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Halomoan, J.[a] , Ramli, K.[a] , Sudiana, D.[a] , Gunawan, T.S.[b c] , Salman, M.[a]

ECG-Based Driving Fatigue Detection Using Heart Rate Variability Analysis with Mutual Information
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[a] Department of Electrical Engineering, Universitas Indonesia, Depok, 16424, Indonesia
[b] Department of Electrical and Computer Engineering, International Islamic University Malaysia, Kuala Lumpur, 53100, Malaysia
[c] School of Electrical Engineering, Telkom University, Bandung, 40257, Indonesia

Abstract
One of the WHO's strategies to reduce road traffic injuries and fatalities is to enhance vehicle safety. Driving fatigue detection can be used to increase vehicle safety. Our previous study developed an ECG-based driving fatigue detection framework with AdaBoost, producing a high cross-validated accuracy of 98.82% and a testing accuracy of 81.82%; however, the study did not consider the driver's cognitive state related to fatigue and redundant features in the classification model. In this paper, we propose developments in the feature extraction and feature selection phases in the driving fatigue detection framework. For feature extraction, we employ heart rate fragmentation to extract non-linear features to analyze the driver's cognitive status. These features are combined with features obtained from heart rate variability analysis in the time, frequency, and non-linear domains. In feature selection, we employ mutual information to filter redundant features. To find the number of selected features with the best model performance, we carried out 28 combination experiments consisting of 7 possible selected features out of 58 features and 4 ensemble learnings. The results of the experiments show that the random forest algorithm with 44 selected features produced the best model performance testing accuracy of 95.45%, with cross-validated accuracy of 98.65%.

Author Keywords
electrocardiogram; ensemble learning; fatigue detection; heart rate fragmentation; heart rate variability analysis; mutual information; non-linear feature

Index Keywords
Adaptive boosting, Classification (of information), Extraction, Feature Selection, Heart, Vehicle safety; Detection framework, Driving fatigue, Ensemble learning, Fatigue detection, Heart rate fragmentation, Heart rate variability analysis, Heart-rate, Mutual informations, Nonlinear features, Vehicle safety; Electrocardiograms

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Correspondence Address
Halomoan J.; Department of Electrical Engineering, Indonesia; email: junartho.halomoan@ui.ac.id
Ramli K.; Department of Electrical Engineering, Indonesia; email: kalamullah.ramli@ui.ac.id

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