Data-driven machine learning and optimization pipelines for real-world applications
Koch, M.

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Acronyms

AMLPA Automated Machine Learning for Production and Analytics. 30, 45, 93

ATM Auto Tune Models. 31, 45, 91–94

AUC Area Under the Curve. 15

AutoML Automated Machine Learning. 1–5, 29–31, 45, 91–95, 113

CNN Convolutional Neural Network. 28, 43, 47, 49

CNN+LSTM Convolutional Neural Network + Long Short-Term Memory. 47, 49, 91, 92, 114

CRISP-DM Cross Industry Standard Process for Data Mining. 97, 103–105

DTW Dynamic Time Warping. 89, 91–93

ECU Electronic Control Units. 107, 108

EEG Electroencephalography. 71–77, 79–81, 84–86

FCN Fully Convolutional Network. 34, 47, 91–93

GAMA Genetic Automated Machine Learning Assistant. 30, 45, 91–93

GDPR General Data Protection Regulation. 97, 108, 111

HCPGP Hand-Crafted Pipeline with Genetic Programming. 42, 44, 92, 93, 95

HCTSA Highly Comparative Time-Series Analysis. 21, 22

KNN k-Nearest-Neighbor. 74

kPCA kernel Principal Component Analysis. 43–45, 92

LRID Likelihood Ratio Imbalance Degree. 88, 89

LSTM Long Short-Term Memory. 28, 47, 49

MIP-EGO Mixed-integer Parallel Efficient Global Optimization. 41, 67, 68, 70

MTSC Multivariate Time Series Classification. 33, 34, 47

PCA Principal Component Analysis. 22, 43, 115

PD Parkinson's disease. 71–74, 81, 84, 85

PHCP Plain Hand-Crafted Pipeline. 35, 40, 41, 51, 54, 62, 63, 91–93

qEEG quantitative Electroencephalography. 73, 74

RECIPE Resilient Classification Pipeline Evolution. 31, 45, 91–93

ResNet Residual Network. 34, 47, 91–93

RFECV Recursive Feature Elimination with Cross-Validation. 24, 65–67

RNN Recurrent Neural Network. 28

ROC Receiver Operating Characteristic. 15, 42, 80

SVM Support Vector Machine. 74

TPOT Tree-based Pipeline Optimization Tool. 29, 30, 45, 91, 92, 94

TSC Time Series Classification. 17, 33, 34

tsfresh Time Series Feature Extraction based on Scalable Hypothesis Tests. 21, 22, 36, 40, 42–44, 55, 56, 65, 70, 77, 78