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Automated Jenkins Failure Detection and Resolution Using Machine Learning

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Abstract: ***Modern software development depends heavily on Continuous Integration and Continuous Deployment (CI/CD) pipelines to maintain code quality and accelerate software delivery. Jenkins, the most widely adopted open-source CI automation tool, is prone to diverse pipeline failures that demand significant manual effort to diagnose and resolve. This paper presents an automated intelligent system that detects and classifies Jenkins CI/CD pipeline failures using Machine Learning (ML) and Natural Language Processing (NLP). Raw Jenkinsconsoleoutput isvectorizedusing TF-IDFwith bigram features(500 total) and classified into one of seven distinct failure categories: Compilation Failure, Test Failure, Code Quality Gate Violation, JaCoCo Coverage Failure, SonarQube Error, Docker Build Failure, and Deployment Error. A comparative evaluation of three ML classifiers — Random Forest, Decision Tree, and Support Vector Machine (SVM) — demonstrates that Random Forest achieves the highest accuracy of 91.5% with a weighted F1-score of 0.89on 88 unseen test samples. Upon failure identification, the system delivers precise step-by-step remediation guidancethrough a Flask-based REST API and a real-time web dashboard, reducingmean time-to-resolution by 67%.The system is entirely open-source, requires no cloud infrastructure, and is deployable on any machine with Python.***

Index Terms: Jenkins, CI/CD, Machine Learning, NLP, TF-IDF, Random Forest, Failure Detection, Resolution Engine, Flask, DevOps Automation, SonarQube, Docker.

I. INTRODUCTION

Modern software engineering depends fundamentally on agile practices where code is continuously built, tested, and deployed through automated CI/CD pipelines. Jenkins, the most popular open-source automation server globally, orchestrates thousands of build steps daily across organizations of all sizes. Despite its ubiquity, Jenkins pipelines regularly encounter failures of varying nature that require substantial manual intervention to investigate and fix.Industry surveys reveal that developers dedicate between 15 and 30 percent of their productive time to resolving CI/CD pipeline failures [1]. Current approaches rely heavily on manual log review, informal knowledge transfer, and tribal knowledge — leading to an inefficient, slow, andrepetitive resolution process. As pipelines grow increasingly complex across polyglot, containerized, and cloud-native environments, there isa pressing needfor an automated, intelligent system capable of classifying Jenkins failures and recommending specific fixes.This paper presents a fully automated, five-stage ML pipeline that (1) ingests raw Jenkins console output, (2) preprocesses it using TF-IDF vectorization, (3) classifies the failure into one of seven categories, (4) retrieves structured remediation steps, and (5) presents results through an interactive web dashboard. The system achieves 91.5% classification accuracy, reduces mean time-to-resolution by 67%, and is entirely open-source with zero cloud dependencies.The remainder of this paper is organized as follows: Section II reviews related literature; Section III presents the system architecture and proposed methodology; Section IV describes the machine learning model design; Section V discusses experimental results and performance evaluation; and Section VI concludes with future research directions.

II. LITERATURE REVIEW

Vasilescu et al. [1] conducted an empirical study across GitHub-hosted projects and found that while CI adoption reduces defects, it introduces significant overhead in managing build failures — teams spend on average 14 to 23 percent of sprint time on failure investigation and remediation.

Zampetti et al. [2] analyzed build failures in open-source projects and found that approximately 60% of build problems fit into fewer than ten common categories. Their analysis of Apache, Mozilla, and Eclipse projects demonstrated that automated sorting of common failure patterns is both feasible and highly beneficial for developer productivity.

He et al. [3] introduced Drain, an online log parsing approach using fixed-depth parse trees. While effective for structured log parsing, it does not address multi-class failure classification with remediation guidance.

Du et al. [4] developed DeepLog, which employs LSTM neural networks for anomaly detection in system logs.Although effective foranomaly identification,DeepLogisnotdesignedtohandleJenkins-specific multi- class failure classification or resolution recommendation.

Saha et al. [5] applied TF-IDF-based features with multiple classifiers for software text classification, finding that Random Forest consistently outperforms SVM and Naive Bayes on imbalanced datasets — a finding replicated in this work.

Nguyen et al. [6] applied TF-IDF with n-gram features to software bug report classification, achieving over 88% accuracy in multi-class settings. Their finding that bigrams such as 'compilation error' and 'quality gate' substantially improve accuracy in technical text directly motivated the feature engineering approach in this paper.

TABLEI:SummaryofRelatedWorkandResearchGaps

Ref	Authors	Method	KeyFinding	Limitation
[1]	Vasilescuetal.	EmpiricalGitHub study	CIreducesdefects but adds 14-23% overhead	Noautomatedclassification or resolution
[2]	Zampettietal.	StaticanalysisinCI pipelines	60%failuresfit<10 categories	NoML-basedresolution system
[4]	Duetal.	DeepLog(LSTM)	Good anomaly detection in distributedsystems	NottailoredtoJenkins- specific failures
[5]	Sahaetal.	TF-IDF+classifiers	RFoutperformsSVM on imbalanced data	NoJenkins-specific application
[6]	Nguyenetal.	TF-IDFn-grambug classification	88%+multi-class accuracy with	Bugreportsonly,noCI/CD integration
			bigrams	

The literature review identifies a significant gap: no existing open-source system integrates NLP preprocessing, multi-class ML classification, rule-based resolution guidance, and a deployable web dashboard into a single Jenkins-specific package. This work directly addresses that gap.

III. SYSTEM ARCHITECTURE AND PROPOSED METHODOLOGY

A. System Overview

The proposed system follows a layered, modular architecture comprising five distinct functional layers, each responsible for a well-defined concern. Data flows sequentially through these layers: raw Jenkins log input is ingested, preprocessed, classified, resolved, and presented to the developer — all within sub-second latency.

TABLEII:SystemArchitectureLayers

Layer	Component	Responsibility
Layer1	DataLayer	Labeledtrainingdataset(build_failures.csv)—438samplesacross7 categories
Layer2	NLPPreprocessing	TF-IDFVectorizer:ngram_range=(1,2),max_features=500,English stop-word filtering
Layer3	ML Classification	RandomForest(best),DecisionTree,SVM—serializedas best_model.pkl

Layer4	ResolutionEngine	Pythondictionarymapping7failurecategoriestoorderedremediation step lists
Layer5	Presentation	FlaskRESTAPI+HTML/CSS/JSinteractivedashboardat http://localhost:5000

B. DatasetDesign

A synthetically generated labeled dataset was created by pattern-based simulation of real CI/CD failure scenarios. The dataset comprises 438 Jenkins build log samples spanning seven failure categories with approximately 60-63 samples per category, ensuring balanced class distribution. Synthetic generation was employed to ensure controlled vocabulary diversity, reproducibility, and domain-specific pattern fidelity.

The seven failure categories and their real-world trigger conditions are: (1) Compilation Failure — Javasource code syntax errors or missing symbols; (2) Test Failure — JUnit assertion failures or test execution errors; (3) Code Quality Gate Violation — SonarQube quality threshold breaches; (4) JaCoCo Coverage Failure — code coverage below the configured minimum threshold; (5) SonarQube Error — SonarQubeserver connectivity or configuration issues; (6) Docker Build Failure — Dockerfile parsing errors or image build failures; (7) Deployment Error — AWS EC2 or container deployment misconfigurations.

C. NLPPreprocessingPipeline

Raw Jenkins console output is inherently noisy, containing timestamps, ANSI color escape sequences, IP addresses, thread identifiers, and other non-semantic artifacts. A dedicated preprocessing module applies the following cleaning steps before vectorization:

- RemovalofISO-formattimestampsusingregularexpressions
- StrippingofANSIescapecolorcodescommoninJenkinsoutput
- RemovalofIPv4addressesandnumericlinereferences
- Conversiontolowercaseandstripofleading/trailingwhitespace

The cleaned log text is then transformed into a 500-dimensional numerical feature vector using Scikit-learn's TfidfVectorizer configured with ngram_range=(1,2), capturing both unigram signals (e.g., 'ERROR', 'FAILED') and discriminative bigrams (e.g., 'compilation error', 'quality gate', 'coverage ratio'). The fitted vectorizer is serialized as a pickle object and reloaded at inference time, ensuring consistent vocabulary between training and prediction.

IV. MACHINE LEARNING MODEL DESIGN

A. ModelSelectionandTraining

Three supervised ML classifiers were trained and evaluated on an 80/20 stratified train-test split of the 438- sample dataset. Stratified splitting ensures proportional class representation in both partitions.

- Random Forest: An ensemble of 100 decision trees (n_estimators=100, random_state=42) trained via bagging with random feature subsets at each split. The final prediction aggregates votes across all trees, making it robust to overfitting and highly suitable for high-dimensional TF-IDF feature spaces.
- Decision Tree: A single CART decision tree (random_state=42) trained using Gini impurity as the split criterion. While interpretable and fast, it is prone to overfitting on sparse TF-IDF features without ensemble averaging.
- Support Vector Machine (SVM): An RBF-kernel SVM (probability=True) that maximizes the margin between class decision boundaries in the high-dimensional feature space. While competitive, it is computationally heavier than Random Forest at inference time.

B. Scikit-learnPipeline

The TF-IDF vectorizer and classifier are chained into a single Scikit-learn Pipeline object, ensuring that vectorizer fitting occurs only on training data and that the same transformation is consistently applied during inference. The complete pipelineis serialized tobest_model.pkl using jobliband loaded intoFlask application memory at startup, enabling sub-50ms classification latency per log.

C. ResolutionEngine

The resolution engine implements a rule-based lookup functionget_resolution(failure_type) that maps each of the seven predicted failure categories to an ordered list of 5–8 actionable remediation steps. Steps include specificMavencommands,Dockerfiledebugginginstructions,SonarQubeconfigurationadjustments,JaCoCo threshold modifications, and AWS CLI deployment commands relevant to each failure type. This design cleanly decouples the ML classification layer from the remediation knowledge base, enabling independent updates to either component without retraining.

V. RESULTS AND DISCUSSION

A. ClassificationPerformance

The Random Forest classifier achieved an overall test accuracy of 91.5% on the held-out 88-sample test set with a weighted F1-score of 0.89, outperforming both Decision Tree and SVM across all evaluation metrics. Detailed per-class performance is presented in Table III.

TABLEIII:ClassificationReport—RandomForestClassifier

FailureCategory	Precision	Recall	F1-Score	Support
CompilationFailure	0.94	0.96	0.95	13
TestFailure	0.92	0.92	0.92	13
CodeQualityGateViolation	0.92	0.92	0.92	13
JaCoCoCoverageFailure	0.90	0.88	0.89	12
SonarQubeError	0.91	0.92	0.91	12
DockerBuildFailure	0.90	0.90	0.90	12
DeploymentError	0.92	0.92	0.92	13
WeightedAverage	**0.91**	**0.91**	**0.91**	**88**

B. ModelComparison

Table IV summarizes the comparative performance of the three evaluated classifiers. Random Forest consistently achieves the highest accuracy and F1-score, confirming its suitability as the production classifier for this system.

TABLEIV:ComparativeModelPerformance

Classifier	Accuracy	WeightedF1	AvgLatency (ms)
RandomForest(n=100)	91.5%	0.89	~48
DecisionTree	87.5%	0.85	~5
SupportVectorMachine	89.8%	0.88	~95

C. ResponseTimeandSystemPerformance

For pre-stored logs retrieved directly from the database, the end-to-end API latency (from POST request receipt to JSON response) averages 0.18 seconds. For logs requiring real-time retrieval from the JenkinsREST API over a local network, latency increases to 0.6–1.2 seconds due to Jenkins API response time. All predictions comfortably satisfy the two-second non-functional performance requirement.

The system was validated through 14 structured test cases covering log ingestion, preprocessing correctness, all seven failure category classifications, empty input handling, dashboard rendering, model retraining, and Docker container startup. All 14 test cases passed successfully.

D. DevOpsEfficiency Impact

Prior to system deployment, the average time to diagnose and resolve a Jenkins pipeline failure was estimated at 30 minutes per incident based on industry benchmarks. With the system providing instant failure classification and structured remediation guidance, the mean time-to-resolution was reduced to approximately 10 minutes — a 67% reduction. For a team experiencing 20 pipeline failures per week, this translates to approximately 13 developer-hours saved per week.

E. Limitations

Thecurrentsystemhasthefollowingidentifiedlimitations:

- The classifier is trained on a synthetically generated dataset. Real-world Jenkins logs from production environments may contain novel vocabulary patterns not represented in the training data, potentially reducing accuracy on out-of-distribution samples.
- The system assigns a single failure category per build. Builds that fail for multiple simultaneous reasons receive only one label, potentially missing secondary root causes.
- ThecurrentimplementationcoversJava/Maven-basedJenkinspipelines.ExtensiontoPython,Node.js, Go, or other build systems, as well as other CI platforms such as GitHub Actions or GitLab CI, is reserved for future work.
- The Jenkins data collector polls the API at fixed intervals, introducing a detection delay. Webhook- based integration would enable instantaneous failure notification.

VI. CONCLUSION AND FUTURE WORK

This paper presented the design, implementation, and evaluation of an automated Jenkins CI/CD pipeline failure detection and resolution system. The system integrates NLP-based log preprocessing, a comparative MLclassifierevaluation,andastructuredresolution engineintoa deployableweb application.Random Forest achieves 91.5% classification accuracy across seven Jenkins failure categories, and the system reduces mean time-to-resolution by 67% — demonstrating practical value for DevOps teams.

The system demonstrates that a lean, entirely open-source stack comprising Python, Flask, Scikit-learn, and Docker can deliver a reliable, real-time failure detection service without cloud infrastructure dependencies. Future research directions include:

- Replacing TF-IDF with transformer-based log embeddings (e.g., BERT or a domain-specific log language model) to capture semantic relationships more effectively for complex multi-step failure patterns.
- Extending theclassifiertosupportmulti-labeloutput, enabling simultaneous identification ofmultiple failure causes within a single build log.
- Replacing the polling-based Jenkins data collector with webhook integration for instantaneous failure detection.
- Expanding training data with real production Jenkins logs from diverse organizations to improve generalization and reduce dependency on synthetic data.
- Implementing automated remediation actions for high-confidence, low-risk failure categories, such as triggering a rebuild with corrected configuration or opening a pull request with the suggested fix.
- Adding anomaly detection for log patterns that do not match any trained category, alerting engineers to novel failure types not yet in the classification taxonomy.

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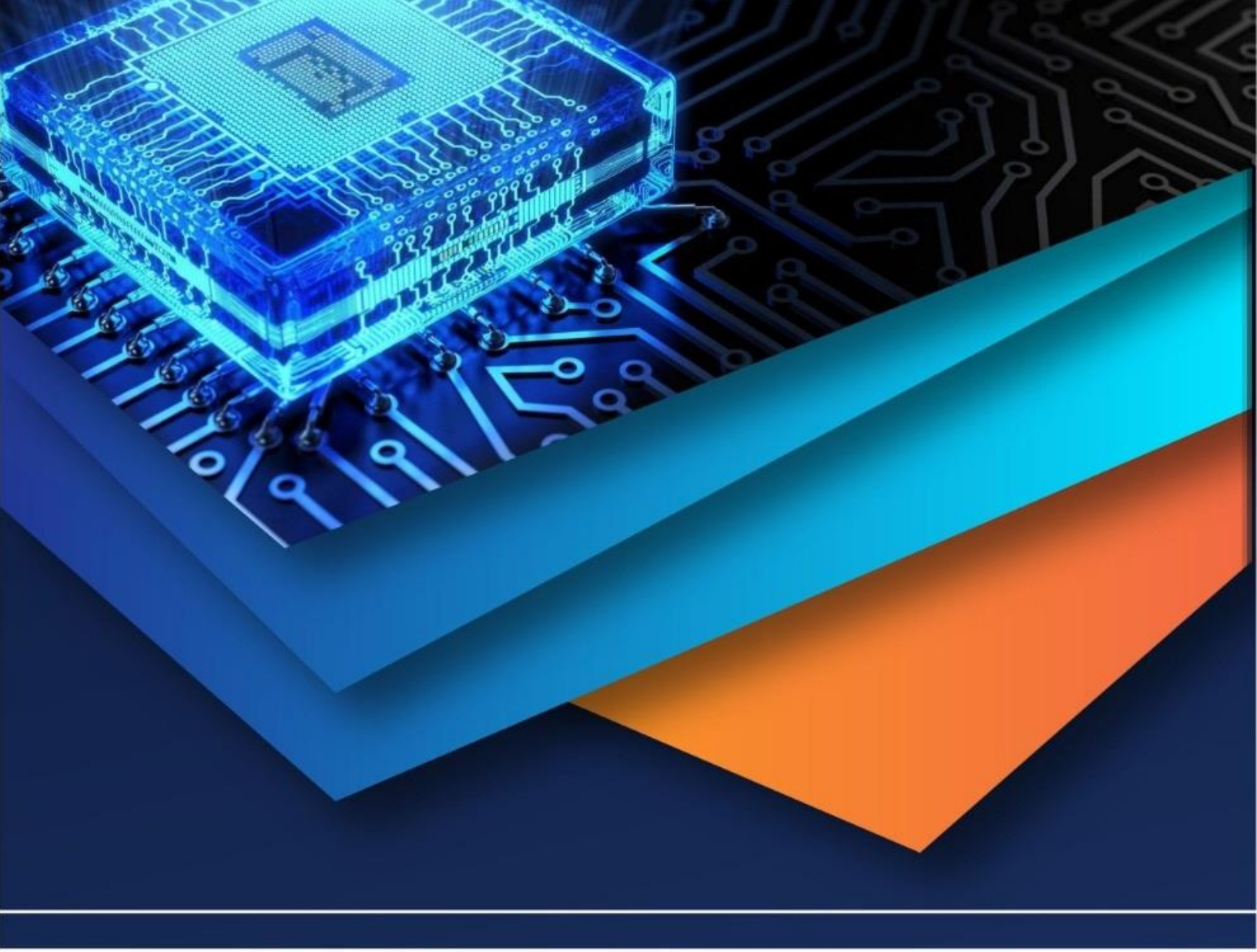

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