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## Hyperparameter tuning of the model for hunger state classification (Book Chapter)

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### Abstract

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To increase the classification, the rate of prediction based on existing models requires additional technique or in this case optimizing the model. Hyperparameter tuning is an optimization technique that evaluates and adjusts the free parameters that define the behaviour of classifiers. Data sets were classified practical with classifiers like SVM, k-NN, ANN and DA. To further improve the design efficiency, the secondary optimization level called hyperparameter tuning will be further investigated. DA, SVM, k-NN, decision tree (Tree), logistic regression (LR), random forest tree (RF) and neural network (NN) are evaluated. The k-NN provided 96.47% of the test sets with the best reliability in classifications. Bayesian optimization has been used to refine the hyperparameter; hence, standardize Euclidean distance metric with a k value of one is the ideal hyperparameters which could achieve classification performance of 97.16%. © The Author(s), under exclusive license to Springer Nature Singapore Pte Ltd 2020.

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Bayesian optimization Classification Hyperparameter tuning K-nearest neighbour Neural network

### Indexed keywords

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Engineering uncontrolled terms: Bayesian optimization Classification performance Hyper-parameter K-nearest neighbours Logistic regressions Optimization levels Optimization techniques State classification

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