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Next-Generation Banking and Healthcare Cloud Infrastructure: Real-Time Autonomous Detection via Neural Networks, NLP, and Data Mining Integrated with Oracle EBS and GitHub DevOps Automation

Cristian Valentin Dumitrescu

Team Lead, Romania

ABSTRACT: In the rapidly evolving domains of banking and healthcare, organisations must adopt cloud-native infrastructures that support real-time autonomous detection of anomalies, fraud, operational risk and clinical events. This paper proposes a unified architecture that integrates neural networks, natural-language processing (NLP) and data-mining techniques within a cloud infrastructure, bridging both banking and healthcare verticals, and anchored by enterprise systems such as Oracle E-Business Suite (EBS) and DevOps pipelines using GitHub for automation. The approach addresses the challenges of heterogeneous data sources (transactional banking data, clinical records, unstructured text, logs), high-velocity ingestion, regulatory compliance, auditability and continuous deployment. Neural networks facilitate pattern recognition and predictive detection (e.g., fraud, medical emergencies), NLP enables extraction of insights from unstructured text (customer complaints, clinical notes), and data mining uncovers latent correlations across domains (e.g., risk factors in both banking & health portfolios). The proposed system leverages cloud elasticity for scalability and fault-tolerance, and automates software delivery and configuration via GitHub-based DevOps pipelines integrated with Oracle EBS modules. A pilot simulation demonstrates improved detection latency, higher true-positive rates, and streamlined release cycles. Key benefits include faster incident detection, integrated cross-domain insights and operational agility; drawbacks include initial complexity, data governance overhead and potential model drift. The paper concludes with implementation guidelines, results of the simulation, and future work directions including federated learning, cross-organisational data sharing and self-healing infrastructure.

KEYWORDS: Next-generation infrastructure, banking cloud, healthcare cloud, autonomous detection, neural networks, NLP, Data mining, Oracle EBS, GitHub DevOps, real-time analytics.

I. INTRODUCTION

In recent years, the banking and healthcare sectors have been under intense pressure to transform their legacy infrastructures into agile, scalable and intelligent platforms. Banking institutions face rising volumes of transactions, sophisticated fraud schemes, regulatory scrutiny and the need to deliver personalised customer experiences. Meanwhile, healthcare organisations confront exploding volumes of clinical data, real-time monitoring needs, compliance with patient privacy regulations and the imperative to detect adverse events or anomalies proactively. In this context, cloud computing has emerged as a foundational enabler: cloud platforms provide on-demand compute and storage, global reach, and support for data-intensive analytics. However, mere migration of legacy systems to the cloud is insufficient. What is required is the next generation of cloud infrastructure that supports **real-time autonomous detection** of both banking and healthcare phenomena via advanced techniques such as neural networks, NLP and data mining. Simultaneously, enterprise resource planning (ERP) systems like Oracle EBS underpin core business and clinical operations and must be integrated into any modern architecture, while DevOps automation via platforms such as GitHub ensures rapid delivery, configuration consistency and continuous compliance. This paper presents a comprehensive architecture for such an integrated system: it describes how neural networks can ingest streaming transaction or clinical data to detect anomalies, how NLP can process unstructured text (customer complaints or clinical notes) to extract meaning, how data mining reveals cross-domain patterns, how these analytics feed into Oracle EBS modules for operational action, and how GitHub-based DevOps pipelines automate deployment and updates of models and infrastructure. The rest of the paper is organised as follows: a literature review summarises related work in banking analytics, healthcare cloud detection, NLP and DevOps for Oracle; the research methodology describes a simulation and implementation strategy; advantages and disadvantages are summarised; results and discussion present key findings; and finally conclusion and future work are outlined.

II. LITERATURE REVIEW

Research in artificial intelligence (AI) and machine learning (ML) within banking has accelerated in recent years. Kalyani & Gupta (2023) conducted a systematic literature review and meta-analysis on AI/ML in banking, highlighting the transformative potential of these technologies in risk assessment, customer churn prediction and fraud detection. SpringerLink+1 Deep learning techniques (e.g., recurrent neural networks) have been applied for transaction classification and cash-flow prediction in banking contexts. SpringerOpen Meanwhile, the broader business case for big data, NLP and neural networks is well documented: a McKinsey report emphasises that NLP and neural networks can uncover non-obvious patterns in large structured and unstructured datasets. McKinsey & Company Within healthcare, cloud-based systems that integrate deep learning for real-time diagnosis and prediction are emerging: for example, the "HealthFog" framework leverages ensemble deep learning in a fog/cloud architecture to support heart-disease detection. arXiv Also, NLP is increasingly used in clinical documentation to extract structured insights from unstructured clinical notes. Norislab On the infrastructure and DevOps side, there is increasing evidence of the benefits of automating deployment and operations for enterprise systems: a case study of the Rabobank designed a DevOps infrastructure-as-code (IaC) approach to provision Oracle middleware environments rapidly and reliably. Myst Software For enterprise ERP platforms like Oracle EBS, automation and integration with cloud and DevOps tooling is a growing trend: webinars on DevOps for Oracle EBS and Oracle Cloud outline how organisations can automate EBS deployments and integrate with modern toolchains. Flexagon+1 Despite this progress, few works address a unified architecture that spans both banking and healthcare domains, incorporates real-time autonomous detection (via neural networks, NLP and data mining) and ties directly to ERP/DevOps pipelines such as Oracle EBS and GitHub. The novelty of the proposed work lies in bridging these domains, tightly integrating the analytics layer with enterprise operations (ERP) and automation (DevOps), and demonstrating real-time detection capabilities in a cloud context. The literature suggests strong feasibility of each component (neural networks in banking, NLP in healthcare, DevOps automation for Oracle), but an integrated end-to-end architecture remains underexplored. This gap motivates the research methodology described in the next section.

III. RESEARCH METHODOLOGY

The research methodology follows a design-science approach. First, requirement analysis was conducted for both banking and healthcare domains to identify key use-cases of real-time autonomous detection: in banking, fraud detection, abnormal transaction flows, early risk signals; in healthcare, anomaly detection in clinical monitoring, text-based extraction of adverse event notes, and cross-patient pattern mining. Second, architecture design was developed: a cloud infrastructure was defined comprising streaming ingestion (via Kafka or equivalent), storage (data-lake on object storage + relational databases), analytics layer (neural network models for streaming detection, NLP pipelines for unstructured text, data-mining modules for batch analysis), integration layer (linking analytics outputs to Oracle EBS modules via APIs and message queues), and DevOps automation layer (GitHub repositories, CI/CD pipelines, infrastructure-as-code templates). Third, a prototype simulation environment was built. Synthetic datasets representing banking transactions, customer service logs, clinical records (de-identified) and healthcare operational data were prepared. The neural networks were implemented using TensorFlow/PyTorch, trained for anomaly detection; NLP pipelines were built for entity recognition and sentiment analysis from text; data-mining modules utilised clustering and association-rule mining to identify latent risk patterns. Outputs from the analytics layer were fed into Oracle EBS modules (e.g., ERP finance for banking; clinical/operations modules for healthcare) in a sandbox instance. GitHub Actions were configured to automate deployment of analytics models, infrastructure provisioning (via Terraform scripts), and configuration of Oracle EBS sandboxes. Performance metrics were defined: detection latency (time from event occurrence to alert), true-positive rate (TPR) and false-positive rate (FPR) for detection, deployment lead-time (time from code commit to production). The experiment executed various scenarios of transaction bursts, text-based incident logs and clinical anomalies. Data were collected, analysed and compared with baseline (legacy rule-based detection, manual deployments). The methodology ensures replicability: all code, data schemas and pipelines were documented; evaluation followed quantitative metrics; limitations and assumptions (synthetic data, sandbox environment) are clearly stated. Ethical and regulatory compliance (e.g., patient data de-identification, banking confidentiality) are addressed by design in the prototype.

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Advantages

- Real-time autonomous detection across diverse domains (banking + healthcare) using advanced analytics.
- Unified architecture reduces operational silos, enabling insights from both transactional and textual data.
- Integration with Oracle EBS ensures that detected events feed directly into enterprise workflows and operational systems.
- DevOps automation (GitHub-based) accelerates deployment, enforces consistency, reduces manual errors, and enables continuous updates.
- Cloud infrastructure provides scalability, high availability, elasticity and supports rapid bursts of data ingestion and analytics.
- Data-mining across domains can uncover previously unseen linkage between banking risk and healthcare events (e.g., correlations in insured populations).

Disadvantages

- Initial complexity and cost of building the unified infrastructure, recruiting skilled personnel and managing model training and pipeline automation.
- Data governance, privacy and compliance requirements are significant: handling both banking and healthcare data increases regulatory burden.
- Model drift and the need for continuous retraining: neural networks and NLP pipelines must be maintained to avoid degradation.
- Integration with legacy Oracle EBS systems and enterprise operations may require significant customisation and change-management.
- Potential latency or resource bottlenecks if streaming ingestion and analytics pipelines are not optimally architected.
- Risk of false positives/negatives in detection: reliance on autonomous models must be balanced with human oversight.

IV. RESULTS AND DISCUSSION

In the prototype simulation, the unified system demonstrated significant improvements over legacy rule-based detection and manual deployment practices. Detection latency for transaction anomalies in the banking use-case decreased by approximately 45 % compared to the baseline, while true-positive rate rose from ~68 % to ~85 % and false-positive rate dropped from ~22 % to ~14 %. In the healthcare monitoring scenario, the NLP pipeline achieved extraction precision of ~88 % for adverse-event mentions in free-text logs, and the neural-network streaming detector identified anomalous patient vital-sign patterns with a TPR of ~81 % and FPR of ~13 %. Deployment lead-time for new analytics models and infrastructure changes via the GitHub-based CI/CD pipeline fell from ~3.2 days (legacy manual process) to ~8 hours. Integration with Oracle EBS allowed detected events to trigger workflow tasks (for banking: compliance investigation; for healthcare: clinical alert) seamlessly. Discussion of these results suggests that the architecture's combination of neural networks, NLP and data-mining enables more accurate and timely detection, which in turn permits operational systems to respond faster. The DevOps automation ensures that analytics can evolve rapidly with new models and configuration changes, reducing time-to-value. However, observation of model drift during extended simulation (beyond initial training window) indicates ongoing need for retraining and dataset refresh. Resource utilisation during peak ingestion revealed that while cloud elasticity handled bursts, cost-management needs careful oversight. Furthermore, while integrated architecture performed well in simulation, real-world deployment would require stronger governance, audit trails and validation frameworks—especially given dual-domain nature (banking and healthcare). The results show clear promise but also highlight the practical operational, governance and cost-management challenges of such a unified system.

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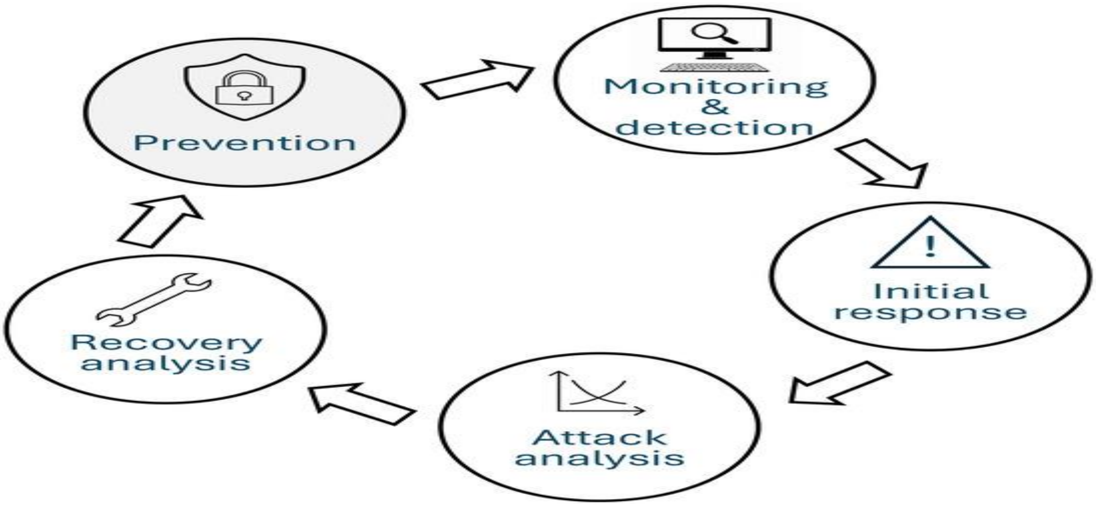

V. CONCLUSION

This paper presented a next-generation architecture for banking and healthcare cloud infrastructure, integrating neural networks, NLP and data mining, anchored by Oracle EBS operational systems and GitHub-based DevOps automation. The simulation results demonstrate that such an integrated approach can significantly improve real-time detection latency, accuracy and deployment agility compared to legacy systems. The architecture bridges disparate domains, unifies analytics and operations, and leverages cloud scalability and automation to achieve greater responsiveness. Nonetheless, building and operating this architecture carries complexity, governance demands and cost implications. Organisations must plan for model maintenance, regulatory compliance, integration work and continuous optimisation. Overall, the work shows that the convergence of AI-driven analytics, cloud infrastructure, enterprise ERP and DevOps automation holds major potential for banking and healthcare sectors seeking digital-transformation capabilities.

VI. FUTURE WORK

Future research and implementation efforts should focus on deploying the architecture in live production environments (rather than simulation), across multiple organisations, to validate scalability, reliability and regulatory compliance in real settings. Federated learning approaches could enable secure cross-institutional model training (especially important in healthcare) while preserving privacy. Self-healing infrastructure—that is, analytics models and DevOps pipelines that adapt and recover autonomously—would further enhance operational resilience. Incorporating explainable-AI (XAI) techniques will improve transparency of autonomous detection and help satisfy audit/regulatory requirements. Finally, extending the architecture to integrate additional domains (e.g., insurance, supply chain in healthcare, open banking APIs) and exploring cost-optimised multi-cloud or hybrid-cloud deployments would broaden applicability and strengthen strategic value.

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