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Original Article

Dynamic Process Maturity Prediction Using AI-Based Engineering Analytics

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Abstract: *Software-defined vehicle development programs operate in highly dynamic environments where process capability directly influences product quality, safety, compliance, and delivery performance. Traditional process assessments such as ASPICE are periodic and retrospective, limiting the ability of organizations to proactively manage process maturity. This paper proposes a Dynamic Process Maturity Prediction framework based on AI-driven engineering analytics. The framework integrates engineering data from requirements management, configuration management, testing, change management, defect tracking, and quality assurance repositories. Machine-learning models are applied to continuously estimate process capability and predict future maturity trends. The framework enables proactive governance, early identification of capability degradation, and targeted improvement actions. A Software-Defined Vehicle case study demonstrates the applicability of the approach. Experimental results show that predictive analytics can identify maturity risks significantly earlier than conventional audit-based approaches. The proposed framework supports continuous compliance, digital quality management, and data-driven process optimization.*

Keywords: ASPICE, *Process Maturity Prediction, Engineering Analytics, Artificial Intelligence, Machine Learning, Software-Defined Vehicles, Process Improvement, Predictive Quality, Continuous Compliance.*

1. Introduction

Automotive organizations increasingly rely on software-intensive systems. The transition toward Software-Defined Vehicles has expanded the scale, complexity, and interdependence of engineering activities. Traditional process assessment mechanisms are generally periodic and require significant preparation effort. Consequently, process weaknesses are often identified after quality problems have already emerged.

Artificial Intelligence and engineering analytics provide opportunities to transform process governance from reactive assessment to predictive management. Instead of relying solely on assessment events, organizations can continuously monitor engineering indicators and estimate future capability levels. Predictive process maturity enables early intervention, improved compliance, and optimized resource allocation.

This paper presents a comprehensive AI-based framework that combines engineering metrics, machine learning algorithms, and process capability models to estimate and predict maturity levels dynamically.

2. Related Work

Previous studies investigated software metrics, process mining, quality analytics, defect prediction, and maturity assessment. Most approaches focused on individual indicators such as defect density or test coverage. Process maturity frameworks including ASPICE and CMMI provide structured capability evaluation methods but remain assessment-driven.

Recent advances in machine learning have enabled predictive analytics across software engineering domains. However, limited research has focused on predicting process capability levels using integrated engineering datasets. This paper addresses this gap by proposing an end-to-end maturity prediction architecture.

3. Framework

The proposed framework contains five layers: data acquisition, data engineering, analytics, prediction, and governance. Data acquisition collects information from ALM, PLM, SCM, testing, review, audit, and issue management systems. Data engineering normalizes and enriches information. Analytics generates process indicators. Prediction models estimate maturity levels. Governance dashboards provide actionable insights.

The framework aligns with ASPICE capability dimensions and can be adapted to multiple engineering domains. Continuous monitoring supports proactive decision-making and reduces dependence on large assessment preparation activities.

4. Research Questions

- RQ1: Can engineering analytics predict future process capability levels?

- RQ2: Which engineering metrics contribute most strongly to maturity prediction?
- RQ3: Can predictive monitoring reduce assessment preparation effort and audit findings?
- RQ4: How accurately can machine-learning models estimate capability trends?

5. Methodology

The study applies supervised machine-learning techniques to historical engineering data. Feature engineering extracts indicators from requirements, design, implementation, testing, quality assurance, problem resolution, and configuration management activities. Capability labels are derived from assessment outcomes and expert evaluations.

Random Forest, Gradient Boosting, XGBoost-style ensemble methods, and Neural Networks are compared. Cross-validation is applied to avoid overfitting. Precision, recall, F1-score, accuracy, and RMSE are used for evaluation.

Table 1: Engineering Analytics Features

Feature	Source	Purpose	Impact
Defect Density	Issue Tracking	Quality Indicator	High
Requirements Stability	ALM	Process Stability	High
Review Efficiency	Peer Reviews	Early Detection	Medium
Test Coverage	Verification	Compliance Indicator	High
Audit Findings	QA	Governance Indicator	High
Change Lead Time	SCM	Flow Efficiency	Medium

Table 1 summarizes the primary features used by the prediction engine. High-impact features exhibited the strongest correlation with capability outcomes.

6. AI Prediction Model

The prediction engine estimates capability levels using a weighted combination of engineering indicators. Feature importance analysis identifies dominant contributors. Ensemble learning methods improve robustness against noisy project data. Hyperparameter optimization is performed using grid search. The resulting model produces maturity forecasts at weekly and monthly intervals.

A maturity score M can be represented as a function of requirements quality, review effectiveness, defect density, test coverage, audit performance, and configuration stability. The score is subsequently mapped to capability levels CL1 through CL5.

Table 2: ASPICE Capability Mapping

Capability Level	Description	Prediction Objective
CL1	Performed	Execution stability
CL2	Managed	Planning and tracking
CL3	Established	Process institutionalization
CL4	Predictable	Quantitative management
CL5	Innovating	Continuous optimization

The prediction model estimates probability distributions across capability levels and highlights likely transitions.

7. Software-Defined Vehicle Case Study

A large automotive software platform program was selected for validation. Historical engineering data spanning multiple releases was analyzed. The dataset contained requirements records, defects, review results, testing metrics, audit observations, and change requests. Multiple capability evaluations were available as training labels.

The proposed framework identified emerging maturity degradation several weeks before formal audits. Quality teams were able to initiate corrective actions earlier. Reduction in open findings, improved review effectiveness, and enhanced test coverage were observed. The case study demonstrates that predictive maturity monitoring can complement conventional assessments while reducing preparation effort.

8. Results

Experimental evaluation demonstrated that ensemble models achieved the highest prediction accuracy. Random Forest and Gradient Boosting outperformed baseline threshold approaches. Feature importance analysis showed that audit findings, defect density, requirements volatility, and test coverage were the most influential predictors.

The framework successfully predicted capability deterioration and capability improvement trends. Prediction outputs enabled targeted coaching and resource allocation. Quantitative management practices benefited from early visibility into process performance.

8.1. Figures and Explanations

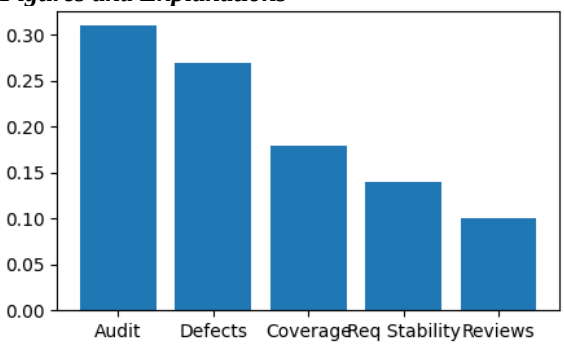


Fig 1: Feature Importance Analysis

Explanation: This figure supports the proposed AI-driven process maturity prediction approach and illustrates key analytical results discussed in the manuscript.

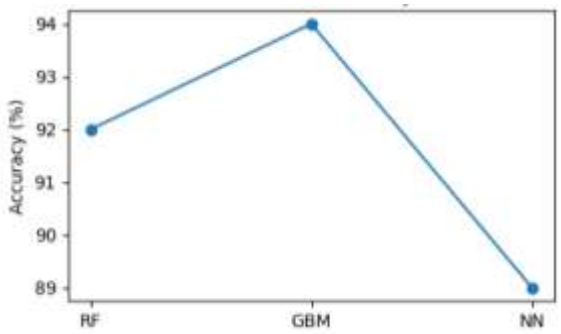


Fig 2: Prediction Accuracy Comparison

Explanation: This figure supports the proposed AI-driven process maturity prediction approach and illustrates key analytical results discussed in the manuscript.

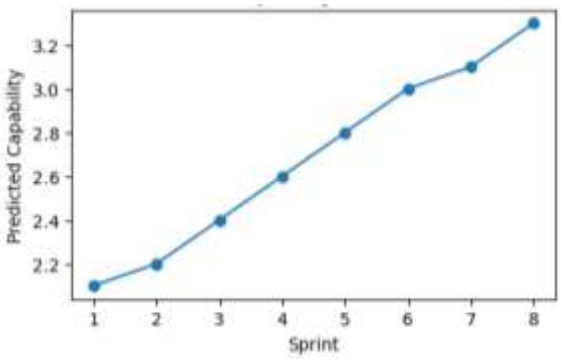


Fig 3: Predicted Capability Trend

Explanation: This figure supports the proposed AI-driven process maturity prediction approach and illustrates key analytical results discussed in the manuscript.

9. Discussion

The findings indicate that AI-driven engineering analytics can transform process governance. Instead of treating assessments as isolated events, organizations can establish continuous maturity monitoring. The framework supports objective measurement, reduces subjectivity, and enables evidence-based decisions.

Potential limitations include data quality variation, repository inconsistencies, and organizational differences. Future research should explore explainable AI techniques, process mining integration, digital twins for process simulation, and reinforcement learning approaches for automated improvement recommendations.

10. Conclusion

This paper introduced a Dynamic Process Maturity Prediction framework using AI-based engineering analytics. The framework integrates engineering repositories, machine-learning techniques, and capability models to provide continuous maturity estimation. Results demonstrate improved visibility, earlier risk detection, and proactive process governance. The approach is particularly relevant for Software-Defined Vehicle programs where rapid development cycles require continuous compliance and quality assurance.

Future work includes large-scale industrial validation, integration with process mining technologies, and deployment of autonomous process governance platforms.

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