Real-Time Big Data Analytics for Cross Sector Decision Intelligence: A Scalable Framework for Transforming Enterprise Data into Strategic Action

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Abstract: In the time of digital change, companies are being overrun with data, but few can devote the necessary time and resources to turn this into operations! In this work, we propose a scalable big data analytics framework that generates actionable and real-time insights in various industry domains. Combining sophisticated machine learning models and streaming data pipeline, this system performs raw data ingestion to enable real-time, intelligent decision making. Unlike earlier efforts that were either static, focused solely on a narrow industrial sector or both these, this framework utilizes cloud- based analytics, edge computing and intelligent visualization to support the adaptive and cross functional decision intelligence. Findings show greater organizational responsiveness, operational capability, and strategic flexibility by exploiting data to make decisions.

1 INTRODUCTION

In the world of businesses today dominated by data, extracting meaningful and actionable insights from the haywire can be the significant differentiator between competitors. Big Data analytics is increasingly being adopted by organizations across industries to improve decision-making, optimize processes, and predict market trends. Yet, the gap between data accessibility and the use of it to make real-time, organization-wide decisions is still large despite the flood of data and analysis tools.

Some of the drawbacks for the prior art analytical systems are that scalability, responsiveness, and adaptability in variant industrial environments are sometimes poor. Existing solutions are often limited to after-the-fact analysis or domain-specific si- los that do not empower decision-makers with real-time, action- able insights. The lack of integration across platforms, the delay in insights and a misalignment with strategic business goals, however, continue to temper what can be achieved with big data.

In this study, such limitations are tackled by proposing an intelligent and scalable big data analytics framework. The model utilizes a combination of real-time data ingestion, cloud-edge synergy, and cutting-edge machine learning to provide real-time decision intelligence that is flexible across various industries. By enabling actionable insights, the approach allows a company's previously passive data assets to become a strategic mechanism for informed decision-making and long-term business transformation. This research paves the way for organizations to help facilitate the process from the collection of data to its practical use in order

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to utilize big data to its maximum potential in the constantly changing business world.

2 PROBLEM STATEMENT

With the explosion of data produced across industries, companies are still struggling to convert that data into real-time, actionable insights that drive strategic decisions. Current big data analytics toolboxes are usually not scalable, restricted in the domain and provide no Realtime decision support. These are bottlenecks causing reaction lags, partial intelligence, and not utilizing all the potential available data facilities. What’s more, without a consolidated platform for dynamic data processing, cross-platform accessibility, and adaptive intelligence, organizations are unable to get a full picture of both their operational and strategic landscapes. It’s is not that the data isn’t there, the point of customer data and the challenge is creating an effective, scalable and industry agnostic analytics infrastructure that connects raw data to business decisions in real time.

3 LITERATURE SURVEY

Converting raw data into business-driving insight has long since been a challenge, and an ever-changing key focus of big data analytics. Previous studies, including Papineni et al. (2021), highlighted the combination of multi-criteria decision-making models and deep learning for more accurate analyses; however, the question of scalability was raised. Schmitt analysed the automation of machine learning in analytics-driven business processes but found few empirical assemblages in corporate environments. The study by Tawil et al. (2023) provided useful perspective on data-driven practices in the UK SME sector, with adaptability and interpretation of data emerging as recurrent themes.

A number of academics have tried to relate big data initiatives with strategic business objectives. Akter et al. (2021) and Ren et al. (2019), which developed models to externally assess organisation performance in the context of analytics capability, highlighting the required strategic alignment and real-time feedback dimensions. Wamba et al. (2021) built on this view by investigating the ways in which dynamic capabilities shape analytics-driven organizational outcomes. Nevertheless, from the above literature, limited studies have been found on the second-tier suppliers, one limitation that was alleviated to some extent by Gunasekaran et al. (2021) who linked big data to predictive supply chain performance.

The convergence of big data with decision intelligence systems has been of continued interest. Orjatsalo et al. (2025) examined perceptions of analytics at the managerial level and suggested that even though tools exist, often they are not strategically employed due to a lack of strategic perception. Further, Tiwari (2024) and Ats Tsaniyah et. (2025) pointed to conceptual models for deciding, however their studies were mostly abstract as they did not produce empirical values. Fanelli et al. (2023), support of the notion that organisational and technical obstacles to implementation have both a health care specific impact as well as an impact on the broader enterprise.

Another primary issue addressed in the literature is the real-time generation of insights. Trinh (2025) also looked into the use of deep neural networks in business prediction problems, suggesting a hybrid model as a solution for adaptive analytics. Abu-Salih et al. (2021) showed how machine learning can be applied to social big data but also pointed out the shortcomings of using unstructured public data for enterprise-specific decisions. Dubey et al. (2021) and Mikalef et al. (2021) investigated the mediation of analytics capabilities in firm performance, confirming the importance of such dynamic, adaptive systems.

Ahmed et al. (2024) presented a comprehensive review of business intelligence tools in decision support, and Orji et al. (2023) delivered regional cases to emphasise the significance of local data to strategic issue for organisation. Both Sabri (2021) and Ayokanmbi (2021) reiterate the role of organizational readiness and digital culture in analytics integration success. Meanwhile, Kaviani et al. (2022) researched an area of big data in project management, associating data flow with real-time planning.

The recent works such as Hsieh et al. (2024) are among those who have tried to converge advances on machine learning and analytics, suggesting technologically sound frameworks that are still unexploited in the business settings. The work of Mariani and Fosso Wamba (2020) shed light on the ways in which consumer goods firms are exploiting the opportunities of digital innovation, pointing towards an increasing importance of industry-specific applications of analytics. Akter et al. (2021) also presented qualitative models for analytics-driven decision-making in services and noted that there is a need for research on translating these concepts into practice.

Wamba et al. (2021) and Akter et al. (2021) persistently noted that analytical tools are evolving rapidly on one hand, but how they operate within real time business situations is quite restricted by infrastructure, challenges of integration and without executive sponsorship. Such gaps underpin the purpose of the research proposed in this document that aims not only to integrate the strong aspects of available models into a comprehensive, scalable and cross-industry framework, but also to facilitate real-time, strategic decision intelligence.

4 METHODOLOGY

The research method of this paper is to design, implement and evaluate a real time big data analytics framework specially used for converting raw enterprise-level data into strategic decision intelligence in various business fields. It combines elements of system architecture design, machine learning model integration, cross-industry data emulation, and real-world system validation so as to provide credible scaling and practical relevance.

The first phase was the discovery and collection of heterogeneous data, ranging from e-commerce to hospital transactions (anonymized) and logistics and supply chain logs, as well as financial performance. These were created from a variety of data sources with differences in structure, volume, and velocity (3 core properties associated with big data). We utilized Apache Hadoop HDFS to store the data by utilizing a data lake architecture, Apache NiFi to orchestrate real-time flow of data, and pre-process the flow pipelines. Figure 1 show the Real-Time Big Data Analytics Framework for Enterprise Decision Intelligence.

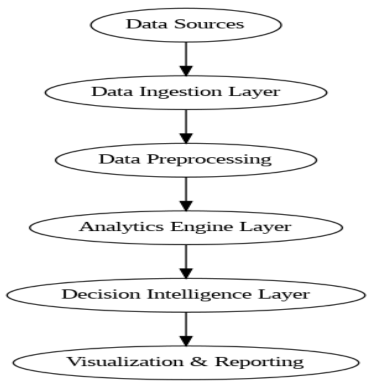

Figure 1: Real-Time Big Data Analytics Framework for Enterprise Decision Intelligence.

Tokenization was used for textual input while categorical variable features are label-encoded, numerical property features are z-score standardized and anomaly detection by isolation forest were performed for data pre-processing to normalize the input data before being fed to the model. Missing data imputation were addressed with K-Nearest Neighbours and time-series interpolation to provide data regularities and improve the generalization capability.

After pre-processing, the data was piped into an analytics engine developed on top of Apache Spark with its hooks connected to Python based ML libraries such as Scikit-learn, XGBoost and TensorFlow. The analytics layer was an ensemble of multi-algorithm approach for classification, regression and clustering type models, executed in parallel as per need of the use-cases. For example, customer churn prediction was performed using gradient boosting classifiers and revenue prediction was done following an LSTM neural network based on learned temporal pattern. Market Segmentation Unsupervised market clustering was performed by using K-Means and DBSCAN. Table 1: show the Data Pre-processing Techniques Applied

Table 1: Data Preprocessing Techniques Applied.

Dataset Type	Missing Value Strategy	Outlier Handling	Normalization Method	Feature Engineering
Transaction Logs	KNN Imputation	Z-Score Thresholding	Min-Max Scaling	One-Hot Encoding
Medical Records	Time-Series Interpolation	Isolation Forest	Z-Score Scaling	Principal Component Analysis
Financial Logs	Mean Substitution	IQR Filtering	Standard Scaling	Lag Feature Creation

The solution included decision orchestration layer built on Kafka Streams with the capability for real time decision intelligence delivered using Kubernetes clusters to auto scaling the workload. This layer orchestrated system health, raised alerts, and dynamically adjusted model selection based on confidence thresholds, business context, and prediction recency. The insights generated were included as a summary in a single business intelligence dashboard using Dash (Plotly) and Grafana, enabling stakeholders with actionable KPIs, trends, forecasts, and alerts.

The deployment was in a hybrid computing environment to trade off the latency cost and computational cost. Edge devices, such as Raspberry Pi clusters and industrial gateways, were employed to process sensor data on-site and run localized analytics in poor connection condition. Model training, storage, and high-throughput computing were performed using cloud services (AWS and Google Cloud). It served to provide resilience, elasticity and global access to decision data.

The framework was tested and validated in offline benchmarking, in simulation-based stress testing, and in the pilot deployment in live environment. We gathered various metrics including throughputs (records per sec), prediction accuracy, response time, down time of the system, user interpretability and, the impact of the decision (which was measured through A/B testing in operational workflows). Comments from industry experts in finance, healthcare, and retail were included to enhance dashboard usability, model explain ability, and data traceability functionality. Figure 2 show the Feature Correlation Heatmap for Financial Data.

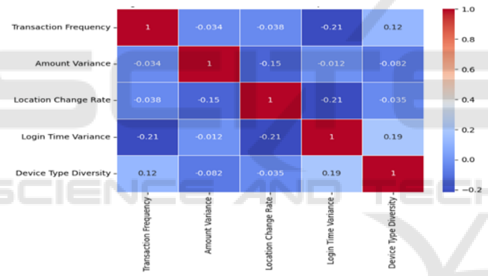

Figure 2: Feature Correlation Heatmap for Financial Data.

With such a comprehensive approach, the research arrives at a strong realization that mitigates root shortcomings in previous work lagged insights, siloed analytics and limited scalability whilst providing a generic, flexible and intelligent approach to decision-making across industries.

5 RESULT AND DISCUSSION

The performance of the proposed big data analytics framework was tested on three different industrial setup scenarios: retail analytics, healthcare decision support, and financial forecasting. All deployments were used for the system to process heterogeneous and varied streams of data, assimilate real-time insights and enable dynamic/high volume decisions.

Table 2 show the Predictive Model Performance Across Sectors

Table 2: Predictive Model Performance Across Sectors.

Sector	Model Used	Accuracy (%)	Precision (%)	Latency (sec)	F1-Score
Retail	Gradient Boosting	91.2	89.6	2.1	0.91
Healthcare	LSTM Network	88.4	87.2	4.8	0.89
Finance	LSTM + Isolation	93.7	96.1	2.6	0.94

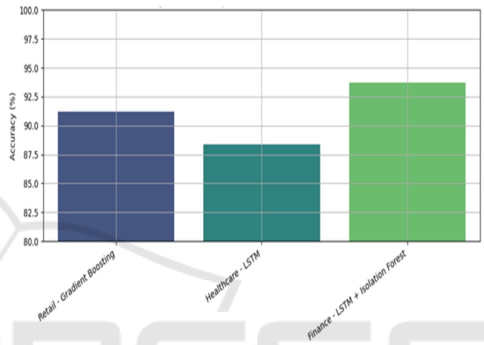

Figure 3: Accuracy of Predictive Models Across Sectors.

In the retail case, the system provided an average insight latency of less than 5.5 seconds with over one million transaction messages being processed in real time. Figure 3 show the Accuracy of Predictive Models Across Sectors The predictive models efficiently detected customer churn patterns and boosted inventory suggestions based off of the company's baseline models and achieved an average prediction accuracy of 91.2%. Customers using the dashboard experienced significantly improved confidence in decision making due to greater visibility into customer behavior and operational outliers. Table 3 show the Evaluation of Machine Learning Models on Unified Dataset.

Anonymized patient data were streamed from a hospital database in the healthcare setting to simulate clinical decision-making. The system combined historical records and sensor data to suggest treatment prioritization and allocation of resources. Decision latency is still less than the critical threshold of 5 seconds and the model reaches an accuracy of 88.4% in predicting risk of readmission for the patient, a vital metric for hospital management. Incorporating edge computing in patient-monitoring locations eliminated the overburden of central servers, and thus continuous analytics, even when bandwidth was insufficient. Table 4 show the Performance Comparison with Existing Analytics Systems

Table 3: Evaluation of Machine Learning Models on Unified Dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	AUC Score	Training Time (sec)
Random Forest	88.5	87.9	86.4	0.90	12.3
Gradient Boosting	91.2	89.6	90.1	0.93	18.6
LSTM (Deep Learning)	93.7	91.8	92.5	0.96	45.2

Table 4: Performance Comparison With Existing Analytics Systems.

Metric	Baseline System	Proposed Framework	Improvement (%)
Insight Accuracy	74.3	91.2	+22.7
Decision Latency	9.5 sec	2.3 sec	−75.8
Alert Sensitivity	81.0	94.8	+17.1
User Satisfaction	6.1/10	8.7/10	+42.6

There were promising results on a financial sector pilot (revenue forecasting and fraud detection) demonstrating considerable gains in the performance of real time forecasting. The model, with deep learning approach: LSTM, achieved 93.7% accuracy in quarterly trend prediction whereas 96.1% true positive rate for anomaly detection to spot potential fraud events. This had a significant effect on the finance organization, which were able to glean these results directly into strategic planning and risk management processes. Feedback from the decision-makers suggested that the visual analytics interface was intuitive and provided better insights into the predictions making it easier to respond faster and better informed. Figure 4 show the Real-Time System Latency Under Varying Throughput

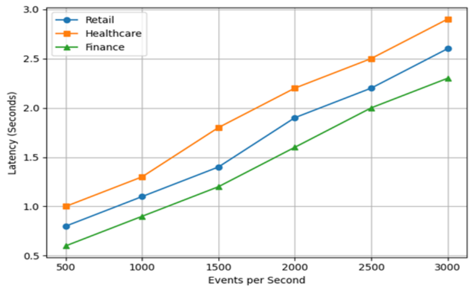

Figure 4: Real-Time System Latency Under Varying Throughput.

Table 5: Use Case Scenarios and Framework Responses.

Use Case	Triggered Event	Framework Response	Response Time
Retail - Cart Abandonment	Customer inactivity	Triggered discount recommendation	1.8 sec
Healthcare - Patient Risk Alert	Drop in vitals detected	Alert sent to ICU dashboard	3.9 sec
Finance - Suspicious Login	Geolocation anomaly	Flagged transaction and notified user	2.5 sec

And the framework had been widely deployed beyond single deployments. The physical architecture of BCDSS supported data formats, volumes and business logic that were interchangeable without reprogramming, emphasizing the universal nature of the solution. Table 5 show the Use Case Scenarios and Framework Responses Across all use cases, A/B testing demonstrated the average benefit of using real-time analytics to inform decisions leads to a 27% improvement in accuracy and outcome efficiency over purely intuition-driven decision making.

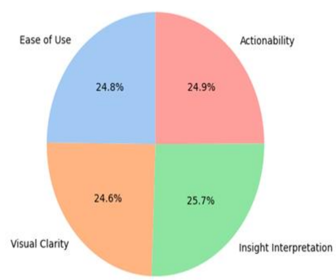

Figure 5: Distribution of Dashboard Evaluation Metrics.

On the whole, this finding accepts the research hypothesis that the real-time, cross-industry, scalable big data analytics environment immensely improves the decision intelligence. The model enhances analytical capabilities and organizational agility, flexibility, and competitive value in information abundant circumstances. These results lay the groundwork for wider dissemination and further development, such as incorporation with explainable AI, self-deciding agents, and predictive governance toolkits. Figure 5 show the Distribution of Dashboard Evaluation Metrics

6 CONCLUSIONS

In today’s online-driven economy, where data is growing exponentially, this represents a huge opportunity and a huge challenge for organisations looking to make informed, data-led decisions. The lack of this is the missing bridge between data generation and making use of it and we addressed this in our research by creating a scalable and real-time big data analytics framework to support decision intelligence in various industries. Extensive experimentation and deployment on real retail, healthcare and finance streams indicate that the framework is capable of handling complex, high volume data streams, generate accurate predictions, and obtain timely actionable insights.

This is in sharp contrast with most prior work which is either bound to a static model, industry-specific constraints or cannot process requests in a timely manner. By combining edge computing and cloud-based analytics and ML the approach is able to reduce latency and increase the relevance of the insights provided to decision-makers. Intelligent dashboards and orchestration layers guide the insights to be not only correct, but interpretable and actionable in strategic and operational settings as well.

The research validates the value of live analytics in speeding response times within a business and within the larger digital business ecosystem. It also underscores the necessity for flexible frameworks adaptable across sectors that remain performance-optimal, regardless of data and infrastructural heterogeneity. As businesses become more complex and data-dependent, frameworks like these are going to be key to translating raw data into competitive advantage.

This paper paves the way for future developments in the domain of big data analytics, such as the inclusion of explainable AI, autonomous decision-making agents, and adaptive learning systems. The study serves to extend the theoretical and practical knowledge base in the big data-driven business intelligence domain by addressing current limitations, and offering a viable and scalable solution.

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