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Electrocardiogram feature selection and performance improvement of sleep stages classification using grid search

Lyra Vega Ugi[1], Fiky Yosef Suratman[1], Unang Sunarya[2]
[1]Faculty of Electrical Engineering, Telkom University, Bandung, Indonesia
[2]School of Applied Science, Telkom University, Bandung, Indonesia

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ABSTRACT

Sleep analysis is often used to identify sleep-related human health. In many cases, sleep disorders could cause a particular disease. One of the approaches to detect sleep disorders is by investigating human sleep stages. However, the selection of the proper electrocardiogram (ECG) features is still considered challenging and becomes an issue to achieve the performance of the algorithm used. Therefore, it is necessary to investigate which ECG features are very significant to the performance of the algorithm. In this study, the support vector machine (SVM) method has been utilized to classify sleep stages into two classes namely awake and sleep. In order to improve the classification performances, an optimization method of grid search was used to find the best parameters of the SVM. Feature selection of information gain was then used to find the most significant ECG features. To validate the performance results, one leave-subject out cross-validation has been conducted during the implementation. There were ten subjects involved in this implementation. The ECG signals from those ten subjects were used to differentiate awake from sleep state. Based on the results, our method obtained an average accuracy of 85.46% a precision of 84.05% and a recall of 85.44% respectively.

Corresponding Author:

Unang Sunarya
School of Applied Science, Telkom University
01 Telekomunikasi Road, Bandung, West Java, Indonesia
Email: unangsunarya@telkomuniversity.ac.id

1. INTRODUCTION

Sleep is a part of someone's activity that has an important role in their daily life. Lack of sleep could influence someone's health [1]. There are some diseases and inflammatory conditions related to sleep disorders namely heart disease, stroke, diabetes, and depression [2], [3]. Analysis of sleep stage classification is often used for sleep quality assessment [4], and for identifying sleep disorders to prevent chronic diseases due to sleep disorders [5]. Sleep stage classification as one of the sleep analysis techniques has been conducted to score the sleep stages of patients in obstructive sleep apnea [6]. However, the selection of the proper electrocardiogram (ECG) features is still considered challenging and becomes an issue to achieve the performance of the algorithm used. Therefore, it is necessary to investigate which ECG features are very significant to the performance of the algorithm. In addition, the method used needs to be optimized to reach the maximum agreement rate.

Some conventional machine learning techniques have been used to classify sleep stages from electroencephalogram (EEG), electromyogram (EMG), and electrooculography (EOG) [7]–[11]. Hanaoka *et al.* [12] conducted automatic sleep scoring using decision tree learning by generating the tree to classify the signal data according to its classes. Khushaba *et al.* [13] conducted sleep stage scoring using orthogonal-locality sensitive fuzzy discriminant analysis using the EEG, EMG, and EOG signals. The identification of sleep stages has been done for EEG signal using multi classes support vector machine (SVM) [14]. Moeynoi and Kitjaidure [15] used dimension reduction based on canonical correlation analysis (CCA) to classify sleep stages using EEG and ECG signals. Sleep stages classification could be derived not only from EEG, ECG but also could be derived from a combination of ECG-derived Heart rate variability (HRV) and respiratory [16]. In recent, deep learning approaches have been used to classify sleep stages. Vilamala *et al.* [17] designed deep convolutional neural network (DCNN) architecture to interpret sleep stages from EEG signals. Similarly, Supratak *et al.* [18] classified sleep stages from raw single-channel EEG data using DeepSleepNet architecture. DCNN also has been used to differentiate awake-state from sleep-state using actigraph data [19]. Even though deep learning approaches showed better performances, but it is hard of getting the most significant ECG features to be recommended.

In this study, we presented conventional machine learning of SVM to classify binary sleep stages from three-channel Holter ECG (V5, CC5, and V5R) of ten subjects referred to the sleep disorders clinic [20]. To improve the performance of classification, the optimization method of grid search has been applied to find the best parameters for the SVM method. In addition, we investigated the most significant ECG features with respect to the performance of the algorithm using feature selection of information gain. The remainder of this paper is organized into four sections. Section 2 describes the methods used for the classification of sleep stages. Section 3 presents the results of classification performances using SVM and optimized SVM. Finally, all works from this paper are concluded in section 4.

2. METHOD

2.1. Segmentation and filtering

The overall process of sleep stages classification in this experiment is shown in Figure 1. The recorded ECG signal was taken from St. Vincent’s University Hospital sleep apnea dataset. In this implementation, the sleep states were differentiated based on the length of segmented data. The ECG signal from each subject was segmented using 30-second epochs and a sampling frequency of 100 Hz producing 3,000 data samples. Each segment data is then filtered using a finite impulse response (FIR) filter at a band frequency of 0.05-35 Hz.

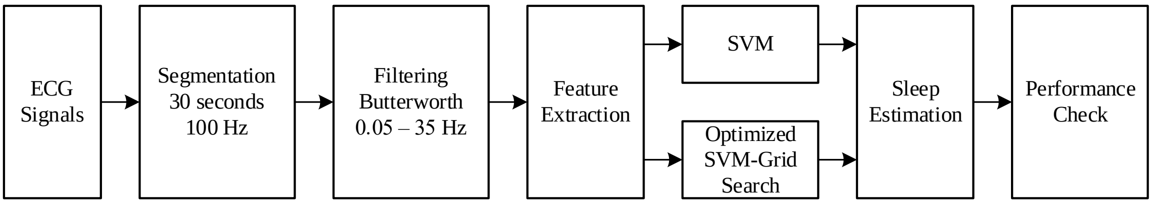


Figure 1. Block diagram of sleep states classification using three-channel Hotler ECGs (V5, CC5, V5R). Benchmark test is conducted using SVM and optimized SVM using grid search method

2.2. Feature extraction

After filtering each segment data, the features from filtered data were then extracted using mean, variance, and standard deviation. The mean of filtered data calculates the average of the data in one segment. It is calculated using (1):

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x(i) \tag{1}$$

where N indicates the length of one segment data and x(i) each sample data of segment.

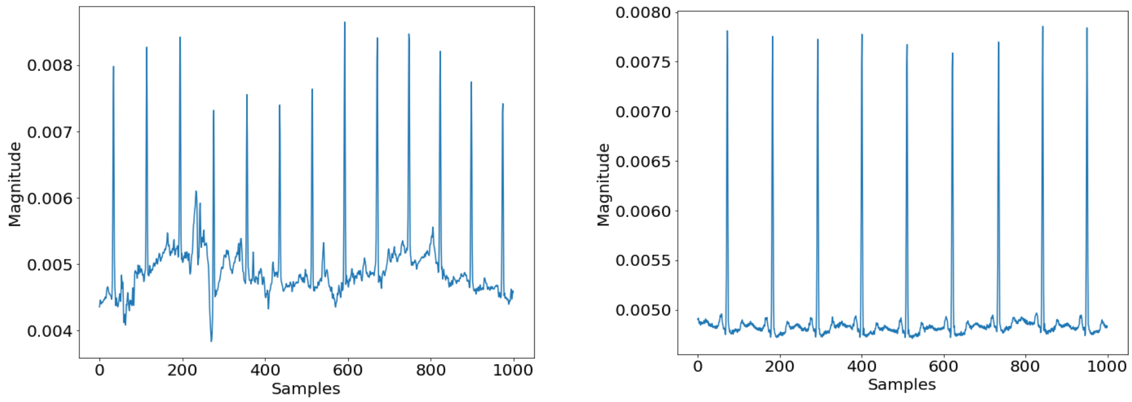
The variation of each segment data was also calculated as a standard deviation of the data. We inspected the variation of each segment data to distinguish sleep stages using (2) and the variance of segment data using (3) as shown in:

$$Std(x) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x(i)-\bar{x})^2} \tag{2}$$

$$Var(x) = \frac{1}{N-1}\sum_{i=1}^{N}(x(i)-\bar{x})^2 \tag{3}$$

where x(i) the i-th sample data and $\bar{x}$ the average of data.

Figure 2(a) describes 1000 samples of ECG signals characterizing the awake state while Figure 2(b) demonstrates ECG signals for the sleep state. Obviously, we may differentiate the awake state from the sleep state by observing the patterns of the ECG signals.



(a) (b)

Figure 2. ECG signals recorded using a Reynolds Lifecard CF system (a) 1000 samples ECG signal of awake state and (b) 1000 samples ECG signal of sleep state

2.3. Support vector machine

SVM is one of the most popular machine learning techniques. The classifier SVM separates the classes by seeking the hyperplane that maximizes the distance between the different classes [21]. There are some kernels that can be used to tackle the input data grouped into linear and nonlinear kernels. In terms of nonlinear processing, the kernel trick is often applied for the SVM to find the best model separation for the classes [22].

In this paper, we utilized grid search as an optimization method for the SVM to automatically find the best parameters of the SVM improving the classification performances. We set up the initial parameters and then defined the sample spaces of the SVM parameters. In Algorithm 1 shows the pseudocode of the optimized SVM using grid search.

Algorithm 1 An optimized SVM using grid search pseudocode:

```
create SVM model as an initial classifier
initial model ← train the initial classifier (train data, train label)
define sample spaces of the SVM parameters candidate:
    'C' ← [0.5, 1.0, 1.5, 2.0, 2.5]
    'kernel' ← ['linear','rbf','poly','sigmoid']
    'degree' ← [2, 3, 4, 5, 6]
    'gamma' ← ['scale','auto']
grid search model ← create model (initial model, sample spaces)
optimized parameters ← train grid search model (train data, train label)
Prediction ← grid search model optimized parameters (test data)
Accuracy ← accuracy score (test label, prediction)
Precision ← precision score (test label, prediction)
Recall ← recall score (test label, prediction)
return Accuracy; precision; recall
```

2.4. Metric evaluation

The performance of the optimized model in classifying sleep stages was evaluated using three metrics evaluation namely accuracy, precision, and recall. The accuracy performance that represents the accumulation of true positive (TP) and true negative (TN) of certain class prediction and the actual class divided by a total number of predictions as formulated in (4):

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{4}$$

False negative (FN) represents a number of incorrectly predicted sleep stages for a certain class label, and false positive (FP) shows a total number of predictions when the classifier falsely predicts sleep stage. In (5), precision represents the rate of TP with respect to the number prediction from the certain sleep states to all actual sleep states.

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

Recall describes ratio of TP to all number prediction class of a certain actual sleep states. The recall is formulated as (6):

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

In this study, we conducted classification of sleep stages into two classes namely awake and sleep states. The class of sleep stages was derived from ECG signals.

3. RESULTS

In this section, we addressed some findings based on simulation. The classification performances were investigated based on three scenarios. Firstly, the performance of SVM was investigated using three statistical features namely mean, variance, and standard deviation. The performance of SVM and optimized SVM were then analyzed. Secondly, in order to validate the performance of the algorithm, seven additional features were added to the first scenario. The seven additional features consist of cress-factor, kurtosis, energy, skewness, spectral frequency, entropy, and zero-crossing, as defined Sunarya *et al.* [23]. In the last scenario, feature selection of information gain was utilized to find the three best significant features then the features were applied to the algorithm.

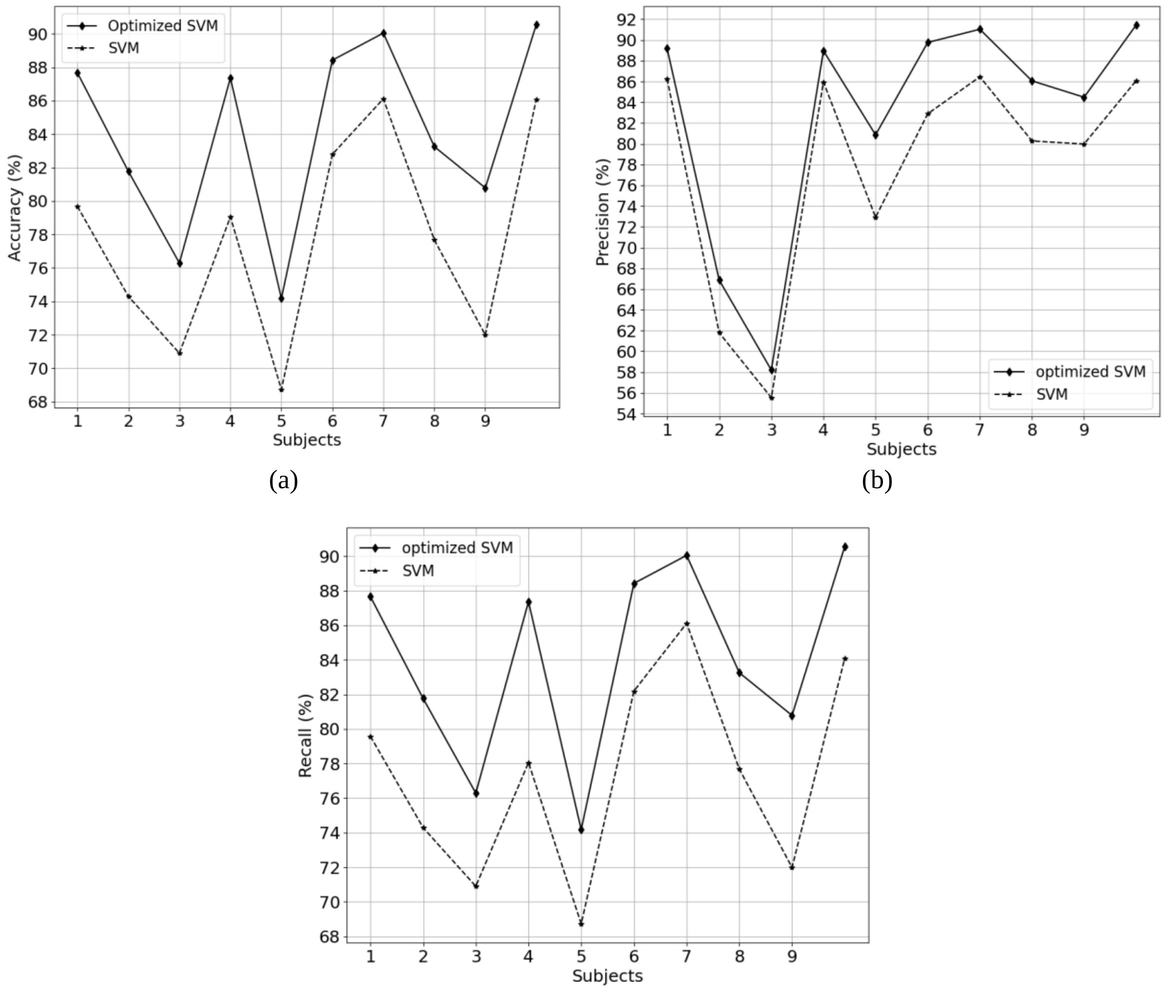
Figure 3(a) illustrates the accuracies of ten subjects using the original SVM and the optimized SVM. There are significant improvements after applying the optimization method of grid search. The grid search has proven to lif up the accuracy score of each subject during implementation with the average accuracy of 84.03% this accuracy score is 6.30% higher than the original SVM (77.73%). The highest score, 90.56% was obtained by subject 10 using the optimized SVM while the lowest one by the subject 5, 68.73% in original SVM and 74.18% in optimized SVM. Overall, the optimized SVM was superior in terms of accuracy performance compared to the original SVM.

Figure 3(b) shows the classification performance in terms of precision score. This performance represents the total number of prediction awake states or sleep states with respect to all actual sleep stages. Similar to the accuracy performances, the average precision using optimized SVM (82.69%) shows superior results than the original SVM (77.82%). Both the optimized and original SVM show the lowest result precision score on subject 3, 58.20% and 55.54% respectively. Based on those results, we could analyze that optimizing SVM parameters has successfully improved the performance of the SVM method.

Figure 3(c) shows the average of recall in each subject. In this case, recall reflects the number of predictions that the classifier correctly predicts the awake and sleep states based on its actual class. Overall, the recall performance using the optimized SVM outperformed compared to the original SVM with the average recall score of 84.03% and this score is 6.67% higher than the original SVM (77.36%). Similar to the accuracy and precision performances, subjects 3, 5, and 9 showed a decreasing trend with the lowest one was subject 5 (68.73%). The highest recall score was obtained by subject 10 (90.56%).

The classification performance of the algorithm was then investigated using 10 features, as shown in Figure 4. The 10 features consist of three statistical features on the first scenario and seven other additional features. Figure 4(a) shows the average accuracy performance on training and testing data both using optimized SVM. Subject 10 reached the highest accuracy score of 93.60% on training and 92.72% on test data, respectively. Meanwhile, the lowest accuracy was happened to subject 9 on training data and subject 1 on testing data. Figure 4(b) shows the performance of the algorithm in terms of precision performance. Among all the subjects, subject 10 reached the highest precision score of 91.28% while subject 9 is the lowest score of 77.72%. Figure 4(c) describes the recall performance. Likewise in the accuracy and precision performances, subject 10 reached the highest score of 92.72% in terms of recall performance.

Compared to the first scenario, the scenario using 10 features relatively has higher performances. In the case of the average accuracy score, the second scenario reached 85.46%. This score is 1.43% higher than the average accuracy of the first scenario with grid search algorithm (84.03%) and 7.73% higher than the first scenario without grid search (77.73%) respectively. Meanwhile, the average precision (84.05%) and recall (85.44%) in the scenario using 10 features are still superior compared to the scenario using three statistical features as in the first scenario 82.69% and 84.03% respectively.



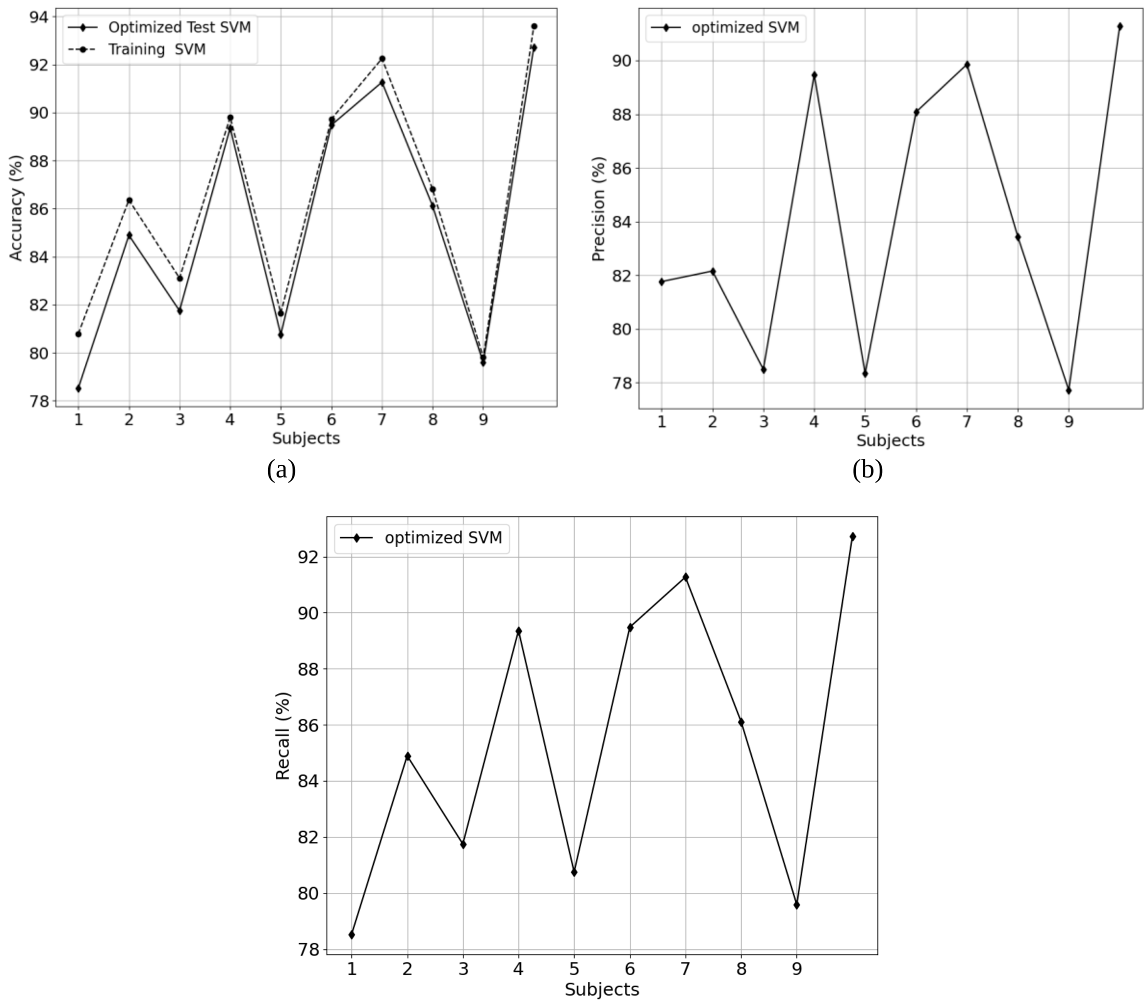
(a) (b)

(c)

Figure 3. The classification performances across 10 subjects using the SVM and optimized SVM based on three statistical features (a) average accuracy, (b) average precision, and (c) average recall

In the last scenario, the 10 ECG features used in the second scenario were investigated to gain which features have the most significant role in the performance of the algorithm. Then the three best features were selected as the features used in the algorithm confirming the classification performance of the algorithm. Feature selection of the information gain (IG) has been used to select and order the features based on the significant rate of the features. The higher the information gain, the more significant the role of features in the performance algorithm. Figure 5 describes the role of the features to the performance algorithm from the most significant to the fewer ones.

Based on the information gain shown in Figure 5, the sorted features are crest factor, standard deviation, kurtosis, energy, mean, skewness, variance, spectral frequency, entropy, and zero-crossing. Then the three best features of crest factor, standard deviation, and kurtosis were applied to the algorithm resulting the average accuracy of 84.83% the average precision of 84.83% and the average recall of 76.17% respectively. Table 1 shows performance classification results from all scenarios in the implementation starting from the SVM using three statistical features as the reference point analysis. The optimization method of grid search was applied to the first scenario resulting significant performances improvement not only in the accuracy but also in the precision and recall. In order to investigate the effect of features then seven additional features were added to the algorithm as a result the performances increased. Based on the information gain score then we picked up the three best features. The results show that the average accuracy performances from the selected features are superior to that reference scenario. It noticed that both the optimization algorithm of grid search and feature selection of information gain took a significant role in improving the performance classification.



(a) (b) (c)

Figure 4. The classification performances across 10 subjects utilizing 10 features (a) average accuracy, (b) average precision, and (c) average recall

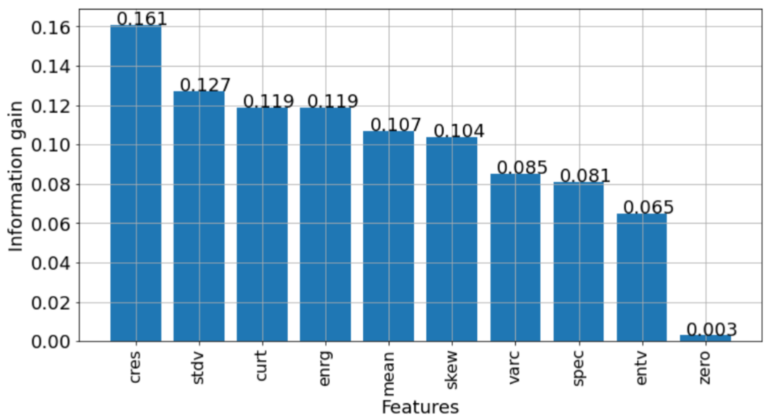


Figure 5. The information gain of 10 features corresponding to performance algorithm

4. DISCUSSION

In this section, the accuracy performances among all scenarios were addressed. The accuracy performance was investigated in each scenario. Figure 6(a) describes the comparison of average accuracy between the SVM using three statistical features with and without optimization algorithm of grid search across ten subjects. The curve without grid search was indicated with label *'acc_3fts'* while the curve with grid search was indicated with label *'acc_*3*fts opt'*. The results show that the average accuracy performance of the method with grid search is higher than the method without grid search. Three subjects i.e., subjects 3, 5 and 9 show significantly lower than the rest of subjects. This phenomenon might happen due to subject conditions. Since all the subjects included in this implementation have high potential sleep disorders that might affect ECG signals while recording. Figure 6(b) describes the average accuracy algorithm when seven additional features were added into the algorithm in the reference scenario. It can be seen that the performance algorithm using ten features is relatively higher than only using three statistical features. Moreover, in the case of applying the grid search. In the scenario of using ten features, the average accuracy increases after using the optimization algorithm of grid search *'acc_*10*fts opt'* compared to the SVM without the grid search *'acc* 10*fts'*. Three out of ten features were selected using the information gain method to gain the best features for ECG sleep classification. Among ten features, the crest factor, standard deviation, and kurtosis were selected as the three best features. Based on these three selected features the average accuracy scores could be compared to that using the same number of features in the reference scenario. Figure 6(c) describes the average accuracy using three selected features. The results show that the SVM with three selected features outperforms the SVM with three statistical features at the same number of features. Furthermore, the SVM using three selected features with grid search algorithm *'acc_*3*ftsAdds opt'* was superior to the SVM without grid search algorithm *'acc* 3*ftsAdds'*.

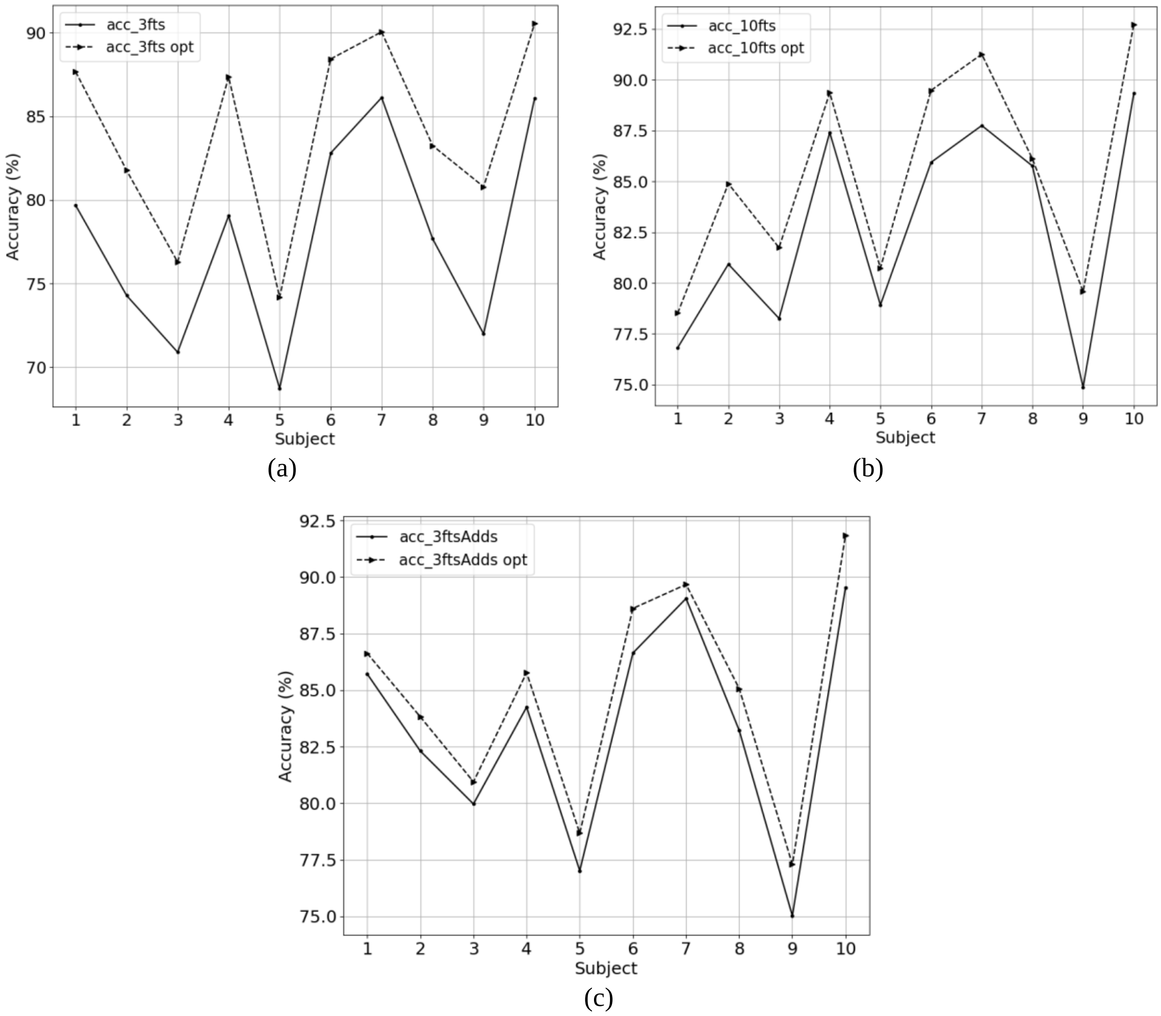
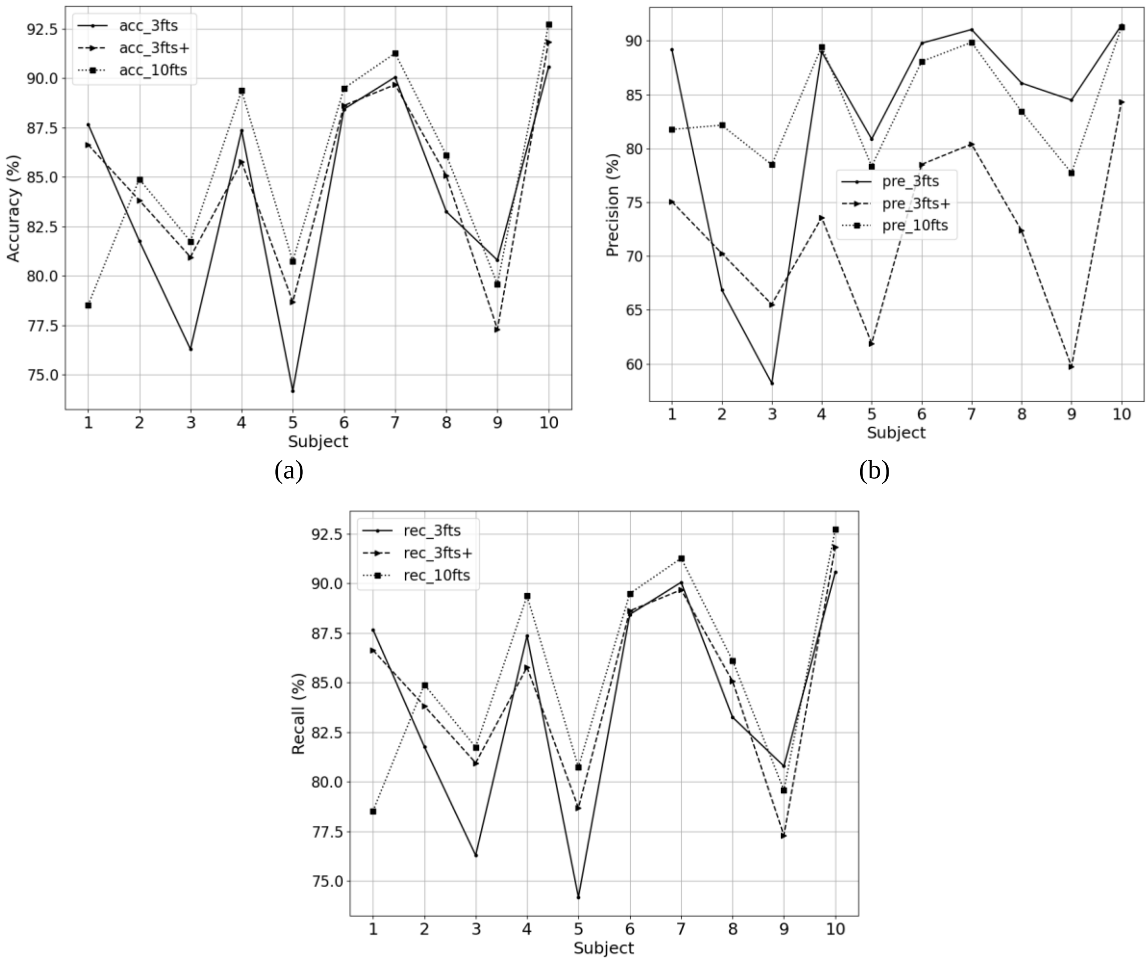


Figure 6. The accuracy performances with and without optimization across ten subjects (a) accuracy using 3 statistical features, (b) accuracy using 10 statistical features, and (c) accuracy using3 selected features

Figure 7 illustrates the overall classification performances of three scenarios using the optimization algorithm of grid search across ten subjects. Figure 7(a) shows the average accuracy of three optimized algorithms. The optimized SVM using ten features *'acc_10fts'* relatively higher compared to the optimized SVM using the three selected features *'acc_3fts+'* or three statistical features *'acc_3fts'*. Similarly, the average precision *'pre_10fts'* and recall *'rec_10fts'* of the optimized SVM using ten features were superior compared to the precision and recall using 3 statistical features and selected features as shown in Figure 7(b) and Figure 7(c), respectively. Overall, the optimized SVM using ten features outperformed among other scenarios. Moreover, the optimized SVM using the three selected features was superior compared to the scenario using three statistical features and slightly inferior to the scenario using ten features. Based on these results, it could be judged that grid search and feature selection of information gain has an important role in lifting the classification performances.



(a) (b)

(c)

Figure 7. Classification performances of optimized methods across ten subjects; (a) accuracy of all scenarios, (b) precision of all scenarios, and (c) recall of all scenarios

Table 2 shows benchmark results of the proposed method with related works. In 2020, sleep stages classification has been conducted using decision tree [24]. The study utilized Poincare plot and DFA as its features yielding 60% of accuracy. linear discriminant analysis (LDA) has been used to classify sleep stages with the average accuracy of 71.93% in [25]. Mehdi *et.al.* used eight frequency domain features, three statistical time-domain features, and two nonlinear features in their study. The SVM methods using HRV time and frequency domain features were used to classify sleep stages resulting in an average accuracy of 79.07% and 76% in [16], [26] respectively. Our proposed method used the SVM optimized with grid search resulting average accuracy of 85.46% using ten features and 84.03% using three statistical features. Furthermore, we introduced feature selection of information gain to select the most significant ECG features. The three significant features were selected and then applied to our method resulting average accuracy of 84.83%. The accuracy using three selected features was superior compared to other methods for the same number of features as can be seen in Table 2. Overall, our method outperformed other related works.

Table 2. Benchmark the optimization SVM using grid search with the related works

Method	Year	Feature	Accuracy (%)
Decission Tree [24]	2020	Poincare plot and DFA	60
LDA [25]	2018	8 frequency domain, 3 statistical time domain and 2 nonlinear features	71.93
SVM-HRV [26]	2012	HRV frequency and time domain features	79.07
SVM-PCA [16]	2019	HRV frequency and time domain features, cross-spectra and magnitude squared coherence features	76
FCM [28]	2012	55 time and frequency features	80.62
SVM + grid search	2022	mean, standard deviation, and variance	84.03
SVM + grid search	2022	crest factor, standard deviation, and kurtosis	84.83
SVM + grid search	2022	crest factor, standard deviation, kurtosis, energy, mean, skewness, variance, spectral flux, entropy, and zero-crossing	85.46

5. CONCLUSION

This paper addressed the binary classification of sleep stages using recorded ECG data. There were 10 subjects involved in this study. The SVM method was used to differentiate the awake state from the sleep state. The optimization method of grid search was then used to improve the classification performances by automatically finding the best parameters for the SVM method. Finally, the results of the optimized SVM were validated using accuracy, precision, and recall. The results showed that the optimized SVM obtained an average accuracy of 85.46% precision 84.05% and recall 85.44%. These results noticed that our optimized SVM using grid search could improve the classification performance of sleep stages. Moreover, we investigated all the ten main features using feature selection of information gain in order to get the most significant features to the algorithm performance namely crest factor, standard deviation, and kurtosis.

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APPENDIX

Table 1. The average accuracy, precision and recall of all scenarios

Method	Feature	Accuracy (%)	Precision (%)	Recall (%)
SVM	mean, standard deviation, and variance	77.73	77.82	77.36
SVM+grid search	mean, standard deviation, and variance	84.03	82.69	84.03
SVM	crest factor, standard deviation, kurtosis, energy, mean, skewness, variance, spectral flux, entropy, and zero crossing	82.60	80.07	82.59
SVM+grid search	crest factor, standard deviation, kurtosis, energy, mean, skewness, variance, spectral flux, entropy, and zero crossing	85.46	84.05	85.44
SVM	crest factor, standard deviation, and kurtosis	83.27	74.93	83.24
SVM+grid search	crest factor, standard deviation, and kurtosis	84.83	76.17	84.83

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BIOGRAPHIES OF AUTHORS

Lyra Vega Ugi is a current Master student in Electrical Engineering Department at Telkom University, Indonesia. She received the bachelor's degree of Telecommunication Engineering in 2015 from school of Electrical Engineering, Telkom University, Indonesia. Her research interest includes signal processing and machine learning. She can be contacted at email: lyraugi@student.telkomuniversity.ac.id.

Fiky Yosef Suratman (Member, IEEE). He received the bachelor's degree in engineering physics and the master's degree from the School of Electrical and Informatics (STEI), Institut Teknologi Bandung, Bandung, Indonesia, in 1998 and 2006, respectively, and the Dr. -Ing. degree from the Technische Universitaet Darmstadt (TU-Darmstadt), Darmstadt, Germany, in 2014. He has been the Head of the Department of Electrical Engineering, Telkom University, since 2014. His research interests include statistical signal processing, radar signal processing, and machine learning. Dr. Suratman is currently a member of the IEEE Signal Processing Society. He is also the Chairman of the Signal Processing Society (SPS)'s Indonesia Chapter. He was awarded the scholarship from the German Academic Exchange Service (DAAD) to continue his Dr. -Ing. degree. He can be contacted at email: fysuratman@telkomuniversity.ac.id.

Unang Sunarya is a current Ph. D student in Computer Engineering Department at Kwangwoon University, South korea. He received Diploma degree from Bandung State Polytechnic (POLBAN) in 2006, bachelor's degree (2009) and master's degree (2012) from Telkom University, Indonesia. His research interest includes machine learning, robotics, and signal processing. He can be contacted at email: unangsunarya@telkomuniversity.ac.id.