Chapter 3

EMG-based Classification of Hemiplegia Using Ensemble Learning

Abstract

This chapter explores the profound impact of hemiplegia resulting from strokes on mobility and gait, emphasizing its significance in global health. Electromyographic (EMG) signals are employed to analyze muscle activity during walking, but signal variability and noise often affect their accuracy. To address this issue, the study utilizes ensemble learning and feature extraction techniques to improve the accuracy of hemiplegic gait classification. The Random Forest Classifier demonstrates exceptional performance, achieving 97.34% accuracy. Further refinement is achieved by combining the top three classifiers in an ensemble, resulting in an increased accuracy of 98%, along with impressive metrics: 98% Precision, 97% Recall, 98% F1-Score, and a 99.70% Area Under the Curve score. This approach shows great promise for improving the diagnosis and rehabilitation outcomes for patients with hemiplegia.

3.1 Introduction

Hemiplegia is a cerebral motor impairment that affects one side of the body and causes gait abnormalities. The affected side is called the ipsilateral limb, while the unaffected side is called the contralateral limb. Medical practitioners frequently assess muscle strength as part of a physical examination to diagnose hemiplegia. Before the intervention, the patient has a low quality of life. Later, physiotherapists and other healthcare professionals aim to regain the patient's muscle strength to improve the quality of life and enable them to perform day-to-day and functional activities, thus allowing them to cope with society. Despite treatment, the patient has some residual abnormalities hampering their quality of life, such as flexion and contracture of upper and lower limbs due to flexor synergy and gait impairments, depending on the severity of the stroke (Winters et al., 1987). Stroke, a global health concern affecting a large population, is among the prominent causes of hemiplegia. According to the World Stroke Organization, stroke incidence has increased by over 70%, costing over US$721 billion in the past two decades (Feigin et al., 2022). Stroke is becoming much more prevalent in India; it is currently the fourth major cause of death and the fifth leading cause of disability (Jones et al., 2022). The earliest epidemiological survey of hemiplegia due to stroke in India was conducted in 1970 (Abraham et al., 1970). It was concluded that the prevalence of hemiplegia in Southern India is 56.9 per 100,000. According to a 2012 stroke factsheet, the total age-adjusted stroke prevalence rate is expected to be between 84 and 262/100,000 in rural regions and between 334 and 424/100,000 in urban areas (Taylor and Suresh, 2002). A hemiplegic patient's gait is crucial in evaluating the patient's walking capability after a stroke (Kim et al., 2015). A significant concern with hemiplegic patients is that their gait patterns differ from those of healthy individuals. Even though hemiplegia occurs on just one side, alterations in the gait parameters are observed on both sides of the body (Woolley, 2001). Gait pattern disparity between the hemiplegic and unaffected sides results in high swing phase ratios (You and Chung, 2015). The patient's gait varies depending on the leg which initiates the motion. When the hemiplegic leg initiates motion, the unaffected leg provides ample support for a longer stride and swing, while when starting with the unaffected leg, the hemiplegic leg cannot provide postural support, thus resulting in a shorter stride (Hesse et al., 1997). A hemiplegic gait characteristic is excessive downward and inward ankle flexing with an abnormal initial contact during stance. The stiff knee hyperextends during stance and does not flex normally during the swing (McGee, 2021). Rehabilitation procedures have been vastly improved in the past few decades. There has been a shift in the paradigm of post-stroke rehabilitation. Advancements in neuroimaging and animal model studies have given researchers valuable insight into the disease and its treatment options (Marque et al., 2014).

3.2 EMG-based Gait Analysis

A comprehensive study of the effect of walking speed change on gait parameters was conducted by (Tomida et al., 2022). Wearable sensor-based gait analysis is a quick and efficient method of obtaining vital information for various health-related tasks and has promising clinical applications in medical diagnosis, rehabilitation, medical research, and sports activities (Tao et al., 2012). The researchers have used wearable sensing devices such as accelerometers, gyroscopes, goniometers, force sensors, and electromyography (EMG). These techniques are classified as gait kinematics, kinetics, and electromyography. The kinematics of the human gait defines the activity of the joints and components in the lower limbs. Gait kinetics studies forces and moments that cause human parts to move (Negi et al., 2020). One of the most used techniques is electromyography (EMG). EMG has been widely utilized for noninvasive neuromuscular evaluation in research and clinical settings. The electrodes must be placed at the proper muscle location to measure the EMG signal accurately (Rainoldi et al., 2004). Recently, efforts have been undertaken to develop and test noninvasive, economical, and precise motion detection systems utilizing compact and power-efficient sensor technology (Boukhennoufa et al., 2022). A multimodal sensor system to recognize daily activities like sitting, standing, and lying down was proposed by De et al. (2015). IMU sensors have been used to demarcate a normal gait from a hemiplegic one (Guo et al., 2013). Misgeld et al. (2015) proposed an EMG-based body network to detect spasticity events in cerebral palsy patients with hemiplegic gait. The raw EMG signals acquired consist of noise, artifacts, and interference. However, most such noises can be easily removed by filters. Once the noise removal is done, certain features or structures must be identified from the EMG signal. This step is called feature extraction (Oskoei and Hu, 2007). A comprehensive list of time-domain and frequency-domain features is detailed in Phinyomark et al. (2009). Much earlier research has demonstrated that the performance of pattern recognition-based myoelectric control is nearly entirely dependent on the extraction and selection of high-quality and representative features since the extracted features reflect the EMG signal properties for categorization (Phinyomark et al., 2018). Once the feature extraction is complete, the data is fed into a machine-learning algorithm for classification.

3.3 Problem Formulation

Classifying human locomotion via EMG signals is challenging due to stochastic properties, sensor inconsistencies, and complex feature extraction (Sharma et al., 2012). Despite using techniques like clustering and support vector machines, challenges persist. External factors like medication can distort results, while cross-talk and motion artifacts further complicate accuracy. Inter-subject variability in anatomy and muscle mechanics makes establishing norms difficult (Taborri et al., 2017). Algorithms tailored to specific individuals limit generalizability. EMG signals' non-stationarity and high dimensionality add computational complexity and overfitting risks.

To effectively categorize hemiplegic signals in this study, ensemble learning was used. Ensemble learning involves combining multiple models to improve prediction accuracy and reduce the risk of overfitting (Lappalainen and Miskin, 2000). By using a group of classifiers, the unique strengths of each model can be leveraged to achieve better performance than any individual model could provide. Ensemble techniques mitigate overfitting, a common concern when dealing with complex and high-dimensional EMG data, by aggregating diverse classifiers (Webb and Zheng, 2004). By considering multiple perspectives, ensemble methods improve classification performance across varying situations. EMG signals often contain intricate and subtle patterns that signify muscle activation, and ensemble methods can effectively capture and classify even the most complex signal variations by combining classifiers with different sensitivities to these patterns (Yaman and Subasi, 2019). They also balance bias and variance, leading to more accurate and stable classifications. Ensemble learning provides flexibility regarding which features to include in the classification process. It can effectively handle a mix of features, such as time-domain, frequency-domain, or time-frequency domain, enabling a comprehensive analysis of the EMG data. Specific ensemble methods like boosting can adapt dynamically to new data, allowing real-time classification of EMG signals (Wang et al., 2022). This is vital for applications requiring immediate response, such as controlling prosthetics or rehabilitation devices. Ensemble methods often provide insight into the importance of different features and their relevance in classification, aiding in better understanding the underlying physiological processes associated with EMG signals (Thakur and Mathew, 2018). The study aims to identify and analyze gait parameters and develop a classifier to identify hemiplegic patients using a wireless EMG sensor.

3.4 Data Collection

This study selected participants from Sir Sunderlal Hospital (IMS), Varanasi, and other local clinics. The Institute Ethics Committee approved the study at the Institute of Medical Science (Banaras Hindu University), and the participants consented. Table 3.1 lists the inclusion and exclusion criteria for the study.

Table 3.1 Inclusion and Exclusion Criteria for the Present Study

Inclusion Criteria	***Exclusion Criteria***
Age between 20-70 years	Bowel and Bladder are unaffected.
Should be able to walk without support	Patients having angina pectoris
Has under moderate recovery stage	Patients with uncontrolled hypertension
Mild to moderate spasticity on the Ashworth scale	
Both traumatic and ischemic stroke patients were included.	

The patients were undergoing the following active physiotherapy rehabilitation procedures:

1. Coordination and balance training exercises.
2. Neurodevelopment therapy is an approach for strengthening the affected group of limbs.
3. Ankle dorsiflexor strengthening exercise.
4. Gait training exercise.

The hardware setup used in the present study was two DataLITE Wireless Surface EMG LE230 (Biometrics Ltd., Newport, United Kingdom) with a sampling frequency of 1000Hz. The sensors were placed at two leg muscles, the tibialis anterior (TA) and medial gastrocnemius (MGAS), according to the scheme suggested in Hesse et al. (1997). Figure 3.1 shows sensor positioning and the muscles' anatomical diagram (Kim et al., 2022). The subject was asked to walk from one point to another. Three healthy subjects and two subjects with hemiplegia were selected for this study. The complete process is shown in Figure 3.2.

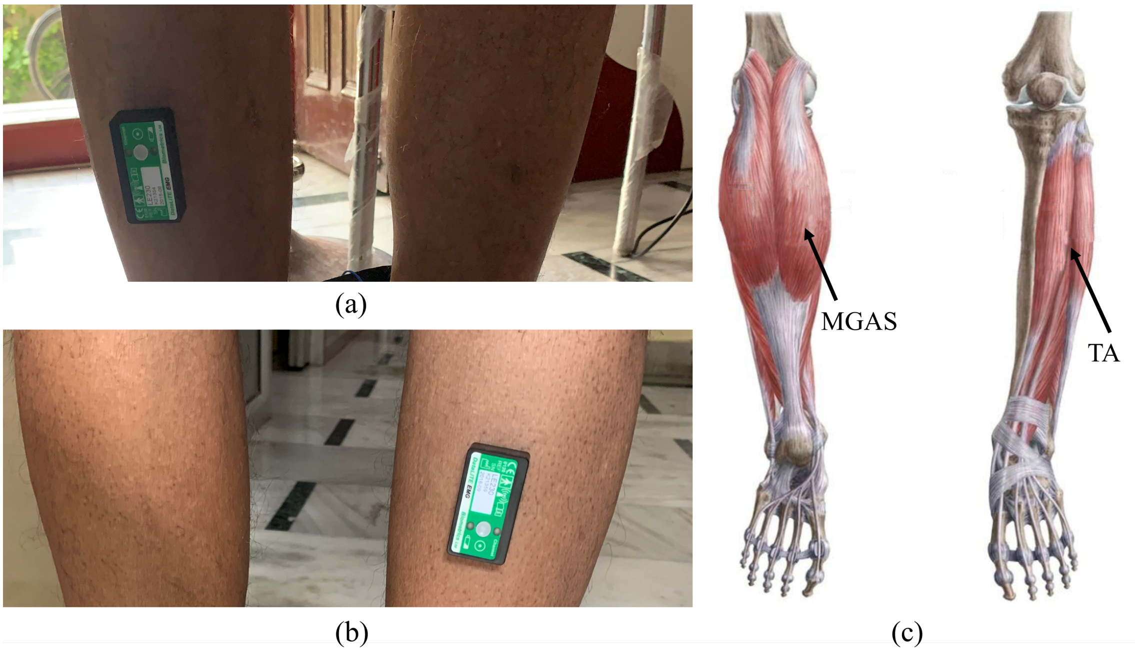


Fig. 3.1 Placement of EMG electrodes: (a) Tibialis anterior, (b) Medial gastrocnemius, (c) Anatomical position of TA and MGAS.

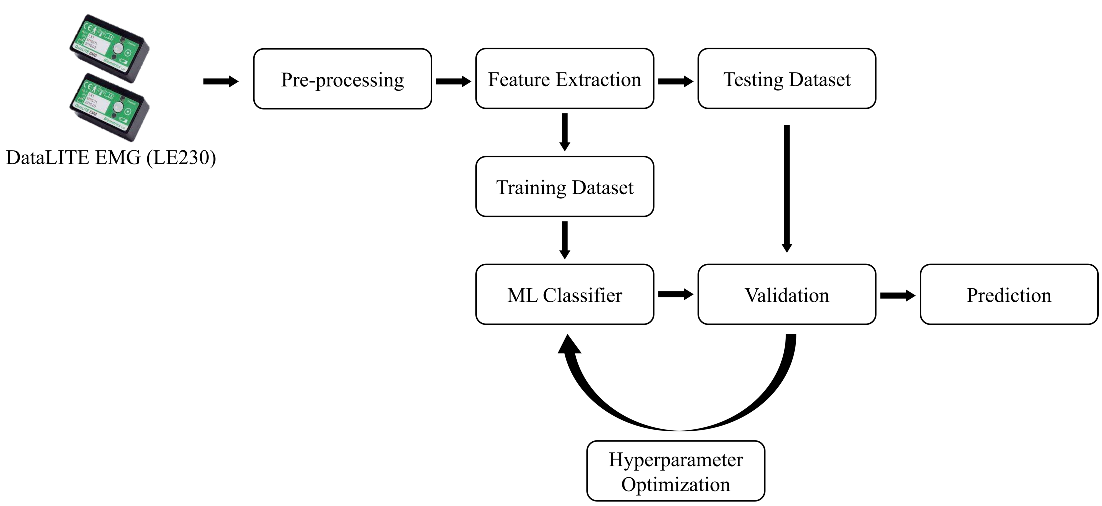


Fig. 3.2 Complete flowchart of the study

3.5 Data Preprocessing and Feature Extraction

After the data acquisition step, the data must be processed and optimized for the machine learning algorithm. This step was completed using Python programming language along with NumPy, Scipy, and pandas libraries. First, the signal is filtered between 20Hz to 450Hz and then rectified. The plots were obtained using the matplotlib library. Feature extraction techniques were used along with the windowing technique, which involves an operation on the part of data (window) to obtain vital insights into data. The features used in the present study are Root Mean Square (RMS), Mean Absolute Value (MAV), Skewness, and Kurtosis. Each feature signifies a specific detail about the signal and thus helps evaluate the correlation of disease with muscle activity (Phinyomark et al., 2009). Table 3.2 provides information on the features used in the current study, where x represents the input sample, N represents the total number of samples, and μ represents the mean.

Table 3.2 EMG features used in the present study

Name	*Formula*	*Description*
MAV	$\frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$	The MAV can assess muscle activation during different tasks or movements.
RMS	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$	The RMS assesses muscle fatigue or changes in muscle activity over time.
Skewness	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3$	Skewness assesses changes in muscle activity during different phases of a movement or task.
Kurtosis	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4$	Kurtosis measures the muscle recruitment or coordination changes in the EMG signal distribution.

3.6 Machine Learning

The extracted features were classified using machine learning algorithms to compare the results with the signal classification approach. These are Linear Discriminant Analysis

(LDA), Logistic Regression (LR), k-nearest neighbor (KNN), gaussian naïve bias (NB), decision tree (DT), and random forest classifier (RFC).

Machine learning algorithms utilize various approaches, each with its unique methodology and underlying assumptions. One such technique is Linear Discriminant Analysis (LDA), which aims to identify a linear combination of features that best separates classes, maximizing inter-class variance and minimizing intra-class variance. Similarly, Logistic Regression (LR) models the odds of a particular class occurrence based on input features, while the k-nearest Neighbor (KNN) algorithm relies on the proximity of data points in feature space to determine class membership. The Gaussian Naïve Bayes (NB) algorithm leverages Bayes' theorem under the feature independence assumption, making it proficient in handling high-dimensional data. In contrast, the decision tree (DT) algorithm recursively partitions the feature space into regions corresponding to class labels, allowing for intuitive interpretation while capturing complex decision boundaries.

On the other hand, the Random Forest Classifier (RFC) creates an ensemble of decision trees, harnessing their collective predictive power to enhance accuracy and robustness. The top-performing classifiers are identified through a rigorous evaluation process. These classifiers showcase an exceptional ability to decipher the intricate relationships between extracted features and class labels, demonstrating their effectiveness in signal classification tasks. An ensemble framework has been created by combining multiple classifiers. This approach combines the strengths of each classifier to improve classification performance.

To ensure robust and accurate classification, the study implemented an extensive Grid Search coupled with 5-fold cross-validation for each classifier. For Linear Discriminant Analysis (LDA) and Logistic Regression (LR), the grid search included parameters such as regularization strength (C), penalty type (L1 or L2), and solver type (e.g., 'liblinear' or 'sag'). These parameters control the trade-off between model complexity and generalization ability, which is crucial for achieving optimal performance. For k-nearest Neighbor (KNN), the search involved tuning the number of neighbors (k), the distance metric (e.g., Euclidean or Manhattan), and variants like 'ball tree' or 'kd tree.' Selecting an appropriate value for k and distance metric is pivotal in determining the algorithm's sensitivity to local patterns and noise. Gaussian Naïve Bayes (NB) typically does not have many hyperparameters to tune. However, in some cases, grid search involved exploring different prior probabilities or adjusting hyperparameters related to handling numerical stability. For Decision Tree (DT) and Random Forest Classifier (RFC), the hyperparameters included tree depth, minimum samples per leaf, and maximum features to consider when splitting.

These parameters control the complexity and depth of the trees, influencing their ability to capture intricate patterns in the data while avoiding overfitting. Furthermore, the ensemble classifier involved tuning hyperparameters related to combining individual classifiers, such as the type of aggregation (voting or averaging) and the weights assigned to each base classifier. This approach systematically explored a wide range of hyperparameters for each algorithm, optimizing their performance while mitigating overfitting.

3.7 Results and Discussion

Figure 3.3(a) shows the EMG pattern of a healthy individual, while Figure 3.3(b) shows the EMG pattern of a hemiplegic patient. Figures 3.4(a) and 3.4(b) show processed EMG waveforms showing an abnormality in the hemiplegic gait cycle. Substantial disparities were observed in the analysis of EMG waveforms from both Healthy and Hemiplegic patients. Specifically, the EMG waveforms exhibited notable abnormalities within the hemiplegic gait cycle. Upon processing the data comprehensively, these waveforms continued to exhibit distortions in the muscle activity of Hemiplegic patients, in stark contrast to the well-defined gait event points evident in healthy subjects' waveforms.

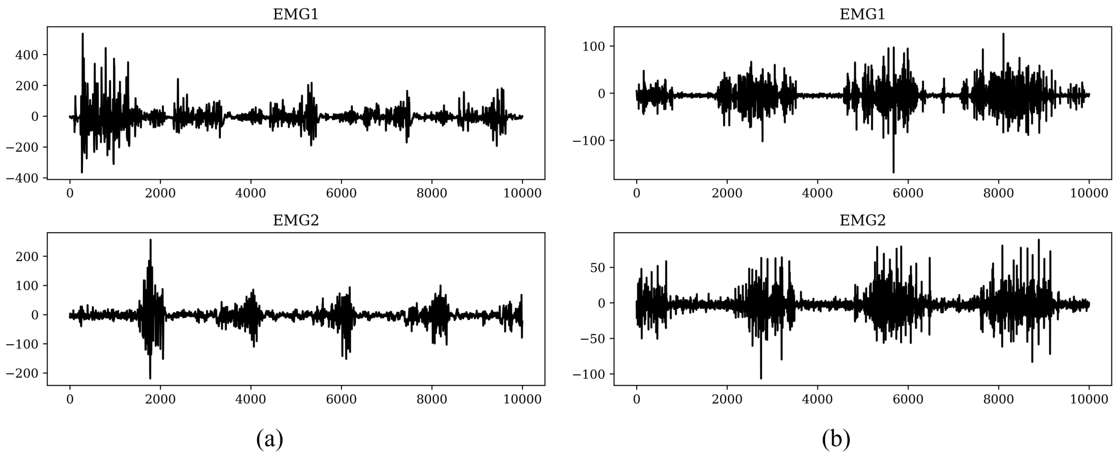


Fig. 3.3 (a) Raw EMG of a healthy subject; (b) Raw EMG of a hemiplegic subject with abnormal baseline

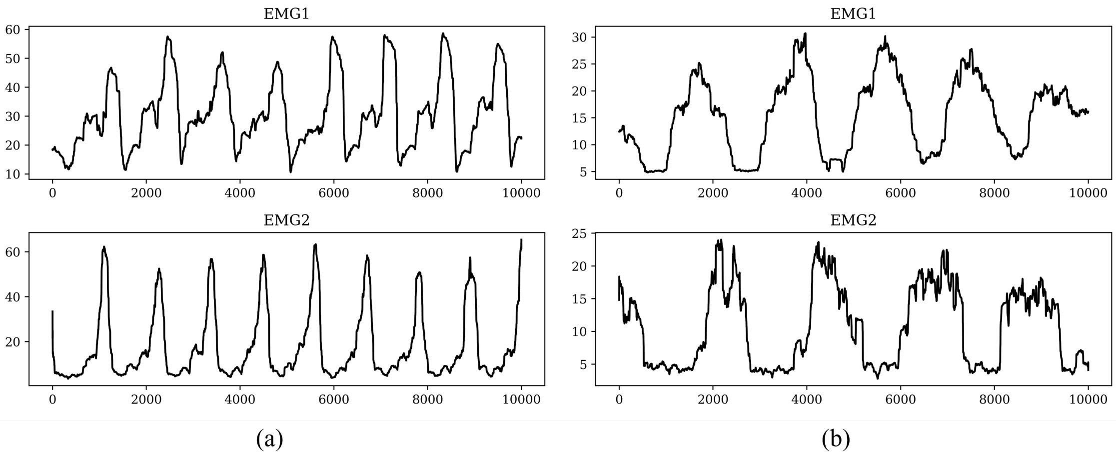


Fig. 3.4 (a) Processed EMG of a healthy subject; (b) Processed EMG of a hemiplegic subject

For the classification, Linear Discriminant Analysis (LDA), Logistic Regression (LR), k-nearest Neighbor (KNN), Gaussian Naïve Bayes (NB), Decision Tree (DT), and Random Forest Classifier (RFC) were used. Among these, the Random Forest Classifier achieved highest classification accuracy of 97.34%. When using the Minkowski distance, the k-Nearest Neighbors algorithm also demonstrated optimal accuracy at a k value of 3. Combining the K-nearest Neighbors, Decision Tree, and Random Forest Classifier improved accuracy to 98%. The ensemble classifier yielded a 98% Precision, 97% Recall, 98% F1-score, and an Area Under Curve score of 99.70%. Linear Discriminant Analysis (LDA) and Logistic Regression (LR) yielded moderate accuracies of 73.45% and 73.77%, respectively. Gaussian Naïve Bayes (NB) displayed lower accuracy at 61.74%, with corresponding precision, recall, and F1-Score values around 0.66. The ensemble approach outperformed individual classifiers, achieving the highest accuracy of 98%, along with precision, recall, and F1-Score values, all above 0.97. The ensemble classifier's ability to combine the strengths of multiple algorithms enhanced overall performance, demonstrating its efficacy in accurately classifying EMG signals. Figure 3.5 visually depict the confusion matrix and Figure 3.6 summarized the performance of all classifiers utilized in the study.

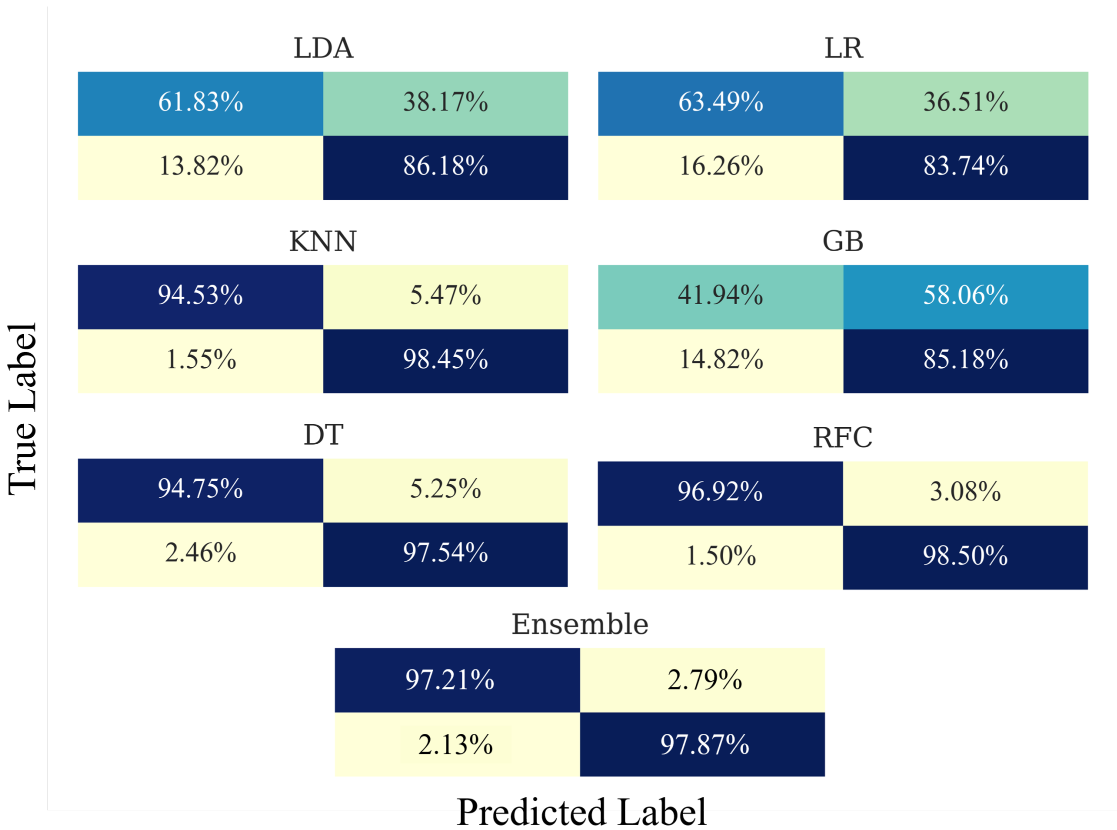
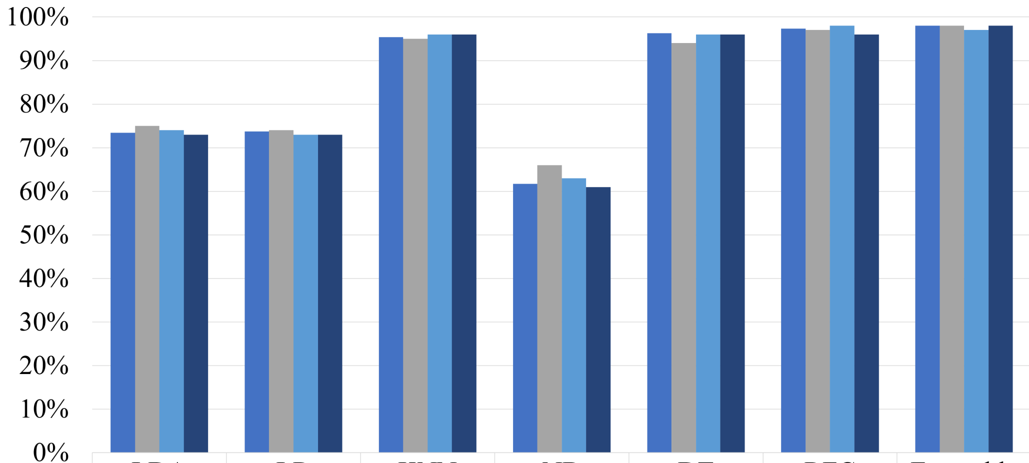


Fig. 3.5 Confusion Matrix of various classifiers



	LDA	LR	KNN	NB	DT	RFC	Ensemble
Accuracy	73.45%	73.77%	95.40%	61.74%	96.29%	97.34%	98.00%
Precision	0.75	0.74	0.95	0.66	0.94	0.97	0.98
Recall	0.74	0.73	0.96	0.63	0.96	0.98	0.97
F1-Score	0.73	0.73	0.96	0.61	0.96	0.96	0.98

Fig. 3.6 Performance metrics of classifiers

3.8 Conclusion

The study utilizes machine learning algorithms to classify hemiplegic gait abnormalities using EMG signals. The EMG signals of hemiplegic patients displayed notable differences compared to healthy subjects, specifically in their gait patterns. A classification framework was developed to address this, leading to the accurate categorization of hemiplegic gait based on EMG data. The Random Forest Classifier achieved an accuracy of 97.34%, while the ensemble approach, combining K-nearest neighbors, Decision Tree, and Random Forest Classifier, resulted in a higher accuracy of 98%. The ensemble classifier exhibited impressive classification metrics, including a Precision of 98%, recall of 97%, an F1-Score of 98%, and an Area Under Curve score of 99.70%. It is helpful for hemiplegic patients to get an accurate diagnosis and seek proper rehabilitative help.