed work, we have taken two datasets one is taken from UCI ML repository and other is taken from real world scenarios. In this subsection of paper, a brief overview of these two datasets is provided.

- **Standard EMG dataset**

For the purpose of performing gesture recognition applications, EMG data was taken from the UCI machine learning library. The Myo Thalmic armband was used to gather the information from the forearm, and the material was then uploaded through bluetooth to the computer. The algorithms employed these 8 EMG channels from myo Thalmic wristband as input sets. 36 volunteers were used to gather data as they made seven fundamental movements. These movements were categorized from 1 to 7, that represent, successively, the hands at rest, clenched in fist, extended palm, wrist flexion, wrist extension, and radial and ulnar deviations. Those gestures make up the class tags that make up the result array of the classifiers. For convenience of calculation, 100 instances at random out of each category were chosen from the database; as a result, 700 EMG data were utilized in the trials. 80 percent of these examples were used for training, while the remaining 20 percent was used for test sets.

- **Real Time EMG dataset**

This is the next dataset that has been used in the proposed work for identifying gestures. The real time dataset is created by developing a hardware module that contains EMG two channels for recording muscle activities. A large number of volunteers gathered for who willingly contributes to the dataset by recording their nerve impulses. The volunteers were asked to do four different types of hand gestures i.e. idle, flexion, fist and extension. The obtained data is stored and preserved within two columns of an excel sheet. One of the significant features of this dataset is that it does not contain any null values as data is collected manually. The final data is then used for analyzing the performance of the proposed Bi-LSTM based HGR system.

b) Data Normalization

Data normalization is a crucial preprocessing stage in classification, when data is scaled or transformed to equalize the impact of every attribute. It is crucial to ML and DL algorithms because it not only ensures that the features contribute equally but also lessens the computational strain by working with fewer numbers. In the proposed work, EMG data is scaled between -1 and 1 using min-max normalization.

c) Feature Extraction

Once the data has been normalized, it is time to implement feature extraction techniques wherein a total of 20 features have been drawn out from EMG signals. In traditional models, no features were extracted and normalized data was directly passed to classifiers for classification purposes which reduced their accuracy rate. However, in the proposed work we have extracted

20 important features like Enhanced Mean Absolute Value, Average Amplitude Change, Waveform Length, Maximum Fractal Length, Root Mean Square, Zeros Crossing, Slope Sign Change, Variance, Auto Regressive, Difference Absolute Mean Value, Difference Absolute Standard Deviation Value, Difference Variance Value, Mean Value Of The Square Root, Log Detector, Maximum Fractal Length, Simple Square Integral, Integrated EMG, Modified Mean Absolute Value, Skewness and Kurtosis from the given EMG signal. By implementing the feature extraction, the dimensionality of datasets is reduced which in return reduces computational complexity and processing time.

d) Classification using Bi-LSTM

Deep Learning (DL) which is basically a type of Machine learning (ML) is a neural network that comprises three or more layers. Such neural networks make an effort to mimic how the actual brain functions, however they fall far short of being able to match it, enabling it to "learn" from vast volumes of data. Even through the neural network with single hidden layer can also make predictions but adding few more hidden layers to the network ensures increased accuracy results. In the proposed work we have implemented an advanced variant of DL namely as: Bi-LSTM for making the predictions and identifying gestures through sEMG signals. To start identifying and predicting gestures, a number of parameters like number of layers, hidden units, maximum epochs, initial learning rate and gradient threshold parameters are defined in the network. The specific value of these parameters are recorded in tabular form and is given in table 1.

Table 1: Bi-LSTM initialization parameters

Sr. No.	Network's Parameters	Value
1	No of layer	5
2	No of Hidden units	100
3	Max Epochs	20
4	Initial Learning Rate	0.01
5	Gradient Threshold	1

Once the Bi-LSTM network is initialized, it is time to pass the final featured data to the Bi-LSTM classifiers. The performance of the Bi-LSTM classifier is analyzed on two datasets– standard and real time datasets. The training data of 80% is passed to the classifier for training purposes and the remaining 20% is used for testing its performance. The Bi-LSTM classifier analyzes the EMG signal and tries to match it with the featured EMG signal to identify gestures on two datasets. On the basis of these results, the efficiency of the proposed Bi-LSTM based HGR system is examined in terms of various performance dependency factors like accuracy, precision, classification error, kappa, RMSA, correlation, sensitivity and specificity respectively. IN addition to this, we have analyzed the performance of our proposed Bi-LSTM based HGR system in terms of accuracy, precision, recall and Fscore for identifying four gestures i.e. idle, fist, flexion and extension on real time dataset. The results obtained for proposed model are explained in the coming up sections of this paper.

e) Performance Metrics

In order to evaluate the performance of the proposed Hand Gesture Recognition system, we have analyzed and compared the effectiveness of the proposed model by comparing it with traditional models in terms of parameters like accuracy, precision, sensitivity, specificity classification error, Kappa, RMSE and Correlation. The formulas for calculating the value of these parameters in proposed work are given in this section of paper.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad ------ \quad --(1)$$

Where, TP, FP, TN and FN represent the True Positive, False Positive, True Negative and False Negative respectively.

$$Precision = \frac{TP}{TP + FN} - - - - - - - - -(2)$$

$$Sensitivity = \frac{TP}{TP + FN} - - - - - - - - -(3)$$

$$Specificity = \frac{TN}{TN + FP} - - - - - - - - -(4)$$

$$classification\ Error = 100 - Accuracy - - - -(5)$$

$$Kappa = \frac{PrPr(a) - PrPr(e)}{1 - \Pr(e)} - - - - - - - - -(6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} - - - - - - - - -(7)$$

$$Correlation = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} - - - - - - - -(8)$$

4. Results and Discussion

The efficacy and efficiency of the proposed HGR system is analyzed and validated by comparing it with few traditional models using MATLAB Software. The simulating outcomes were determined for standard dataset as well as for real time dataset in terms of various performance dependency factors mentioned above. In this section of paper we are going to discuss the results obtained for two cases separately.

- **Performance Analysis on standard Dataset**

Using the MATLAB software, the efficiency of the proposed HGR system was firstly analyzed and compared with traditional models in terms of Accuracy. Fig 1 shows the comparative graph obtained for accuracy. After analyzing the given graph, it is observed that value of accuracy was only 91% in ANN, 92% in KNN and DT, 96% in SVM, NB and RF models. While as, when accuracy score was analyzed in proposed Bi-LSTM based HGR system, it came out to be 99% which is significantly more than other similar models.

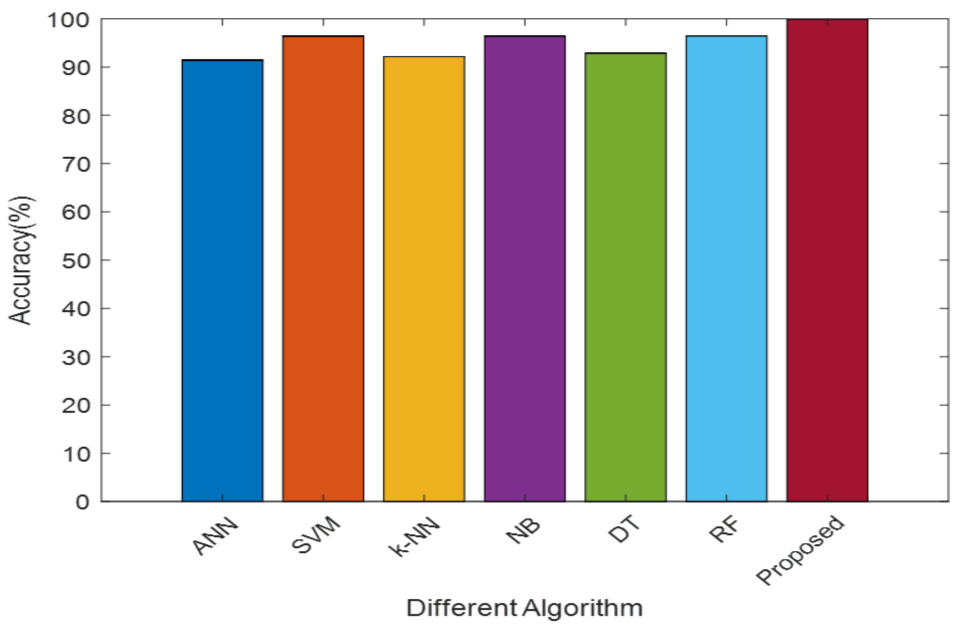

Fig 1. Comparison for accuracy

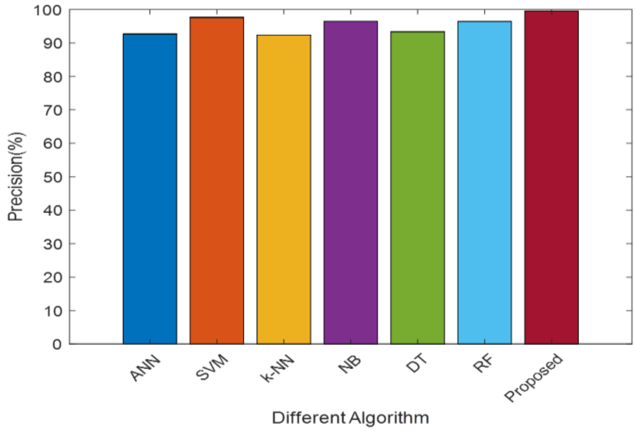

Fig 2. Comparison for Precision

Likewise, we have also analyzed and validated the performance of proposed HGR system in terms of precision score. The comparative graph obtained for the precision is shown in Fig 2, with x-axis depicting various HGR models and y-axis depicting their precision value. From the given graph, it can be seen that the value of precision was lowest in KNN model with 92.3%, followed by ANN model with 92.6%, followed by DT with 93.3% and then NB and RF with 96% and SVM with 97% respectively. However, the value of precision in the proposed HGR model came out to be close to 99.58%, that in itself is a great number.

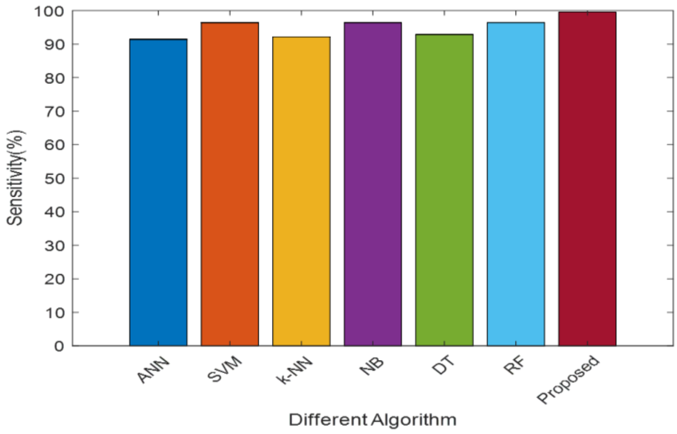

Fig 3. Sensitivity comparison graph

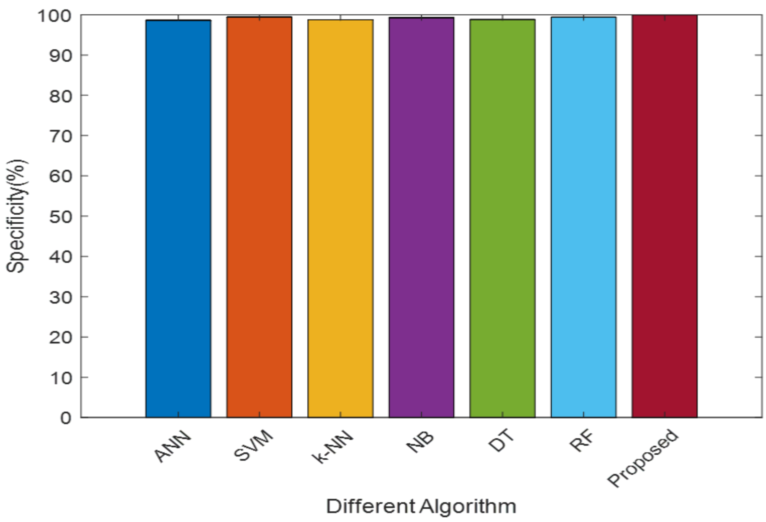

Fig 4. Specificity comparison graph

Furthermore, the supremacy of the proposed HGR model is validated by comparing it with traditional models in terms of their sensitivity and specificity scores. The comparison graph obtained for sensitivity and specificity are shown in Fig 3 and Fig 4 respectively.

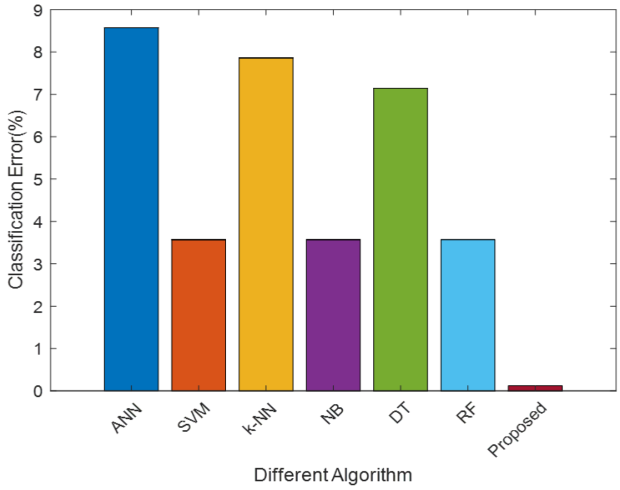

Fig 5. Comparative graph for classification error

After analyzing the above graphs, it is observed that the value of sensitivity came out only 91.4%, 96.4%, 92.1%, 96.4%, 92.8% and 96.4% in ANN, SVM, KNN, NB, DT and RF models respectively. On the contrary, the sensitivity value in the proposed model was mounted at 99.5%, higher than other similar models. Similarly, the specificity values attained in traditional models were 98.5%, 98.7% and 98.8% in ANN, KNN and DT models, whereas, specificity values were 99.4%, 99.2% and 99.4% in SVM, NB and RF models. However, the specificity value was 99.92% in the proposed HGR model, depicting its supremacy over other approaches.

Moreover, we have also analyzed and compared the performance of the proposed HGR model with standard HGR models in terms of their classification error. Fig 5 depicts the comparative graph obtained for the same. Classification error graph depicts the rate of errors obtained for every determination class. After analyzing the graph closely, the error came out to be least in the proposed HGR model with only 0.123% while as, it was 3.57% in SVM, NB and RF models, 7.8%, 7.1% and 8.57% in KNN, DT and ANN models respectively. These high errors degrade the accuracy of traditional systems while recognizing gestures.

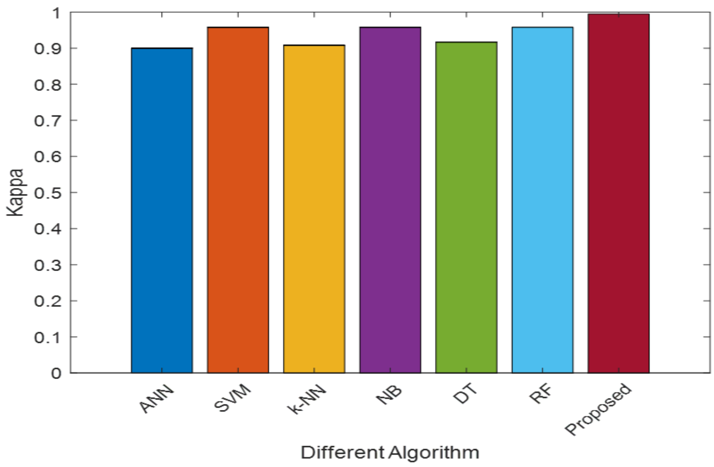

Fig 6. Comparison for Kappa

Also, we have examined and compared the performance of proposed model with traditional models in terms of their Kappa score. The comparative graph obtained for the same is shown in fig 6. The kappa value of the proposed model depicts its reliability among relative deals between parameters. From the given graph, the value of kappa came out to be 0.9, 0.95, 0.90, 0.95, 0.91 and 0.95 in traditional ANN, SVM, KNN, NB, DT and RF models. While the value of kappa was 0.99495 in the proposed model, which is significantly better than other similar approaches.

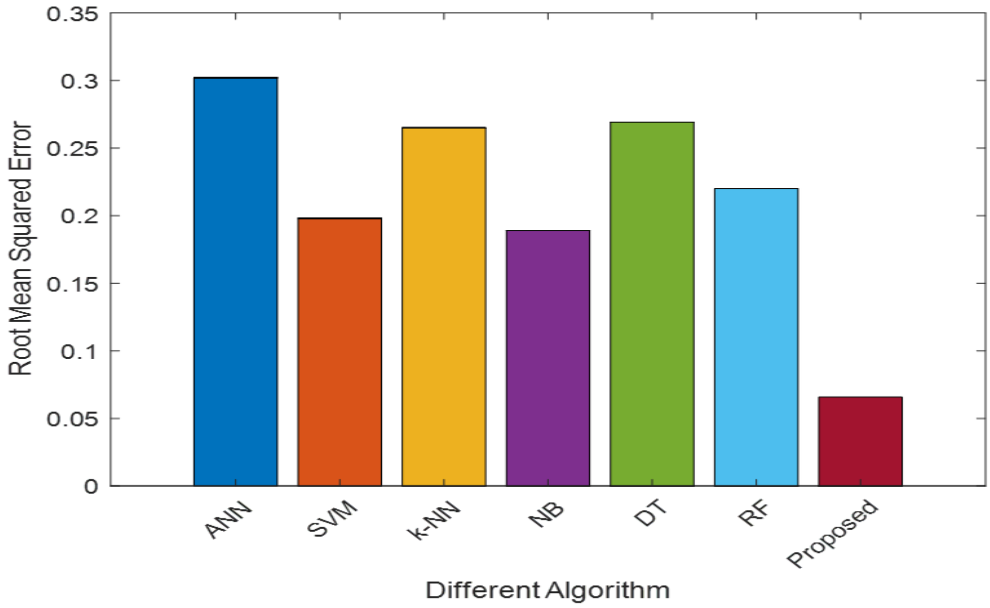

Fig 7. Comparison for RMSE

In addition to this, we have also analyzed and compared the performance of the proposed model with standard HGR models in terms of their RMSE value. The comparative graph obtained for the same is shown in Fig 7. After analyzing the given graph, it is observed that the value of RMSE came out to be the least in the proposed model with only 0.065. This is not the case in traditional models whose RMSE values were 0.30, 0.19, 0.26, 0.18, 0.26 and 0.22 in traditional ANN, SVM, KNN, NB, DT and RF models respectively. These high RMSE value in traditional models reduce their efficiency.

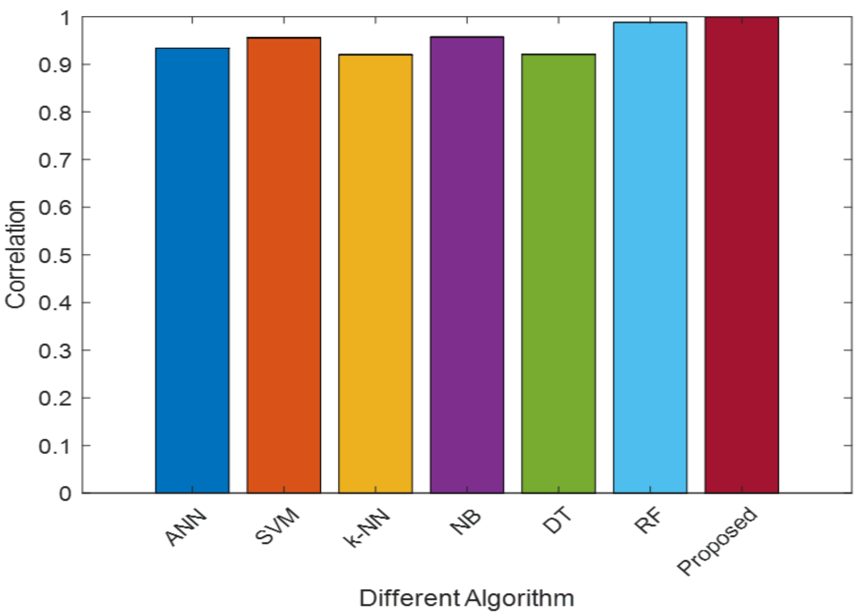

Fig 8. Comparison graph for Correlation

Finally, the performance of the proposed model is also analyzed and compared with traditional models in terms of their correlation values. The comparison graph obtained for correlation is shown in fig 8. Correlation can be defined as the degree of linear relationship among two variables. From the given graph, the value of correlation was 0.999 in the proposed model while it was only 0.93 in ANN, 0.95 in SVM, 0.92 in KNN, 0.95 in NB and 0.92 and 0.98 in DT and RF respectively. The specific value of all parameters is given in table 2.

Table 2: Specific value of various parameters on standard dataset

Technique	Accuracy	Precision	Sensitivity	Specificity	Classification error	Kappa	RMSE	Correlation
ANN	91.43	92.63	91.43	98.57	8.57	0.9	0.302	0.934
SVM	96.43	97.62	96.43	99.41	3.57	0.958	0.198	0.956
KNN	92.14	92.35	92.14	98.74	7.86	0.908	0.265	0.92
NB	96.43	96.49	96.43	99.29	3.57	0.958	0.189	0.957
DT	92.86	93.35	92.86	98.81	7.14	0.917	0.269	0.921
RF	96.43	96.43	96.43	99.41	3.57	0.958	0.22	0.988
Proposed	99.876	99.58	99.567	99.928	0.12369	0.99495	0.065795	0.99946

- **Performance analysis for real Time dataset**

In this phase of proposed work, the efficacy and efficiency of proposed Bi-LSTM based HGR model is analyzed and compared with standard HGR models on real time dataset. The simulating outcomes were determined in terms of confusion matrix, accuracy, precision, recall and Fscore for four hand gestures namely; Idle, Flexion, Fist and extension. The values obtained for these parameters are given in table 3.

Table 3: Specific values for identifying different hand gestures

Class	Accuracy	Recall	Precision	Fscore
Idle	0.96732	1	0.88636	0.93976
Flexion	0.99346	0.97368	1	0.98667
Fist	0.98693	0.94737	1	0.97297
Extension	0.98693	0.94737	1	0.97297

After analyzing the above table, it is observed that the proposed model achieved an accuracy of 96% while identifying idle hand gestures. While as, the proposed model achieved 99%, 98% and 98.6% for identifying Flexion, Fist and extension hand gestures. Similarly, it has been observed that recall value was 1, 0.97, 0.94 and 0.947 for identifying idle, flexion, fist and extension hand gestures. Likewise, precision values were attained which came out to be 0.88 for idle gesture recognition, while as, it came out to be 1 for identifying flexion, fist and extension gestures. In addition to this, the value of Fscore was only 0.93, 0.98, 0.97 and 0.972 for identifying idle, flexion, fist and extension hand gestures. These values prove that the proposed model is generating effective results for identifying different hand gestures.

5. Conclusion

In this paper, an effective and efficient Hand gesture recognition system is proposed that is based on Bi-LSTM model. The efficacy of the proposed model was tested and validated on standard dataset and real time datasets in MATLAB Software. The simulation outcomes were obtained in terms of accuracy, precision, sensitivity, specificity, classification error, RMSE, Kappa and correlation respectively. After analyzing the results, we observed that the proposed model achieves an accuracy of 99.8% for identifying different gestures on a standard dataset. However, the accuracy values were only 91% in SVM, 96% in SVM, 92% in KNN, 96% in NB, 92% in DT and 96% in RF models. Similarly, the proposed model is outperforming traditional models in terms of precision, sensitivity and specificity whose values were 99.5%, 99.56% and 99.9% respectively. Also, the classification error and RMSE values obtained in proposed models were less, i.e. 0.12 and 0.065 respectively, which ensured the proposed model's high performance. The kappa and correlation score attained in the proposed model also ensures proposed HGR system efficient performance whose values were mounted at 0.99 and 0.999 respectively. In addition to this, the proposed Bi-LSTM based HGR system also attains accuracy of 98.366% while identifying four gestures on real time dataset to prove its efficacy.

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