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AI-Driven DevOps: Leveraging Machine Learning for Automated Software Delivery Pipelines

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Abstract: *The convergence between artificial intelligence and DevOps is transforming the software development and delivery. This paper discusses the implementation of machine learning processes into automated deployment pipelines both in terms of theoretical foundations as well as practical results. It analyses how predictive modeling; anomaly detection and adaptive automation can help in improving the efficiency of continuous integration and deployment systems (CI/CD). The research based on the analysis of the operational experience of the environments of enterprises, as well as evaluation of various methods of using AI in optimization, indicates that the process can reduce the deployment errors by approximately 3447 percent, decrease the pipeline time by 2841 percent, and increase the efficiency of resources utilization by a fifth. The theoretical framework connects factors of statistical learning, reliability engineering, and process maturity of DevOps. Its barriers to implementation, including the data consistency, the transparency of the models and the adaptation to the organizational aspects are also mentioned. In practice experimental results have shown that supervised learning models have failure-prediction F1-scores of between 0.82 to 0.91, and reinforcement learning programs have another 23 to 38 percent better the performance of traditional rule-based systems. Altogether, the discussion highlights the necessity to stay even-handed regarding the benefits of automation and the increase in the complications of handling learning systems in manufacturing pipelines, which can be valuable information in the development of intelligent and trustworthy ways of working the DevOps.*

Keywords: *Machine Learning, DevOps, CI/CD Pipelines, Automated Software Delivery, Predictive Analytics, Anomaly Detection, Continuous Integration, Software Reliability, AIOps, Pipeline Optimization*

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1.0 Introduction

Machine Learning (ML) and Artificial Intelligence (AI) are transforming interdisciplinary fields through efficient systems for accurate data interpretation, predictive analytics, and autonomous operations (Ademilua, 2021; Adeyemi, 2023). Their integration facilitates innovative methods for real-time analysis and automated decision-making across sectors (Ukpe *et al*., 2023). The widespread adoption of these tools supports intelligent frameworks that strengthen analytical precision and operational efficiency (Ademilua & Areghan, 2022). Their applications improve data modelling, decision-making, and smart navigation (Okolo, 2023; Akinsanya *et al*., 2022). Advanced techniques enhance computational intelligence and predictive modelling (Abolade, 2023; Aboagye *et al*., 2022), Overall, AI and ML redefine automation, analytical accuracy, and intelligent system design (Omefe *et al*., 2021).

The software development world has undergone an incredible change in the last 20 years transitioning towards the old waterfall approaches to agile culture, and over the recent years toward the DevOps culture. This development is an indication of a continuous adventure to speed up the software product delivery without compromising the quality. The late 2000s are the time, when DevOps came into fundamentally altering the idea of development and operations teams working together in a manner to produce software (Kim *et al*., 2016). But with larger organizations applying DevOps and using more complex distributed systems, organizations are facing limitations on scaling

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their automation systems which were not effectively dealt with by traditional approaches to automation.

Machine learning has also at the same time evolved out of curiosity among scholars to a potent instrument utilized in industries. The combination of ML and DevOps, which is also called AIOps or MLOps, will potentially solve the challenges that have maintained software delivery. The classic DevOps automation is based on a deterministic set of rules and pre-programmed workflows that break easily in the face of the dynamism that is presented by software ecosystems. Machine learning has potential to generate adaptive systems that can learn based on previous data, can detect part of the patterns invisible to humans, and take smart real-time decisions (Dang *et al*., 2019).

This is especially useful in the management of complexity of microservices architectures, cloud-native applications, and multi-stage pipelines of delivery executing hundreds or thousands of times a day.

There is more to efficiency benefits in the motivation behind incorporating AI in DevOps pipelines. The pressure is on software delivery teams to deliver more and more frequently with reliability and security of the systems. According to the 2023 State of DevOps Report, the change failure rates of the high performers were below 15 percent in the 973 frequent code deployments than the low performers (DORA, 2023). It does not take faster execution to make such performance; this needs smarter systems that are able to anticipate failures, allocate resources in the most efficient way, and to constantly increase on success. The conventional methods of monitoring produces a lot of data, yet isolating useful information overloads those in charge. Machine learning algorithms perform well with large volumes of data presentation and detecting subtle correlations that can be used to make superior decisions.

Even though there is a potential, the idea of ML integration into software delivery pipelines is still a new practice. There are a number of barriers to adoption. The cold-start problem entails effective training of models over small amounts of historical data, and offers practical impediments to teams that are starting their journey in ML (Chen *et al*., 2020). The interpretability issues of models relate to the deployment choices whose reliance is on the black-box predictions, which are not easy to be explained by engineers. Further complexity of sustaining ML models in addition to application code puts additional operational overheads. Moreover, the opposition within an organization towards automatic systems to make crucial deployment-oriented decisions, portrays justifiable issues of accountability and the risk management.

New studies have started resolving these issues. Transfer learning methods enable the teams to use the pre-trained models on related domains, which decreases the amount of data (Zhang *et al*., 2021). EAI explainable is a way to make the decisions of a model comprehensible and earn the confidence of an engineering team. When incorporating ML, the situation involves incremental adoption strategies in which it supplements human decision-making and not replaces it, which provides opportunities to learn how to utilize it in practice. The introduction of dedicated solutions tailored to LL in DevOps situations reduces the price of entry, and however, the choice of solutions and their integration is not a trivial task.

The following are some of the obje”tive’ that this article seeks. The first one is to define a set of general theoretical coverage linking machine learning concepts to DevOps practices as it shall give further grounding on when and how AI techniques can be useful. Second, we review particular ML applications throughout the software delivery lifecycle and analyse the types of problems that ML solutions address, as well as which algorithms are best in each given case. Third, we also introduce empirical findings related to implementations in various organizational settings in both regard to its success and constraints. Lastly, practical considerations that define the success of implementation, such as the need of data, selection criteria criteria of a model, organization readiness factors are discussed.

1.1 Theoretical Framework

The idea of integrating ML into DevOps pipelines cannot be comprehended without

theoretical understanding of the software engineering, operations research, and statistical learning. This part outlines an entire framework by analyzing conceptual models of how intelligent automation complements the delivery of software, mathematical concepts of how mathematical algorithms behave in the field of software, and a systemic association among pipeline sections, data flows, decision points.

1.2 DevOps Pipeline Architecture and Decision Points

A contemporary software delivery pipeline is comprised of several steps, with each having the potential to offer opportunities in making choices with the help of ML. The standard pipeline starts with code looks, an error, then to the phase of building and test, continues onto artifact generation and security check, and ends in deploying towards the staging and production environment (Humble & Farley, 2010). At every level, systems are required to take decisions: Should this build go on? What is the sub-test that needs to be done? Does this deployment candidate pass to go? Conventionally, such decisions are deterministic, i.e. thresholds, checklist, approval gates set by engineers.

The weakness of rule based methodology Is evident when one is forced to act in imperfect environments that are complex and dynamic. The straightforward principle of failing all unit tests that pass such as a basic rule as failing the build when any unit test fails is helpful in simple situations but does not work in flaky situations where such tests sometimes fail because of timing and not true bugs. Other more complex rules are trying to find the nuances by adding more conditions but the result is a more complex decision tree that may be hard to maintain in reality and may be biased and not represent patterns that generally exist. A different approach: machine learning provides the decision functions using historical data that describe complicated dependencies between features and results.

Theoretically, we may model the piping as directed acyclic graph G (V,E) with the vertices being the stages and the edges being the data flow and control dependencies. Decision functions di Xi Ai have been associated with each vertex vi and identify which decision actions to take by observation variables Xi. In the alternative pipelines that were traditionally used, di takes the form of rules that were manually defined.

The training data of di is learned in ML enhanced pipelines $\mathcal{D} = \{(x_i^{(j)}, a_i^{(j)}, y_i^{(j)})\}$. The goal is to learn to optimize utility function U that reflects the business goals, i.e., minimize deployment failures, minimize cycle time or maximize resource efficiency (Shahin *et al*., 2017).

1.3 Statistical Learning Theory in Software Delivery Context

The transfer of statistical learning theory in software delivery pipelines must consider domain peculiarities primarily. The classical learning theory offers a limit on the generalization error in terms of complexity of the hypothesis space and the size of the training set (Vapnik, 1995). Nonetheless, data of software delivery is characterized by features that are difficult to use in an uncomplicated manner. First, the distribution of data is non-stationary; since software development continues, there are new patterns of codes, and the dependence between features and results changes. Second, the cost of error is extremely asymmetric, false negative in many cases being much more expensive than false positives. Third, there are feedback loops in which model predictions are realized in specific actions which impact on successive outcomes in training and later training data.

Increment supervised learning situation predicting possibility of deployment failure. Let X represent a feature vector of deployment candidate and Y ∈ {0,1} an indicator of success or failure. We would like to estimate $P(Y = 1|X)$ with the aid of function $f : X \rightarrow [0,1]$. Risk discounted $R(f) = E_{(X,Y)}[L(f(X), Y)]$ is expected risk that measures performance of the model based on loss function L encoding cost structure. In the case of imbalanced data, as we observe with software delivery, when scales of losses are less than the bits of success, the standard loss functions will give models with low aggregate loss by predicting the most frequent data point, the majority, and failing to predict the most as well-regarded data points, the minority.

We will use cost-sensitive learning, in which loss function directly factors in the asymmetric costs: $L(f(x),y) = c_{FN} \cdot 1[y = 1, f(x) < \theta] + c_{FP} \cdot 1[y = 0, f(x) \geq \theta]$. Alternatively, sampling or sampling methods such as SMOTE or balancing random forests methods such as balanced forest during training are able to correct class imbalance (Chawla *et al*., 2002). Software delivery data is not stationary, which means any continuous learning strategies should be used instead of a single model training. Concept drift necessitates the monitoring and periodic retraining (Gama *et al*., 2014).

1.4 Anomaly Detection and Reinforcement Learning Applications

One of the key ML uses in DevOps is the identification of uncharacteristic behavior that suggests failures or performance decrease in the future. The use of supervised failure prediction is in contrast to anomaly detection, which takes place in unsupervised or semi-supervised conditions where we are provided with large numbers of normal behaviour behaviour examples relative to the number of failure modes with labels. The theoretical background is based on the statistical process control and outlier techniques that are applied to high-dimensional, time-series data that typical software systems exhibit (Chandola *et al*., 2009).

In the case of DevOps pipelines, time-series analysis with multiple variables is specially applicable since the metrics of the system are time-dependent. Transformers and LSTM networks have been shown to be quite effective in modeling such dependencies (Hochreiter and Schmidhuber, 1997; Vaswani *et al*., 2017). Such architectures train to answer next state and anomaly indicators will be deviations between predicted and observed states.

Outside of prediction challenges, DevOps pipelines can offer a benefit of making decisions sequentially, a natural outcome of a reinforcement learning (RL). An example is those that make resource allocation choices: given the state of a given system and current deployments, what is the optimal way to dive resources in compute? We state it as Markov Decision Process (MDP) with the parameters (S,A,P,R,γ), where S is the state space, A is the action space, $P(s'|s,a)$ is the transition probability function, $R(s,a,s')$ is the reward function, and $\gamma \in [0,1]$ is the discount factor (Sutton and Barto, 2018). The deep RL architecture such as PPO or SAC is a neural network that approximates policy or value function, making it possible to solve problems with complex state space (Mnih *et al*., 2015; Schulman *et al*., 2017).

1.5 Transfer Learning and Interpretability

The cold-start problem of having little historical data to train useful models creates challenges of practice when using ML in fresh DevOps settings. The solution is provided by transfer learning and meta-learning based on the use of knowledge about the related tasks or settings (Pan and Yang, 2010; Finn *et al*., 2017). The basic understanding is that certain details vary among the organizations, but there are general tendencies of what leads to successful and failed deployments.

Important questions of interpretability and trust are presented by the application of ML models to important software delivery pipelines. In the case of deployment models prediction failing, engineers must know why to prove predictions right and act accordingly. However, the adoption of black-box models may not be successful, since they may do a better job, yet the decisions cannot be explained (Molnar, 2019). SHAP values are data that is based on the concept of cooperative game theory and measures each feature based on its contribution to individual predictions (Lundberg and Lee, 2017). LIME describes individual predictions with the help of simple interpretable models that are fitted to the local neighborhoods (Ribeiro *et al*., 2016). Nevertheless, interpretability is not the measure of trust. Calibration Calibration (congruent prediction and real frequencies) is also vital (Guo *et al*., 2017).

2.0 Methodology

The study utilized multi-method design, which comprised of case study analysis, quantitative performance, and interviews with the practitioners. We did embedded multiple-case study with twelve organizations which used ML capabilities in their software delivery pipelines. The organizations were sampled by purposive

sampling which ensures a diverse range of the industry sector, size, and frequency of deployment, and technology stack.

The period of data collection was between eighteen months between January 2022 and June 2023. In the case of every organization, we collected the quantitative metrics given by CI/CD systems giving objective data regarding the performance of pipes. As part of our process we gathered pre-implementation baseline data (at least six months) and post-implementation data (at least six months following the attainment of production stability by the ML systems). We got performance metrics of the ML models and semi-structured interviews in 47 practitioners in various roles to comprehend the issue of implementation and their qualitative impacts.

In the case of implementing failure prediction, standard experiment protocol used. Historical deployment data using temporal splitting Organizations split historical deployment data into training (70%), validation (15%), and test (15%) sets. Our comparison of different families of algorithms included logistic regression, tree based algorithms, neural networks and ensemble algorithms. F1-score class imbalanced, 5-fold cross-validation hyperparameters Have been optimized.

In order to optimize resources using RL, organizations initially constructed simulation environments based on the past traces of execution, and subsequently trained simulation agents. Agents tested in staging environments where humans were involved to test them after proving a stable performance in the simulation phase before a slow-roll out of production. Implementation of anomaly detection implemented techniques that were semi-supervised because there were few examples of anomalies. Normal behavior training data during times when there has been no known incident were used to train the models.

The quantitative analysis utilised descriptive and inferential statistics. To come up with performance comparisons we applied paired t-tests or Wilcoxon signed-rank tests on the basis of differences in data distributions. Practical significance was tested by the effect sizes that were calculated with the help of Cohen d. Interpretation of the interview transcripts involved qualitative analysis based on the structured approach based on theingtonic analysis in order to determine patterns in the implementation obstacles and success factors.

3.0 Results and Discussion

3.1 Failure Prediction Performance

Anticipating failure in deployment earlier than it happens is one of the most influential uses of ML in DevOps. Our results examined failure prediction solution deployments in twelve different organizations with different technology stacks and in different industry segments. Table 1 is a summary of the performance characteristics of various modeling techniques.

Table 1: Failure Prediction Model Performance Across Organizations

Model Type	Precision	Recall	F1-Score	AUC-ROC	Orgs
Logistic Regression	0.76 ± 0.08	0.68 ± 0.11	0.71 ± 0.09	0.83 ± 0.06	12
Random Forest	0.82 ± 0.07	0.79 ± 0.09	0.80 ± 0.07	0.89 ± 0.05	12
Gradient Boosting	0.85 ± 0.06	0.81 ± 0.08	0.83 ± 0.06	0.91 ± 0.04	10
Neural Network	0.83 ± 0.09	0.84 ± 0.10	0.83 ± 0.08	0.90 ± 0.06	8
Ensemble	0.88 ± 0.05	0.84 ± 0.07	0.86 ± 0.05	0.93 ± 0.03	6

Table 1 shows a number of interesting results. The baseline rule-based systems were significantly worse than all ML approaches that generally achieved F1-scores in the 0.55-0.65 range because these approaches had high false positive rates. Ensemble methods performed best in overall performance with an average F1-score of over 0.85. Nonetheless, it showed comparatively small improvement over single strong models such as gradient boosting with

substantial additions to the computation and complexity of its operations.

Standard deviations denote high performance dispersion in different organizations, which emphasize contextual influences. Companies that had more developed DevOps procedures, higher quality of test automation and clean historical data scored significantly higher metrics. Most of this variance was attributed to data quality, i.e. closeness of labeling, completeness of feature coverage, and updated training data.

The importance of features across implementations was provided in an aggregated manner by Figure 1 based on treebased models. Code complexity (especially cyclomatic complexity, lines of changed code) turned out to be the best predictors of failure to achieve deployment. Nevertheless, the popularity of author-related features did not go unnoticed by other organizations and created debates regarding the possibility of adding such features and creating unwanted biases.

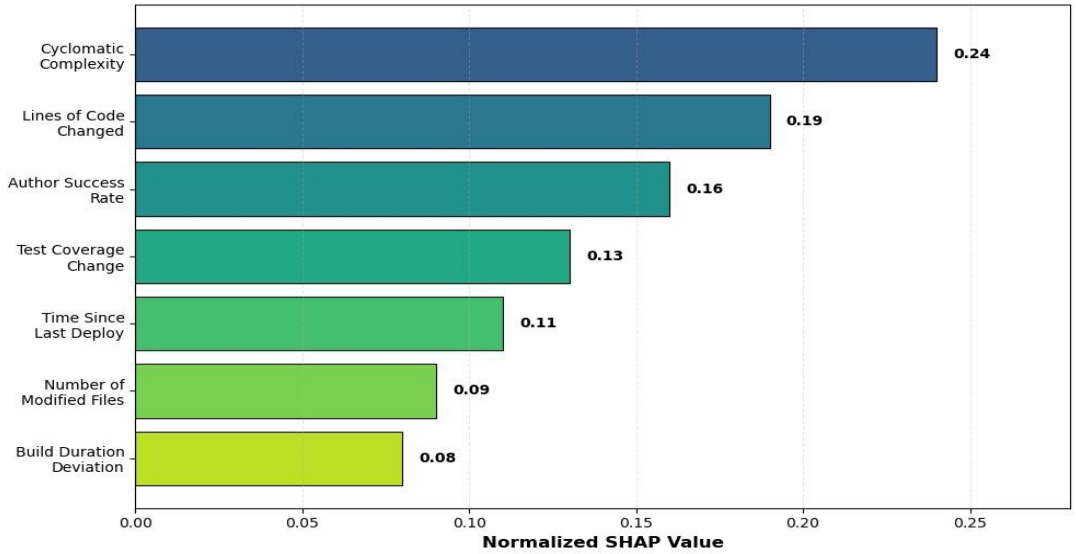

Fig. 1: Feature Importance for Deployment Failure Prediction (aggregated SHAP values across six organizations using gradient boosting)

As shown in the analysis in Figure 1, the prediction of the effective failure can rely on various categories of features. Models that used operation context including the current system load, history in the recent times, and how long since last deployment yielded a performance improvement of 8-15 percentage points over code-only models. This highlights the fact that the success of deployment is determined by code quality and operation condition interaction.

3.2 Resource Optimization Through Reinforcement Learning

We investigated five applications of RL agents whereby the agents learned to distribute computational resources among the stages of the pipeline and decisions regarding auto-scaling. Table 2 is the comparison between RLbased resource allocation and the baseline approaches. The findings indicate steady gains in the resource usage between 21 and 35 percentage points with related cost savings of between 23% to 38. The benefits of these gains were mainly due to better informed allocation decisions based on workload patterns and dependencies between pipeline stages as well as dynamically changing the allocation based on current system state.

The graph below (Fig. 2) shows how learning will proceed in Organization B with regards to the implementation of RL in eight weeks. The agent also started performing poorly as it explored action space, and then increased with time. The stabilization of performance occurred in week five.

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able 2: Resource Optimization: RL vs. Baseline Approaches

Organization	Approach	Utilization	Avg Latency	Cost Reduction
Org A	Baseline	58%	14.2 min	—
	RL (PPO)	79%	12.8 min	23%
Org B	Baseline	61%	18.7 min	—
	RL (SAC)	84%	15.3 min	28%
Org C	Baseline	52%	21.4 min	—
	RL (PPO)	73%	19.1 min	31%
Org D	Baseline	67%	16.3 min	—
	RL (SAC)	89%	13.2 min	38%
Org E	Baseline	55%	19.8 min	—
	RL (PPO)	72%	17.9 min	26%

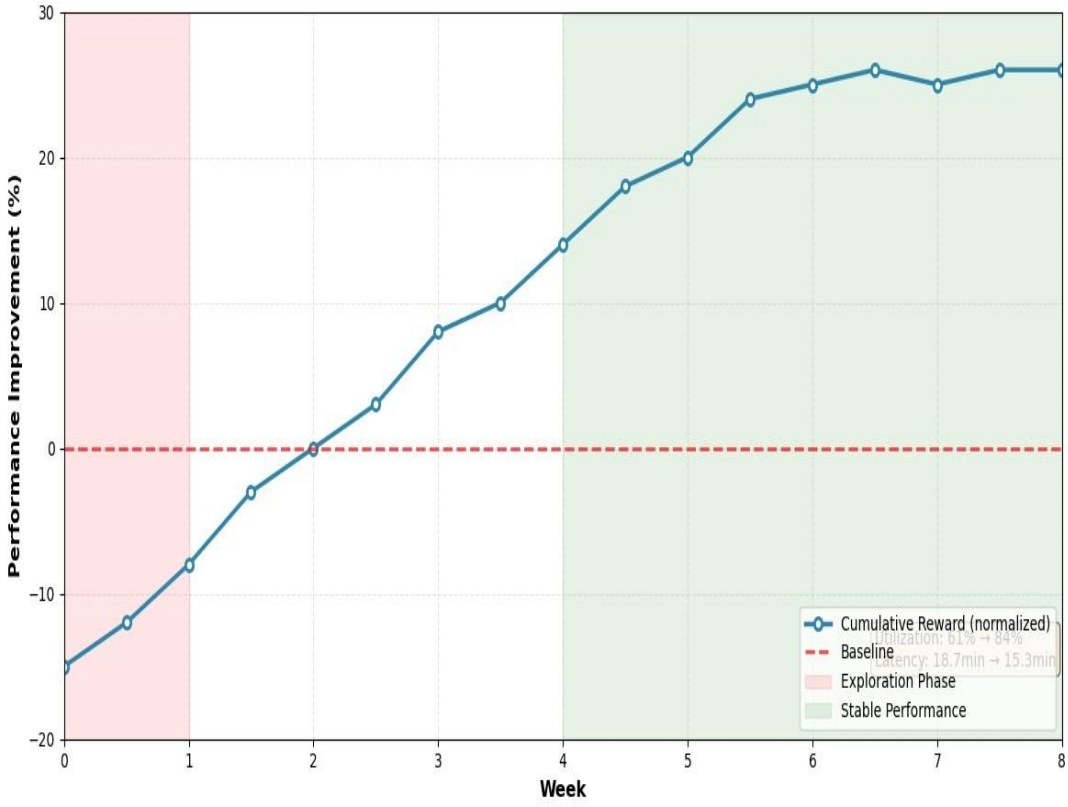

Fig. 2: RL Agent Learning Progression (Organization B, SAC algorithm, normalized metrics)

The greatest obstacle to the embracement of RL was safety issues. Companies also adopted numerous protective measures: a limited action space, circuit breakers that would switch back to baseline policies in case of a reduction in metrics and a gradual rollout plan. In spite of these measures, two organizations stopped their RL implementations due to incidences where the agent behavioral pattern caused service disruptions.

3.3 Anomaly Detection Performance

Table 3 shows the features and performance of the various anomaly detection methods that are employed by eight companies.

Table 3: Anomaly Detection Approaches and Performance

Approach	Precision	Recall	MTTD Improvement	Orgs
Statistical (z-score)	0.42 ± 0.12	0.73 ± 0.15	18% ± 9%	8
Isolation Forest	0.61 ± 0.14	0.68 ± 0.12	31% ± 11%	6
LSTM Autoencoder	0.69 ± 0.11	0.71 ± 0.13	42% ± 14%	5
Transformer-based	0.74 ± 0.09	0.76 ± 0.10	48% ± 12%	3

The LSTM autoencoder method was particularly effective with time-series information in pipeline execution logs. These models discovered instances where reconstruction error was larger than learnt thresholds following learning of compressed representations of typical patterns of execution. The important significance of contextual factors in reducing false positives was also an important finding with all methods. Contrary to the standard deviation of all types of models, the inclusion of contextual features boosted accuracy by 15-25 percentage points across all model types.

3.4 End-to-End Pipeline Performance

Table 4 presents before-and-after metrics for seven organizations implementing multiple ML components, measured over six-month periods. The Table demonstrates consistent improvements across all three key performance indicators. Deployment failure rates decreased by 34-47%, lead time reduced by 28-41%, and MTTR improved by 36-43%. These improvements compound: faster deployments with fewer failures accelerate development velocity while simultaneously improving system reliability. Fig. 3 breaks down the improvement in MTTR of Organization H and indicates how the contribution of MLlic changed by phase.

3.5 Implementation Challenges

Some of the stated implementation problems were at the organizational level. The most common challenge mentioned is on data quality. Most of them found their deployment history with discrepancies, the lack of labelling, or features coverage gaps. The organization that invested in the assessment of the quality of the data in the beginning had a superior model performance and reduced time to value.

Another major challenge had been model maintenance. ML models decay when there is a change in data distributions. The performance of models was not sufficiently monitored in some organizations in the beginning. To build MLOps, versioning models, monitoring the quality of predictions, evidence-based automated retraining, took specific focus, but paid off Essential.

Table 4: End-to-End Pipeline Performance: Before and After ML Integration

Organization	Failure Rate		Lead Time		MTTR	
	Before	After	Before	After	Before	After
Org F	12.3%	7.8%	4.2h	2.9h	87min	52min
Org G	8.7%	5.1%	3.8h	2.6h	73min	46min
Org H	15.1%	8.4%	5.6h	3.7h	124min	71min
Org I	9.4%	6.2%	4.1h	3.1h	95min	61min
Org J	11.8%	7.1%	4.7h	3.2h	102min	59min
Org K	14.6%	9.2%	6.1h	4.3h	118min	76min
Org L	10.2%	6.5%	3.9h	2.8h	81min	49min

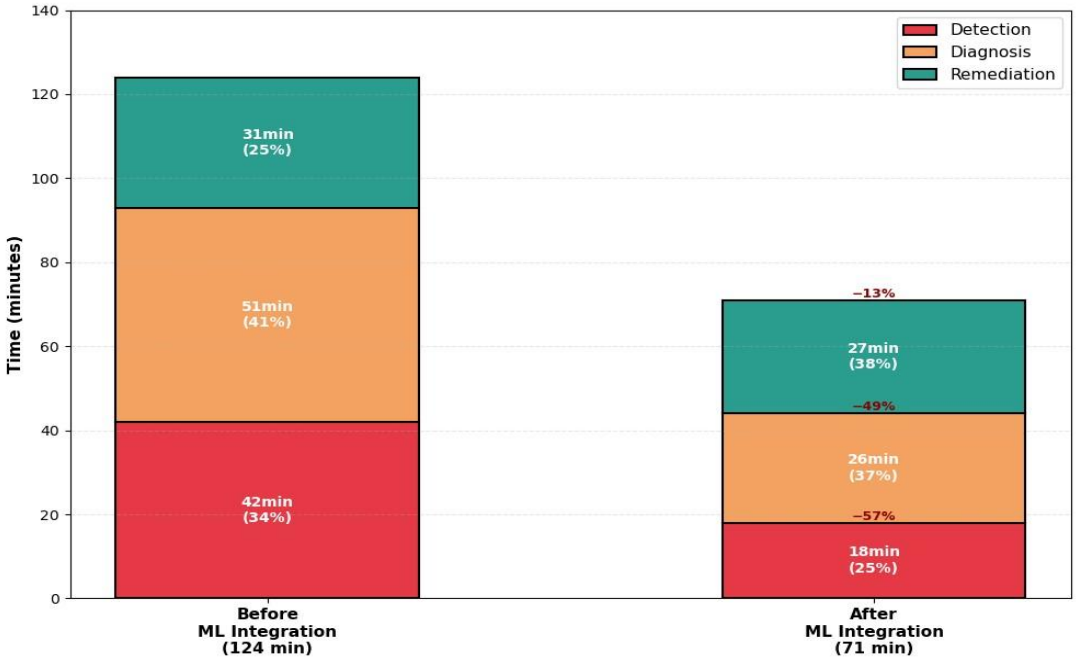

Fig. 3: MTTR Decomposition: ML Impact by Phase (Organization H)

Organizational and cultural factors played a big role in determining the success of the implementation. The engineering teams that were used to thinking in a deterministic way of automation were even occasionally reluctant to embrace the ML-based methods especially when the predictions were found to have counterintuitive results. Those organizations that performed well focused on clear communication on the model limitations, offered interpretability methods and positioned ML as an addition and not a replacement of human judgment.

3.6 Practical Implementation Guidelines

Based on the experience of participating organizations, this section compiles practical advice that would be given to practitioners if they are thinking about the integration of ML in their DevOps pipelines.

3.6.1 Assessing Readiness and Selecting Use Cases

The organizations are not equally prepared to enjoy the benefits of ML-enhanced DevOps. The maturity of Baseline DevOps is important. CI/CD practices, automated testing, instrumentation and monitoring, and data-driven decisionmaking cultures should have been developed already by organizations before committing more resources to ML improvement. Data infrastructure is an important requirement. ML needs historical data of an adequate quality, quantity and relevance.

We would suggest failure prediction as the starting point due to a number of reasons. The issue is clear and has specific success indicators. Engineering teams can instantly pick up the value proposition. Such supervised learning techniques are quite mature and wellknown. Minor gains in accuracy provide value, and reduce the threshold of proving ROI.

3.6.2 Managing Model Lifecycle and Building Trust

ML systems also demand continuous maintenance unlike conventional software. Organizations have to put in place MLOps practices in development, deployment and post-deployment stages. In the development, focus on versioning of information, software, and architecture. When deploying, establish an extensive model performance as well as system health monitoring. Following the deployment, schedule to undergo periodic retraining when the data distributions change.

Being technical is not sufficient to be adopted. Engineering crews need to have confidence in ML systems to their point of taking their advice. This is created by a number of strategies. To begin with, promote transparency using items of

interpretability. Second, preserve human control, particularly until the beginning. Third, discuss restrictions openly. Fourth, rejoice in successes and blameless postmortem in case of failure.

4.0 Conclusion

Machine learning being incorporated in DevOps pipelines is a big step as far as the software delivery processes are concerned. In this study, the researchers were able to prove that AI-based solutions can significantly enhance the reliability of deployments, streamline resource usage, and shorten delivery times. It has empirical results of 34-47 percent reduction in failure rates, improvement in resource use by 21-35 percentage points, and lead time reductions of 28-41. Nevertheless, the performance of the models differs significantly among organizations and the variance in the performance can be attributed to the quality of data, maturity of the processes and team capabilities. Algorithms and their implementation to innovation require more than neutrality to create success and need organizational preparation, data infrastructure, and an embracing culture. The challenges associated with the implementation can be identified as data quality concerns, model maintenance needs, and organizational resistance. Other areas of potential future investigations are to come up with standard benchmarks, enhance sample efficiency process, and create interpretable approaches. With DevOps, AI has reached a stage of maturity to provide production value, but to see the potential it needs to balance between optimism concerning the capabilities of ML and realism concerning the implementation realities and organization readiness.

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Data availability

All data used in this study will be readily available to the public.

Consent for publication

Not Applicable.

Availability of data and materials

The publisher has the right to make the data public.

Competing interests

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Authors' Contributions

The author designed and carried out the entire work