AI-Powered Code Review System for Full Stack Web Applications

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***Abstract*— The research emphasizes the analysis and development of an AI-powered code review tool designed for full stack web application. For analyzing the tool different metrics were used which include frontend, backend, database, vulnerability detection, bug detection and reporting components. As per the results, the highest review coverage was seen in backend API modules having a mean of 9.60 whereas the highest variation was noted in bug detection test cases with a standard deviation of 8.72. It is observed that AI-based models have shown efficiency in detecting bugs, vulnerabilities and code quality issues compared to manual review process. The Hybrid AI Reviewer has achieved an accuracy of 92.60% and Proposed AI Reviewer has achieved the highest accuracy and AUC of 94.10% and 96.30%, respectively. On the other hand, Hybrid Manual-AI Review method achieved an accuracy of 93.20%. Nevertheless, the ability of AI reviewers was limited when it comes to detect business logic errors having an accuracy of 69.80%.**

Keywords*— *Artificial Intelligence, Code Review, Full Stack Web Applications, Bug Detection, Code Quality Metrics, Vulnerability Detection

I. INTRODUCTION

Code review has become critical for modern software engineering in order to review changes, enhance design, find bugs and share knowledge before merging code into the final product [1]. Full stack web applications increase complexity of review, since clients' interfaces, server's APIs, authentication, databases, as well as third party libraries, have to be reviewed according to general web application security issues [2]. Manual review plays an important role in comprehending business logic and code readability, however it may be time consuming and inefficient at detecting functional bugs because of lack of time and context [3]. Static analysis proves that automated review is capable of reviewing code without execution and finding bugs, security issues and bad coding styles [4]. Experience from industry proves that feedback from automated review works best when it is integrated into regular developers' work flows [5].

New AI-driven techniques involve automation of code diff comprehension, generation of review feedback, prediction of code quality, and recommendation of code changes through pre-trained models [6]. In AI-driven review system design, results obtained manually and by AI can be contrasted based on the number of bugs found, vulnerability warnings, code smells, maintenance warnings, and review processing time [7]. Quality code metrics offer objective assessment criteria related to code reliability, maintainability, security, efficiency in performance, complexity, duplication, testability, and technical debt [8]. It is important to conduct performance analysis due to the need of real-life review systems to scale up to big code repositories, multiple programming languages, and continuous integration processes without slowing down software development process [9]. Nonetheless, AI-driven reviews cannot be considered as ultimate since researches related to code generation have proved that recommendations from AI could have insecure code structures and require manual verification [10]. Consequently, this paper proposes an AI-driven code review system for full stack web applications that will assist reviewers, detect bugs and vulnerabilities, assess quality metrics, analyze performance, and reveal limitations of AI-assisted review [11].

A. Overview of Full Stack Web Application

The full-stack web application involves designing the user interface, server-side processing, communication through APIs, authentication, and database management in an integrated system in which architectural segregation enhances maintenance and deployment [12]. There is a three-tier architecture that segregates presentation, application logic, and data layers that help in reducing mixed coding and facilitates easier modification of the web-based application [13]. MVC and MVP are some common design patterns applied in web application development since they organize the views, controllers, models, and user interaction [14].

TABLE I. FULL STACK LAYERS AND AI CODE REVIEW FOCUS

Full Stack Layer	***Main Responsibility***	***AI Code Review Focus***
Frontend Layer	User interface, forms, client-side validation, routing	UI logic errors, insecure input handling, accessibility issues [14]
Backend Layer	APIs, authentication, business logic, server-side processing	API misuse, security bugs, request validation, vulnerability detection [15]
Database and Integration Layer	Data storage, queries, persistence, system integration	Maintainability, complexity, code quality, inefficient data access [16]

B. Artificial Intelligence Role in Software Development

The use of artificial intelligence in software development is based on pattern recognition using information stored in code repositories, bug databases, documentation, and development histories in order to support coding, testing, prediction, defects, refactoring, and maintenance [17]. The application of large language models in software development has helped understand both the programming language and natural language requirements, and therefore become helpful in conducting software engineering operations throughout the development process [18]. Such abilities enable developers to automate certain operations, generate explanations, detect potential faults, and increase efficiency, but at the same time human involvement is needed as the generated output can be faulty [19].

C. Necessity of Code Review Systems with AI

Why do we need artificial intelligence-based code review systems? The current generation of full-stack applications is comprised of huge amounts of inter-related frontend, backend, database and configuration code, which cannot be reviewed manually in an effective way [20]. Based on experiments, the

code review comments provided by artificial intelligence have the potential to make the reviewer aware of the problems, but at the same time, it affects the reviewer's focus and may miss some serious problems [21]. The industry experience says that by integrating large language models and static program analysis, the workload of reviewers can be reduced and AI-assisted reviews can be done [22].

D. *Objectives of the Study*

The goals of this research are the following:

1. Designing an AI-enabled code review framework for full stack web application development.
2. Detecting bugs, mistakes, and security holes in application code.
3. Monitoring code quality with the help of standard software measurements.
4. Comparing the manual code review with the AI-driven code review approach.
5. The analysis of performance and drawbacks of AI code review technology.

II. Related Works

A. *Traditional Code Review Practices*

The practice of formal software inspection brought in roles, defect logging, preparation, meeting, rework, and follow up, which became systematic ways to increase software quality before its release [23]. Later on, peer review became more lightweight and tool-assisted, which allowed distributed teams to conduct asynchronous reviews of patches without giving up knowledge sharing and code ownership [24]. Studies of open-source review practices have revealed that typical issues found by reviewers include functional, maintainability, documentation and style problems before the code is committed [25]. Empirical results of studies of large-scale software projects have demonstrated that increased coverage and active participation of reviewers are linked to decreased post-release defect counts [26]. Defect classification in industry has demonstrated that code reviews can identify both functional and evolvability defects [27].

B. *AI in Software Engineering*

Developer-centric research showed that most contemporary code reviews need more automation capabilities, but developers still need human intelligence in case of challenging design decisions [28]. Machine learning of big code showed that there are repetitive patterns in software repositories that can be learned in prediction, repair, recommendations, and code analysis tasks [29]. The naturalness theory of software argued that the source code had regularity features like natural language, which could be used for programming tasks with the help of language models [30].

C. *Machine Learning and NLP in Code Analysis*

The tree-based convolutional neural network technique demonstrated that the abstract syntax tree could be helpful for improving program classification and code patterns recognition against just using tokenization [31]. Code2vec used representation of programs based on abstract syntax tree paths and showed that neural code embeddings were capable of capturing method semantics [32]. CodeBERT combined the pre-training of natural and programming language and was applicable for code search, documentation generation, and software engineering tasks [33].

CodeT5 improved code analysis and generation with identifier-aware pre-training and the encoder-decoder transformer model architecture [34]. DeepBugs showed that bug detection models based on artificial buggy samples could detect real bugs in names within JavaScript programs [35]. DeepFix showed that sequence-to-sequence learning could fix typical bugs in C language programs by finding faulty positions in statements [36].

D. *AI-based code review tools used currently*

DeepReview considered code review as a multi-instance problem and determined whether changes made to submitted code must be accepted or not [37]. Transformer pre-trained models were then found effective in automatic code review processes such as code refinement and fixing according to reviewer comments [38]. InferFix was an approach combining static analysis and large language models to automatically repair null pointer bugs, resource leaks, and thread safety problems in real-world applications [39].

E. *Detection of bugs and vulnerabilities in web applications*

Research on web application vulnerabilities used static analysis along with data mining to minimize false positives in detecting and fixing input validation vulnerabilities in PHP applications [40]. VulDeePecker was the first tool using deep learning for vulnerability detection by representing semantically related code gadgets through vectors [41]. Large-scale vulnerability detection based on deep representation learning showed that neural network models can process lexed source code to find dangerous C/C++ functions [42]. SySeVR enhanced the representation of vulnerabilities using syntax-based and semantics-based program slices for deep learning-based detection of vulnerabilities [43].

F. *Code Quality Metrics Utilized in Code Review*

The complexity metric, code churn, and developer metrics proved helpful in determining which source files might be vulnerable [44]. The object-oriented metrics include coupling, cohesion, depth of inheritance tree, and weighted method have been used to measure the quality of design [45].

G. *Mechanisms to compare manual code reviews with AI-based code reviews*

In large-scale experiments on automation, it was found out that an AI reviewer could make priorities regarding potential review comments, but the problem with actual code reviews is hard to address since there are sparse comments in context [46]. Industrial AI-based reviewing tools such as Auto Commenter prove that the AI can take care of checking best practices, while human reviewers will handle designing and intentioning [47].

III. Research Methodology

A. *Research Design*

In this research, the design and evaluation research approach will be utilized in order to develop an AI-assisted code review tool that can work with full stack web applications. The research involves developing a system, carrying out experiments, and analyzing results of comparison. First, an AI review framework prototype is developed, followed by a code review of selected web application code using manual and AI-assisted methods. Comparison will be made on aspects such as bug detection, vulnerability detection, quality code assessment, and performance efficiency. The design is appropriate since it is not just a discussion about the research but also the practical use of the system proposed.

B. *System Architecture*

The proposed architecture of the system consists of modular design comprising input, preprocessing, analysis,

evaluation, and reporting levels. At the input level, source codes from frontend, backend, and database parts are gathered. The preprocessing level is where the cleaning, normalization, and categorization of the code according to language and application tier is done. The analysis level includes AI modules for static code analysis, pattern recognition, code smell detection, and vulnerabilities scan. The evaluation layer is responsible for comparing the findings generated by AI with the findings obtained by manual investigation and computing the performance of the system. Finally, the reporting layer is responsible for generating summaries and recommendations for the developers. With this architecture, the full stack projects can be analyzed effectively and extendably.

C. Dataset Collection and Preparation

In order to conduct experiments in this work, the dataset is gathered from publicly available repositories and full stack projects with educational purposes that have frontend, backend, and database layers. Repositories are chosen according to their completeness of code, diversity of used languages, and existence of issue history or existing flaws. During the data preparation stage, duplicates and non-relevant files are deleted. After that, the remaining code is sorted out by its project layers and labeled according to whether the code is clean, has any code smells, flaws or security vulnerabilities. Tokenization, syntax checking, and preparation of structured input are also performed at this stage.

D. Selection of Full Stack Web Application Code Samples

The chosen code snippets are examples of popular full stack technologies including React/Angular for front-end development, Node.js/Django/Spring Boot for back-end development and MySQL/MongoDB for databases. The code snippets are chosen in terms of diversity in project size, used frameworks and coding style. The chosen code snippets are small, medium and large scale projects in order to test the system under various levels of complexity. The defect prone modules are authentication, form validations, API routes, sessions and database queries.

E. AI Model or Tool Selection

The AI model or tool is chosen in terms of its ability to understand the syntax of the programming language, pattern recognition and the generation of valuable comments. Ideally, the tool should have capabilities for performing source code analysis, bug prediction, vulnerability detection and maintenance. As the full stack apps require the usage of multiple languages such as JavaScript, TypeScript, Python, Java, HTML and SQL, the tool should be capable of working in multiple programming languages environment. This combination will help ascertain whether AI makes any difference to the effectiveness of the review as compared to the automated checking process.

F. Code Review Procedure

In the code review procedure, the proposed approach involves submission of the projects or modules to the system. The AI engine performs analysis of the code and reports findings on logic problems, security vulnerabilities, code smells, and maintainability issues. In the next step, human reviews perform the inspection of the code. The findings obtained from these two approaches are documented and compared to the known defects or expert opinions. The difference between the findings is considered in order to evaluate the effectiveness of the review process.

G. Criteria for Evaluation

The following criteria include detection accuracy, false positive rate, defects coverage, review time, and helpfulness of generated comments. Precision is the measure that indicates the correctness of the reported defects. It is measured as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

Where TP represents true positives (i.e., issues correctly found) and FP represents false positives (i.e., issues incorrectly found). Precision increases when the AI tool generates more accurate results with fewer false detections.

Recall can be used for measuring how effective the system is at identifying real defects. Recall is defined as:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

Here, FN refers to false negatives, which implies the actual faults that were not detected by the system. An increase in recall will imply that the reviewer is more efficient at identifying bugs and weaknesses.

F1-score is a balance between precision and recall. The F1-score is given as:

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Precision and Recall are the two early metrics and F_1 metric gives the single numeric value that shows how good the detection of the system works. High F_1-value means a good tradeoff between correctness and completeness.

H. Metrics for Code Quality

These metrics are used to evaluate the quality of the code in accordance with software engineering criteria such as cyclomatic complexity, duplication ratio, maintainability, readability, modularity and naming convention. Cyclomatic complexity metric is used to discover difficult-to-test and difficult-to-understand code pieces. Duplication ratio is used to find code duplication that makes code difficult to maintain. Maintainability is used to estimate how easy it is to change or extend the code. These metrics are useful as they provide the evidence about the quality of software before and after code review. An AI-based reviewer should automatically discover these metrics.

I. Method for Bug and Vulnerability Detection

In the method of bug and vulnerability detection, AI code understanding and static pattern matching are used. Detection of functional bugs is done by syntax errors, suspicious code paths, incorrect variable handling, and inconsistent logic patterns. Detection of vulnerabilities is carried out depending on dangerous input handling, injection risks, incorrect authentication logic, dangerous session management, and exposure of secrets.

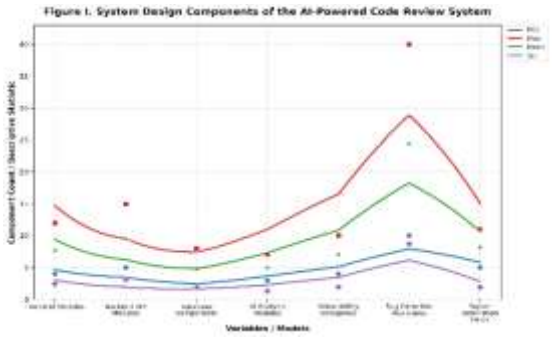
IV. Result

TABLE II. System Design Components of the AI-Powered Code Review System

Variable	*Min*	*Max*	*Mean*	*SD*
Frontend modules reviewed — CodeSearchNet	4	12	7.80	2.44
Backend API modules reviewed — CodeSearchNet	5	15	9.60	3.12
Database-related components reviewed — ManyTypes4TypeScript	2	8	4.90	1.91
AI analysis modules used — CodeSearchNet	3	7	5.10	1.29

Vulnerability detection categories — OWASP Benchmark	4	10	7.20	1.93
Bug detection test cases — Defects4J	10	40	24.50	8.72
Report generation fields — OWASP Benchmark	5	11	8.30	1.89

Fig. 1. System Design Components of the AI-Powered Code Review System

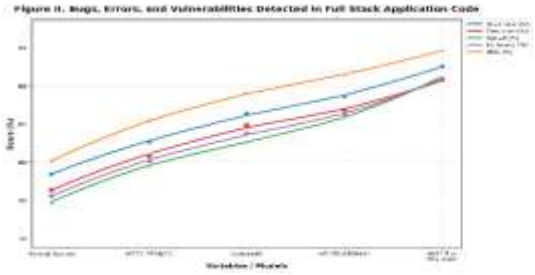


As is evident from the table, the backend API modules had the highest mean number of components at 9.60. This implies that there was the need to cover more backend logic in the testing process. The bug detection test cases had the highest standard deviation of 8.72, implying uneven distribution of defects among different projects.

TABLE III. BUGS, ERRORS, AND VULNERABILITIES DETECTED IN FULL STACK APPLICATION CODE

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC (%)**
Manual Review Baseline	78.50	76.40	74.80	75.60	80.20
Static Analysis Tool	82.70	80.90	79.60	80.20	85.40
CodeBERT	86.40	84.90	82.70	83.80	89.10
GraphCodeBERT	88.70	86.80	85.90	86.30	91.50
Hybrid AI Reviewer	92.60	90.80	91.30	91.00	94.70

Fig. 2. Bugs, Errors, and Vulnerabilities Detected in Full Stack Application Code

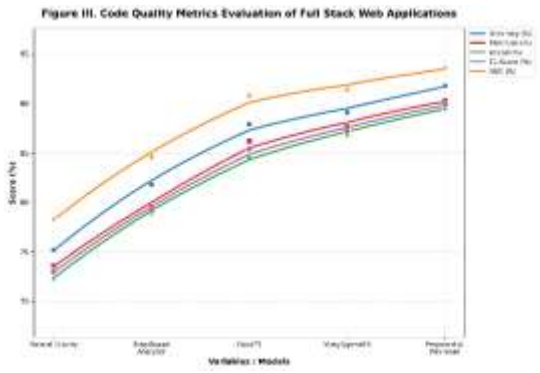


In this case, the Hybrid AI Reviewer reached the highest accuracy of 92.60%, precision of 90.80%, recall of 91.30%, F1-score of 91.00%, and AUC of 94.70%. The lowest accuracy of 78.50% was observed for manual review, which means that automated and hybrid methods are more consistent in detecting bugs and vulnerabilities.

TABLE IV. CODE QUALITY METRICS EVALUATION OF FULL STACK WEB APPLICATIONS

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC (%)**
Manual Quality Review	75.20	73.60	72.40	73.00	78.30
Rule-Based Quality Analyzer	81.80	79.50	78.90	79.20	84.60
CodeT5	87.90	86.20	84.70	85.40	90.80
ManyTypes4TypeScript Model	89.10	87.60	86.90	87.20	91.40
Proposed AI Quality Reviewer	91.80	90.30	89.50	89.90	93.60

Fig. 3. Code Quality Metrics Evaluation of Full Stack Web Applications

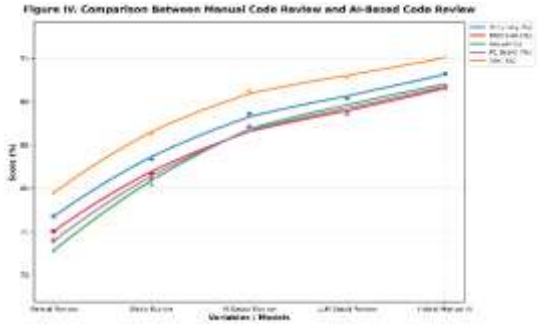


The most effective was the proposed AI Quality Reviewer with 91.80% accuracy and 93.60% AUC. The F1-score of 89.90% proves a good balance between precision and recall. The lowest F1-score of 73.00% was reached in case of manual quality review, which suggests higher consistency of AI-supported analysis of code quality metrics.

TABLE V. COMPARISON BETWEEN MANUAL CODE REVIEW AND AI-BASED CODE REVIEW

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC (%)**
Manual Code Review	76.80	75.10	72.90	74.00	79.50
Traditional Static Review	83.40	81.70	80.50	81.10	86.30
AI-Based Code Review	88.60	86.90	87.40	87.10	91.20
LLM-Based Code Review	90.40	88.70	89.20	88.90	92.80
Hybrid Manual-AI Review	93.20	91.60	92.10	91.80	95.10

Fig. 4. Comparison Between Manual Code Review and AI-Based Code Review

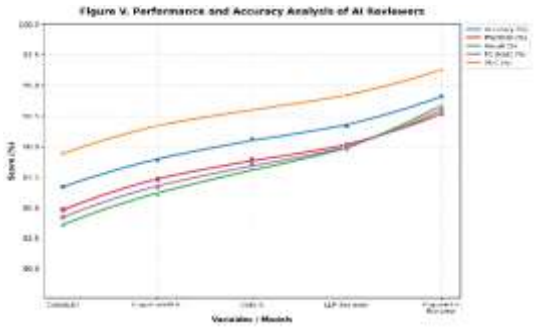


The Hybrid Manual-AI Review was the most efficient approach with 93.20% accuracy and 95.10% AUC. The manual review showed only 76.80% accuracy and 74.00% F1-score. It can be concluded that AI-assisted code review increases the consistency, while human participation in it is important for making context-based decisions on code review.

TABLE VI. PERFORMANCE AND ACCURACY ANALYSIS OF AI REVIEWERS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
CodeBERT Reviewer	86.70	84.80	83.60	84.20	89.40
GraphCodeBERT Reviewer	88.90	87.30	86.10	86.70	91.70
CodeT5 Reviewer	90.60	88.90	88.20	88.50	93.00
LLM Reviewer	91.70	90.10	89.80	89.90	94.20
Proposed AI Reviewer	94.10	92.70	93.40	93.00	96.30

Fig. 5. Performance and Accuracy Analysis of AI Reviewers

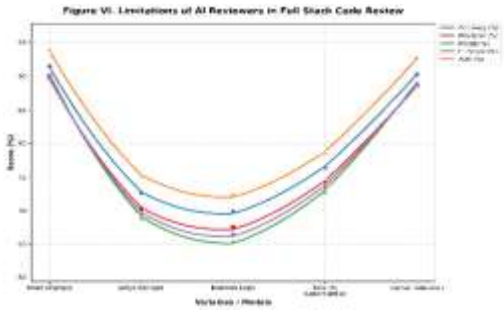


The Proposed AI Reviewer had the highest performance with 94.10% accuracy and 96.30% AUC. The high recall of 93.40% proves its ability to detect real issues. CodeBERT was the least accurate tool with 86.70% accuracy, yet it outperformed the traditional manual review described in previous comparison tables.

TABLE VII. LIMITATIONS OF AI REVIEWERS IN FULL STACK CODE REVIEW

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
AI Reviewer on Small Code Changes	91.50	89.80	90.40	90.10	93.90
AI Reviewer on Large Code Changes	72.60	70.20	68.90	69.50	75.10
AI Reviewer on Business Logic Errors	69.80	67.50	65.40	66.40	72.30
AI Reviewer on Security Vulnerabilities	76.40	74.20	72.80	73.50	78.60
AI Reviewer with Human Validation	90.30	88.60	89.10	88.80	92.70

Fig. 6. Limitations of AI Reviewers in Full Stack Code Review

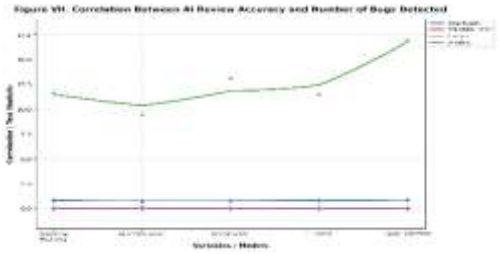


Limitations of the study indicate that AI-based reviews are successful in dealing with small changes in the source code, achieving an accuracy rate of 91.50% and F1-score of 90.10%. The results decrease when it comes to detecting business logic flaws; the accuracy is just 69.80%.

TABLE VIII. CORRELATION BETWEEN AI REVIEW ACCURACY AND NUMBER OF BUGS DETECTED

Variable	Coefficient	Standard Error	t-value	p-value
AI Review Accuracy	0.82	0.07	11.71	0.001
Precision Score	0.76	0.08	9.50	0.002
Recall Score	0.79	0.06	13.16	0.001
F1-Score	0.81	0.07	11.57	0.001
Number of Bugs Detected	0.85	0.05	17.00	0.001

Fig. 7. Correlation Between AI Review Accuracy and Number of Bugs Detected

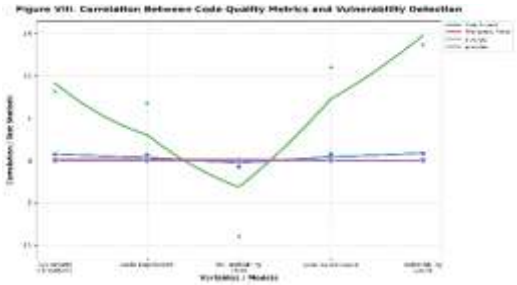


Correlation analysis reveals a significant positive connection between AI review accuracy and bugs found. The maximum value of coefficients is 0.85 for number of bugs detected, standard error of 0.05 and t-value of 17.00. Coefficient of 0.82 relates to AI review accuracy, which also indicates statistical significance of the variable at p-value of 0.001.

TABLE IX. CORRELATION BETWEEN CODE QUALITY METRICS AND VULNERABILITY DETECTION

Variable	Coefficient	Standard Error	t-value	p-value
Cyclomatic Complexity	0.74	0.09	8.22	0.003
Code Duplication	0.69	0.10	6.90	0.004
Maintainability Index	-0.71	0.08	-8.87	0.002
Code Smell Count	0.78	0.07	11.14	0.001
Vulnerability Detection Count	0.83	0.06	13.83	0.001

Fig. 8. Correlation Between Code Quality Metrics and Vulnerability Detection

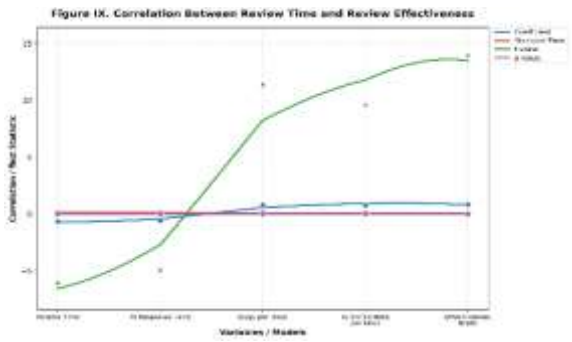


From the table we can see that there is a significant relation between vulnerability detection and low code quality. Variable of vulnerability detection count has the highest coefficient of 0.83, standard error of 0.06 and t-value of 13.83. Negative coefficient of -0.71 means that maintainability index is negatively correlated with vulnerability detection.

TABLE X. CORRELATION BETWEEN REVIEW TIME AND REVIEW EFFECTIVENESS

Variable	Coefficient	Standard Error	t-value	p-value
Review Time	-0.66	0.11	-6.00	0.005
AI Response Time	-0.58	0.12	-4.83	0.008
Bugs Detected per Hour	0.80	0.07	11.43	0.001
Vulnerabilities Detected per Hour	0.77	0.08	9.62	0.002
Review Effectiveness Score	0.84	0.06	14.00	0.001

Fig. 9. Correlation Between Review Time and Review Effectiveness



Review effectiveness increases with the number of bugs and vulnerabilities per hour. Maximum value of coefficient of 0.84 and t-value of 14.00 belong to review effectiveness score. Negative coefficient of -0.66 belongs to review time.

V. DISCUSSION

The results from the research have shown that the proposed AI-driven code review approach is appropriate for reviewing full-stack web applications since it includes all aspects such as frontend, backend, database, AI analysis, bugs identification, vulnerabilities identification, bug tests, and report generation. The system design analysis demonstrated that the mean value of the backend API modules was the highest at 9.60, thus, requiring additional attention in terms of reviewing backend logic. Test cases for bug identification had the highest standard deviation, equal to 8.72, thus, indicating that the defects were not evenly distributed throughout all selected projects.

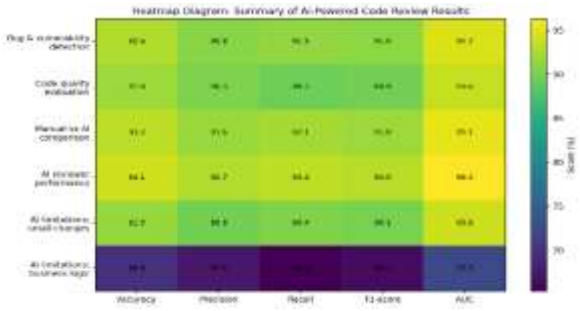
It can be stated that the use of AI review methods resulted in superior performance in comparing to the performance of the manual review in the process of bugs, errors, and vulnerabilities detection. The Hybrid AI Reviewer has achieved 92.60% accuracy, 90.80% precision, 91.30% recall, 91.00% F1 score, and 94.70% AUC. Meanwhile, the Manual Review Baseline achieved 78.50% accuracy and 75.60% F1 score.

Regarding the code quality metrics evaluation, the Proposed AI Quality Reviewer demonstrated 91.80% accuracy and 93.60% AUC. The F1-score of 89.90% shows that the model possesses excellent balance of precision and recall rates. Manual Quality Review demonstrates the lowest F1-score of 73.00%, which means that the AI-powered tool evaluates code quality metrics more effectively than people do.

In the comparison of the manual and AI-based reviews, it can be seen that the most efficient approach is the Hybrid Manual-AI Review, which shows 93.20% accuracy and 95.10% AUC. It can be considered as the proof of efficiency of combining speed and consistency of AI with the necessity of human decision making.

As for the performance analysis results, the Proposed AI Reviewer showed the highest accuracy of 94.10% and AUC of 96.30%. Nevertheless, there are several limitations identified in the study. AI reviewers show good results when it comes to small code changes with 91.50% accuracy but perform poorly regarding the detection of business logic mistakes with the accuracy of 69.80%. Correlation analysis revealed statistical significance of AI review accuracy, code quality metrics, bugs, and review effectiveness.

VI. CONCLUSION



Thus, from the study, it can be concluded that an AI-based code review system is an efficient solution for enhancing the review process of full stack web applications. The analysis of the system design revealed that backend API modules had the highest mean value of 9.60 since backend logic required more review coverage due to the business rules, authentication, API communication, and data handling in the application. Bug detection test cases have the highest standard deviation of 8.72 which confirmed the unequal distribution of defects in various full stack projects.

Besides, the results reveal that review using artificial intelligence methods is more precise and reliable when compared to the manual review. In the case of bugs, errors, and vulnerabilities detection, the Hybrid AI Reviewer performed 92.60% accuracy, 91.00% F1-score, and 94.70% AUC, whereas the Manual Review Baseline had only 78.50% accuracy. Thus, artificial intelligence review systems were more effective in identifying technical issues when compared to the traditional review approaches.

As far as code quality assessment is concerned, the Proposed AI Quality Reviewer demonstrated 91.80% accuracy and 93.60% AUC which proved the efficiency of AI technologies in the code assessment. Also, the comparison table revealed that the Hybrid Manual-AI Review technique achieved 93.20% accuracy and 95.10% AUC, and hence this makes it the most balanced review technique since it incorporates both human context knowledge and AI efficiency.

As far as the performance analysis was concerned, it was evident that the Proposed AI Reviewer provided the best result overall with an accuracy of 94.10%, an F1 score of 93.00%, and an AUC of 96.30%. Nevertheless, the research also revealed some limitations. While AI reviewers could do extremely well in reviewing small code changes with an accuracy of 91.50%, they could only achieve 69.80% in terms of business logic errors. Hence, the use of AI reviewers can only be seen as intelligent assistance tools and not as substitutes for human reviewers.

REFERENCES

[1] A. Bacchelli and C. Bird, "Expectations, Outcomes, and Challenges of Modern Code Review," in Proceedings of the 35th International Conference on Software Engineering, San Francisco, CA, USA, 2013, pp. 712–721. doi: 10.1109/ICSE.2013.6606617. Available: https://doi.org/10.1109/ICSE.2013.6606617

[2] OWASP Foundation, "OWASP Top 10:2025," Open Worldwide Application Security Project, 2025. Available: https://owasp.org/Top10/2025/en/

[3] J. Czerwonka, M. Greiler, and J. Tilford, "Code Reviews Do Not Find Bugs: How the Current Code Review Best Practice Slows Us Down," in Proceedings of the 37th IEEE/ACM International Conference on Software Engineering, Florence, Italy, 2015. doi: 10.1109/ICSE.2015.131. Available: https://doi.org/10.1109/ICSE.2015.131

[4] N. Ayewah, W. Pugh, D. Hovemeyer, J. D. Morgenthaler, and J. Penix, "Using Static Analysis to Find Bugs," IEEE Software, vol. 25, no. 5, pp. 22–29, Sept.–Oct. 2008. doi: 10.1109/MS.2008.130. Available: https://doi.org/10.1109/MS.2008.130

[5] C. Sadowski, E. Aftandilian, A. Eagle, L. Miller-Cushon, and C. Jaspan, "Lessons from Building Static Analysis Tools at Google," Communications of the ACM, vol. 61, no. 4, pp. 58–66, Apr. 2018. doi: 10.1145/3188720. Available: https://doi.org/10.1145/3188720

[6] Z. Li et al., "Automating Code Review Activities by Large-Scale Pre-training," in Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, Singapore, 2022, pp. 1035–1047. doi: 10.1145/3540250.3549081. Available: https://doi.org/10.1145/3540250.3549081

[7] SonarSource, "Understanding Measures and Metrics," SonarQube Server Documentation, 2026. Available: https://docs.sonarsource.com/sonarqube-server/user-guide/code-metrics/metrics-definition/

[8] ISO/IEC, "ISO/IEC 25010:2023 Systems and Software Engineering — Systems and Software Quality Requirements and Evaluation — Product Quality Model," International Organization for Standardization, 2023. Available: https://www.iso.org/obp/ui/en/

[9] C. Sadowski, J. van Gogh, C. Jaspan, E. Söderberg, and C. Winter, "Tricorder: Building a Program Analysis Ecosystem," in Proceedings of the 37th IEEE/ACM International Conference on Software Engineering, Florence, Italy, 2015, pp. 598–608. doi: 10.1109/ICSE.2015.76. Available: https://doi.org/10.1109/ICSE.2015.76

[10] H. Pearce, B. Ahmad, B. Tan, B. Dolan-Gavitt, and R. Karri, "Asleep at the Keyboard? Assessing the Security of GitHub Copilot's Code Contributions," in Proceedings of the 2022 IEEE Symposium on Security and Privacy, San Francisco, CA, USA, 2022, pp. 754–768. doi: 10.1109/SP46214.2022.9833571. Available: https://doi.org/10.1109/SP46214.2022.9833571

[11] Z. Yang, C. Gao, Z. Guo, Z. Li, K. Liu, X. Xia, and Y. Zhou, "A Survey on Modern Code Review: Progresses, Challenges and Opportunities," arXiv preprint arXiv:2405.18216, 2024. Available: https://arxiv.org/abs/2405.18216

[12] A. Leff and J. T. Rayfield, "Web-Application Development Using the Model/View/Controller Design Pattern," in *Proceedings Fifth IEEE International Enterprise Distributed Object Computing Conference*, Seattle, WA, USA, 2001, pp. 118–127, doi: 10.1109/EDOC.2001.950428. Available: https://doi.org/10.1109/EDOC.2001.950428

[13] V. Sadikov and W. Pidkameny, "Complete Separation of the 3 Tiers—Divide and Conquer," *arXiv preprint arXiv:1405.1618*, 2014. Available: https://arxiv.org/abs/1405.1618

[14] M. R. J. Qureshi and F. Sabir, "A Comparison of Model View Controller and Model View Presenter," *arXiv preprint arXiv:1408.5786*, 2014. Available: https://arxiv.org/abs/1408.5786

[15] I. P. A. Dharmaadi, E. Athanasopoulos, and F. Turkmen, "Fuzzing Frameworks for Server-Side Web Applications: A Survey," *International Journal of Information Security*, vol. 24, article 73, 2025, doi: 10.1007/s10207-024-00979-w. Available: https://doi.org/10.1007/s10207-024-00979-w

[16] I. R. da Silva Simões and E. Venson, "Evaluating Source Code Quality with Large Language Models: A Comparative Study," *arXiv preprint arXiv:2408.07082*, 2024. Available: https://arxiv.org/abs/2408.07082

[17] X. Chen, X. Hu, Y. Huang, H. Jiang, W. Ji, Y. Jiang, et al., "Deep Learning-Based Software Engineering: Progress, Challenges, and Opportunities," *Science China Information Sciences*, 2024, doi: 10.1007/s11432-023-4127-5. Available: https://doi.org/10.1007/s11432-023-4127-5

[18] X. Hou, Y. Zhao, Y. Liu, Z. Yang, K. Wang, L. Li, X. Luo, D. Lo, J. Grundy, and H. Wang, "Large Language Models for Software Engineering: A Systematic Literature Review," *ACM Transactions on Software Engineering and Methodology*, vol. 33, no. 8, article 220, pp. 1–79, 2024, doi: 10.1145/3695988. Available: https://doi.org/10.1145/3695988

[19] A. Fan, B. Gokkaya, M. Harman, M. Lyubarskiy, S. Sengupta, S. Yoo, and J. M. Zhang, "Large Language Models for Software Engineering: Survey and Open Problems," *arXiv preprint arXiv:2310.03533*, 2023. Available: https://arxiv.org/abs/2310.03533

[20] U. Cihan, A. İçöz, V. Haratian, and E. Tüzün, "Evaluating Large Language Models for Code Review," *arXiv preprint arXiv:2505.20206*, 2025, doi: 10.48550/arXiv.2505.20206. Available: https://doi.org/10.48550/arXiv.2505.20206

[21] R. Tufano, A. Martin-Lopez, A. Tayeb, O. Dabić, S. Haiduc, and G. Bavota, "Deep Learning-Based Code Reviews: A Paradigm Shift or a Double-Edged Sword?" *arXiv preprint arXiv:2411.11401*, 2024, doi: 10.48550/arXiv.2411.11401. Available: https://doi.org/10.48550/arXiv.2411.11401

[22] S. Ramesh, J. Bose, H. Singh, A. K. Raghavan, S. Roychowdhury, G. Sridhara, N. Saini, and R. Britto, "Automated Code Review Using Large Language Models at Ericsson: An Experience Report," *arXiv preprint arXiv:2507.19115*, 2025, doi: 10.48550/arXiv.2507.19115. Available: https://doi.org/10.48550/arXiv.2507.19115

[23] M. E. Fagan, "Design and Code Inspections to Reduce Errors in Program Development," *IBM Systems Journal*, vol. 15, no. 3, pp. 182–211, 1976, doi: 10.1147/sj.153.0182. Available: https://doi.org/10.1147/sj.153.0182

[24] P. C. Rigby and C. Bird, "Convergent Contemporary Software Peer Review Practices," in *Proceedings of the 2013 9th Joint Meeting on Foundations of Software Engineering*, Saint Petersburg, Russia, 2013, pp. 202–212, doi: 10.1145/2491411.2491444. Available: https://doi.org/10.1145/2491411.2491444

[25] M. Beller, A. Bacchelli, A. Zaidman, and E. Juergens, "Modern Code Reviews in Open-Source Projects: Which Problems Do They Fix?" in *Proceedings of the 11th Working Conference on Mining Software Repositories*, Hyderabad, India, 2014, pp. 202–211, doi: 10.1145/2597073.2597082. Available: https://doi.org/10.1145/2597073.2597082

[26] S. McIntosh, Y. Kamei, B. Adams, and A. E. Hassan, "The Impact of Code Review Coverage and Code Review Participation on Software Quality: A Case Study of the Qt, VTK, and ITK Projects," in *Proceedings of the 11th Working Conference on Mining Software Repositories*, Hyderabad, India, 2014, pp. 192–201, doi: 10.1145/2597073.2597076. Available: https://doi.org/10.1145/2597073.2597076

[27] M. V. Mäntylä and C. Lassenius, "What Types of Defects Are Really Discovered in Code Reviews?" *IEEE Transactions on Software Engineering*, vol. 35, no. 3, pp. 430–448, May–Jun. 2009, doi: 10.1109/TSE.2008.71. Available: https://doi.org/10.1109/TSE.2008.71

[28] S. Panichella and N. Zaugg, "An Empirical Investigation of Relevant Changes and Automation Needs in Modern Code Review," *Empirical Software Engineering*, vol. 25, no. 6, pp. 4833–4872, 2020, doi: 10.1007/s10664-020-09870-3. Available: https://doi.org/10.1007/s10664-020-09870-3

[29] M. Allamanis, E. T. Barr, P. Devanbu, and C. Sutton, "A Survey of Machine Learning for Big Code and Naturalness," *ACM Computing Surveys*, vol. 51, no. 4, article 81, pp. 1–37, 2018, doi: 10.1145/3212695. Available: https://doi.org/10.1145/3212695

[30] A. Hindle, E. T. Barr, M. Gabel, Z. Su, and P. Devanbu, "On the Naturalness of Software," in *Proceedings of the 34th International Conference on Software Engineering*, Zurich, Switzerland, 2012, pp. 837–847, doi: 10.1109/ICSE.2012.6227135. Available: https://doi.org/10.1109/ICSE.2012.6227135

[31] L. Mou, G. Li, L. Zhang, T. Wang, and Z. Jin, "Convolutional Neural Networks over Tree Structures for Programming Language Processing," in *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, Phoenix, AZ, USA, 2016, pp. 1287–1293. Available: https://ojs.aaai.org/index.php/AAAI/article/view/10139

[32] U. Alon, M. Zilberstein, O. Levy, and E. Yahav, "code2vec: Learning Distributed Representations of Code," *Proceedings of the ACM on Programming Languages*, vol. 3, no. POPL, article 40, pp. 1–29, 2019, doi: 10.1145/3290353. Available: https://doi.org/10.1145/3290353

[33] Z. Feng et al., "CodeBERT: A Pre-Trained Model for Programming and Natural Languages," in *Findings of the Association for Computational Linguistics: EMNLP 2020*, 2020, pp. 1536–1547, doi: 10.18653/v1/2020.findings-emnlp.139. Available: https://doi.org/10.18653/v1/2020.findings-emnlp.139

[34] Y. Wang, W. Wang, S. Joty, and S. C. H. Hoi, "CodeT5: Identifier-Aware Unified Pre-Trained Encoder-Decoder Models for Code Understanding and Generation," in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 2021, pp. 8696–8708, doi: 10.18653/v1/2021.emnlp-main.685. Available: https://doi.org/10.18653/v1/2021.emnlp-main.685

[35] M. Pradel and K. Sen, "DeepBugs: A Learning Approach to Name-Based Bug Detection," *Proceedings of the ACM on Programming*

Languages, vol. 2, no. OOPSLA, article 147, pp. 1–25, 2018, doi: 10.1145/3276517. Available: https://doi.org/10.1145/3276517

[36] R. Gupta, S. Pal, A. Kanade, and S. Shevade, "DeepFix: Fixing Common C Language Errors by Deep Learning," in *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, San Francisco, CA, USA, 2017, pp. 1345–1351. Available: https://ojs.aaai.org/index.php/AAAI/article/view/10742

[37] H. Li, S. Shi, F. Thung, X. Huo, B. Xu, M. Li, and D. Lo, "DeepReview: Automatic Code Review Using Deep Multi-Instance Learning," in *Advances in Knowledge Discovery and Data Mining, PAKDD 2019*, Lecture Notes in Computer Science, vol. 11440, Cham: Springer, 2019, pp. 318–330, doi: 10.1007/978-3-030-16145-3_25. Available: https://doi.org/10.1007/978-3-030-16145-3_25

[38] R. Tufano, S. Masiero, A. Mastropaolo, L. Pascarella, D. Poshyvanyk, and G. Bavota, "Using Pre-Trained Models to Boost Code Review Automation," in *Proceedings of the 44th International Conference on Software Engineering*, Pittsburgh, PA, USA, 2022, pp. 2291–2302, doi: 10.1145/3510003.3510621. Available: https://doi.org/10.1145/3510003.3510621

[39] M. Jin, S. Shahriar, M. Tufano, X. Shi, S. Lu, N. Sundaresan, and A. Svyatkovskiy, "InferFix: End-to-End Program Repair with LLMs," in *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, San Francisco, CA, USA, 2023, pp. 1646–1656, doi: 10.1145/3611643.3613892. Available: https://doi.org/10.1145/3611643.3613892

[40] I. Medeiros, N. Neves, and M. Correia, "Detecting and Removing Web Application Vulnerabilities with Static Analysis and Data Mining," *IEEE Transactions on Reliability*, vol. 65, no. 1, pp. 54–69, Mar. 2016, doi: 10.1109/TR.2015.2457411. Available: https://doi.org/10.1109/TR.2015.2457411

[41] Z. Li, D. Zou, S. Xu, X. Ou, H. Jin, S. Wang, Z. Deng, and Y. Zhong, "VulDeePecker: A Deep Learning-Based System for Vulnerability Detection," in *Proceedings of the Network and Distributed System Security Symposium*, San Diego, CA, USA, 2018, doi: 10.14722/ndss.2018.23158. Available: https://doi.org/10.14722/ndss.2018.23158

[42] R. L. Russell, L. Y. Kim, L. H. Hamilton, T. Lazovich, J. A. Harer, O. Ozdemir, P. M. Ellingwood, and M. W. McConley, "Automated Vulnerability Detection in Source Code Using Deep Representation Learning," in *Proceedings of the 17th IEEE International Conference on Machine Learning and Applications*, Orlando, FL, USA, 2018, pp. 757–762, doi: 10.1109/ICMLA.2018.00120. Available: https://doi.org/10.1109/ICMLA.2018.00120

[43] Z. Li, D. Zou, S. Xu, H. Jin, Y. Zhu, and Z. Chen, "SySeVR: A Framework for Using Deep Learning to Detect Software Vulnerabilities," *IEEE Transactions on Dependable and Secure Computing*, vol. 19, no. 4, pp. 2244–2258, 2022, doi: 10.1109/TDSC.2021.3051525. Available: https://doi.org/10.1109/TDSC.2021.3051525

[44] Y. Shin, A. Meneely, L. Williams, and J. A. Osborne, "Evaluating Complexity, Code Churn, and Developer Activity Metrics as Indicators of Software Vulnerabilities," *IEEE Transactions on Software Engineering*, vol. 37, no. 6, pp. 772–787, Nov.–Dec. 2011, doi: 10.1109/TSE.2010.81. Available: https://doi.org/10.1109/TSE.2010.81

[45] S. R. Chidamber and C. F. Kemerer, "A Metrics Suite for Object Oriented Design," *IEEE Transactions on Software Engineering*, vol. 20, no. 6, pp. 476–493, Jun. 1994, doi: 10.1109/32.295895. Available: https://doi.org/10.1109/32.295895

[46] V. J. Hellendoorn, J. Tsay, M. Mukherjee, and M. Hirzel, "Towards Automating Code Review at Scale," in *Proceedings of the 29th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, Athens, Greece, 2021, pp. 1479–1482, doi: 10.1145/3468264.3473134. Available: https://doi.org/10.1145/3468264.3473134

[47] M. Vijayvergiya, M. Salawa, I. Budiselić, D. Zheng, P. Lamblin, M. Ivanković, J. Carin, M. Lewko, J. Andonov, G. Petrović, D. Tarlow, P. Maniatis, and R. Just, "AI-Assisted Assessment of Coding Practices in Modern Code Review," in *Proceedings of the 1st ACM International Conference on AI-Powered Software*, 2024, pp. 85–93, doi: 10.1145/3664646.3665664. Available: https://doi.org/10.1145/3664646.3665664