

# Machine Learning-Powered Identification of Source Code Vulnerabilities

Purushottam Borse<sup>1</sup>, Rushabh Gangurde<sup>2</sup>, Chaitanya Joshi<sup>3</sup>, Prof. N.V. Kapade<sup>4</sup>  
Department of AIML (Artificial Intelligence & Machine Learning)<sup>1,2,3,4</sup>

Loknete Gopinathji Munde Institute of Engineering Education & Research (LOGMIEER)s, Nashik, India

**Abstract:** *These methods for identifying source code defects face limitations, including false positives and negatives, resource demands, and integration issues in modern software projects. This article explores cutting-edge research in using ML to enhance source code security. As ML gains traction in bug prediction, numerous studies investigate its potential. This research contributes to the growing interest in applying ML to source code, addressing the need for more efficient, accurate, and scalable defect detection methods. By leveraging ML techniques, software development processes can become more robust, reducing vulnerabilities and enhancing overall code quality.*

**Keywords:** Machine Learning, Source Code, Vulnerability, Analysis.

## REFERENCES

- [1] MITRE, Common Weakness Enumeration. <https://cwe.mitre.org/data/index.html>.
- [2] T. D. LaToza, G. Venolia, and R. DeLine, "Maintaining mental models: A study of developer work habits," in Proc. 28th Int. Conf. Software Engineering, ICSE '06, (New York, NY, USA), pp. 492–501, ACM, 2006.
- [3] D. Yadron, "After heartbleed bug, a race to plug internet hole," Wall Street Journal, vol. 9, 2014.
- [4] C. Foxx, "Cyber-attack: Europol says it was unprecedented in scale." <https://www.bbc.com/news/world-europe-39907965>, 2017.
- [5] C. Arnold, "After Equifax hack, calls for big changes in credit reporting industry." <http://www.npr.org/2017/10/18/558570686/after-equifaxhack-calls-for-big-changes-in-credit-reporting-industry>, 2017.
- [6] NIST, Juliet test suite v1.3, 2017. <https://samate.nist.gov/SRD/testsuite.php>.
- [7] Z. Xu, T. Kremenek, and J. Zhang, "A memory model for static analysis of C programs," in Proc. 4th Int. Conf. Leveraging Applications of Formal Methods, Verification, and Validation, pp. 535–548, 2010.
- [8] J. C. King, "Symbolic execution and program testing," Commun. ACM, vol. 19, pp. 385–394, July 1976.
- [9] M. Allamanis, E. T. Barr, P. T. Devanbu, and C. A. Sutton, "A survey of machine learning for Big Code and naturalness," CoRR, vol. abs/1709.06182, 2017.
- [10] A. Hovsepian, R. Scandariato, W. Joosen, and J. Walden, "Software vulnerability prediction using text analysis techniques," in Proc. 4th Int. Workshop Security Measurements and Metrics, MetriSec '12, pp. 7–10, 2012.
- [11] Y. Pang, X. Xue, and A. S. Namin, "Predicting vulnerable software components through n-gram analysis and statistical feature selection," in 2015 IEEE 14th Int. Conf. Machine Learning and Applications (ICMLA), 2015.
- [12] L. Mou, G. Li, Z. Jin, L. Zhang, and T. Wang, "TBCNN: A tree-based convolutional neural network for programming language processing," CoRR, 2014.
- [13] Z. Li et al., "VulDeePecker: A deep learning-based system for vulnerability detection," CoRR, vol. abs/1801.01681, 2018.
- [14] J. Harer et al., "Learning to repair software vulnerabilities with generative adversarial networks," arXiv preprint arXiv:1805.07475, 2018.

## BIBLIOGRAPHY

- [1]. Purushottam Borse, Under Graduate Student, Logmieer, Nashik, Maharashtra, India
- [2]. Rushabh Gangurde, Under Graduate Student, Logmieer, Nashik, Maharashtra, India
- [3]. Chaitanya Joshi, Under Graduate Student, Logmieer, Nashik, Maharashtra, India