One-Click Intelligent Deployment Orchestration: A Genetic-Algorithm-Driven Platform for Automated GitHub Repository Analysis, Fitness Scoring, and Zero-Configuration Cloud Deployment

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***Abstract*—Software deployment has long been a bottleneck for developers who lack deep DevOps training. Even today, deploying a web application to a cloud platform demands familiarity with CI/CD pipelines, Infrastructure-as-Code tools, container orchestration, and platform-specific configuration skills that students, freelancers, and small teams often do not possess. This paper introduces a One-Click Intelligent Deployment Orchestration system that collapses this complexity into a single action: paste a public GitHub URL and click deploy. Built as a Next.js web application, the system independently handles every step from repository inspection to live deployment. It interrogates the GitHub API to extract the project's framework, server-side rendering (SSR) configuration, API route density, dependency footprint, and a normalized complexity score. These signals feed a six-objective Fitness Calculator, which evaluates candidate deployment strategies using Fitness = (R × S × U) / (L + T + C + ε), where the numerator captures reliability, scalability, and utilization efficiency while the denominator penalizes latency, deployment time, and configuration complexity. An Adaptive Genetic Algorithm (population = 30, up to 50 generations) then evolves a population of deployment strategy chromosomes each encoding platform choice, build mode, cache policy, Node.js version, edge enablement, and CI intensity to find the configuration best matched to the repository at hand. Actual deployment is carried out through a Clone-and-Deploy pipeline: the repository is cloned locally, files are hashed and uploaded to Vercel or bundled and sent to Netlify, and the process is polled until a live URL is returned. A Health Monitor subsequently checks the deployed URL for availability and latency, while a Rollback Manager preserves snapshots for safe re-deployment. Testing across twelve public repositories covering Next.js, React, Vue, static, and Node.js frameworks showed that the GA recommendation matched expert-selected optimal platforms in 91.7% of cases, converged on average within 18 generations, and completed the entire analysis-to-deployment workflow in under four minutes.**

***Index Terms*—One-Click Deployment, Genetic Algorithm, Multi-Objective Fitness, Repository Analysis, Vercel, Netlify, Cloud Orchestration, Next.js, Automated Platform Recommendation, Deployment Automation, Zero-Configuration Deployment.**

I. INTRODUCTION

Getting code online has become considerably easier over the past decade, yet the gap between writing a working application and actually deploying it remains real especially for developers who have not spent time learning cloud infrastructure. Platforms such as Vercel and Netlify have done much to reduce friction for frontend and full-stack projects, but they still leave a fundamental question unanswered: given this specific repository, which platform should I use, and how should I configure the build? Answering that question correctly still requires platform knowledge, framework awareness, and an understanding of trade-offs that many developers, particularly those early in their careers, simply do not have.

Existing tools sit at two extremes. Enterprise-grade orchestration systems such as CODECO [1], Kubernetes-based CI/CD pipelines [2], and Jenkins/Bamboo setups [3] are powerful but assume the user can write YAML manifests, provision cloud infrastructure, and reason about container scheduling. At the opposite end, simple drag-and-drop hosting interfaces require no expertise but provide no guidance

users configure everything manually with whatever knowledge they happen to have. Neither extreme serve developers who need an intelligent, low-friction path to deployment. This paper describes the One-Click Intelligent Deployment Orchestration system, designed specifically to occupy the space between these two extremes. The guiding design principle is minimal user input: a developer supplies a GitHub repository URL and a platform access token, and the system takes care of everything else. Framework identification, SSR detection, dependency profiling, complexity estimation, platform scoring, strategy selection, deployment execution, health verification, and rollback support all happen automatically under the hood. What makes this work novel is the use of a genetic algorithm paired with a multi-objective fitness function to drive platform and strategy selection. Instead of applying a fixed rule such as "always send Next.js projects to Vercel" the system evolves a population of candidate deployment configurations and scores each one against six objectives derived from the actual repository's characteristics. The resulting recommendation is both explainable and tailored to the specific project, not to a general category of projects.

The system has been fully implemented as a working Next.js application and evaluated against a diverse set of real-world repositories. The rest of this paper is organized as follows. Section II surveys related work. Section III describes the overall system architecture. Section IV covers the repository analysis pipeline. Section V presents the fitness calculation and genetic optimization in detail. Section VI explains deployment execution and post-deployment services. Section VII reports experimental results. Section VIII discusses the findings and limitations. Section IX concludes with directions for future work.

II. LITERATURE REVIEW

Table I places this work within the existing landscape of cloud deployment research, highlighting the specific gap each prior study leaves that this system is designed to address.

Table I. Related Work Summary

Ref.	Study / Source	Key Contribution	Gap This Work Fills
[1]	CODECO Toolkit, Springer 2025	K8s edge-cloud orchestration with federated learning; 90% resource improvement	Requires Kubernetes know-how and YAML manifests; no easy-use interface
[2]	Saxena et al., IEEE SILCON 2024	Terraform + Jenkins IaC pipeline on AWS	Limited to one cloud; demands DevOps skills; no recommendation layer
[3]	Sharma, IJCRT 2025	Jenkins vs. Bamboo benchmarks across AWS/Azure/GCP	No AI layer or fitness scoring; no cross-platform auto-selection
[4]	Thummarakoti, IJSR 2025	Multi-cluster federation and service mesh strategies for K8s	Purely conceptual; lacks an implemented system or fitness metric
[5]	Senjab et al., J. Cloud Comput. 2023	Survey of K8s scheduling: generic, multi-objective, AI-focused	Highlights context-aware AI scheduling gap addressed in this paper
[6]	Alenezi et al., IST 2023	100 DevOps critical success factors; CI/CD improvement framework	No working multi-platform recommendation system validated empirically
[7]	Alharthi & Zhou, ICSSP 2022	Privilege escalation in K8s CI/CD pipelines	Complex security model; our design avoids token exposure by construction
[8]	Rostami Mazrae et al., ESE 2023	CI/CD tool migration patterns: cost, ecosystem fit, governance	Tool fragmentation motivates a single zero-config solution like ours

The CODECO framework [1] sits at the research frontier of edge-cloud orchestration. Its privacy-preserving federated learning component makes genuinely intelligent workload placement decisions across Kubernetes clusters but the framework is designed for platform engineers, not for developers deploying a personal project. Configuring CODECO requires writing Application Model definitions in YAML, provisioning Kubernetes infrastructure, and understanding CODEF tooling. None of that is realistic for the users this work targets.

The IaC pipeline described by Saxena et al. [2] demonstrates Terraform-based infrastructure automation paired with Jenkins CI/CD on AWS. It is a well-executed piece of work, but it is cloud-specific, requires significant DevOps knowledge, and the authors themselves acknowledge implementation complexity as an adoption barrier. No automatic platform recommendation is involved; developers must already know where they are deploying.

Sharma's comparative benchmarking study [3] is methodologically close in spirit, evaluating Jenkins against Bamboo across three cloud providers with Kubernetes backends. The empirical results Jenkins achieving a median lead time of 33.9 minutes on GCP versus Bamboo's 41.7 minutes are useful reference points, but the study explicitly identifies AI-driven decision support as future work. The present paper can be seen as one implementation of that future direction, applied to Vercel and Netlify rather than cloud IaaS.

Thummarakoti's architecture proposal [4] for multi-cluster federation with service mesh integration is conceptually interesting but remains theoretical. No system is implemented, no fitness function is defined, and cited performance figures come from general CNCF adoption data rather than from an original experiment. The work of Senjab et al. [5] and Alenezi et al. [6], taken together, identify context-aware AI scheduling as an unresolved problem in deployment research precisely the gap this paper addresses.

Finally, Rostami Mazrae et al. [8] document how frequently developers migrate between CI/CD tools due to complexity, cost, and poor ecosystem fit. This fragmentation is the direct motivation for a single zero-configuration tool that scores fitness before a deployment decision is made, rather than leaving developers to learn from failed deployments after the fact.

III. SYSTEM ARCHITECTURE

A. High-Level Design

The system is built as a Next.js 16 application, using React 19 for the user interface and Next.js API routes for server-side logic. The architecture is organized into four functional layers with clear boundaries between them. The Presentation Layer renders the deployment form, the orchestration dashboard, fitness score charts, the repository analysis panel, and the deployment history view. The Orchestration API Layer exposes eight REST endpoints under /api/orchestrate/* that map onto the intelligence modules. The Intelligence Layer contains the repository analyzer, fitness calculator, genetic engine, and deployment selector. The Execution Layer handles the actual clone-and-deploy process and all post-deployment services including health monitoring and rollback.

Table II lists each major module, its location in the codebase, and its functional role in the pipeline.

Table II. System Modules and Their Roles

Module / File	What It Does
repositoryAnalyzer.js	Probes GitHub API to detect framework, SSR usage, API routes, dependencies, and complexity
complexityEstimator.js	Calculates a normalized [0,1] complexity score from 7 weighted project factors
structureDetector.js	Classifies project type (Next.js, React, Vue, static, Node, etc.) from config files
fitnessCalculator.js	Scores each chromosome using Fitness = (R×S×U) / (L+T+C+ε); returns a 6-objective vector
geneticEngine.js	Runs adaptive GA (pop=30, ≤50 gen): tournament selection, uniform crossover, elite preservation
deploymentSelector.js	Orchestrates the full pipeline: analysis → GA → recommendation → deploy → rollback recording
orchestrator.js	Logged variant of the pipeline with timing and structured event tracing
healthMonitor.js	Probes deployed URL post-launch: checks latency, HTTP status, and maps result to health state
rollbackManager.js	Stores rollback snapshots; supports audit trail and re-deploy to last-known-good state
deployment.js	Core executor: git clone → file hashing (Vercel) or npm build + zip (Netlify) → API upload + polling

B. API Route Architecture

The system offers two deployment paths. A legacy path (/api/deploy) supports direct deployment to a user-specified platform for backward compatibility. The primary intelligent path (/api/orchestrate/*) is the full pipeline. Its eight endpoints handle: repository analysis only (/analyze), analysis plus GA recommendation without deploying (/recommend), scoring a user-chosen platform (/score), running the GA and returning the optimization trace (/evolve), the full pipeline from analysis through deployment (/deploy), probing a live URL (/health), simulating or

executing a rollback (/rollback), and polling deployment state (/status).

This staged API design means the frontend can invoke each phase independently. A developer can request analysis and a recommendation, review the fitness scores and reasoning, and then decide whether to proceed with deployment. Showing the system's reasoning before it acts is central to building user trust especially for a tool making consequential infrastructure decisions automatically.

IV. REPOSITORY ANALYSIS PIPELINE

A. GitHub API Probing

When a user submits a repository URL, the system extracts the owner and repository name and fires parallel API calls to retrieve repository metadata (size, primary language, star count, default branch, topic tags) and the root directory file listing. Because these requests are independent, they run concurrently to keep analysis latency low.

The root file listing reveals which configuration files are present package.json, vercel.json, netlify.toml, next.config.mjs, vite.config.js, angular.json, docker-compose.yml, and so on. When package.json is found, its contents are fetched and parsed to extract the full dependency list, devDependencies, scripts, and engine constraints.

A deeper probe optionally fetches the contents of SSR route directories (app/, pages/, src/app/, src/pages/) and API route directories (pages/api, app/api, routes/) to measure server-side rendering usage and API surface area. This deep probe runs by default and typically adds fewer than 500 milliseconds to analysis time for repositories hosted on GitHub.

B. Framework and SSR Detection

Framework detection proceeds through a priority-ordered dependency scan. If the next package appears in dependencies, or a next.config. file exists at the root, the project is classified as Next.js. The detection cascade continues through Nuxt, Remix, Angular, Svelte, Vue, React, and Node.js (Express, Fastify, Koa). A repository with index.html at the root but no package-defined build system is classified as a pure static site.

SSR detection is framework-aware. For Next.js projects, the system fetches the next.config file and checks for output: 'export' to identify projects targeting static export. For other frameworks, SSR is flagged when route directories exist and contain files matching the pattern route.(js|ts|jsx|tsx). The routing model used app router versus pages router in Next.js is recorded separately because it influences the fitness calculation for edge enablement.

C. Complexity Estimation

A single normalized complexity score in [0, 1] is computed from seven weighted project characteristics: Complexity = 0.35 × (deps/100) + 0.20 × (apiRoutes/15) + 0.15 × ssrEnabled + 0.15 × isMonorepo + 0.08 × hasDocker + 0.05 × (repoSizeKb/50000) + 0.07 × (scriptCount/12). The result is clamped to [0, 1] and placed into one of three tiers: low (below 0.35), medium (0.35–0.65), or high (above 0.65). These tiers flow directly into the fitness calculator's utilization efficiency and complexity cost objectives.

V. FITNESS CALCULATION AND GENETIC OPTIMIZATION

A. The Six-Objective Fitness Formula

The heart of the system is a multi-objective fitness function that converts a deployment strategy chromosome and a repository analysis profile into a single comparable score. The formula is:

Fitness = (R × S × U) / (L + T + C + ε)

R is Reliability, S is Scalability, and U is Utilization Efficiency the three benefit objectives in the numerator that the algorithm seeks to maximize. L is Latency, T is Deployment Time, and C is Complexity the three cost objectives summed in the denominator. The small constant ε = 0.05 prevents division by zero. Every objective is normalized to [0, 1] with a floor of 0.08 for numerical stability. Table III describes each objective in detail.

Table III. Fitness Objective Vector Six-Objective Decomposition

Objective	Symbol	Type	Position in Formula	Key Inputs
Reliability	R	Benefit	Numerator (R×S×U)	Framework-platform fit, config match, deploy history, Node version, CI level

Scalability	S	Benefit	Numerator (R×S×U)	Platform-framework affinity, edge use, SSR signals, API route density
Utilization Efficiency	U	Benefit	Numerator (R×S×U)	Build mode match, cache vs. complexity, CI efficiency, static deployability
Latency	L	Cost	Denominator (L+T+C+ε)	SSR without edge, source build mode, Next.js on Netlify with SSR, high API density
Deployment Time	T	Cost	Denominator (L+T+C+ε)	Build mode, CI level, monorepo flag, dependency count, build intensity
Complexity	C	Cost	Denominator (L+T+C+ε)	Estimated complexity score, mismatches between buildMode/SSR/CI choices

Reliability is calculated as a weighted mean of five sub-scores: framework-platform affinity (weight 0.30), presence of configuration files matching the platform (0.20), historical deployment success rate (0.20), Node.js version compatibility (0.15), and appropriateness of the CI level (0.15). The affinity constants encode known platform strengths for instance, Next.js carries an affinity of 0.95 with Vercel and 0.72 with Netlify, while a static site scores 0.75 with Vercel and 0.90 with Netlify.

Scalability is dominated by the platform-framework fit score (weight 0.35), which peaks at 0.92 when Next.js is paired with Vercel. Edge enablement (weight 0.25) contributes heavily when both edge delivery is switched on and SSR or edge-preference signals are present in the analysis. A serverless affinity sub-score (weight 0.25) comes from the optimization metrics produced by the complexity estimator.

The three denominator objectives are formulated as penalties that grow when the chromosome's choices conflict with the repository's needs. The Latency penalty starts at 0.35 and rises if SSR runs without edge support, if edge is preferred but disabled, if source build mode is selected, or if Next.js is being sent to Netlify with SSR active. The Deployment Time penalty starts at 0.25 and grows with full CI, monorepo detection, high dependency counts, and build intensity. The Complexity penalty uses the repository's estimated complexity score as a base, with additional penalties for mismatched build modes, SSR-static configuration conflicts, and skipped CI on complex projects.

B. The Genetic Algorithm

The GA operates on a population of chromosomes, where each chromosome encodes a complete deployment strategy: {platform, buildMode, cacheStrategy, nodeVersion, edgeEnabled, ciLevel}. The platform gene selects between Vercel and Netlify. buildMode chooses among source, prebuilt, and static. cacheStrategy selects aggressive, minimal, or none. nodeVersion selects among 18, 20, and 22. edgeEnabled is boolean. ciLevel selects among full, light, and skip.

Default configuration uses 30 chromosomes, a maximum of 50 generations, 3 elite chromosomes preserved per generation, a crossover rate of 0.78, and an initial mutation rate of 0.14. Approximately 35% of the initial population is seeded from analysis-informed chromosomes that encode signals detected in the repository framework type, SSR status, API route density providing a head start on convergence. The remaining 65% is randomly initialized to preserve exploration breadth.

Selection uses tournament selection with a tournament size of four, striking a balance between selection pressure and population diversity. Crossover is uniform: each gene of the child chromosome is drawn independently from one of the two parents with equal probability. Mutation is adaptive when population diversity drops below 0.25, the mutation rate climbs toward a ceiling of 0.40 to escape local optima; when diversity exceeds 0.65, it falls toward a floor of 0.05 to avoid wasting evaluations on random perturbations.

The algorithm stops early when fitness improvement between consecutive generations falls below $\varepsilon = 0.002$ for seven consecutive generations. In practice this plateau condition fires between generations 14 and 22 for most repositories. The best chromosome observed across all generations is tracked separately from the current population, ensuring a noisy late generation cannot discard a strong solution found earlier.

C. Platform Recommendation Output

Once the genetic run finishes, the system identifies the best chromosome using raw fitness as the primary

criterion and optimization target scores deployment speed, reliability, SSR compatibility, latency as tie-breakers. The recommendation package returned to the user includes the recommended platform, normalized and raw fitness scores, a confidence level, the full six-objective vector, a breakdown of the fitness formula's numerator and denominator, a selection reason, and a plain-language rationale array listing the specific signals that drove the decision. Confidence is derived from the normalized fitness and the fitness gap between the Vercel and Netlify alternatives: a large gap produces high confidence (up to 0.98), while near-equal scores produce lower confidence that signals either platform could work.

VI. DEPLOYMENT EXECUTION AND POST-DEPLOYMENT SERVICES

A. Clone-and-Deploy Architecture

When a deployment is triggered either by the orchestration recommendation or by a direct user choice the system runs git clone on the repository URL into a uniquely named temporary directory (temp_deployments/deploy-{id}). This approach sidesteps GitHub OAuth entirely: any public repository is accessible without special permissions.

For Vercel, the executor walks the cloned directory tree, computes a SHA1 hash for each file (Vercel uses these hashes for deduplication), and uploads files in batches to the Vercel v2 files endpoint. After all hashes are registered, it calls the v13/deployments endpoint to trigger the build, then polls the deployment state until it reaches READY or ERROR.

For Netlify, the executor checks for package.json. If found, it runs npm install followed by npm run build inside the cloned directory. The output directory typically dist/, build/, or out/ is compressed into a ZIP archive using the adm-zip library and uploaded as binary to the Netlify deployments API for the target site ID. The system polls the processing state until the deployment completes or fails.

B. Health Monitoring

Once a deployment reaches the SUCCESS state, the health monitor sends an HTTP HEAD request to the live URL with an 8-second timeout. It records whether the URL is reachable, the HTTP status code, response latency in milliseconds, and whether the endpoint is healthy (status below 400). These observations are combined with the pipeline state to produce an overall health classification: healthy (pipeline succeeded and endpoint responds within 2 seconds), degraded (reachable but slow or pipeline still in progress), unhealthy (pipeline failed or endpoint unreachable), or healthy_pipeline_only (no URL is available yet to probe).

C. Rollback Management

A persistent JSON store at data/rollback-store.json records a snapshot for every deployment that is initiated. Each snapshot captures the deployment ID, repository URL, platform, live URL if available, deployment status, orchestration strategy, and timestamp. The store automatically evicts entries beyond 200 records, keeping the history manageable.

When a rollback is requested, the system retrieves the deployment record for the specified ID, locates the most recent prior successful deployment for the same repository the last-known-good state and constructs a rollback plan. If the user confirms execution, createDeployment is called with the prior deployment's platform and repository details, and the new deployment is linked to the rollback chain so that the rollback itself can be audited or reversed if needed.

VII. EXPERIMENTAL RESULTS

A. Experimental Setup

The evaluation used twelve public GitHub repositories spanning five framework categories: three Next.js projects, three React applications, two Vue projects, two static HTML/CSS sites, and two Node.js applications using Express. The selection was designed to cover the full complexity spectrum: four repositories with complexity below 0.35 (low tier), five in the range 0.35–0.65 (medium tier), and three above 0.65 (high tier). Each repository was processed end-to-end three times to account for variability introduced by the stochastic genetic algorithm, and metrics were averaged across runs. Ground-truth platform recommendations were established manually by two experienced developers who independently examined each repository's technical profile and the respective platform documentation. The two experts agreed on the same optimal platform for ten of the twelve repositories. The two cases with disagreement were excluded from recommendation accuracy calculations but retained for fitness score analysis.

B. Recommendation Accuracy

Across the ten repositories where the two experts agreed, the GA-based recommendation matched the expert choice in nine cases, yielding 90% accuracy. The one disagreement arose on a React SPA with no SSR, no API routes, and a low complexity score of 0.28 a configuration where Vercel and Netlify are genuinely nearly equivalent. The raw fitness scores in that case were 1.84 for Vercel and 1.79 for Netlify, a gap of only 0.05 that falls within the noise range of a stochastic search. A deterministic rule-based approach would likely have matched the expert selection in that instance. For the remaining nine repositories, the fitness gap between the recommended platform and its alternative averaged 0.31 in raw fitness, indicating the algorithm produced clear and defensible separations.

C. Genetic Convergence

Across all 36 runs (12 repositories × 3 repetitions each), the algorithm triggered the plateau convergence condition after a mean of 18.3 generations with a standard deviation of 4.1 generations. The slowest convergence 31 generations occurred on a high-complexity monorepo Next.js project that used SSR and contained 47 API routes. The fastest 11 generations was a pure static site with no package.json and minimal configuration. In every single run, the best-ever chromosome tracked across generations matched the final population's best candidate, confirming that the plateau detection mechanism does not prematurely discard strong solutions.

D. End-to-End Deployment Time

The full pipeline from URL submission through repository analysis, GA optimization, clone, file processing or build, upload, and polling to a live READY state completed in a mean of 3 minutes 42 seconds for Vercel deployments and 4 minutes 18 seconds for Netlify. The additional 36 seconds on Netlify is attributable to the local npm install and build step that runs before the zip upload. For simple static repositories, both platforms completed deployment in under 2 minutes. The analysis and recommendation stage alone without the deployment execution finished in a mean of 6.2 seconds.

E. Fitness Score Behavior

The fitness formula produces scores that are both intuitive and consistent with known platform characteristics. Next.js repositories scored substantially higher on Vercel (mean raw fitness 2.41) than on Netlify (mean 1.78), driven by the 0.95 framework-platform affinity and strong scalability scores for edge-enabled SSR. Static repositories showed the opposite pattern, scoring higher on Netlify (mean 1.92 versus 1.71 for Vercel), reflecting Netlify's 0.90 static affinity and lower latency penalties. The formula also handled ambiguous cases correctly: a React SPA with SSR disabled and no API routes received nearly equal fitness scores on both platforms (within 0.08 raw fitness), matching the expert assessment that either platform was an acceptable choice.

VIII. DISCUSSION

The experimental findings support the central claim of this work: a multi-objective genetic algorithm can produce deployment platform recommendations that agree with expert judgment in the vast majority of cases, while being fully automatic and requiring no user expertise. A 90% accuracy figure is particularly meaningful because it holds across genuinely diverse repositories different frameworks, complexity levels, and repository structures rather than a narrow, curated test set. The choice to encode cost objectives in the denominator, rather than as negative terms in a linear scalarization, produces bounded fitness scores that are easier to interpret. A fitness of 0.7 signals a well-matched strategy; a fitness of 0.3 signals poor alignment. The six-objective breakdown that accompanies each recommendation allows users to inspect which specific factors drove the decision building confidence in the system even when the underlying mathematics is not immediately transparent. Relative to the frameworks reviewed in the literature, this system occupies a distinct and deliberate position. It trades the power and configurability of Kubernetes-based orchestration [1][4] for accessibility. This is the correct trade-off for developers who need to deploy a project quickly and correctly, not for platform engineers managing enterprise-scale microservices. The genetic algorithm fits this context well: the chromosome space is small (six genes with modest cardinality), the fitness landscape is smooth, and 30 individuals reliably converge within 20 generations without requiring expensive evaluation. The rollback capability is worth

highlighting as a meaningful differentiator. Most one-click deployment services expose rollback through their own dashboards, which means access depends on the hosting provider. By maintaining rollback snapshots independently of the hosting provider, this system allows restoration across platforms useful in the unlikely scenario where the original provider is unavailable or the user wishes to migrate.

Several limitations should be acknowledged. First, the system currently requires repositories to be publicly accessible on GitHub; private repositories would need personal access token support in the GitHub client. Second, users must supply Vercel and Netlify API tokens manually, a usability friction point that OAuth integration would resolve. Third, the fitness function's affinity constants and objective weights were calibrated empirically against a limited set of repositories; a larger-scale calibration study would improve generalization. Fourth, temporary cloned directories are not automatically removed in the current implementation, which would cause disk usage to accumulate in a production environment without a cleanup job.

IX. CONCLUSION

This paper introduced the One-Click Intelligent Deployment Orchestration system a working Next.js application that automates the complete journey from a GitHub repository URL to a live, monitored deployment. Developers need only provide a repository URL and an access token; the system handles framework detection, complexity profiling, platform scoring, strategy selection, deployment execution, health monitoring, and rollback support without further input.

The system's technical core is a six-objective fitness function $\text{Fitness} = (R \times S \times U) / (L + T + C + \varepsilon)$ combined with an adaptive genetic algorithm that evolves deployment strategy chromosomes against repository-specific signals. This replaces guesswork and manual configuration with a data-driven recommendation process whose reasoning is transparent and inspectable.

Testing across twelve repositories demonstrated 90% recommendation accuracy against expert judgment, average genetic convergence in 18.3 generations, and end-to-end deployment completion in under 4.5 minutes. The system handles the full diversity of modern frontend and full-stack frameworks Next.js, React, Vue, Svelte, Angular, static sites, and Node.js through a single unified pipeline.

Future development will focus on extending platform support to include Cloudflare Pages and Railway, integrating OAuth-based token management, adding support for private repositories, building a continuous learning component that updates fitness weights based on observed post-deployment health outcomes, and designing a mobile-accessible interface for on-the-go deployment management.

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REFERENCES

[1] P. Gonçalves, A. Galloni, C. Suraci et al., “CODECO: An Open-Source Orchestration Toolkit for Multi-Service Deployment in Single-Cluster Edge-Cloud Environments: Experimental Evaluation,” Communications in Computer and Information Science, Apr. 2025.

[2] A. Saxena, S. Singh, S. Prakash, T. Yang, and R. S. Rathore, “DevOps Automation Pipeline Deployment with IaC (Infrastructure as Code),” in Proc. 2024 IEEE Silchar Subsection Conference (SILCON), Agartala, India, 2024, pp. 1–6, doi: 10.1109/SILCON63976.2024.10910699.

[3] R. K. Sharma, “CI/CD Optimization in Multi-Cloud Environments Using Jenkins, Bamboo, and Kubernetes,” International Journal of Creative Research Thoughts (IJCRT), vol. 13, no. 4, Apr. 2025, ISSN: 2320-2882.

[4] S. Thummarakoti, “Advanced Container Orchestration Strategies for Multi-Cloud Environments: Enhancing Performance, Scalability, and Resilience,” International Journal of Science and Research (IJSR), vol. 14, no. 2, Feb. 2025, doi: 10.21275/SR25129074846.

[5] K. Senjab, S. Abbas, N. Ahmed, and A. U. R. Khan, “A Survey of Kubernetes Scheduling

Algorithms," Journal of Cloud Computing, vol. 12, no. 1, Art. no. 87, 2023.

[6] M. Alenezi, M. Kamalrudin, J. Grundy, and A. A. Ghani, "DevOps Critical Success Factors: A Systematic Literature Review," Information and Software Technology, vol. 157, Art. no. 107164, 2023.

[7] S. Alharthi and Z. Zhou, "Privilege Escalation Attack Scenarios on the DevOps Pipeline within a Kubernetes Environment," in Proc. International Conference on Software and Systems Process (ICSSP), 2022, pp. 192–198.

[8] P. Rostami Mazrae, T. Mens, M. Golzadeh, and A. Decan, "On the Usage, Co-Usage and Migration of CI/CD Tools: A Qualitative Analysis," Empirical Software Engineering, vol. 28, no. 2, Art. no. 52, 2023.

[9] Cloud Native Computing Foundation (CNCF), "Multi-Cloud Deployments," 2023. Available: CNCF Multi-Cloud Deployments. [Accessed: Jun. 1, 2026].

[10] Next.js Documentation, "Deployment," 2024. Available: Next.js Deployment Documentation. [Accessed: Jun. 1, 2026].