Android Financial Malware Detection Through Network Flow Analysis

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THE OVERVIEW

"Android financial malware exists because information has value now" - *Anonymous*

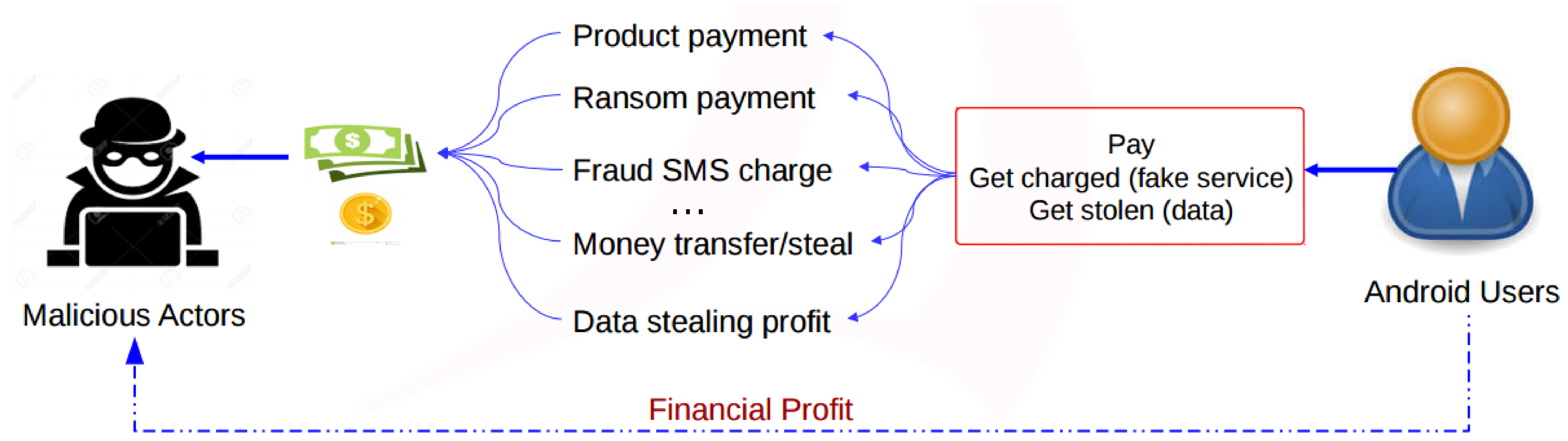
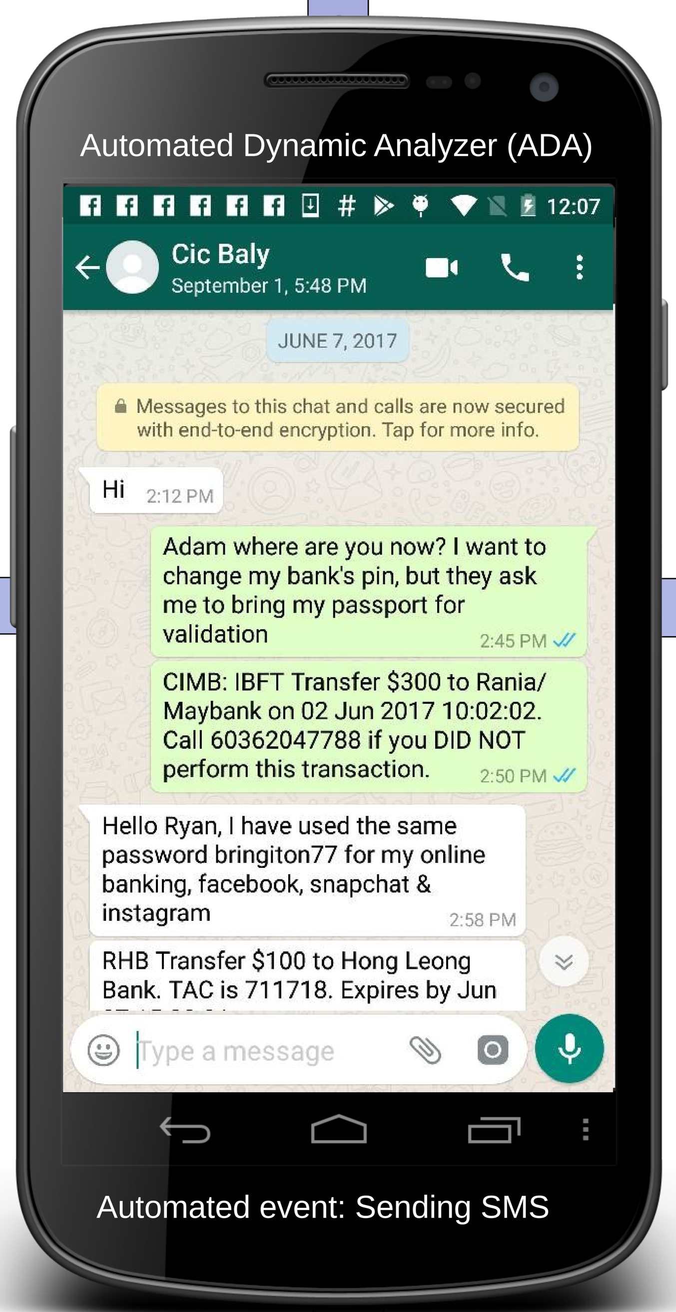


Fig 1. Android Financial Malware

Definition:
- ✔ Direct financial profit or money exchange to the fraudsters
- ✔ Financial transaction includes any reselling or direct transactions
- ✔ Without the user's knowledge or consent

Problem:
- ✔ What constitutes Android financial malware (AFM) is still ambigous
- ✔ Current solution focused more on malware binary detection
- ✔ Most of the available datasets are crafted for static analysis
- ✔ More sophisticated techniques to thwart malware detection

Goal:
We focus on detecting malware and categorizing its type based on the defined taxonomy



THE SOLUTION

"For every one second, there is a new malware" - *Ralf Benzmüller*

- ✔ Define a comprehensive taxonomy (unified terminology)
- ✔ Run analysis on real environment (ADA on smartphone, user profile)

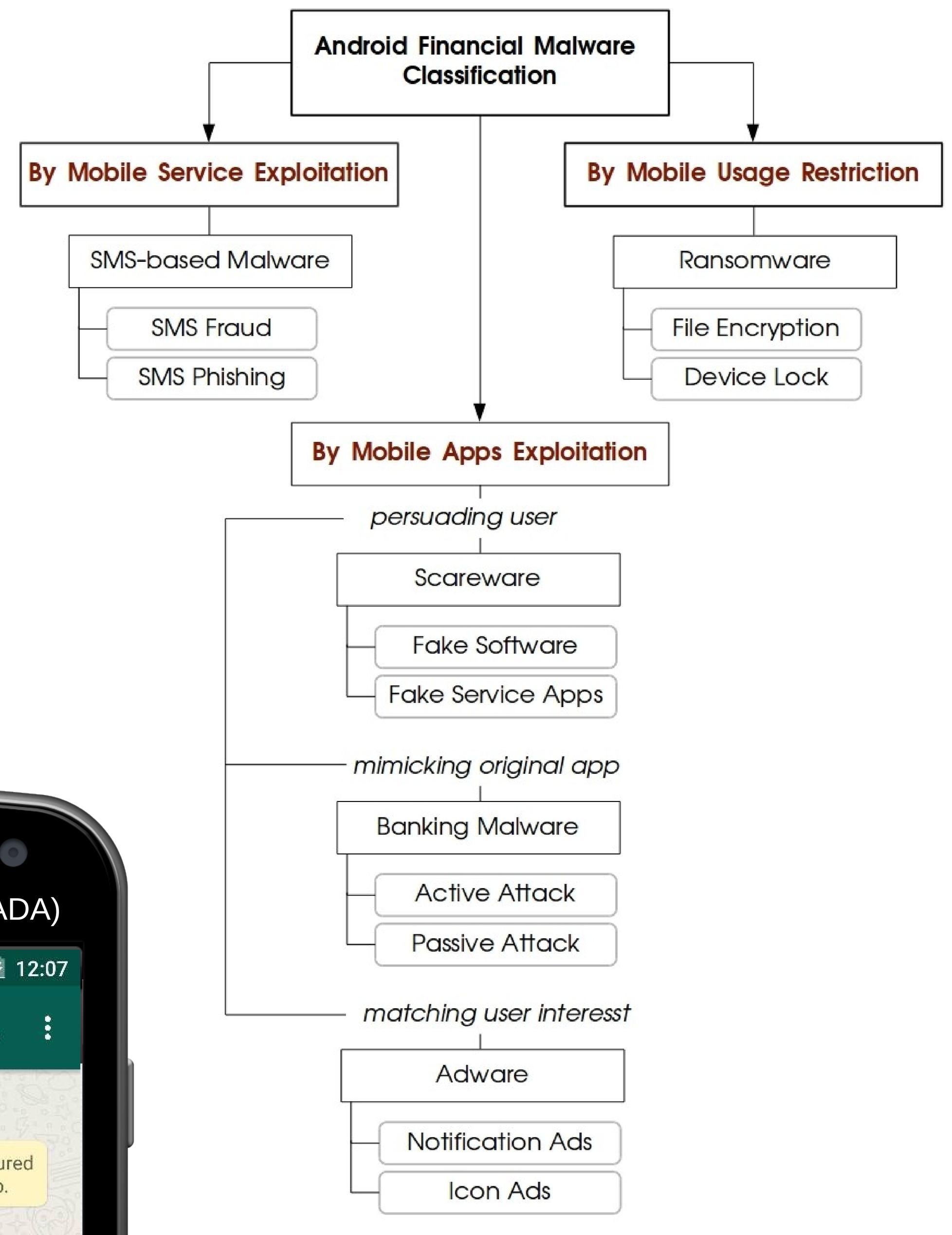


Fig 2. Proposed Taxonomy

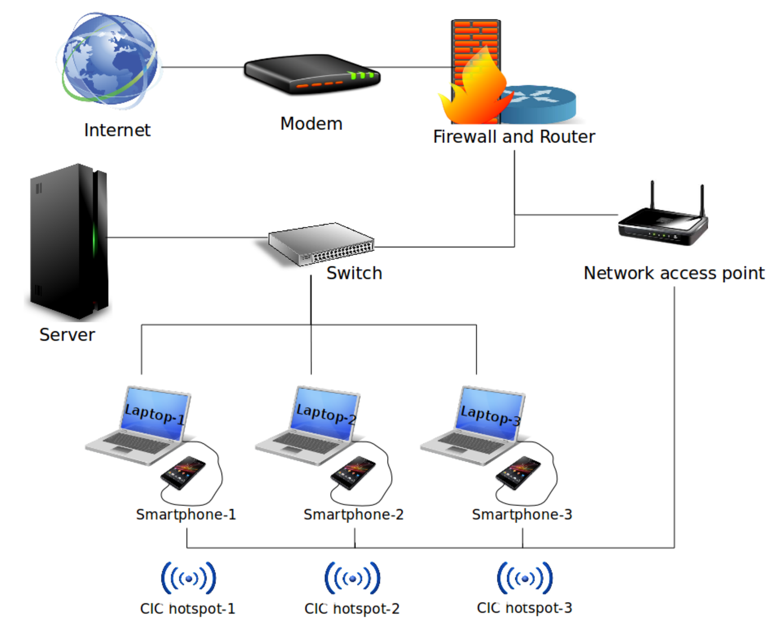


Fig 3. Configuration architecture

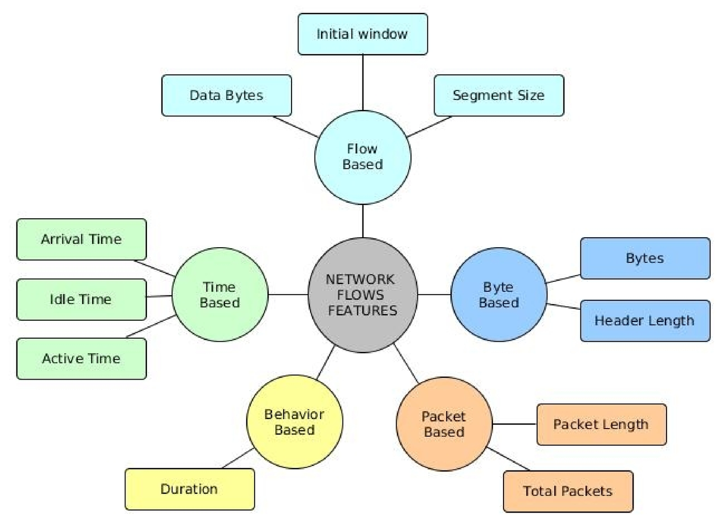


Fig 4. Network flow features extracted

THE EXPERIMENTS

Dataset:
- ✔ 52 Malware families; 503 unique samples (2010 – 2017)
- ✔ 5k Benign sample (2015 - 2017)
- ✔ 5 categories; 10 sub-categories (see Fig.2 of Taxonomy)

Table 1. Dataset splitting for training and evaluation

Dataset	Dataset Ratio	Training	Evaluation
1	50:50	500 (250 M, 250 B)	500 (250 M, 250 B)
2	60:40	750 (300 M 450 B)	500 (200 M, 300 B)
3	70:30	1200 (350 M, 850 B)	500 (150 M, 350 B)
4	80:20	2000 (400 M, 1600 B)	500 (100 M, 400 B)
5	90:10	4500 (450 M, 4050 B)	500 (50 M, 450 B)

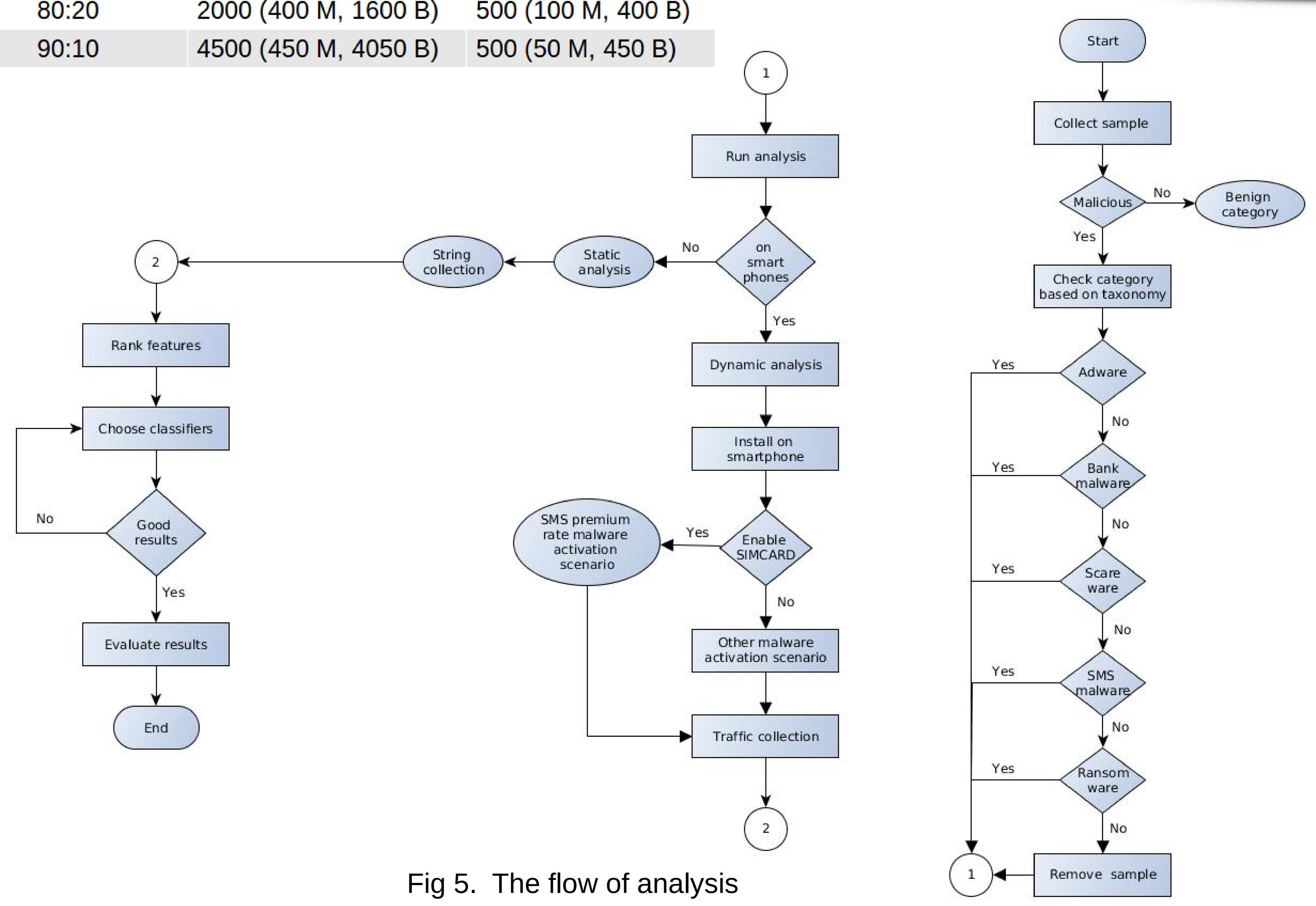


Fig 5. The flow of analysis

THE RESULTS

Scenario A: Malware Detection

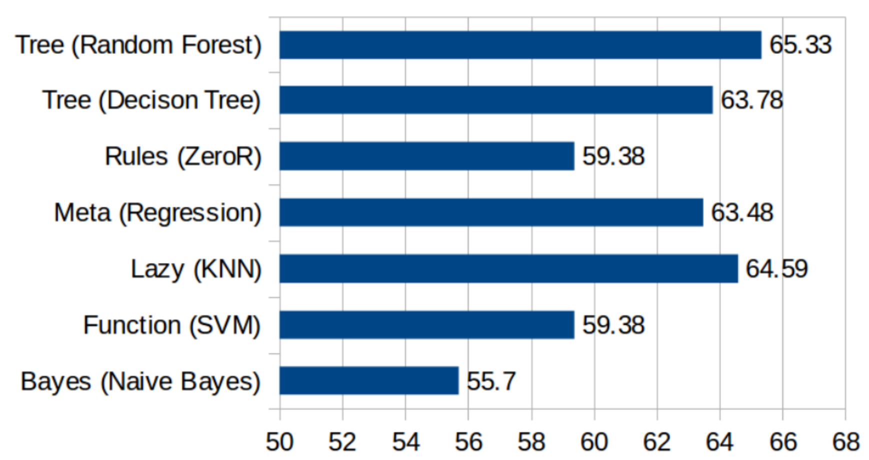


Fig 6. Best classifier (Random Forest)

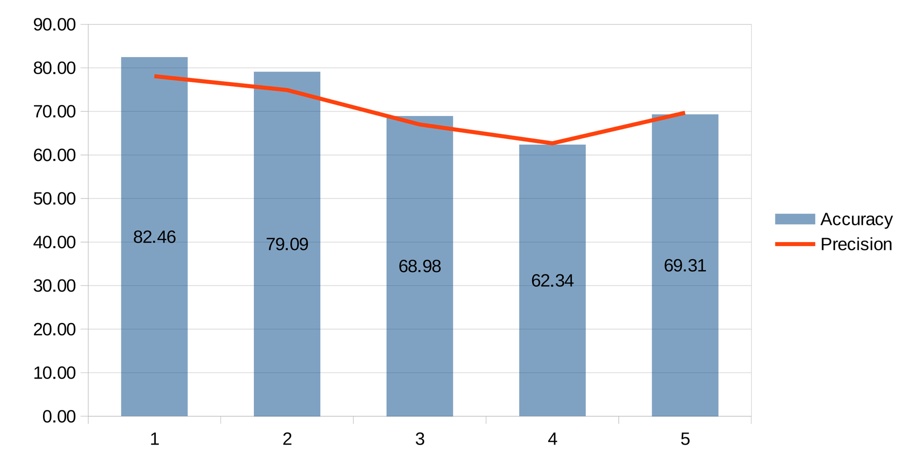


Fig 7. Malware vs Benign (Random Forest)

Scenario B: Malware Categorization

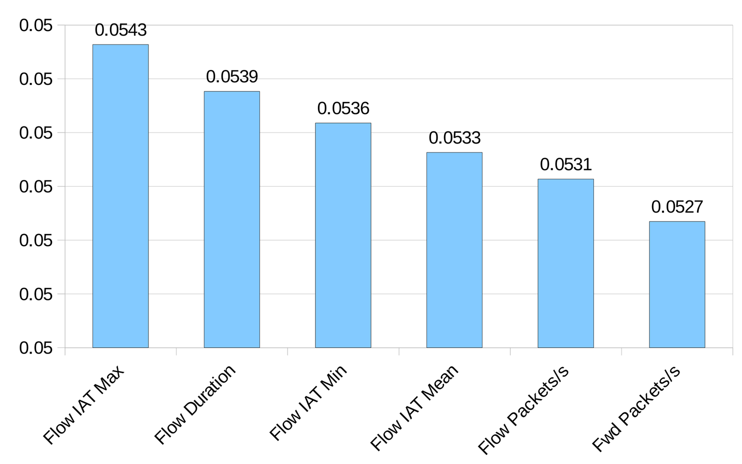


Fig 8. Feature ranks via Random Forest Importance

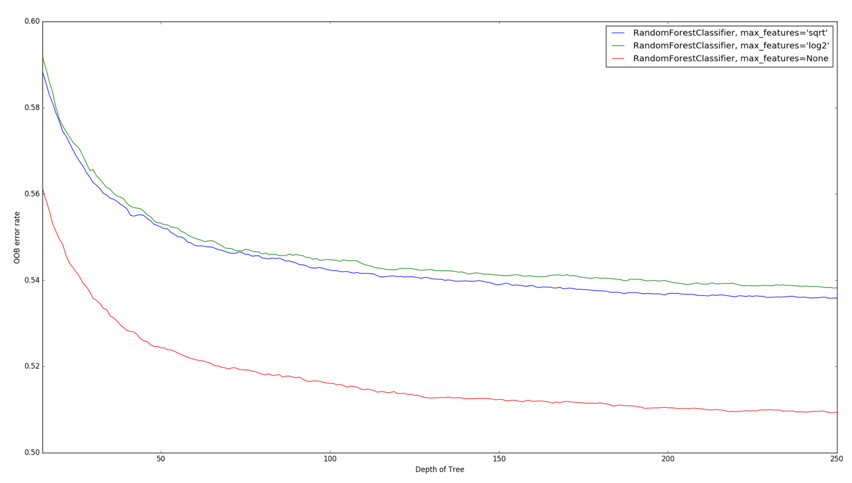


Fig 9. Sub-category: Out-of-bag error of Random Forest

Dataset:	Set-1	Set-2	Set-3
ROC:	87.5	83.5	82.4
F1-Score:	55.5	46.6	45.6
FP Rate:	0.065	0.066	0.074

Fig 10. Sub-category results (10 classes)