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Evaluation of Random Forest for Complex Human Activity Recognition Using Wearable Sensors

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Joint work with

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Outline

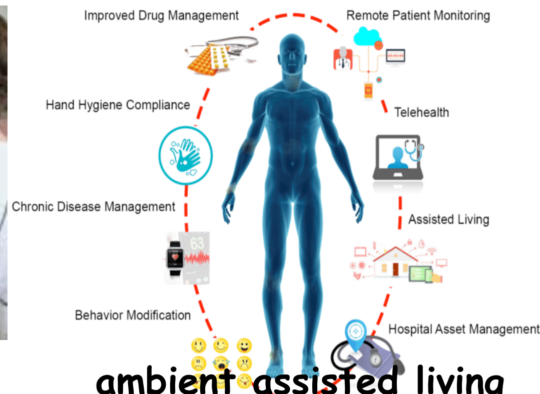
- **Activity recognition**
- Random forest-based activity recognition
- Experimental setup
- Results and analysis
- Conclusion

games

sports training

fall detection

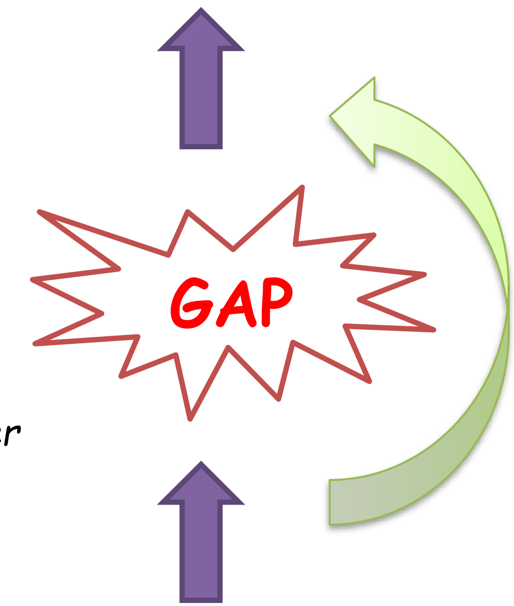
rehabilitation training



ambient assisted living

...

High-level applications, *e.g., smart home, elderly healthcare, ambient assisted living, human computer interaction*



Human Activity Recognition

SENSORS

Camera
Accelerometer
Gyroscope
RFID
Infrared
Pressure
Temperature
Humidity
...

Low-level sensor data, *e.g., wearable sensors, vision sensors, environment sensors*

https://www.researchgate.net/publication/303096601_Progress_in_ambient_assisted_systems_for_independent_living_by_the_elderly/figures?lo=100

Human activity recognition challenge

Modelling and Evaluation

- ✓ behavior computable?
- ✓ no standard evaluation metrics or systems as the context of human behavior varies
- ✓ what performance should be considered (e.g., accuracy, time-efficiency, energy efficiency, robustness)
- ✓ …

- ✓ data fragmentation
- ✓ data heterogeneity
- ✓ data representativeness
- ✓ data sparsity
- ✓ imbalanced data distribution
- ✓ spatial-temporal correlation
- ✓ …

CHALLENGE

Data

Human Behavior Itself

- ✓ capriciousness
- ✓ evolution
- ✓ null class
- ✓ multiple granularity (action, activity, behavior, plan, goal, intention, etc.)
- ✓ …

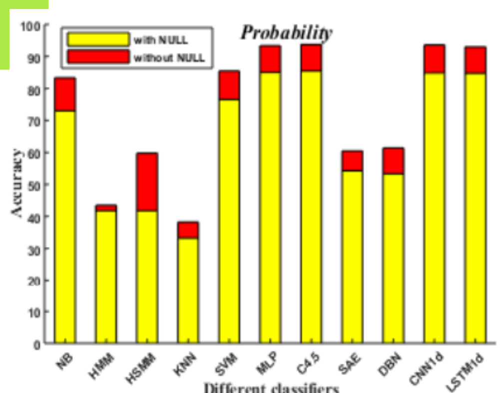


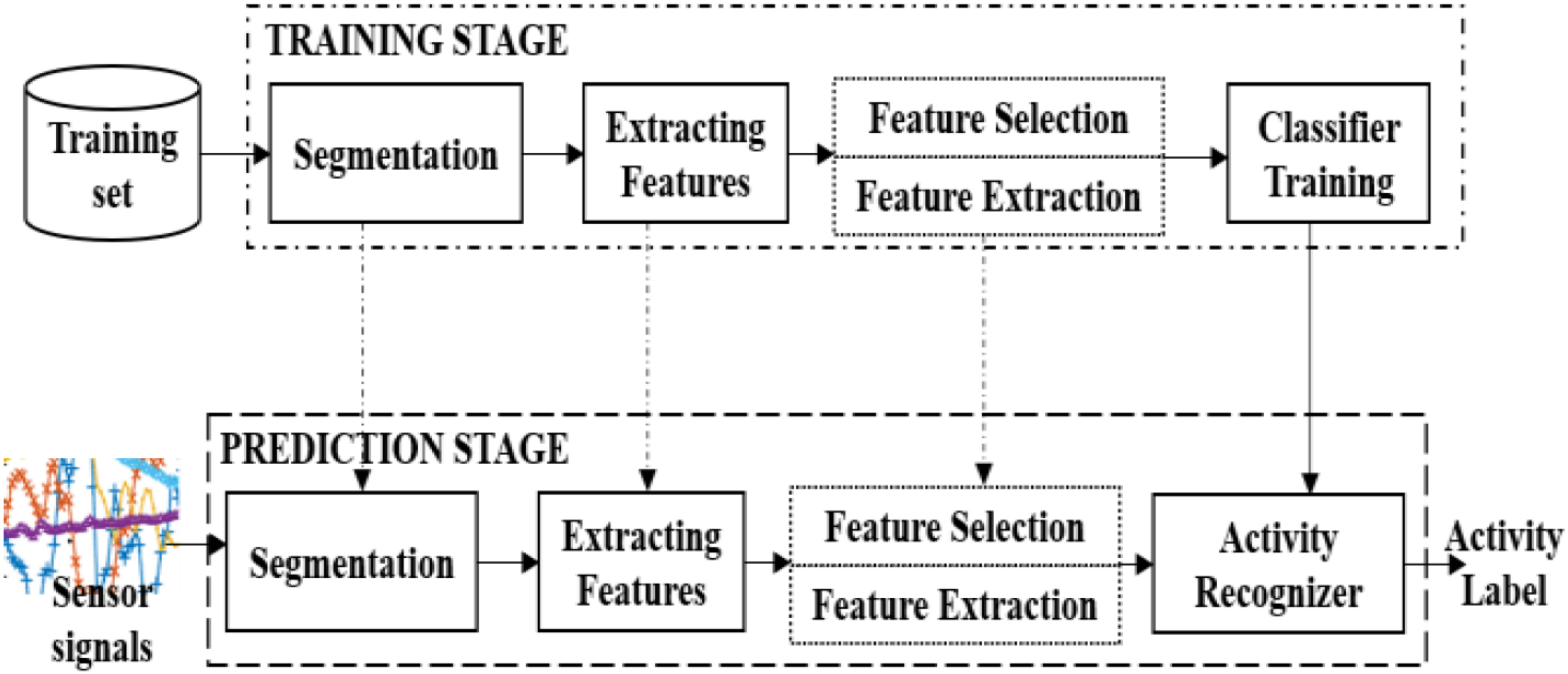
Fig. Influence of null class

Yu, Zhiwen, et al. "Ten scientific problems in human behavior understanding." *CCF Transactions on Pervasive Computing and Interaction* 1.1 (2019): 3-9.

Categorization according to the used sensing units

- Vision-based methods
  - utilize a camera or video to capture human movement, such as Kinect
  - easily influenced by ambient occlusion, background noise, and illumination variations
  - privacy issues, fixed place
- Environment sensor-based methods
  - place or embed sensors in the household objects
  - infer the on-going activities based on the interaction between an individual and the surroundings
  - fixed place, not trivial to setup and maintain the system
- Wearable sensor-based methods
  - recognize human activities according to the wearable sensor data collected by someone performing an activity
  - suitable for both indoor and outdoor scenarios
  - less invasive to users

Activity Recognition Chain (ARC)



- Consist of the training stage and prediction stage
- Key components: *segmentation, extracting features, feature reduction, choice of classifiers*

Segmentation

- Divide time-series sensor data into segments
- Segmentation methods
  - explicit segmentation
  - sliding window
    - time-based vs. event-based (how many sensor events in a window)
    - fixed size vs. dynamic (adaptive) size
    - overlap vs. non-overlap between two segments
  - change-point-based
- Time-based sliding window technique is widely used and works well in practical use

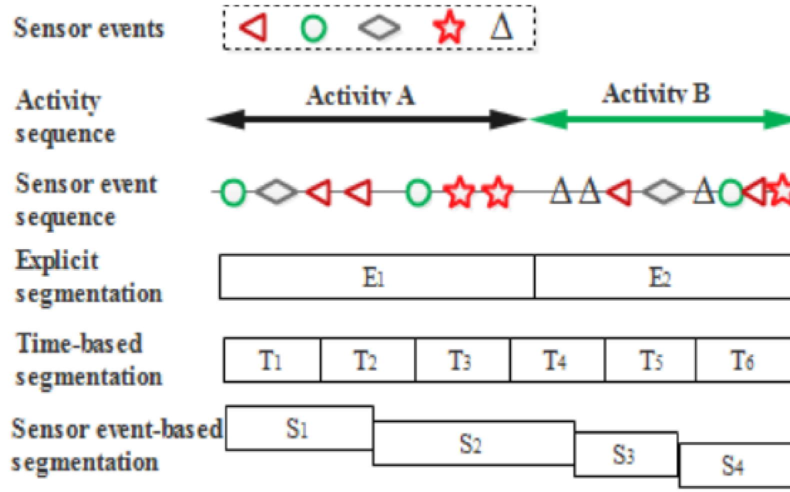


Fig. 1(a). Illustration of three specific sliding window techniques. Each symbol of the sensor events denotes a specific sensor. The activity sequence consists of two activities, activity A and activity B

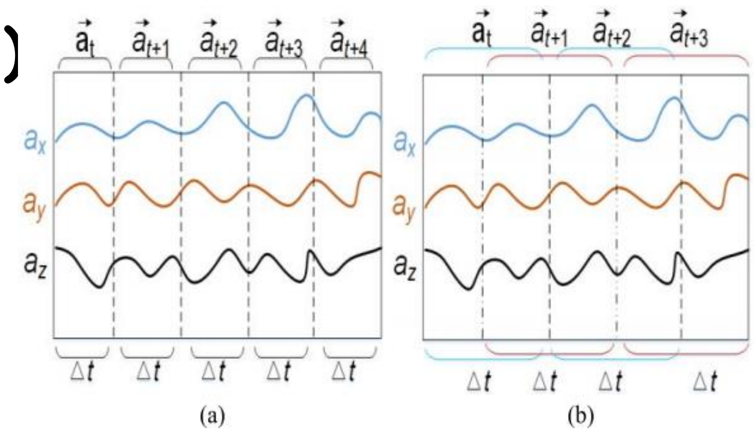
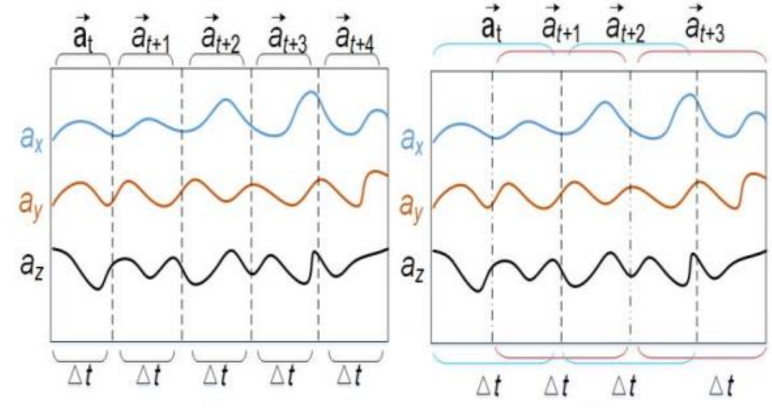


Fig. 1(b). Two types of sliding window techniques. (a) Non-overlapping. (b) Overlapping

Extracting Features



- **Time domain**
  - ✓ mean, std, maximum, minimum
  - ✓ autoregression coefficients
  - ✓ signal magnitude area, energy
  - ✓ correlation coefficient between two signals
  - ✓ …
- **Frequency domain**
  - ✓ skewness, kurtosis, the frequency component with largest magnitude
  - ✓ …
- **Time-frequency domain**
  - ✓ wavelet transformation
- **Structural features**
  - ✓ try to find interrelation or correlation between the signals
  - ✓ This means that the signal can fit a previously defined mathematical function to the current state of the variables

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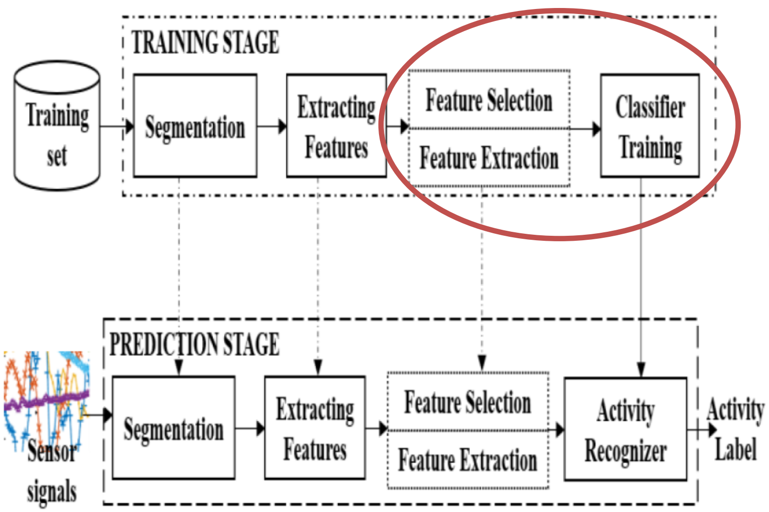
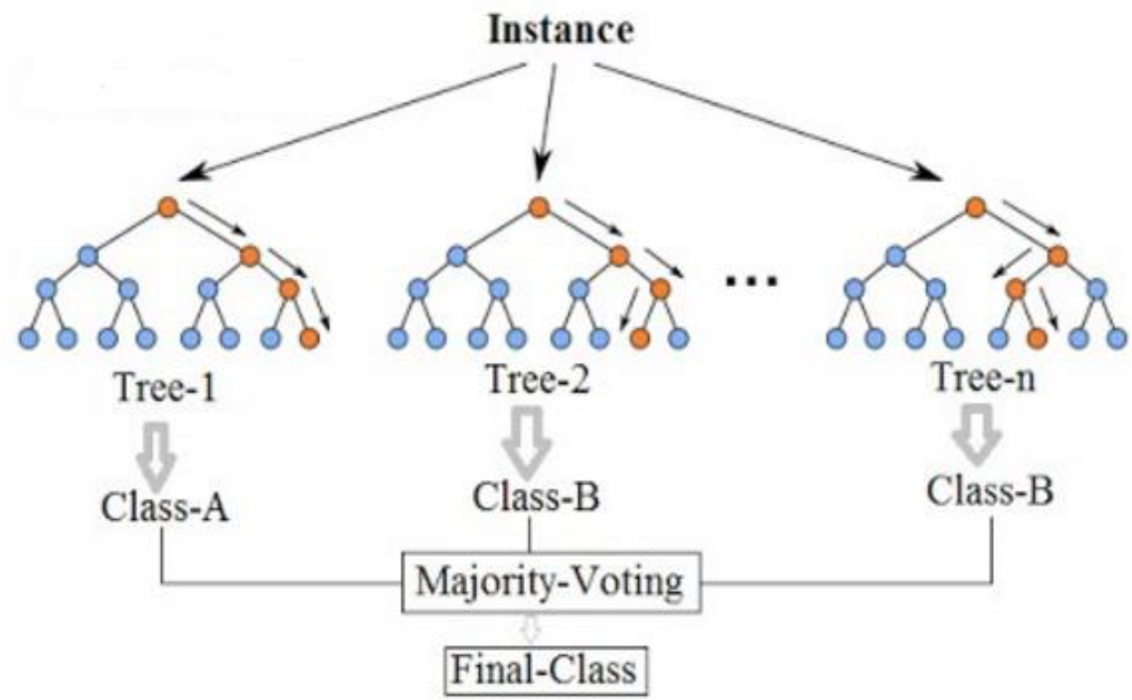
Random forest-based activity recognizer

- The choice of features and classifiers largely determine the performance of an activity recognizer
- Random forest
  - a collection of decision tress (*ensemble learning*)
  - uses the majority voting rule to make predictions
  - essentially utilizes bagging (bootstrap sample) and the random subspace method (random feature selection) to construct randomized trees





KEY ISSUES

In the context of wearable-based complex activity recognition

I. *how does it perform when compared with other widely used individual classification models and ensemble learning models?*

II. *How does it perform in comparison with the feature selection and feature extraction methods?*

III. *What are the empirically recommended default values for its parameters (e.g., the number of trees and the number of features randomly selected at each node of a tree)?*

IV. *Is the random forest-based activity recognizer suitable for wearable devices that have limited resources? (edge computing)*

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- *PAMAP* has six human activities and *PAMAP2* consists of fifteen activities
  - both are collected by asking nine subjects wearing three inertial measurement units (IMU) and a heart rate monitor to do activities
  - the sampling frequency of the IMU is 100 Hz and the sampling rate of the heart rate monitor is 9 Hz
  - data is processed using a sliding window of 5.12 seconds with a shifting of 1 second

- *SkodaMiCP* contains the sensor signals of ten manipulative gestures performed by the assembly-line worker in a car maintenance environment
  - it was collected for about three hours with USB sensors placed on the right and left lower and upper arm
  - each USB sensor is a 3-axis accelerometer working at a 64 Hz
  - the data were divided into 1s segments with 50% overlap between two adjacent windows

- Time domain, frequency domain and time-frequency domain features, such as mean, maximum, minimum, variance, skewness, 25th percentile, and 75th percentile, are extracted from the segments to form a feature vector

Dataset	***Activities of Interest***
PAMAP	lie, sit/stand, walk, run, cycle, Nordic walk
PAMAP2	lie, sit, stand, walk, run, cycle, Nordic walk, ascending stairs, descending stairs, vacuum clean, iron, fold laundry, clean house, play soccer, rope jump
SkodaMiCP	write on notepad, open hood, close hood, check gaps on the front, open left front door, close left front door, close both left door, check trunk gaps, open and close trunk, checking steering wheel

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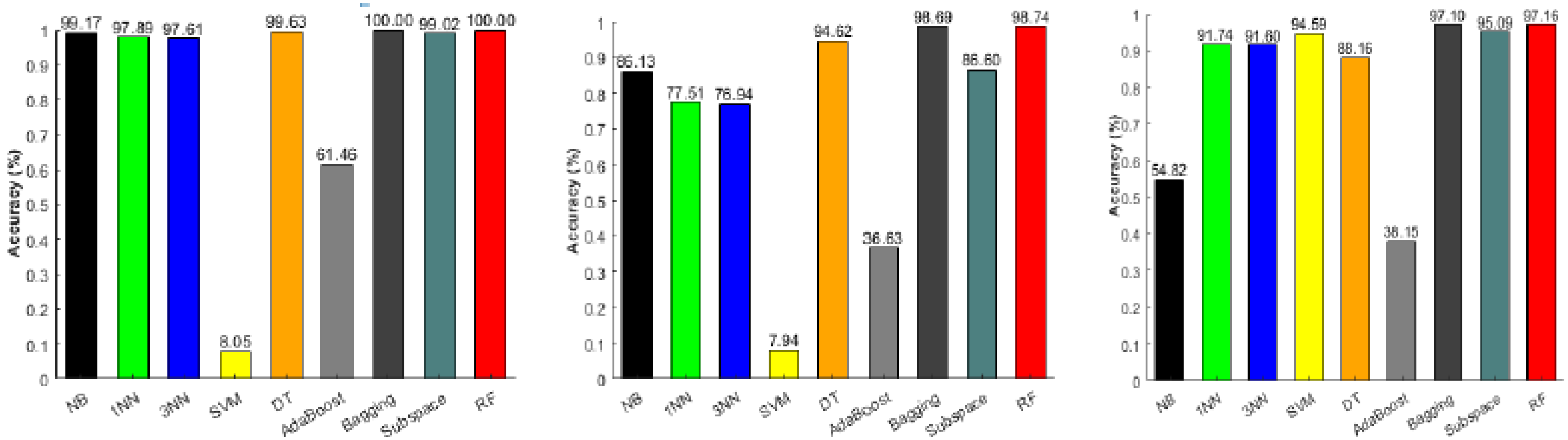
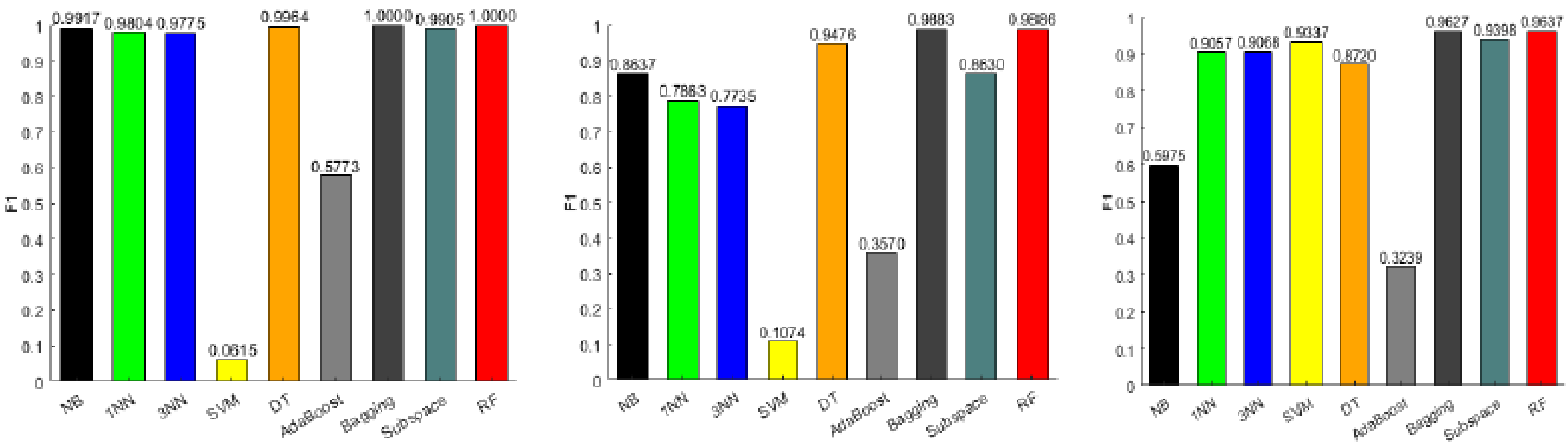
Comparisons with Other Classifiers

- Competitors: five individual classifiers (NB, 1NN, 3NN, SVM, and DT) and three ensemble classifiers (AdaBoost, Bagging, and Subspace)
- Two metrics: accuracy & F1



(a) *PAMAP* (b) *PAMAP2* (c) *SkodaMiCP*

Figure 2. Comparison of accuracy with other five individual classifiers and three ensemble methods on the datasets.

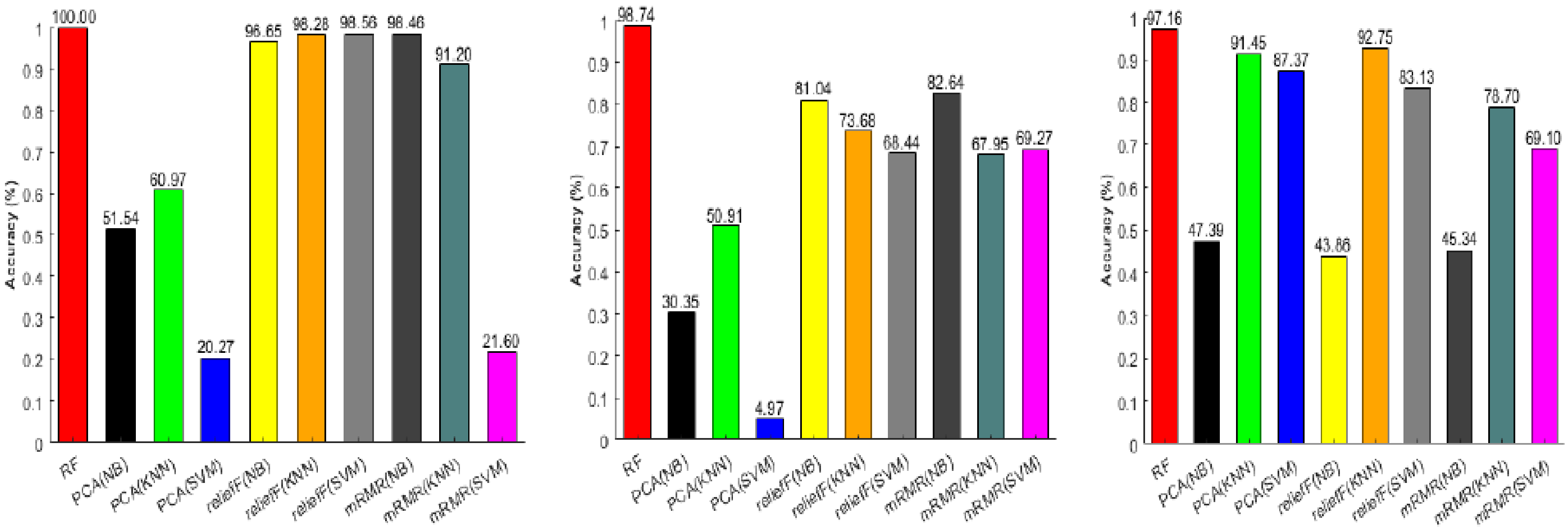


(a) *PAMAP* (b) *PAMAP2* (c) *SkodaMiCP*

Figure 3. Comparison of F1 with other five individual classifiers and three ensemble methods on the datasets.

Comparisons with Feature Reduction Methods

- Competitors: three feature reduction methods (PCA, reliefF, and mRMR)
- PCA (keep 99.0% variance information)
- reliefF and mRMR (select the top twenty-five features to return an optimal feature subset)
- Coupled with NB, KNN, SVM

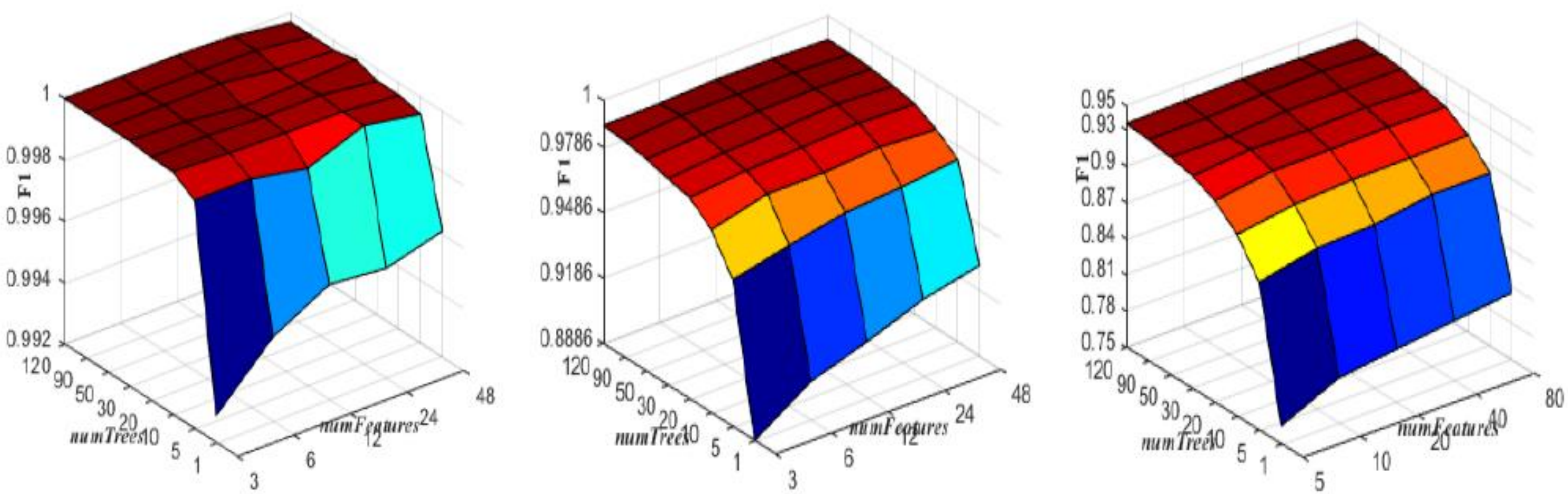


(a) *PAMAP* (b) *PAMAP2* (c) *SkodaMiCP*

Figure 4. Comparison of accuracy with two feature selectors and one feature extractor on three datasets.

Parameter Sensitivity Analysis

- The parameters *numTrees* and *numFeatures* in building a random forest are two crucial parameters in lowering the correlation between individual trees of the forest and they largely influence the generalization ability
- Values tested for the *numTrees* : 1, 5, 10, 20, 30, 50, 90, and 120
- Values tested for the *numFeatures*: *mtry/4*, *mtry/2*, *mtry*, *2*mtry*, *4*mtry*, where *mtry* is the square root of the number of features



(a) *PAMAP* (b) *PAMAP2* (c) *SkodaMiCP*

Figure 5. Parameter sensitivity analysis with regards to the number of trees and number of splitting features on the datasets.

- The activity recognizer is less sensitive to the number of splitting features
- The use of 50 trees is tradeoff between the time costs and recognition accuracy

Time Costs

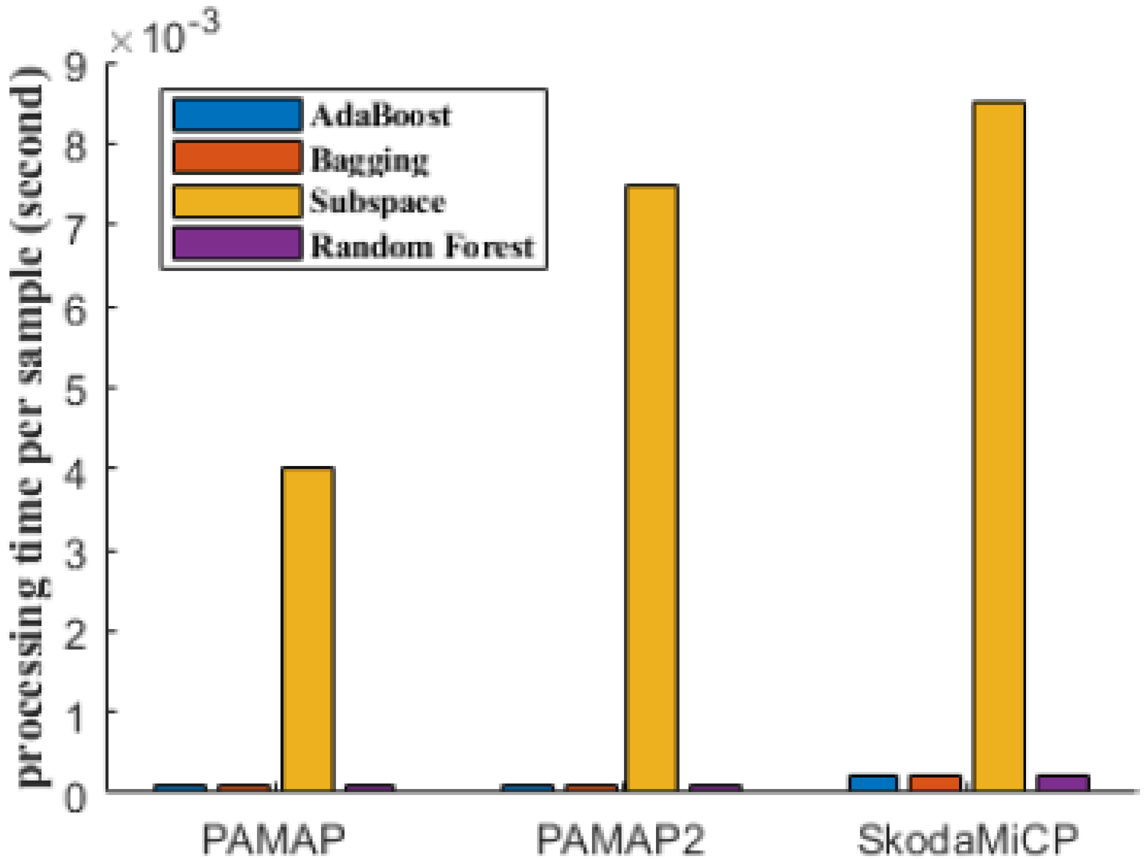


Figure 6. Time cost comparison on the datasets.

- Random forest-based activity recognizer has a comparable time cost to the those of AdaBoost and Bagging and can process more than one thousand samples per seconds on all the datasets, which demonstrates its applicability to practical applications

Conclusion

- ◆Present the random forest-based activity recognizer under the framework of activity recognition chain, where we detail its components and discuss its mechanism in getting an accurate and diverse set of trees
- ◆Conduct extensive experiments on three public datasets to compare it with five individual classifiers, three ensemble learning methods, and two feature selectors and one feature extraction method
- ◆The results of parameter sensitivity analysis indicate the recommended empirically values of the parameters
- ◆Besides, we initially analyze its time costs in making predictions, which indicates its applicability to practical applications

Thank you
For Your Attention

Q & A