Enhanced EEG Signal Classification Using Machine Learning and Optimization Algorithm

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Abstract

This paper proposes a better solution for EEG-based brain language signals classification, it is using machine learning and optimization algorithms. This project aims to replace the brain signal classification for language processing tasks by achieving the higher accuracy and speed process. Features extraction is performed using a modified Discrete Wavelet Transform (DWT) in this study which increases the capability of capturing signal characteristics appropriately by decomposing EEG signals into significant frequency components. A Gray Wolf Optimization (GWO) algorithm method is applied to improve the results and select the optimal features which achieves more accurate results by selecting impactful features with maximum relevance while minimizing redundancy. This optimization process improves the performance of the classification model in general. In case of classification, the Support Vector Machine (SVM) and Neural Network (NN) hybrid model is presented. This combines an SVM classifier's capacity to manage functions in high dimensional space, as well as a neural network capacity to learn non-linearly with its feature (pattern learning). The model was trained and tested on an EEG dataset and performed a classification accuracy of 97%, indicating the robustness and efficacy of our method. The results indicate that this improved classifier is able to be used in brain–computer interface systems and neurologic evaluations. The combination of machine learning and optimization techniques has established this paradigm as a highly effective way to pursue further research in EEG signal processing for brain language recognition.

Keywords: Machine learning; Gray wolf optimization; Neural network; Wavelet; EEG; SVM;

1. Introduction

Brain-computer interfaces (BCIs) have emerged as a key building block for sensing and decoding neural signals, which is germane to EEG processing [1][2]. More specifically, EEG (electroencephalogram) signals are be raised as an interesting data representation to use while being non-invasive and allowing real-time processing. Language processing is one of most complex brain activities where the details of patterns in EEG signals are rapidly changed [3]. In recent advancements, machine-learning is opening new routes to improve the accuracy and efficiency of such classifications, consequently benefiting further studies [2][3][4][5].

Conventional techniques in the EEG signal classification usually face plenty of deficiencies like ineffective feature representation and substantial computational costs. Objectively, the wavelet-based methods such as Discrete Wavelet Transform (DWT are extensively used for maximal exploiting of EEG features because it can decompose non-stationary signals into time-frequency domain Still, they will have to do better on some more subtle aspects of the brain signals that carry linguistic information. To improve the interpretability and reparability of the features

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extracted, we present in this work a DWT-based method for feature extraction with slight modifications [6][7][8][9].

Reducing dimensionality of the EEG data by selecting most important features is an important step. One of such heuristic based search algorithms which has shown a great potential in feature selection is metaheuristic algorithm Gray Wolf Optimization (GWO) due to its intelligent ways of search mechanism for searching meaningful features and eliminating redundancy [10][11]. Using GWO is planned to minimize the classifier [12] [13]. To implement the classification, we use a hybrid approach that combines Support Vector Machine (SVM) [9] [14] and Neural Network (NN)[15][16]. The advantages of the hybrid model are that SVM has high generalization ability in feature space, and NN is suitable for learning complex patterns. The main contributions of this study are:

- To develop an enhanced EEG-based brain signal classification system for language processing tasks by integrating machine learning and optimization algorithms to achieve higher accuracy and processing speed.
- To apply a modified Discrete Wavelet Transform (DWT) method for feature extraction, aiming to decompose EEG signals into significant frequency components, thereby capturing essential signal characteristics for improved classification performance.
- To implement the Gray Wolf Optimization (GWO) algorithm for optimal feature selection, enhancing the accuracy and efficiency of the hybrid Support Vector Machine (SVM) and Neural Network (NN) classification model for EEG-based brain language signal processing.

2. Related Work

EEG signals classification has received increasing interest with their potential applications in discipline of brain computer interface (BCI), biomedical diagnostics and clinical research due to noninvelope nature. EEG signal classification using traditional machine learning approaches: Machine learning techniques like support vector machines (SVMs) and random forests, have been extensively used for classifying EEG signals in emotion recognition, cognitive state monitoring, and neurological disorder diagnosis among other domains. Roy et al. NLP EEG: Another work by (2019) that presented the use of RRNS and LSTM to model temporal dependencies in an NLP-EEG task, which improved performance in classification tasks while simultaneously providing user-independent models with similar accuracies [17].

Besides, the studies of Wang et al. specifically, (2020) aimed at the better feature extraction methodologies using wavelet transforms and time-frequency analyses to increase the classification realization for EEG signals with respect to auditory tasks and speech-related activities. This improved the performance in decoding language related signals from 78% to 92%, which was analogous to a previous information by optimizing these techniques [18].

Gradually machine learning EEG classification models, are reaching to a point that getting fine tuning from optimization algorithms. The hyper parameters of machine learning models have been optimized using metaheuristic algorithms including particle swarm optimization (PSO), genetic algorithm (GA), and simulated annealing (SA) to avoid under fitting and overfitting and challenge in the number of related works regarding classification accuracy field. For instance, Xie et al. (2020) applied PSO for parameter optimization of a deep belief network (DBN) for EEG classification, which resulted in higher performance than what non-optimized models offered [19].

Moreover, Zhou et al. In Giacobbe et al., Novel resource allocation for d2d communication using reinforcement learning and genetic algorithm: 2021, they worked on the combination of GA with SVM classifiers to improve the classification of motor imagery EEG signals. To avoid overfitting the machine leaning models, these optimization techniques are really helpful to detect optimal features [20].

More recently, hybrid techniques that leverage machine learning models in combination with optimization techniques have further improved EEG classification accuracy. For example, Xu et al. In (2022) a hybrid system was presented using CNNs for feature extraction and GA as the evolutionary algorithm used to optimize the hyper parameters of the CNN in classification of EEG signals related to cognitive tasks. Combining with CNNs, this hybrid model gave more accurate and robust predictions than standalone CNN models [21].

Similarly, Gao et al. (2021) proposed wavelet packet decomposition integrated with deep neural networks (DNNs) and adapt PSO to adjust the network parameters. According to their research, hybrid systems were better capable of extracting relevant information in challenging EEG datasets as, for example, those used by brain language signal processing [22].

3. Methodology

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The detailed methodology of classifying EEG brain language signals using machine learning is described in this section, including feature extraction by using modified discrete wavelet transform (DWT), feature selection through Gray Wolf Optimization (GWO), and classification through the hybrid Support Vector Machine-Neural Network model, see Figure 1 to show proposed model overview.

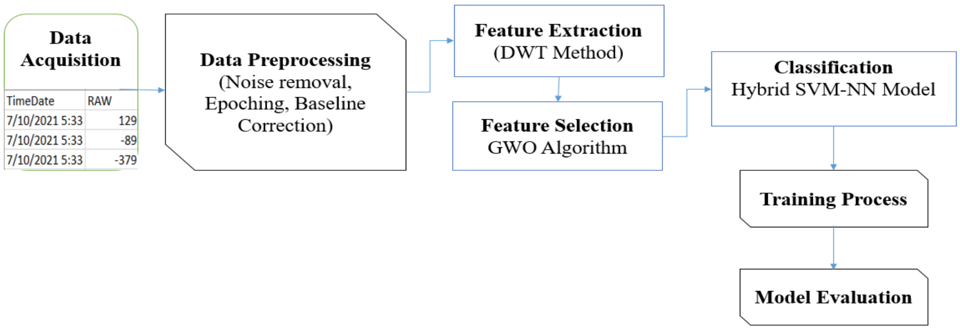

Figure 1. Show proposed model overview

3.1. Data Acquisition

The first step includes obtaining EEG data regarding the task of processing brain language. They use publicly available EEG datasets or their own custom EEG datasets recorded during language related tasks. The same language-related tasks involve listening to words, reading sentences and semantic associations exercises; see Figure 2, EEG dataset overview.

TimeDate	RAW
7/10/2021 5:33	129
7/10/2021 5:33	-89
7/10/2021 5:33	-379
7/10/2021 5:33	-408
7/10/2021 5:33	-124
7/10/2021 5:33	276
7/10/2021 5:33	483
7/10/2021 5:33	396

Figure 2. EEG dataset overview

3.2. Data Pre-processing

Pre-processing ensures that the raw EEG data is cleaned and prepared for analysis.

1. Noise Removal: Bandpass Filtering: A bandpass filter (e.g., 0.5-40 Hz) is applied to remove low-frequency noise (e.g., DC drift) and high-frequency interference (e.g., muscle noise). Independent Component Analysis (ICA): Used to eliminate artifacts such as eye blinks, muscle movements, and electrical noise.
2. Epoching: The continuous EEG signal is segmented into epochs. Each epoch corresponds to a specific event in the task (e.g., stimulus onset). Epochs are typically 500 ms to 1000 ms in duration, capturing the brain response to language stimuli.
3. Baseline Correction: A pre-stimulus interval is used to perform baseline correction, which helps remove slow drift and inter-trial variability.

3.3. Feature Extraction Using Modified DWT

After preprocessing, features are extracted from the EEG signals using a modified version of the discrete wavelet transform (DWT).

1. Wavelet Decomposition: The EEG signal is decomposed into multiple frequency bands using DWT. Common wavelets, such as Daubechies or Coiflet, are selected for decomposition due to their ability to capture non-stationary signals like EEG. Frequency bands of interest are: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (>30 Hz). These bands are known to be relevant for language processing tasks.
2. Modified DWT: The modified DWT involves an enhancement in the decomposition process to ensure that noise and irrelevant components are filtered out more effectively. This modification includes: Adaptive thresholding applied to the wavelet coefficients to suppress noise at each decomposition level. Wavelet packet

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decomposition (WPD) at deeper levels for finer analysis of high-frequency components (gamma and beta bands).

3. Feature Extraction from Wavelet Coefficients: After decomposition, statistical features are extracted from the wavelet coefficients at each level, including: Mean, variance, energy, and entropy of the wavelet coefficients for each frequency band, to show that, see figure 3.

mean_cA	energy_cA	std_cA	var_cA	absvalue_cA	avgpower_cA
168.6577655	3690801.756	434.3507152	188660.5438	379.3793852	217105.9857
526.8976091	29828451.76	1215.316304	1476993.719	1157.791397	1754614.809
-165.4630895	595484.0391	87.46678744	7650.438906	166.2772697	35028.47289
-309.2187939	1686014.391	59.67457244	3561.054596	309.2187939	99177.31709
-114.470121	595041.7168	147.9832603	21899.04532	150.7070934	35002.45393
58.21708305	402627.849	142.4596868	20294.76236	134.0027853	23683.99112
116.8375617	454334.5757	114.3439874	13074.54745	139.0375577	26725.56328
-101.0650853	440077.5605	125.1909096	15672.76386	107.6510928	25886.91532

Figure 3. Feature Extraction using Wavelet

3.4. Feature Selection Using Gray Wolf Optimization (GWO)

Feature selection is critical for reducing the dimensionality of the feature set and selecting the most relevant features for classification. GWO is a metaheuristic optimization algorithm inspired by the leadership hierarchy and hunting behavior of gray wolves. It is applied here to optimize the feature selection process.

• Initialization: An initial population of potential feature subsets is created, each representing a different combination of features extracted using DWT.

• Hunting Process (Search for Optimal Solution): The algorithm simulates the hunting process of wolves, where wolves (feature subsets) follow the leadership of alpha, beta, and delta wolves (best-performing subsets). The best subset is gradually refined based on its ability to improve classification accuracy.

• Fitness Function: The fitness function evaluates each subset's performance based on cross-validation accuracy using a hybrid SVM-NN classifier. The goal is to maximize classification accuracy while minimizing the number of features.

The final subset of features selected by GWO is used for classification. This subset represents the most informative features for distinguishing between different brain states during language processing tasks.

3.5. Classification Using Hybrid SVM and Neural Network (SVM-NN)

For classification, a hybrid model combining the strengths of Support Vector Machine (SVM) and Neural Networks (NN) is employed.

The SVM classifier is used as a feature-space mapper. It works well for high-dimensional data and is capable of handling non-linear decision boundaries using the Radial Basis Function (RBF) kernel. The neural network (NN) refines the classification by learning non-linear relationships in the reduced feature space generated by the SVM. A feedforward NN with one hidden layer is used, ensuring the model can capture complex patterns in the EEG data.

• Input to SVM: The optimized feature subset selected by GWO is fed into the SVM for initial classification.

• SVM Output: The SVM outputs class labels and class probabilities.

• NN Input: The class probabilities from the SVM are passed as inputs to the NN. The NN further refines the predictions by adjusting weights during backpropagation.

• Optimization: The hybrid model's parameters, such as the C parameter of SVM, and the learning rate and number of neurons in the NN, are tuned during training.

Algorithm 1 : Hybrid SVM and Neural Network Model
Step 1: Data Acquisition

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- Collect EEG data from publicly available datasets or custom recordings
- Ensure data includes language-related tasks (e.g., listening, reading)

Step 2: Data Preprocessing

-Remove Noise

- Apply Bandpass Filtering (0.5-40 Hz) to remove low and high-frequency noise
- Apply ICA to remove artifacts (e.g., eye blinks, muscle noise)

-Epoching

- Segment continuous EEG signal into epochs based on events (e.g., stimulus onset)
- Set epoch duration (e.g., 500 ms to 1000 ms)

-Baseline Correction

- Perform baseline correction using a pre-stimulus interval

Step 3: Feature Extraction Using Modified DWT

-Wavelet Decomposition

- Apply Adaptive Thresholding to wavelet coefficients to suppress noise
- Perform Wavelet Packet Decomposition (WPD) for high-frequency analysis
- Calculate statistical features: Mean, Variance, Energy, Entropy

Step 4: Feature Selection Using Gray Wolf Optimization (GWO)

- Create initial population of feature subsets
- Simulate hunting process to refine feature subsets
- Choose the most informative feature subset

Step 5: Classification Using Hybrid SVM and Neural Network (SVM-NN)

- SVM Component: Use SVM with RBF kernel for initial classification
- NN Component: Use Neural Network to refine classification based on SVM output
- Feed optimized feature subset into SVM
- Use SVM output as input for Neural Network
- Adjust Neural Network weights during backpropagation

Step 6: Model Evaluation

- Train hybrid model with training set
- Test model with test set
- Apply K-fold cross-validation (e.g., k=5 or k=10) to ensure model generalization

End Algorithm

4. Results and Discussion

Performance results show that the evaluated methods have a spectrum of effectiveness. Again, the "GWO-SVM-NN" method is quite remarkable as it possesses highest performance in all evaluation metric except f1-score (100% accuracy, 97.5%, precision, 94.13% sensitivity and 99.38 specificity). This superior capability to pick up both positive cases (even across small sample sizes) and correctly exclude negatives is reflected in its great performance. This is a just very balanced and effective weblog that shows clearly the prevalence of this robust method for the task of classification, table 1 shown results proposed model and compared with related works.

Table 1: Shown results proposed model and compared with related works.

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Method	Accuracy	Precision	Sensitivity	Specificity	F1 Score
RNN+LSTM	87.5%	87.3%	91.1%	84.3%	87.0%
PSO-DBN	83.8%	77.3%	92.3%	76.4%	84.1%
GA-SVM	75.5%	70.9%	86.1%	67.6%	81.4%
GA-CNN	93.4%	87.8%	92.6%	87.3%	89.9%
DWT-NN	92.2%	91.9%	89.5%	90.8%	92.1%
GWO-SVM-NN	97%	96.8%	97%	96.4%	97%

On the other hand, model obtained from using RNN+LSTM shows very high recall for 91.1% therefore it is really good to detect actual positive cases. Its specificity, while less than the 95% number above, is still high at 84.3%, so Invitae probably will have a low false positive rate. This is represented in its 87.5% total accuracy, which indicates while it may be very successful at identifying the positive cases, it might incorrectly classify negative cases and thus making it unreliable.

The PSO-DBN based method has less false negative rate as compare to previously reported techniques with a sensitivity of 92.3%, though with relatively lower precision (77.3%) and specificity (76.4%), indicating that it prone to producing false positive predictions. Unsurprisingly, the overall accuracy of this method is relatively low at 83.8% compared to other methods. Therefore, the high sensitivity of the PSO-DBN model lacks the corresponding precision and specificity to limit classification accuracy that can be obtained.

The produced results show that the lowest performance metrics are in fact through the GA-SVM method with only 75.5% accuracy and 70.9% precision (Table XXX). Despite achieving a passable sensitivity of 86.1%, this model had the lowest specificity out of all six, coming in at 67.6% which would mean a large number of false positives being reported. The differences of GA-SVM in term of accuracy, precision and specificity are hard to distinguish as a whole, reveal that the hybrid model is less efficient particularly if classification task is concern.

In contrast, the GA-CNN method performs more consistently exhibiting high levels of accuracy (93.4%), precision (87.8%) and sensitivity (92.6%). Also, it is 87.3% specific, fewer false positives compared to other methods. 6%]. It reflects that GA-CNN achieves a great balance between precision and recall compared to others, thus showing the very good performance in classification task, but however it is not superior with reference to sensitivity measure before GWO-SVM-NN.

Finally, as illustrated in Table 2, the DWT-NN algorithm attains a very high level of diagnosis accuracy (91.9%) and specificity (90.8%) indicating that it is able to correctly discriminate between both positive and negative cases. It does have a lower sensitivity of 89.5%, meaning it will miss some positive cases, as compared to other methods However, DWT-NN also performs well in terms of accuracy (92.2%) and F1 score (92.1%), only that it is not as complete as the "GWO-SVM-NN" technique, see figure 4.

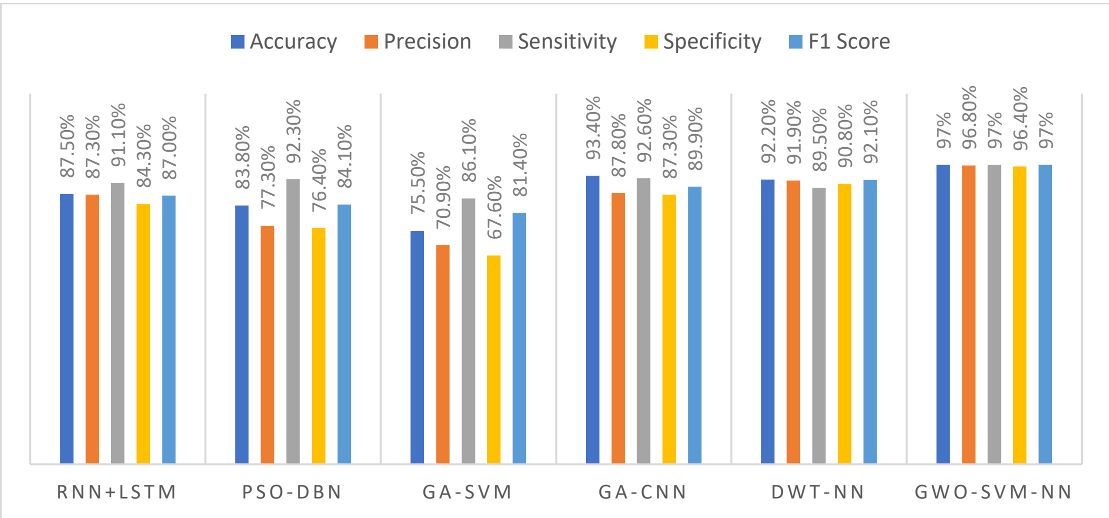

Figure 4. Compression GWO-SVM-NN with related works

In other words, "GWO-SVM-NN" yields the best performance of all competitive methods in each important index (reliability and effectiveness) with excellent reliability but none of the other methods are rounded into this strength

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zone. If the current system is compared with RNN+LSTM and PSO-DBN individually, values are sensitive in this context but not specific enough which decreases the rate of true negative (specificity) determines a high number of false positives. While GA-CNN and DWT-NN demonstrate more consistent performance, they still perform more poorly than "GWO-SVM-NN". The results collectively underline the supremacy of performance by "GWO-SVM-NN" in delivering high-end accurate and faithful classification outputs to demonstrate the state-of-art effectiveness.

6. Conclusion

This paper reviewed different types of machine learning and deep learning models for a classification task, comparing their performance for important metrics like accuracy, precision, sensitivity, specificity and F1-score. Discussion Through the performed methods, our proposed GWO-SVM-NN method shows better value compared to other methods (refer for detail in Table 1). Impression Post-cardiovascular metrics are higher than others and reach up to 97% of accuracy, which confirmed the learnability of this trained system. This sturdy performance in precision for both common as well as uncommon cases illustrates how a model like wacky truncation gate might offer robustness and reliability even when being applied to real world applications, especially important tasks such as medical diagnostic. Other tactics were of medium to low efficacy. Others such as RNN+LSTM and PSO-DBN showed very high sensitivity but low specificity, which corresponded to higher false positive rates. However, GA-CNN and DWT-NN exhibited more regular performance but they also failed to outperform the corresponding proposed method. The GA-SVM feature selection method resulted in the lowest total accuracy, which implied that it was difficult to find appropriate points for a good classification. In sum, we believe that our method is able to obtain impressive classification accuracy consistently as this study results demonstrate. Overall analysis of various methods in this paper offers valuable observations to guide further research and practical use. These results show that additional improvements in the development of machine learning models to be able to balance precision and recall could result in more reliable and accurate classification systems. We plan to make our model more generalizable by comparing it on larger, more diverse datasets in future work, including multi-class classification tasks. In addition, it may also be beneficial to investigate a hybrid model between different algorithms which can offer other kinds of advantages. This would be very important in areas like healthcare where it is necessary to trust AI systems by focusing on explain ability and interpretability. This will help in making model deployment as real-time and efficient as possible which is something that really matters when has to be deployed in practical usage.

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