

Improving Vulnerability Prediction of JavaScript Functions Using Process Metrics



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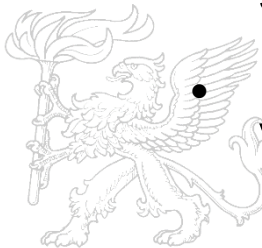
Motivation

- Code security is a crucial non-functional property
 - E.g., IoT, network enabled devices, everything is „connected”
 - Vulnerabilities in source code are one of the enablers of cyber-crime
- Detecting vulnerabilities in source code
 - SAST tools
 - High false-positive rates
 - ML models
 - What should be the features?



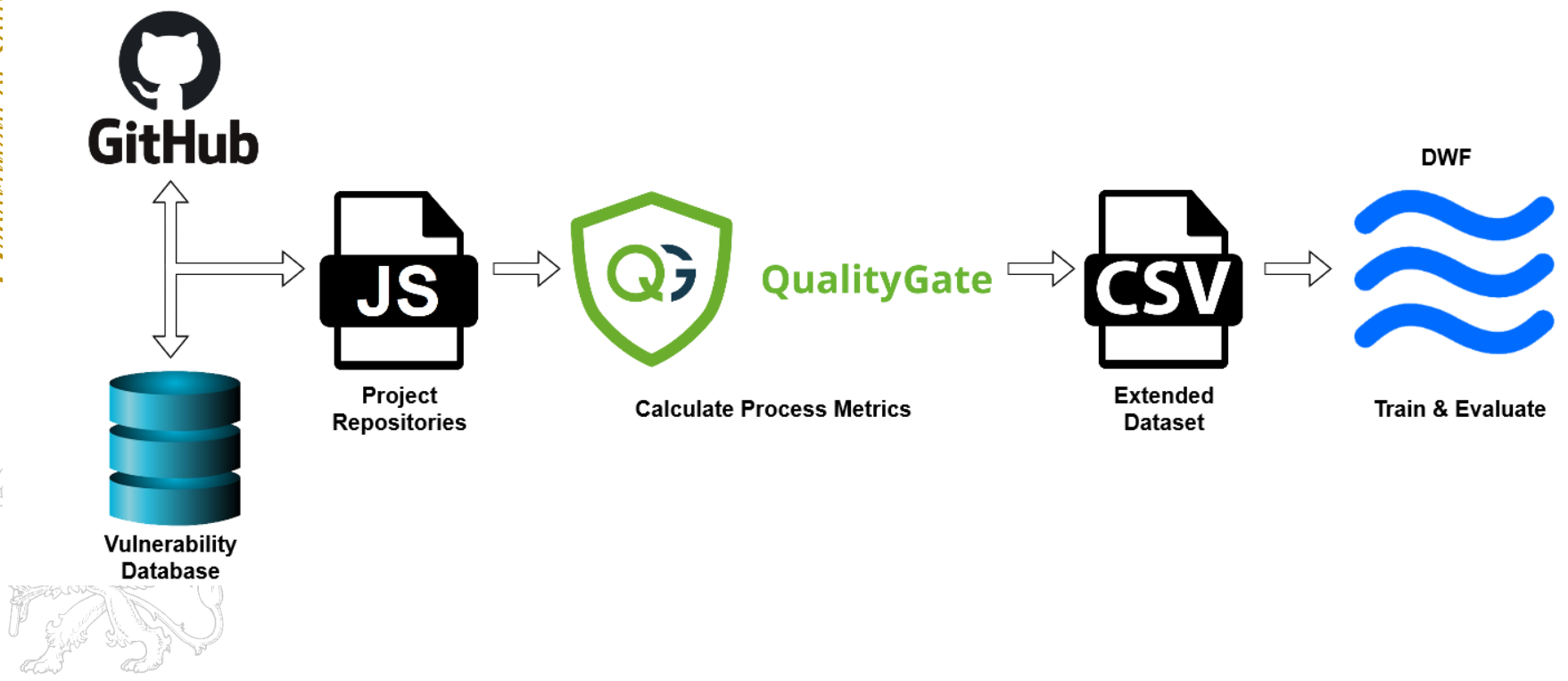
Research Goals

- Context
 - We showed in a previous work [1] that **static source code metrics** are good predictors of JS vulnerabilities
- Goal of current research
 - Investigate the impact of **process metrics** on ML prediction
- RQs
 - **RQ1:** Can process metrics as features improve existing JavaScript vulnerability prediction models based only on static source code metrics?
 - **RQ2:** If process metrics do improve the performance of vulnerability prediction models, how significant it is in terms of precision, recall, and F-measure?



[1] Ferenc, R., Hegedűs, P., Gyimesi, P., Antal, G., Bán, D., and Gyimóthy, T. (2019). Challenging Machine Learning Algorithms in Predicting Vulnerable JavaScript Functions. In Proceedings of the 7th International Workshop on Realizing Artificial Intelligence Synergies in Software Engineering, RAISE '19, page 8-14. IEEE Press.

Research Process



<https://doi.org/10.5281/zenodo.4590021>

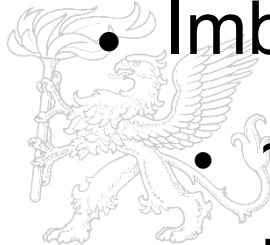
Features and ML Models

- 42 static source code metrics (baseline)
 - Results from previous work [1]
 - McCabe's Complexity, Lines of Code, number of Parameters, ...
- 19 process metrics
 - Extracted from version control system
 - Average Time Between Changes, Average Number of Modified Lines, Number of Contributors, ...
- Applied ML models
 - SVM, KNN, Linear/Logistic Regression, Naive Bayes, Decision Trees, Random Forest, Neural Networks



Vulnerability Dataset

- 12,125 JavaScript functions
 - Vulnerable/not vulnerable flags
 - Set of features
 - Static source code metrics
 - Process metrics
- Imbalanced
 - ~15% vulnerable entries
 - Data re-sampling is needed before ML



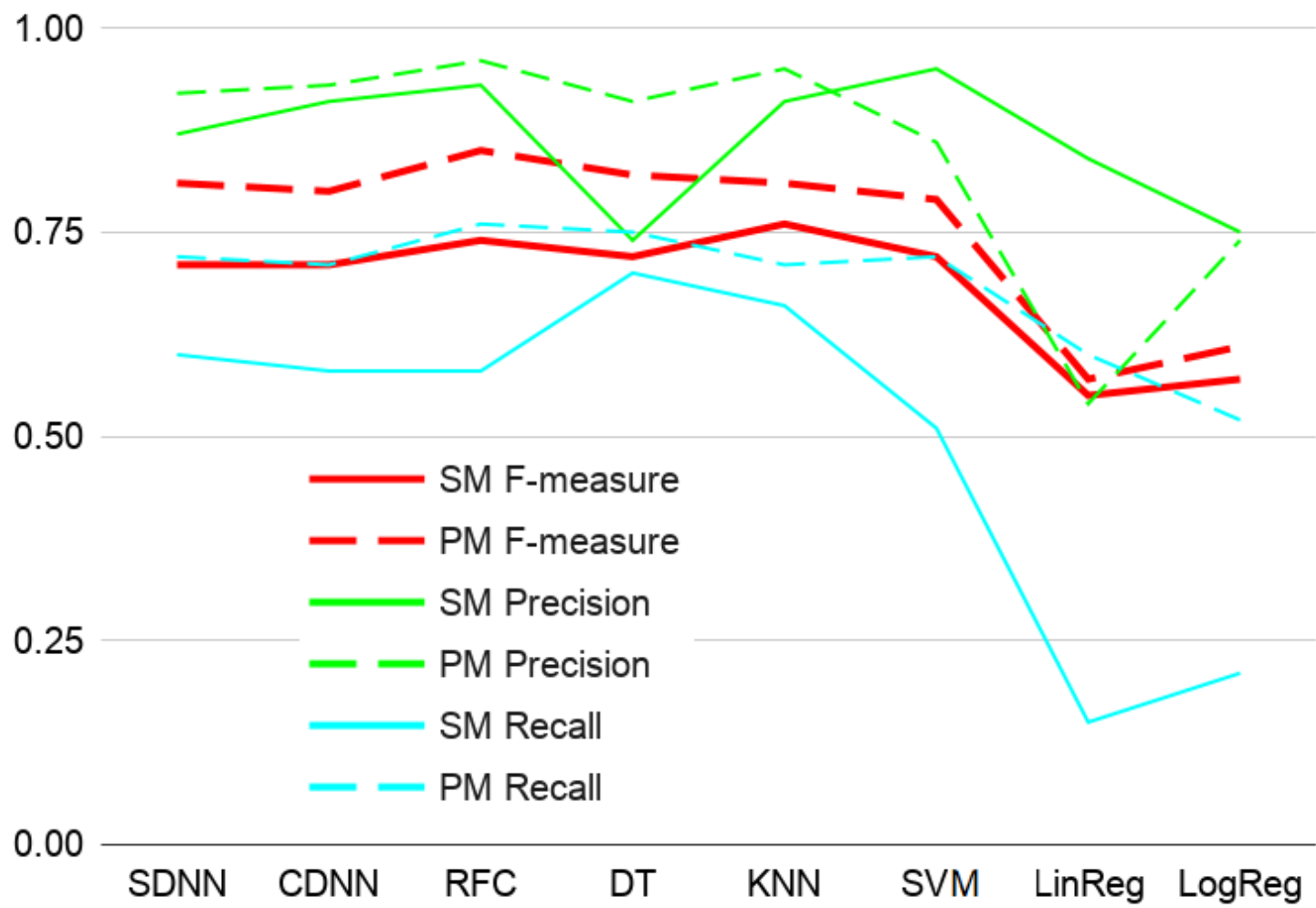
Results – Improvement

Classifier	TP	TN	FP	FN	Accuracy	Precision	Recall	F-measure
RFC	699	7054	24	261	96.5%	96.7%	72.8%	83.1% (+11.8%)
DT	723	7006	72	237	96.2%	90.9%	75.3%	82.4% (+10.8%)
CDNN	685	7027	51	275	95.9%	93.1%	71.4%	80.8% (+10%)
SDNN	665	7037	41	295	95.8%	94.2%	69.3%	79.8% (+8.7%)
KNN	613	7059	19	347	95.5%	97.0%	63.9%	77.0% (+0.6%)
SVM	548	7060	18	412	94.7%	96.8%	57.1%	71.8% (+5%)
LogReg	332	7007	71	628	91.3%	82.4%	34.6%	48.7% (+15.6%)
LinReg	274	7051	27	686	91.1%	91.0%	28.5%	43.5% (+17.4%)
NB	115	6779	299	845	85.8%	27.8%	12.0%	16.7% (+1.4%)





Results – Overview



Conclusions

- Process metrics significantly improve the predictive power of JavaScript vulnerability prediction models
 - Average improvement
 - 8.4% in F-measure
 - 3.5% in precision
 - 6.3% in recall
 - All significant based on a McNemar's test
 - Best performing model was Random Forest
 - F-measure of 0.85 (0.96 precision and 0.76 recall)



Acknowledgement

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