Malware Detection in Android Applications with Machine Learning Techniques

Thesis presentation

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Summary

- Context and Motivation
- Goals
- Proposed Approach
- Datasets
- Experimental Results
- Conclusions and Future Work
- Contributions

Context and Motivation

- 70% of mobile phones use the Android operating system (OS)
- In Q3 2022, Google Play Store hosted around 3.5 million applications (apps)
- These apps deal with a great amount of user-sensitive data

- Thus, they are a prized target for malicious software (malware) developers
- In 2020, 5.7 million Android malware packages were detected, tripling 2019's 2.1 million

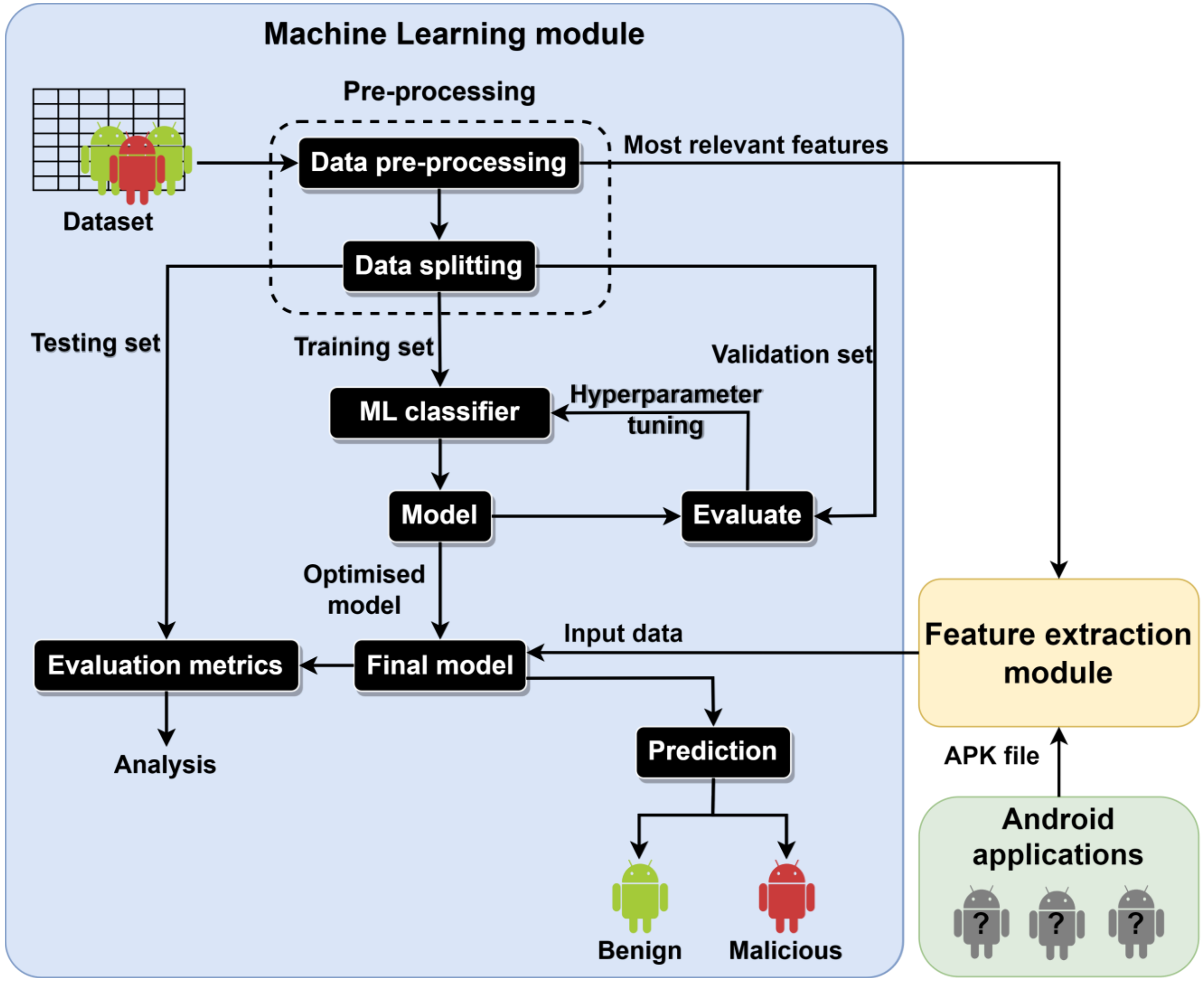
Context and Motivation (2)

- Existing security measures to mitigate malware are to some extent successful
- However, malware keeps growing in both sophistication and diffusion, sometimes easily bypassing security measures
- Machine Learning (ML) approaches are known to be efficient and versatile
- Thus, we explore the use of ML techniques to detect malware in Android apps

Goals

- Identify the most decisive features for Android malware classification
- Recognise the ML classifiers that provide the most satisfying results in detecting malware in Android applications
- Assess the impact of different data pre-processing techniques applied to this problem's datasets
- Develop a prototype that resorts to ML techniques to detect malware in Android applications

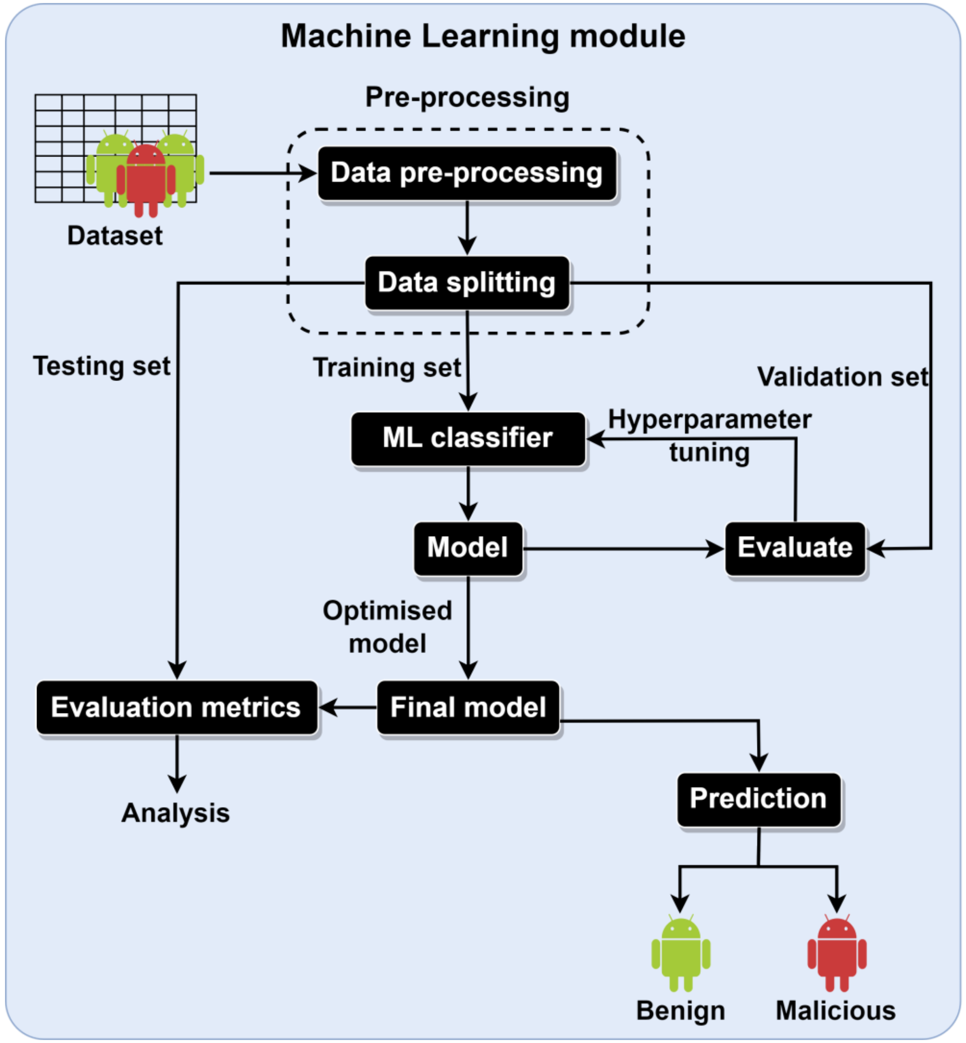
Proposed Approach



- Formulated as a binary classification problem

- The proposed approach can be divided into two major parts:
  - Machine Learning module
  - Feature extraction module and Android applications

Machine Learning module



Datasets – Data Acquisition

- Features can be obtained via different types of analysis:
  - **Static analysis** - Analysis in a non-runtime environment
  - **Dynamic analysis** - Requires the Android application to be running
  - **Hybrid analysis** - Combination of the two previous analysis
- Static analysis is the most common approach
- A static analysis approach is followed, thus, dynamic features were removed from the datasets

Dataset analysis & Data processing

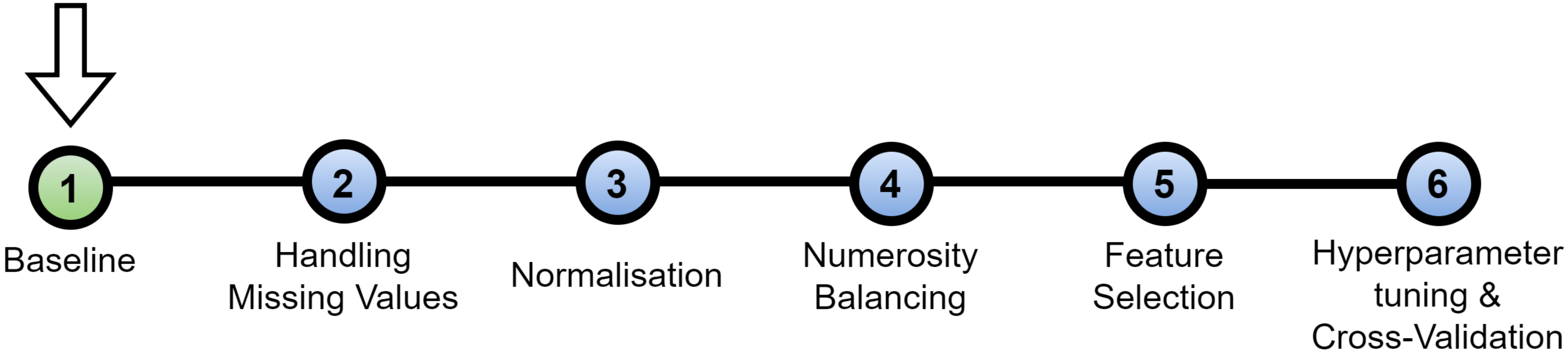
	Drebin	CICAndMal2017	Android Malware (AM)	Android Malware static feature (AMSF)
instances (n)	15036	29999	11476	5019
features (d)	215	110	182	966
Release year	2014	2018	2016	-
Categorical features	1	5	12	0
Missing values	0	204	19888	0
Class label majority	63.02%	66.67%	70.22%	50.03%

- The following experiments were performed after:
  - Converting categorical features to numerical via label encoding
  - Removal of the instances containing missing values

Evaluation Metrics

- **Confusion Matrix**
  - True Positive (TP) – Malicious app as malicious
  - False Positive (FP) – Benign app as malicious
  - True Negative (TN) – Benign app as benign
  - False Negative (FN) – Malicious app as benign
- **Accuracy**
  - correct predictions rate
- **Recall**
  - true positive rate
- **Precision**
  - positive predictive value
- **F1-Score**
- **AUC-ROC** (Area Under the Curve-Receiver Operating Characteristic)

Experimental Results: Baseline



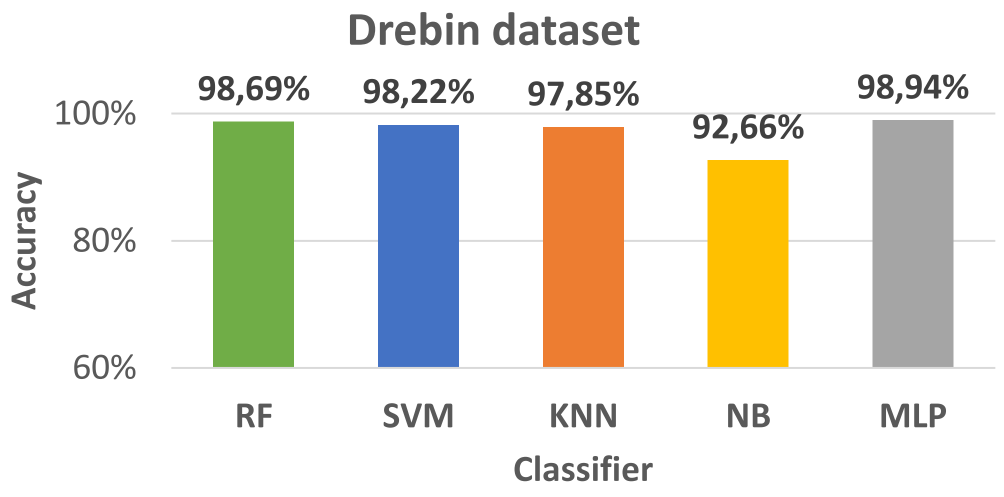
Experimental Results: Baseline

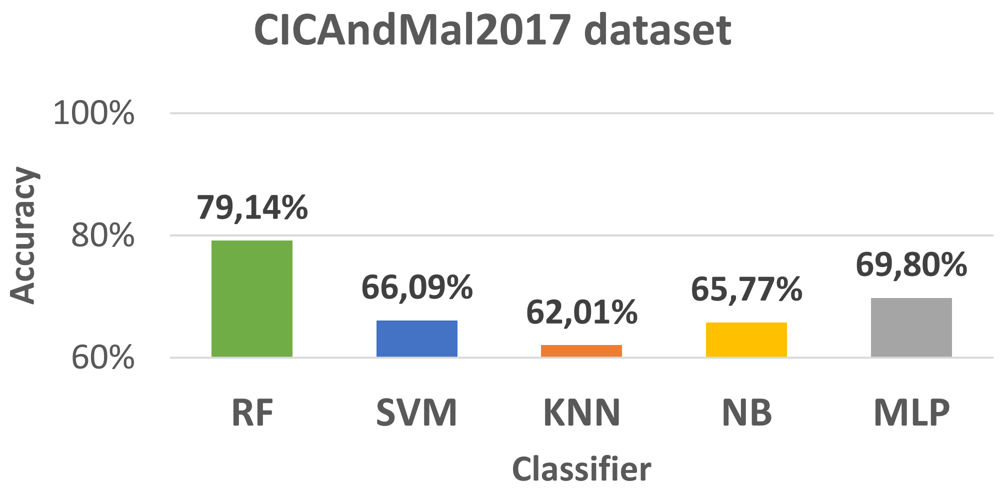
- Stratified random split of 70-30 for train-test was applied

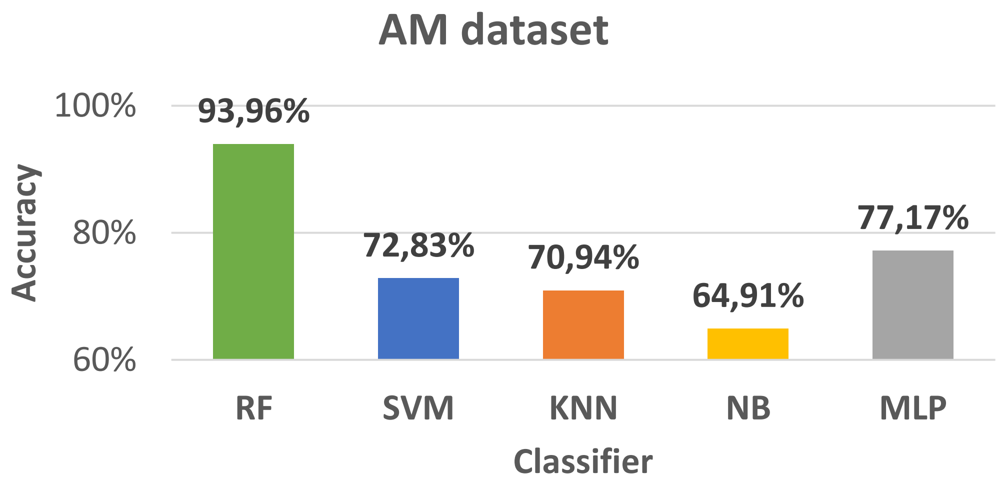
- Experiments with different classifiers:

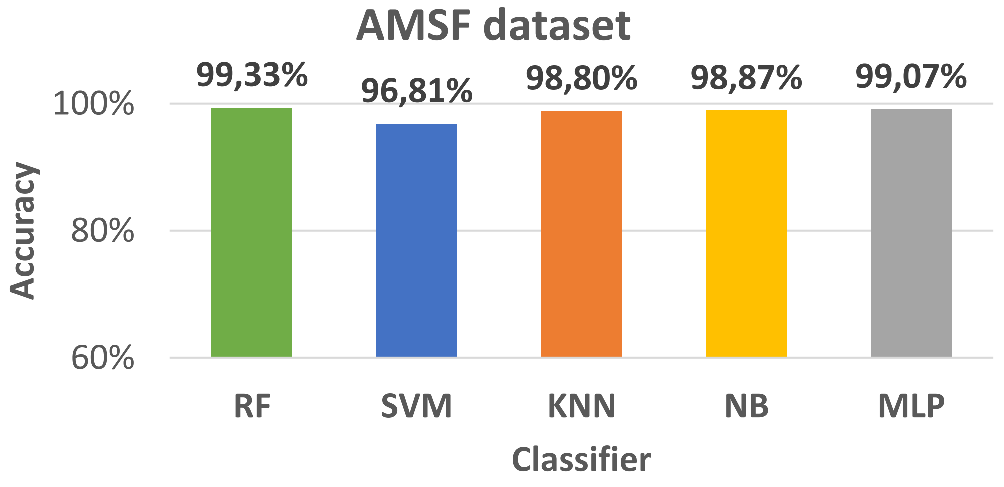
  - Random Forest (RF)
  - Support Vector Machines (SVM)
  - K-Nearest Neighbours (KNN)
  - Naive Bayes (NB)
  - Multi-layer Perceptron (MLP)

Experimental Results: Baseline (2)

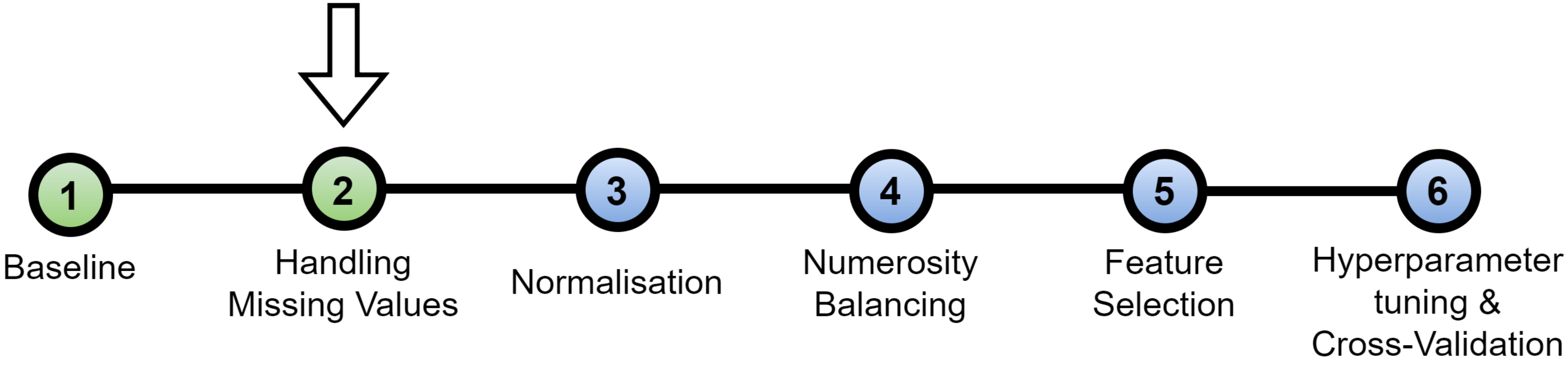








Experimental Results: Handling Missing Values

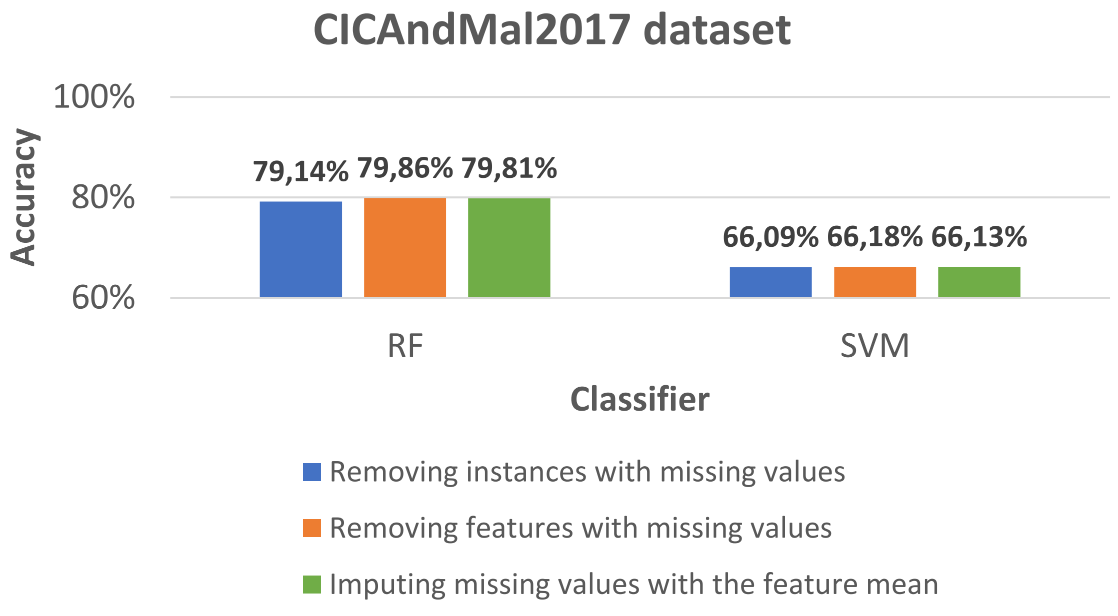


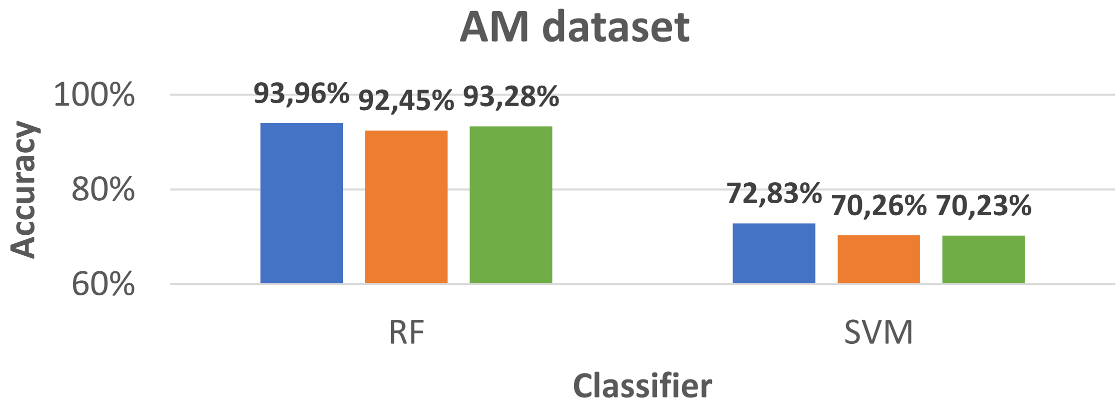
Experimental Results: Handling Missing Values

- Experiments with different methods to deal with missing values

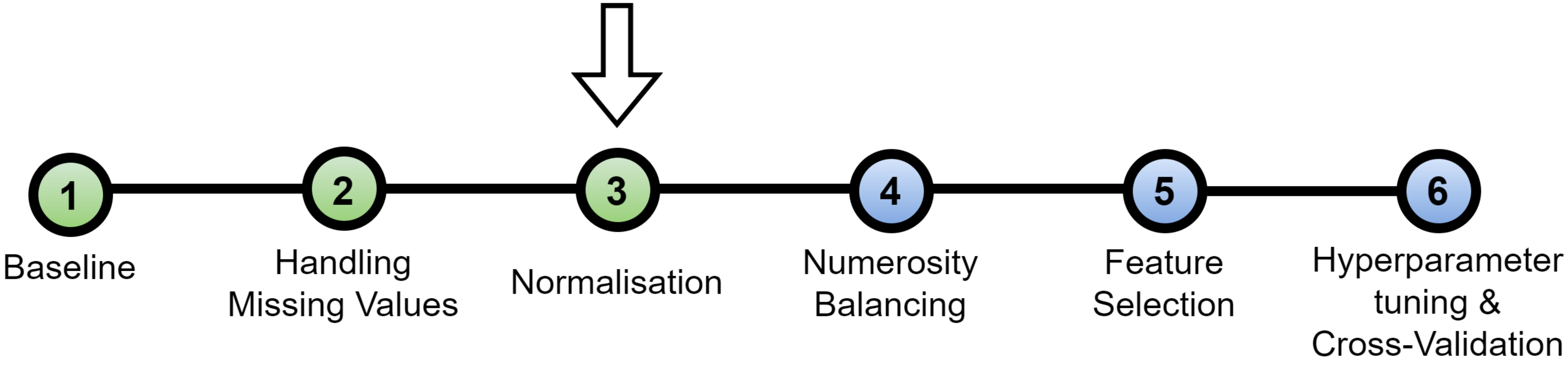
- The results do not differ significantly between the tested methods

- May be an indicator of the presence of redundant and/or irrelevant features





Experimental Results: Normalisation

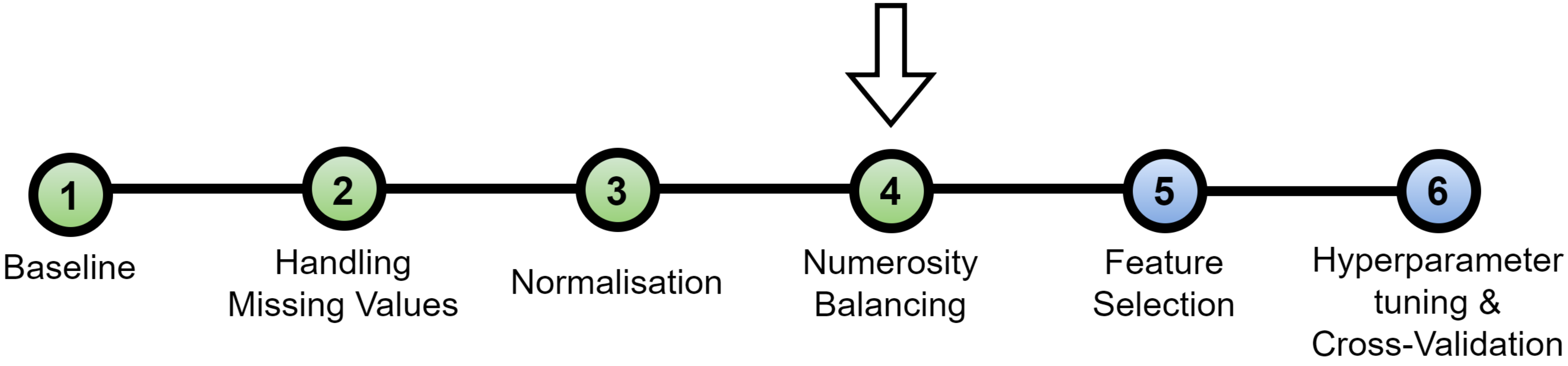


Experimental Results: Normalisation

- Min-max normalisation was applied to deal with large differences in the scales of features
- Results did not differ significantly with the RF classifier and with datasets that previously had essentially no categorical features

Classifier	Dataset	Min-max normalisation	Acc (%)	F1-Score (%)	AUC-ROC (%)
SVM	CICAndMal2017	✗	66.13	78.96	51.51
		✓	70.81	79.71	63.22
	AM	✗	70.23	00.00	50.00
		✓	90.88	82.77	85.89

Experimental Results: Numerosity Balancing

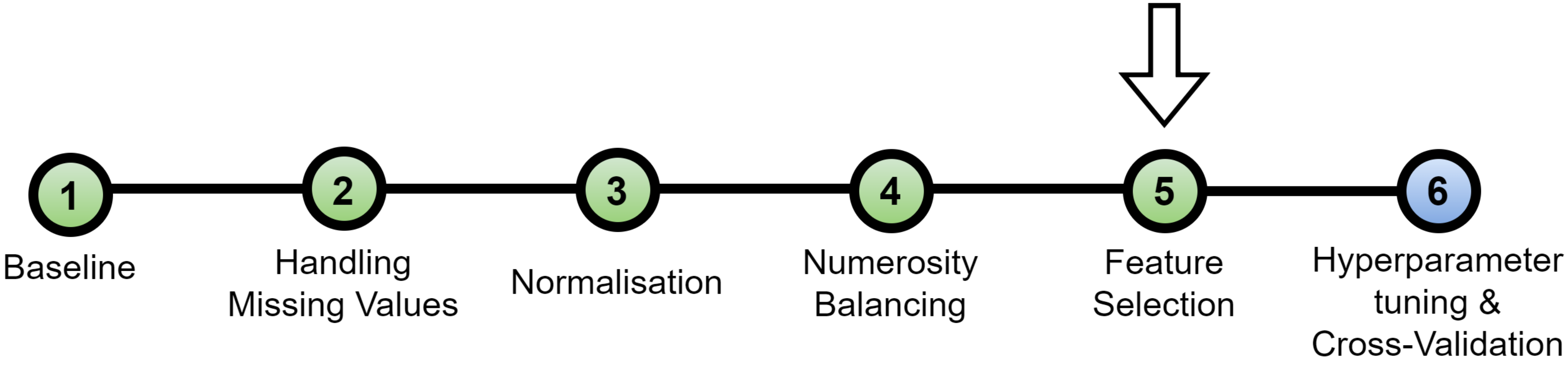


Experimental Results: Numerosity Balancing

- Dealing with numerosity balancing:
  - Use of the AM dataset (the most imbalanced dataset)

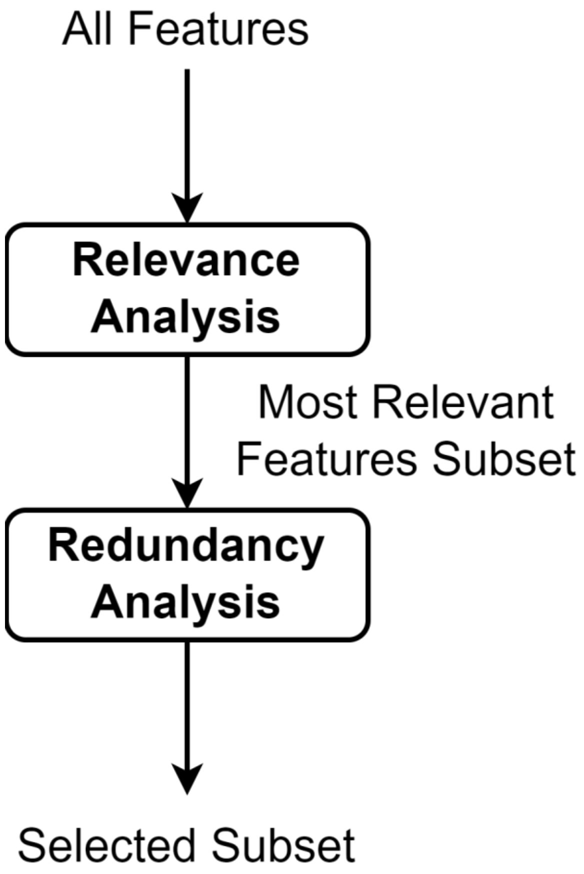
Classifier	Numerosity balancing method	Acc (%)	Rec (%)
RF	None	93.28	83.02
	Random undersampling	91.36	86.44
	Random oversampling	**96.28**	**96.07**
	Synthetic Minority Oversampling Technique (SMOTE)	94.06	91.39
SVM	None	70.81	**86.00**
	Random undersampling	89.18	82.44
	Random oversampling	**89.47**	82.75
	Synthetic Minority Oversampling Technique (SMOTE)	88.81	81.42

Experimental Results: Feature Selection

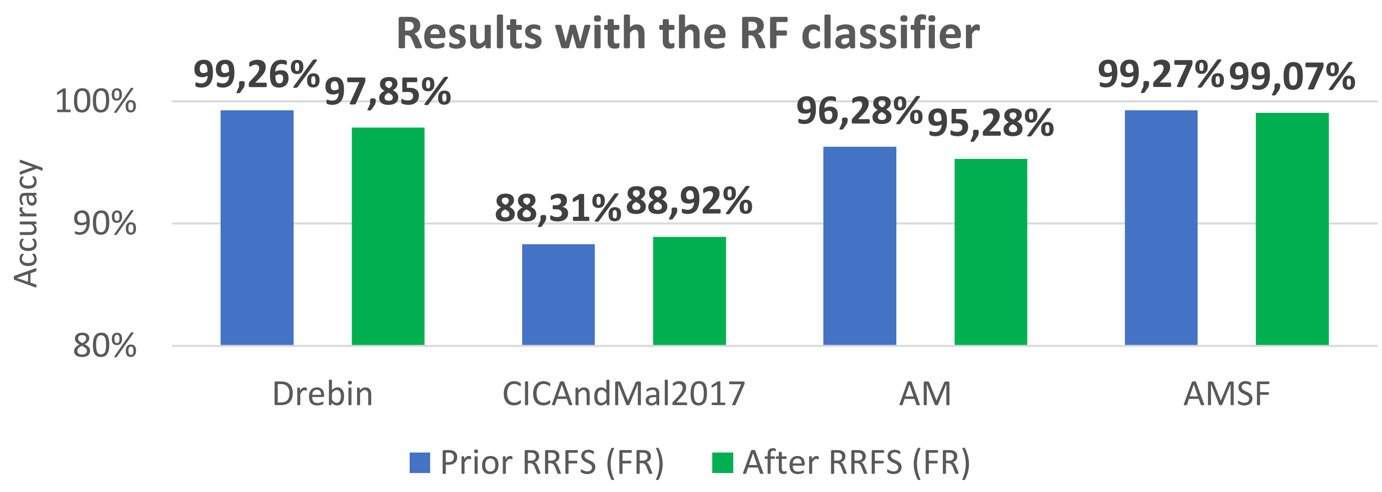


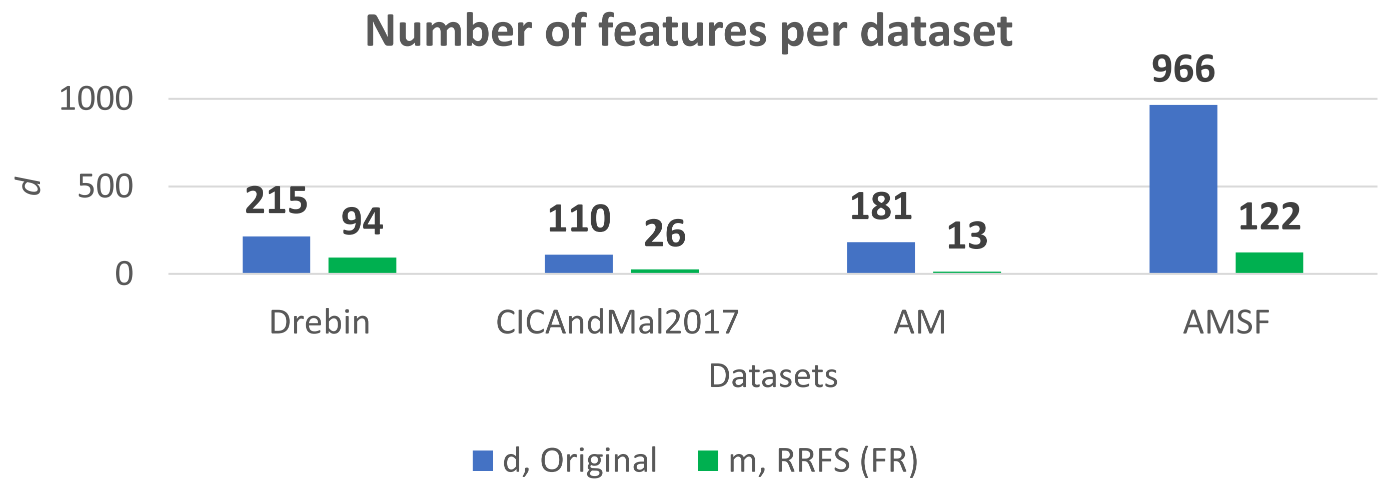
Experimental Results: Feature Selection

- A filter method was applied
- Relevance-Redundancy Feature Selection (RRFS)
  - Fisher ratio (FR) relevance measure (supervised)
  - Mean-median (MM) relevance measure (unsupervised)
  - Overall, FR (supervised) outperformed MM (unsupervised)
  - Thus, the class label data is impactful to the result
  - Absolute cosine (AC) redundancy measure



Experimental Results: Feature Selection (2)





- Substantial dimensionality reduction compensated for a slight metric decrease
  - Drebin dataset:
    ≈56% reduction
  - CICAndMal2017 dataset:
    ≈76% reduction
  - AM dataset:
    ≈93% reduction
  - AMSF dataset:
    ≈87% reduction

Experimental Results: Feature Selection (3)

- 4 most indicative features of malware presence in each dataset

Drebin dataset

1. transact
2. SEND_SMS
3. Ljava.lang.Class.getCanonicalName
4. android.telephony.SmsManager

CICAndMal2017 dataset

1. Category
2. Price
3. Network communication : view network state (S)
4. Your location : access extra location provider commands (S)

AM dataset

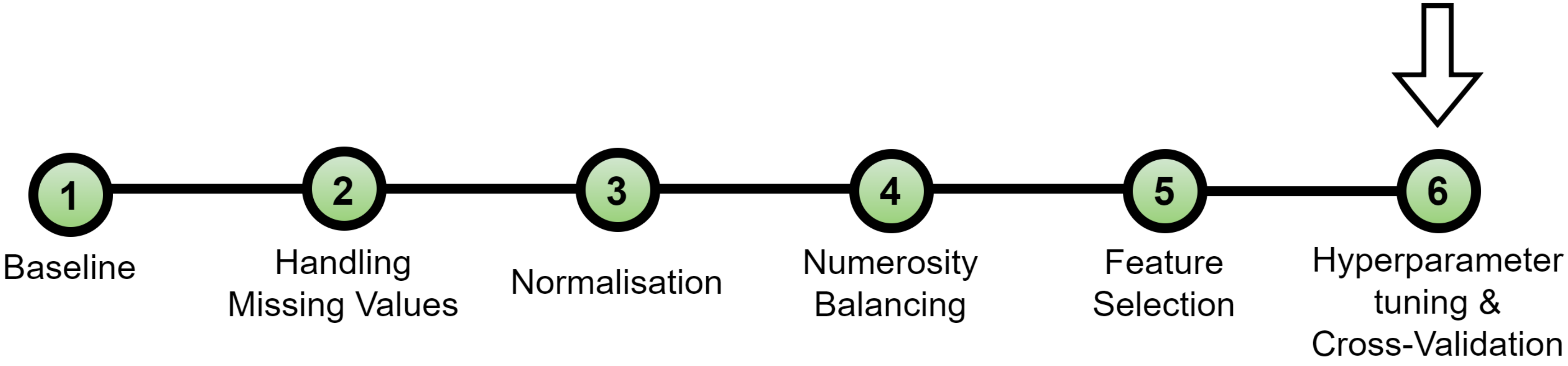
1. com.android.launcher.permission.UNINSTALL_SHORTCUT
2. android.permission.VIBRATE
3. android.permission.ACCESS_FINE_LOCATION
4. name

AMSF dataset

1. androidpermissionSEND_SMS
2. android.telephony.SmsManager.sendTextMessage
3. float-to-int
4. android.telephony.SmsManager

- Overall, permissions seem to have a prevalent presence among the most relevant features for Android malware detection

Experimental Results: Hyperparameter tuning & CV



Experimental Results: Hyperparameter tuning & CV

- **Hyperparameter tuning**
  - Optimisation of the hyperparameters deemed more impactful
  - Use of a function that optimises the hyperparameters. It uses 5-fold CV with the training and validation sets
  - The metrics results improved slightly (about 2%)

- **Cross-Validation (CV)**
  - 10-fold CV and Leave-one-out CV were applied to the training and testing sets, leading to nested CV
  - Often challenging due to “training time bottlenecks”
  - Mean and standard deviation values for the different metrics
  - Standard deviation values were low

Comparative Analysis of Results

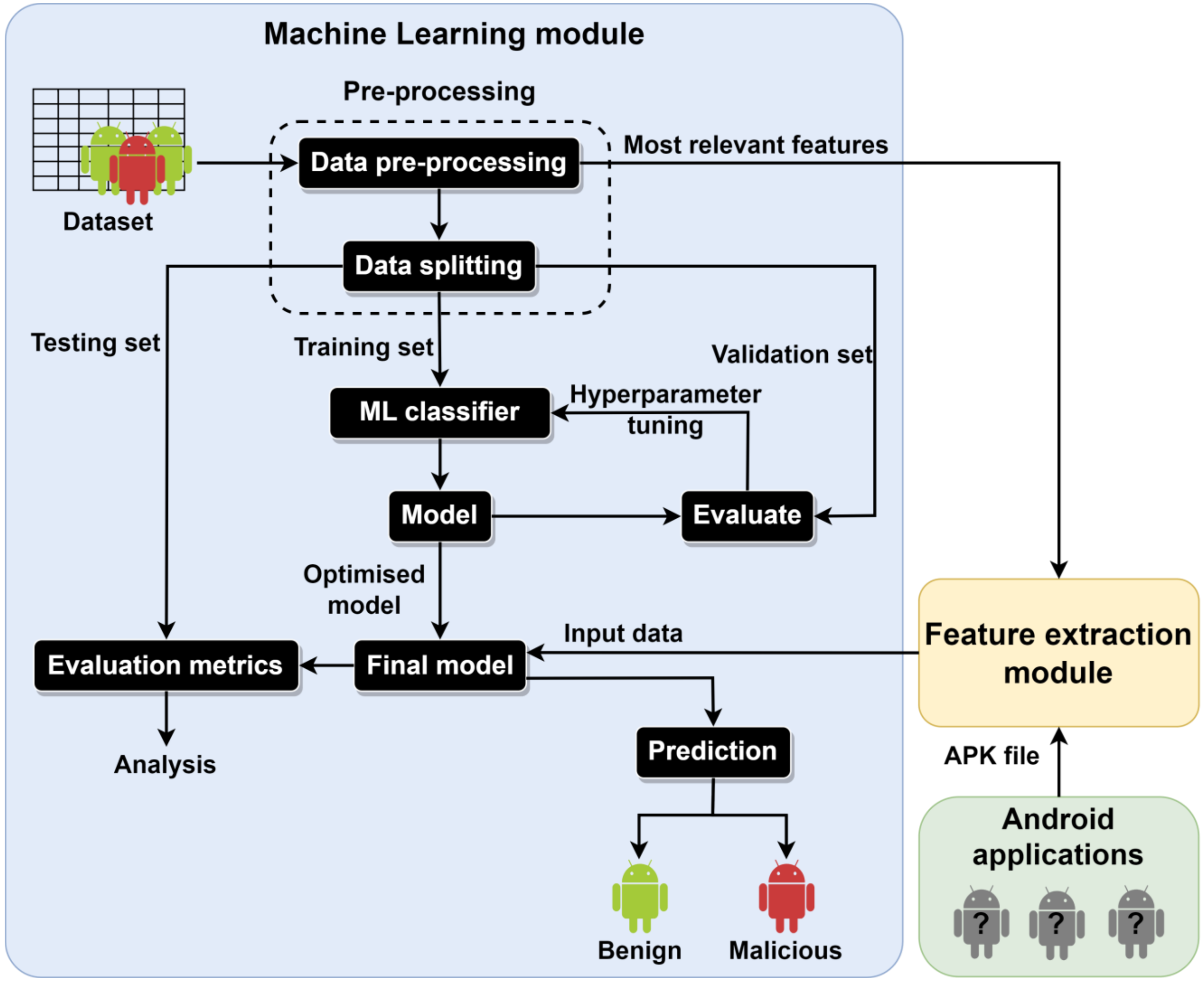
- *'Artificial Intelligence Algorithms for Malware Detection in Android-Operated Mobile Devices'*, Alkahtani and Aldhyani, 2022

Classifier	Dataset	Accuracy (%)	
		Alkahtani and Aldhyani	Proposed
SVM	Drebin	80.71	**97.47**
	CICAndMal2017	**100.00**	73.22

  - Data pre-processing greatly impacts the results

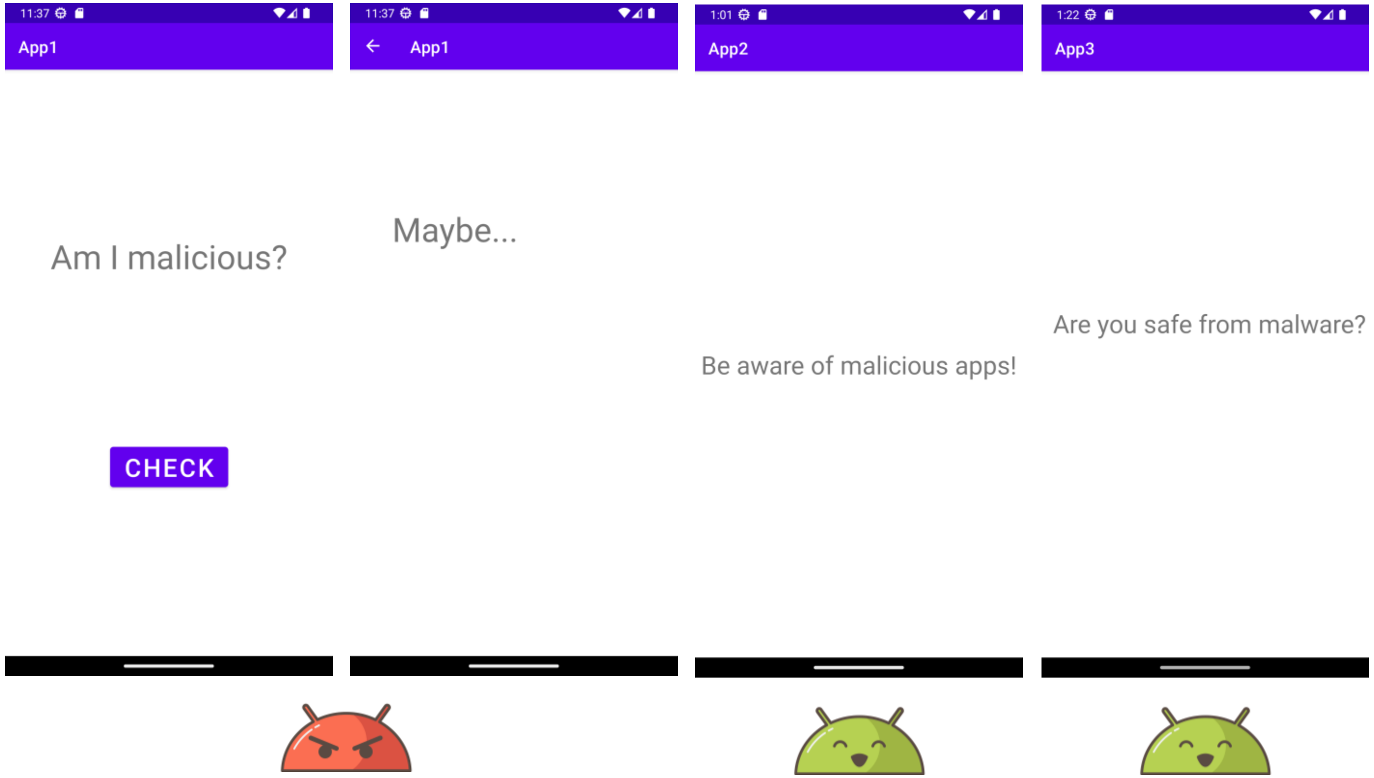
- *'Android malware detection applying feature selection techniques and machine learning'*, Keyvanpour *et al.*, 2023
  - The authors applied FS techniques to the Drebin dataset
  - Reported features, SEND_SMS and android.telephony.SmsManager, were also selected on the Drebin and AMSF datasets by RRFS

Complete approach



Experimental Results: Real-world Applications

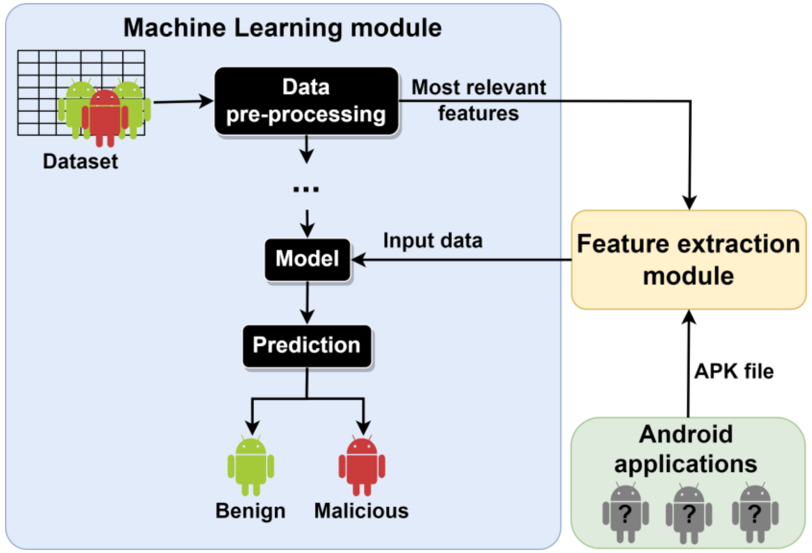
- Simple Android apps built for testing:



  - App1 - requests permissions regarding SMS and other features selected as the most relevant in the Drebin and AMSF datasets
  - App2 - doesn’t request/use any unnecessary features
  - App3 – requests some permissions selected as the most relevant features in the Drebin and AM datasets

Experimental Results: Real-world Applications (2)

- Experiments performed with the RF classifier
- App1 classified as malicious
  - with models trained with the Drebin, CICAndMal2017, and AMSF datasets
- App2 and App3 are classified as benign
  - with models trained with the Drebin, AM, and AMSF datasets
- Experiments performed with other APK found online



- The non-standardization of feature names presents a major challenge
  - Example: 'android.permission.SEND_SMS' ≠ 'SEND_SMS' ≠ 'androidpermissionSEND_SMS'

(Drebin dataset) (AMSF dataset)

Conclusions

- The RF and SVM classifiers present the best results
- We were able to identify the most relevant features in each dataset for malware detection in Android apps
- Overall, permissions have a prevalent presence among the most relevant features for Android malware detection
- ML and FS approaches effectively mitigate this problem
- No model performs globally best for all datasets
- Use of the ML model in real-world scenarios is not straightforward

Future Work

- Use more up-to-date datasets
- Aim to use datasets more standardised
- Expand the proposed approach to hybrid analysis
- Further explore Deep Learning approaches and others
- Address this problem as multiclass

Contributions

- Catarina Palma, Artur Ferreira, and Mário Figueiredo, "*On the use of machine learning techniques to detect malware in mobile applications*", Simpósio em Informática (INForum), September 2023, Porto, Portugal
- Catarina Palma, Artur Ferreira, and Mário Figueiredo, "*A study on the role of feature selection for malware detection on Android applications*", Portuguese Conference on Pattern Recognition (RECPAD), October 2023, Coimbra, Portugal
- Catarina Palma, Artur Ferreira, and Mário Figueiredo, "*Explainable Machine Learning for Malware Detection on Android Applications*", *Information* journal, MDPI, January 2024
- Public GitHub repository for the code developed in the context of the thesis

Contributions (2)

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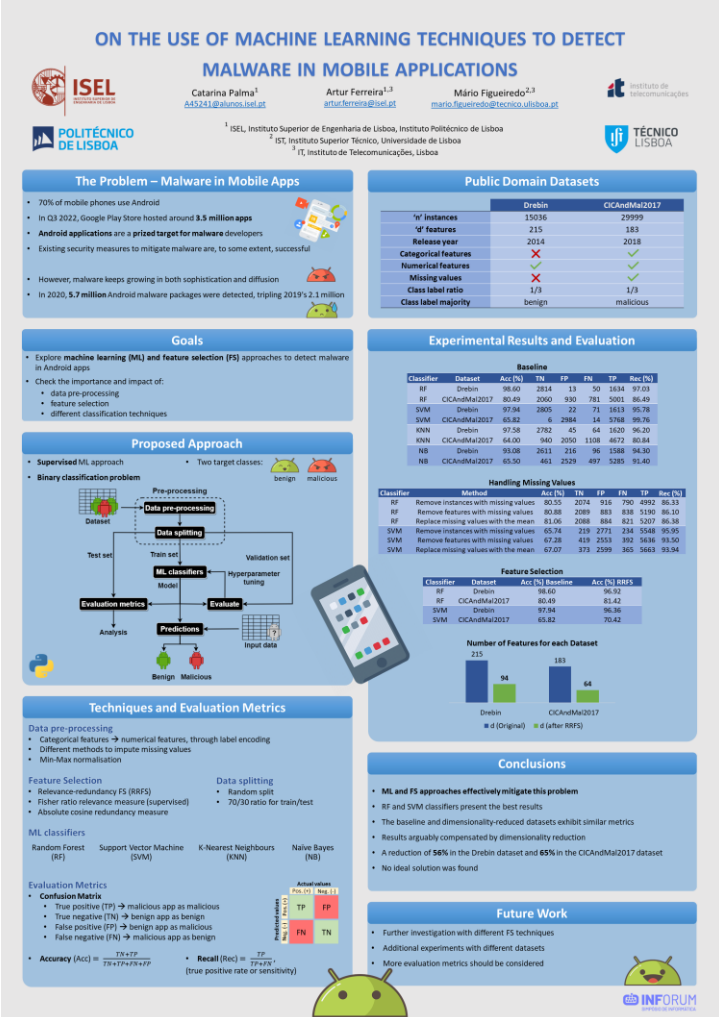

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