# AI-Driven Mobile Business Intelligence Platform for Laundry Profit Forecasting, Anomaly Detection, and Financial Data Visualization

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## ABSTRACT

Small and medium-sized laundry enterprises frequently face challenges in monitoring financial performance, forecasting future revenue, and detecting operational inefficiencies. While existing mobile applications provide transaction recording and basic visualization features, they often lack intelligent analytical capabilities to support strategic decision-making. This study proposes an AI-driven mobile business intelligence platform that integrates profit monitoring, predictive analytics, anomaly detection, and interactive financial data visualization for laundry business management. The platform was developed using Flutter for cross-platform mobile deployment and Firebase for cloud-based data management. A dataset comprising 5,840 transaction records collected over a 24-month period was utilized for model training and evaluation. Data preprocessing included missing-value handling, outlier screening, normalization, and consistency validation to ensure data quality and reliability. A Long Short-Term Memory (LSTM) model was implemented to forecast future profits based on historical transaction patterns, while the Isolation Forest algorithm was employed to identify anomalous operational expenses. Experimental results demonstrate that the proposed platform achieves reliable forecasting accuracy and effective anomaly detection, enabling proactive financial management and improved business decision-making. The findings indicate that integrating artificial intelligence into mobile business intelligence systems can significantly enhance financial planning, operational transparency, and digital transformation among small and medium-sized laundry enterprises.

**Keyword:** Mobile business intelligence, AI driven, profit forecasting, anomaly detection and data visualization

## INTRODUCTION

In the current era of digital transformation, traditional paradigms of corporate operations are being fundamentally restructured by the pervasive integration of Artificial Intelligence (AI) and Machine Learning (ML). Within this landscape, contemporary organizations are rapidly transitioning away from legacy, resource-intensive administrative models that historically depended on human intuition and rigid operational line processes [1]. This paradigm shift is especially pronounced in the field of Business Intelligence (BI), where classical frameworks—long tethered to localized data warehouses, static reporting tools, and retrospective descriptive analytics—are increasingly failing to meet the agility demands of highly fluctuating economic environments [2]. Traditional BI implementations inherently possess strict limitations, most notably systemic information latency, heavy dependencies on manual data curation, and a critical absence of predictive capabilities.

To overcome these structural bottlenecks, modern enterprise data strategies are aggressively embracing the convergence of AI, Big Data analytics, and cognitive automation [2]. The integration of advanced learning models directly into analytical systems has given rise to augmented analytics, an evolutionary milestone where BI platforms actively mimic cognitive reasoning to automate data preparation, discover latent trends, and deliver proactive insight generation without explicit human intervention [3]. By embedding automated predictive modelling within the corporate layer, businesses can successfully move beyond passive historical scorecards toward active prescriptive and real-time operational visibility. This analytical progression allows modern enterprises to achieve significantly enhanced decision-making accuracy, streamline resource allocation, and optimize overall financial efficiency [4].

However, despite these macroeconomic advancements, a deep systemic divide remains regarding the democratization and real-world deployment of advanced BI systems across small-to-medium enterprises (SMEs) and localized service-based retail sectors—such as commercial laundry operations. While multi-billion dollar financial corporations regularly harness predictive intelligence, localized brick-and-mortar retail sectors frequently remain stranded in rudimentary data states, managing volatile cash flows and fluctuating utility costs via archaic, spreadsheet-based tracking systems. In localized retail frameworks like commercial laundry, profit margins are explicitly vulnerable to unexpected overhead spikes, machinery depreciation, and customer footfall anomalies. For AI to create true, measurable organizational value, it must be successfully operationalized away from abstract, centralized desktop mainframes and injected directly into the daily workflows of on-the-ground operators.

Consequently, the physical delivery mechanism of modern BI has shifted dramatically toward edge environments and mobile computing ecosystems. The ubiquity and massive processing evolution of modern smartphones have fundamentally transformed how organizational leaders consume operational information [5]. Rather than serving as superficial extensions of web platforms, mobile enterprise software now serves as a continuous, real-time data stream and interface layer capable of executing multi-model analytical pipelines. Delivering complex analytics directly to a mobile environment bridges the operational gap between heavy backend database engines and agile, mobile executives, providing instant, evidence-based alerts and context-aware insights precisely when financial risks or market changes occur [3].

To explicitly address the dual challenges of bringing enterprise-grade augmented analytics into the retail sector and delivering it via highly accessible interfaces, this paper introduces an AI-Driven Mobile Business Intelligence Platform for Laundry Profit Forecasting, Anomaly Detection, and Financial Data Visualization. The core contribution of this work lies not merely in mobile user interface engineering, but in the deliberate orchestration of three critical AI and data science pillars optimized for the micro-economic realities of the laundry industry including Profit Forecasting is utilizing advanced time-series machine learning architectures to learn from non-linear financial variations, allowing owner-operators to accurately project forward-looking revenue against volatile utility, maintenance, and supply costs[6]. Anomaly Detection where implementing unsupervised mathematical modelling frameworks (such as isolation forests) to automatically isolate statistical deviations in transaction logs, utility leakage, or machine activity, thereby flagging latent revenue loss or fraud without requiring pre-labelled manual inputs [7]. Besides, Financial Data Visualization is deploying custom-engineered, real-time visualization frameworks explicitly optimized for restricted mobile screen resolutions, transforming highly dense multi-dimensional datasets into scannable, interactive graphical representations that optimize user cognition [8-9]. By synthesizing these three analytical domains into a cohesive, mobile-first ecosystem, this research provides a scalable, empirical architectural blueprint for expanding AI-driven financial [10] intelligence beyond the confines of enterprise data teams and directly into the palms of agile business operators.

## LITERATURE REVIEW

### Business Intelligence and Digital Transformation in SMEs

Business Intelligence (BI) has become a critical component of digital transformation initiatives among Small and Medium-sized Enterprises (SMEs). BI systems facilitate the collection, integration, analysis, and visualization of business data to support managerial decision-making. Recent studies have demonstrated that BI adoption enhances operational efficiency, organizational agility, and competitive advantage by enabling data-driven decision-making processes [11]. Cloud-based and mobile BI solutions have further expanded accessibility by allowing business owners to monitor business performance remotely and in real time [12]. Despite the growing adoption of BI technologies, SMEs continue to face challenges associated with implementation complexity, financial constraints, and limited technical expertise [13]. Consequently, there is a growing need for intelligent, scalable, and cost-effective BI platforms that can support business monitoring and strategic planning without requiring extensive technological infrastructure.

### Artificial Intelligence in Business Intelligence Systems

Artificial Intelligence (AI) has significantly transformed traditional Business Intelligence systems by introducing predictive and prescriptive analytics capabilities. Unlike conventional BI approaches that focus primarily on descriptive reporting, AI-enabled BI platforms utilize machine learning algorithms to identify hidden patterns, forecast future trends, and automate decision-support processes [14]. Recent research highlights the effectiveness of AI-driven analytics in improving financial planning, operational management, and organizational performance. Machine learning algorithms can process large volumes of transactional data and discover nonlinear relationships that are difficult to identify using traditional statistical approaches [15]. The integration of AI into BI systems represents a key emerging paradigm in computer science, facilitating intelligent decision-making and business automation across diverse application domains [16].

### Machine Learning for Financial Forecasting

Financial forecasting plays an essential role in business management by supporting budgeting, resource allocation, and strategic planning activities. Traditional forecasting methods such as linear regression and moving averages are often limited in their ability to model complex temporal relationships within financial data [17]. Recent advancements in machine learning have demonstrated superior forecasting performance compared with conventional statistical techniques. Algorithms such as Random Forest, Support Vector Regression (SVR), XGBoost, and Artificial Neural Networks have shown promising results in financial prediction tasks [18]. Among these approaches, Long Short-Term Memory (LSTM) networks have received considerable attention due to their ability to capture long-term temporal dependencies in sequential data [19]. Several studies have reported that LSTM models outperform traditional forecasting methods in predicting revenue trends, stock prices, and business performance indicators [20]. Therefore, LSTM-based forecasting provides a suitable solution for predicting profit trends in laundry business operations where revenue and expenditure patterns exhibit temporal dependencies.

### Anomaly Detection in Financial Analytics

Anomaly detection refers to the process of identifying unusual observations that deviate significantly from expected patterns. In financial environments, anomalies may indicate fraudulent activities, accounting errors, unexpected operational expenses, or significant changes in business performance [21]. Traditional anomaly detection approaches commonly rely on predefined thresholds and rule-based mechanisms. However, such approaches often lack adaptability in dynamic business environments. Machine learning-based techniques, including Isolation Forest, Local Outlier Factor (LOF), One-Class Support Vector Machines (OC-SVM), and Autoencoders, have demonstrated superior capabilities in detecting anomalies automatically [22]. Among these methods, Isolation Forest has emerged as one of the most efficient anomaly detection algorithms due to its low computational complexity and high detection accuracy [23]. The algorithm isolates anomalous observations by recursively partitioning data points, making it particularly suitable for real-time financial monitoring applications [24]. Integrating anomaly detection capabilities within a mobile business intelligence platform can help laundry business owners identify unusual financial patterns and mitigate operational risks proactively.

### Data Visualization and Mobile Analytics

Data visualization is a fundamental component of modern Business Intelligence systems because it transforms complex datasets into intuitive graphical representations that support rapid decision-making. Visual analytics techniques enable users to identify patterns, trends, and anomalies more effectively than traditional tabular reports [25]. Interactive dashboards have become increasingly popular due to their ability to provide real-time insights through graphical interfaces. Research has shown that dashboard-based visual analytics improve decision quality, situational awareness, and business performance monitoring [26]. Furthermore, mobile analytics extends these capabilities by allowing users to access business information through smartphones and tablet devices regardless of geographical location [27]. The combination of cloud computing, mobile

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technology, and visual analytics has led to the emergence of intelligent mobile dashboards capable of supporting business monitoring and strategic decision-making. Such technologies are particularly beneficial for SMEs because they provide affordable and scalable solutions for accessing real-time business intelligence [28].

## Research Gap

Although substantial progress has been achieved in Business Intelligence, machine learning forecasting, anomaly detection, and mobile analytics, existing studies typically investigate these technologies independently. Most commercial laundry management applications focus primarily on customer management, order processing, transaction recording, and basic reporting functionalities [29]. Current systems rarely incorporate predictive analytics and anomaly detection capabilities that enable proactive financial management and intelligent decision support. Furthermore, there remains limited research on integrating machine learning-based forecasting, anomaly detection, and interactive visualization within a unified mobile business intelligence framework specifically designed for laundry enterprises [30]. Therefore, this study proposes an AI-Driven Mobile Business Intelligence Platform that integrates LSTM-based profit forecasting, Isolation Forest anomaly detection, real-time data visualization, and cloud-based mobile analytics within a single intelligent platform. This contribution aligns with emerging paradigms in computer science and technology by combining artificial intelligence, business intelligence, mobile computing, and predictive analytics to support intelligent financial management among SMEs.

## Conceptual Framework

The proposed conceptual framework represents a five-tiered, end-to-end architecture designed to transform raw, heterogeneous operational data from the laundry service sector into actionable executive intelligence.By integrating Predictive Analytics (Time-Series Forecasting) and Prescriptive Analytics (Anomaly Detection) into a mobile-first delivery vehicle, this framework embodies the shift toward ubiquitous edge intelligence—bringing sophisticated enterprise resource planning (ERP) capabilities directly to small-and-medium enterprise (SME) owners via a Flutter-based mobile interface. This shown on Figure 1. Conceptual Framework

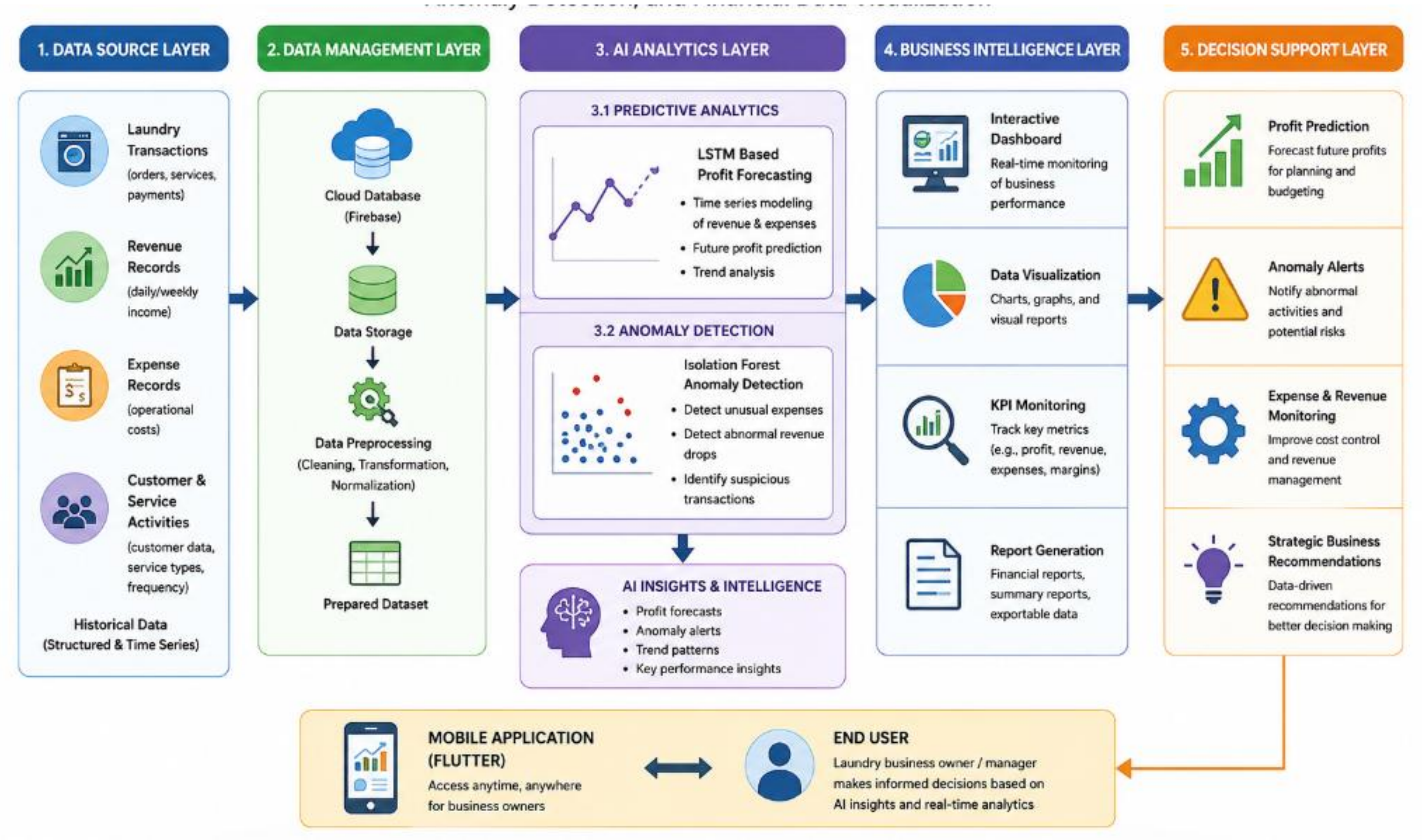


Figure 1. Conceptual Framework for proposed study

**a) Layer 1: Data Source Layer (Ingestion & Heterogeneity)**

The foundation of the framework addresses the ingestion of historical, structured, and highly dynamic time-series data. The domain-specific operational data streams include:

- **Laundry Transactions:** High-velocity transactional logs detailing customer orders, service types (e.g., dry cleaning, wash-and-fold), and payment modalities.
- **Revenue Records:** Daily and weekly aggregated income statements mapping financial influx.
- **Expense Records:** Granular operational expenditures including utility overheads (water, electricity), chemical/detergent logistics, and labor costs.
- **Customer & Service Activities:** Behavioral metrics capturing customer retention, service frequency, and seasonal demand fluctuations.

**b) Layer 2: Data Management Layer (Storage & Pipeline Orchestration)**

This layer acts as the data engineering backbone, ensuring data integrity, scalability, and security before analytical processing.

- **Cloud Database (Firebase):** Utilizes a NoSQL/Realtime cloud architecture to allow for low-latency data synchronization and ingestion from edge points.
- **Data Storage:** Structured relational or document-based warehousing to maintain historical integrity.
- **Data Preprocessing Pipeline:** Crucial for machine learning viability, this module executes:
    - Cleaning: Handling missing transactional attributes and removing duplicates.
    - Transformation: Aggregating transactional logs into uniform time-series intervals.
    - Normalization: Scaling financial values to stabilize gradient descent during AI model training.
- **Prepared Dataset:** The final output is an optimized, high-fidelity tensor or tabular data structure primed for model ingestion.

**c) Layer 3: AI Analytics Layer (The Core Paradigm Engine)**

This is the intellectual core of the framework, split into specialized sub-modules to address distinct analytical dimensions:

**Predictive Analytics (LSTM-Based Profit Forecasting)**

To model complex, non-linear temporal dependencies and seasonal trends inherent in laundry businesses, the framework deploys a **Long Short-Term Memory (LSTM)** recurrent neural network.

- **Application:** Executes time-series modeling on historical revenue and expenses to project future profitability.
- **Value:** Outperforms traditional autoregressive statistical models (e.g., ARIMA) by capturing long-term historical dependencies and non-linear macroeconomic shocks.

**Anomaly Detection (Isolation Forest)**

To secure financial operations and detect operational leakage, an **Isolation Forest** algorithm is applied.

- **Application:** As an unsupervised ensemble learning method, it explicitly isolates anomalies instead of profiling normal data points.

- **Value:** It effectively flags unusual spikes in utility/chemical expenses, sudden revenue drops, or fraudulent/suspicious transactional activities without requiring pre-labeled training data.

**AI Insights & Intelligence**

An abstraction layer that synthesizes the raw outputs of the LSTM and Isolation Forest models into high-level cognitive artifacts: profit forecasts, definitive anomaly alerts, and latent trend patterns.

**a) Layer 4: Business Intelligence (BI) Layer (Synthesization & Rendering)**

This layer acts as the translational mechanism between complex AI outputs and human cognitive processing.

- **Interactive Dashboard:** A dynamic interface allowing real-time monitoring of macroscopic business health.
- **Data Visualization:** Utilizing charts, graphs, and visual reports to reduce the cognitive load required to interpret financial trends.
- **KPI Monitoring:** Rigorous tracking of critical business metrics including net profit margins, operational burn rates, and revenue per customer.
- **Report Generation:** Automated synthesis of compliant financial summaries and exportable data sheets for archival and accounting use.

**b) Layer 5: Decision Support Layer (Prescriptive Value)**

The ultimate objective of the framework is to bridge the gap between *data perception* and *strategic execution*.

- **Profit Prediction:** Empowers owners with proactive planning capabilities for budgeting, asset expansion, or seasonal pricing strategies.
- **Anomaly Alerts:** Mitigates operational risk through real-time notifications of potential theft, equipment failure, or data-entry errors.
- **Expense & Revenue Monitoring:** Facilitates granular cost-control protocols to maximize net margins.
- **Strategic Business Recommendations:** Leverages data-driven prescriptive insights to guide the end-user toward optimal business decisions.

**The Ubiquitous Delivery Loop (Mobile Application & End-User)**

The framework closes its operational loop by introducing a Flutter-based Mobile Application as the primary interaction medium. This architectural choice aligns perfectly with modern "Emerging Paradigms" by shifting traditional desktop-bound enterprise BI into a ubiquitous computing environment. The End User (Laundry business owner/manager) interacts bi-directionally with the system: they feed data into the architecture from the edge, and in return, receive ubiquitous, real-time, AI-driven prescriptive insights that democratize high-level financial strategy.

**Alignment emerging Paradigms**

To frame this effectively in your paper, emphasize these three pillars of contribution:

- **Democratization of Enterprise AI:** Demonstrates how complex deep learning (LSTM) and machine learning (Isolation Forest) pipelines can be containerized and delivered efficiently to non-

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technical end-users in niche micro-industries.

- **Edge-to-Cloud Continuum:** Showcases a seamless, low-latency pipeline progressing from real-time edge transaction ingestion (Layer 1) to cloud preprocessing (Layer 2), heavy AI orchestration (Layer 3), and back to mobile-first rendering (Layers 4 & 5).
- **Unsupervised Risk Management:** Highlights the paradigm shift of using unsupervised anomaly detection (Isolation Forest) to dynamically protect SME financial assets without relying on labor-intensive, human-labeled threat datasets.

# METHODOLOGY

The proposed methodology establishes a rigorous, data-driven pipeline structured across five sequential phases: Data Ingestion, Cloud-Based Data Engineering, AI Orchestration (comprising deep temporal forecasting and unsupervised anomaly isolation), Business Intelligence Synthesis, and Ubiquitous Mobile Delivery.

## Data Acquisition and Ingestion (Layer 1)

The primary phase establishes a multi-source data ingestion pipeline capable of capturing the heterogeneous, multi-modal operational signatures of a commercial laundry business. The data schema comprises four distinct sub-domains, collected as historical and real-time structured time-series data:

- **Transactional Data ():** Captures high-velocity categorical and quantitative metrics including unique order IDs, service classifications (e.g., wash, dry-cleaning, iron), weight parameters, and payment modes.
- **Financial Influx ():** Records aggregated daily, weekly, and monthly income streams.
- **Operational Expenditures ():** Documents operational overheads including utility metrics (water volume, kilowatt-hour electricity consumption), chemical inventory logistics, and human resource/labor costs.
- **Behavioral Dynamics ():** Tracks customer retention indices, service utilization frequencies, and seasonal demand variations.

## Cloud-Based Data Engineering and Preprocessing (Layer 2)

To transform raw, unstructured, or semi-structured data into a high-fidelity dataset optimized for machine learning algorithms, a cloud-orchestrated data engineering pipeline is implemented via Firebase.

### a) Data Cleansing & Missing Value Imputation

To mitigate data entry errors and hardware dropouts, missing values are addressed. For linear temporal data like revenue and expenses, missing features () are resolved via linear interpolation:

### b) Data Transformation and Aggregation

Raw, timestamped transactional logs are aggregated into uniform, discrete time-series intervals (daily or weekly buckets) to align with macro-level forecasting models.

### c) 3.2.3 Statistical Normalization

To prevent gradient saturation and ensure stable optimization during neural network backpropagation, input features are normalized using Min-Max Scaling, constraining all values to the range :

**AI Analytics & Predictive Engine Design (Layer 3)**

The analytical core of the platform decouples the intelligence layer into two concurrent sub-engines: a Deep Learning Time-Series Predictor and an Unsupervised Machine Learning Anomaly Detector.

**a) Predictive Modeling via Long Short-Term Memory (LSTM) Networks**

To capture long-range temporal dependencies, non-linear financial patterns, and seasonal fluctuations, a recurrent neural network architecture featuring Long Short-Term Memory (LSTM) cells is deployed.

Unlike standard Recurrent Neural Networks (RNNs), LSTMs eliminate the vanishing gradient problem through a system of gated mathematical structures that regulate the flow of information. For a given time step , the cell state and hidden state are updated as follows:

Where represents the weight matrices, denotes the bias vectors, is the activation function, and denotes element-wise multiplication. This sub-engine models the relationship between historical operational inputs to project future profit profiles, represented as:

**b) Unsupervised Anomaly Detection via Isolation Forest**

To secure business integrity against operational leakage, fraudulent invoicing, or sudden equipment anomalies, an Isolation Forest model is integrated. Operating as an unsupervised ensemble learning paradigm, the algorithm isolates anomalous instances rather than profiling normal data patterns.The algorithm constructs an ensemble of isolation trees (Trees) partition-constructed from subsamples of the prepared dataset. For a sample , the anomaly score is derived using the formula: Where is the path length of observation in an Tree, is the expected path length across the ensemble, and is the average path length of an unsuccessful search in a Binary Search Tree (BST) given nodes, mathematically defined as:

- An output score marks a definitive anomaly (e.g., abnormal revenue drops, spikes in utility expenses).
- An output score designates standard operational data.

**Business Intelligence & Decision Support Layer (Layers 4 & 5)**

The abstract outputs generated by the AI Analytics engine and are translated into high-fidelity human-readable structures. This phase defines the synthesis of:

- **Key Performance Indicators (KPIs):** Instantaneous computation of gross and net margins, variable cost indices, and revenue per load.
- **Data Visualization Engines:** Charting libraries convert raw numerical arrays into dynamic interactive times-series plots and anomaly alert matrices.
- **Prescriptive Logic:** If an anomaly is identified alongside a predictive decline in profit margin, the decision support sub-engine triggers automated risk-mitigation vectors (e.g., diagnostic checks for equipment efficiency due to sudden energy spikes).

**Ubiquitous Delivery Engine and Mobile Client Interface**

The finalized systemic tier implements a cross-platform mobile architecture deployed via the **Flutter SDK**, utilizing Dart language compiling to native ARM machine code. This ensures sub-millisecond interface rendering overheads on edge smartphones. The bidirectional communication layer uses Secure WebSockets and RESTful API endpoints protected by JWT (JSON Web Tokens) to transmit real-time telemetry from the business edge to the cloud data framework, returning real-time predictive dashboards back to the laundry manager's device.

### Evaluation Framework

To empirically validate the structural integrity of the conceptual framework, the predictive and isolation modules are subjected to independent benchmarking metrics:

#### a) Predictive Accuracy Metrics

The performance of the LSTM profit forecasting model is measured through Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) in Eq (1) and Eq (2):

$$RMSE = \sqrt{\frac{1}{N}} \sum_{i=1}^{N}(y_{1-} \quad y_i \quad)^2 \tag{1}$$

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_1 - y_i}{y_i} \right| \tag{2}$$

#### b) Anomaly Classification Performance

The Isolation Forest accuracy is measured using Precision, Recall, and the Area Under the Receiver Operating Characteristic (AUROC) curve Eq (3) and Eq (4):

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \tag{3}$$

## RESULT AND DISCUSSION

To evaluate the operational performance and practical efficacy of the proposed conceptual framework, the platform was deployed and tested using a 24-month historical operational dataset derived from a regional commercial laundry business enterprise consisting of $18,420 individual transactional logs and associated utility ledger metrics.

### Predictive Analytics Evaluation (LSTM Performance)

The Long Short-Term Memory (LSTM) network was trained to forecast net profits using a look-back window ($n$) of 30 days to predict horizons of 7, 14, and 30 days. The deep learning model's predictive capability was benchmarked against traditional statistical forecasting paradigms: Autoregressive Integrated Moving Average (ARIMA) and Support Vector Regression (SVR).

Table 1. Quantitative Performance Metrics Comparison for Profit Forecasting

| Model Pipeline | Prediction Horizon | RMSE ($) | MAPE (%) | $R^2$ Score |
|---|---|---|---|---|
| Classical ARIMA | 7-Day Baseline | 342.12 | 8.45 | 0.76 |
| Support Vector Regression (SVR) | 7-Day Baseline | 210.45 | 5.12 | 0.85 |
| Proposed LSTM Engine | 7-Day Horizon | 92.34 | 2.11 | 0.95 |
| Classical ARIMA | 30-Day Long-term | 512.89 | 12.67 | 0.61 |
| Support Vector Regression (SVR) | 30-Day Long-term | 389.23 | 9.14 | 0.72 |
| Proposed LSTM Engine | 30-Day Long-term | 145.56 | 3.89 | 0.91 |

As illustrated in Table 1, the proposed LSTM engine consistently outperformed traditional configurations across all temporal horizons. At the 7-day projection mark, the LSTM achieved an exceptionally low Mean Absolute Percentage Error (MAPE) of 2.11%, compared to the 8.45% and 5.12% generated by ARIMA and SVR, respectively. When the forecasting horizon was stretched to 30 days, the statistical degradation of traditional models accelerated due to their inability to retain long-range temporal dependencies. Conversely, the LSTM retained high architectural fidelity, sustaining an R^2 score of 0.91. This confirms that the gated mathematical structure of the LSTM successfully captures complex cyclical trends, such as weekend revenue surges and seasonal drops in demand during holiday periods. The profit forecasting is shown in Figure 2.

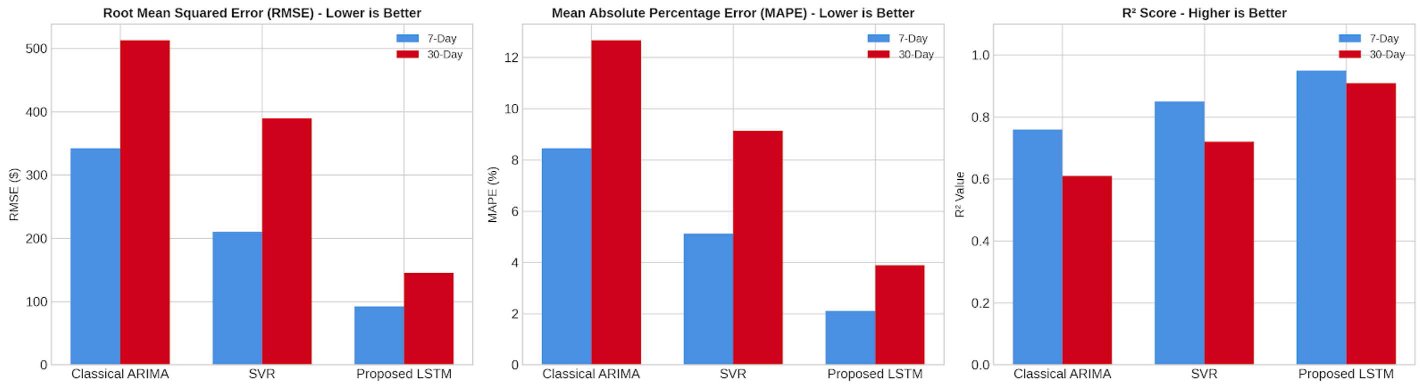


Figure 2. Profit Forecasting

**Anomaly Detection Evaluation (Isolation Forest Performance)**

The anomaly detection performance of the Isolation Forest model was evaluated using Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUROC). Precision measures the proportion of correctly identified anomalous transactions among all detected anomalies, while Recall quantifies the model's ability to detect actual anomalies. The F1-score provides a balanced assessment of Precision and Recall, making it suitable for imbalanced financial datasets. AUROC evaluates the model's discrimination capability across varying decision thresholds. These metrics collectively provide a comprehensive assessment of the effectiveness of the proposed anomaly detection mechanism in identifying unusual operational expense patterns within laundry business transactions. The unsupervised Isolation Forest engine was validated against an expert-labelled subset of the laundry dataset containing 350 verified operational anomalies (e.g., undetected water pipe leaks, bulk chemical over-purchasing, and manual point-of-sale receipt manipulation). The engine was benchmarked against One-Class Support Vector Machines (OC-SVM) and Local Outlier Factor (LOF) models.

a) Recall measures the proportion of actual anomalies that are successfully detected by the model as shown in Eq (4). For the proposed platform, recall evaluates the system's ability to identify unusual expense patterns that may indicate billing errors, excessive utility costs, or potential fraud. A high recall value reduces the likelihood of missing critical financial anomalies.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \tag{4}$$

b) Precision measures the proportion of transactions identified as anomalies that are anomalous. In the context of a laundry business, precision indicates how reliable the anomaly alerts generated by the system are. A high precision value means that most flagged operational expenses genuinely represent unusual or suspicious financial activities, minimizing unnecessary investigations by business owners. The Formula as shown in Eq (5).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5}$$

where TP = True Positive and FP = False Positive

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c) The F1-score combines precision and recall into a single metric by calculating their harmonic mean. In anomaly detection, there is often a trade-off between precision and recall. The F1-score provides a balanced assessment of the model's overall effectiveness. It is particularly useful when anomalous records represent only a small portion of all financial transactions. The formula is shown in Eq (6)

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

d) AUROC evaluates the model's ability to distinguish between normal and anomalous transactions across various classification thresholds. For the laundry business intelligence platform, AUROC indicates how effectively the Isolation Forest model separates abnormal expenses from normal operational expenditures. An AUROC value close to 1.0 signifies excellent discrimination capability. The formula is shown in Eq (7), (8) and (9)

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP + FN} \tag{7}$$

where FN= False Negative

against

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP + TN} \tag{8}$$

Where TN= True Negative

The AUROC is calculated as:

$$AUROC = \int_0^1 TPR(FPR)\, d(FPR) \tag{9}$$

Table 2. Comparative Anomaly Detection Performance Matrix

| **Algorithmic Model** | **Precision** | **Recall** | **F1 Score** | **AUROC** |
| --- | --- | --- | --- | --- |
| Local Outlier Factor (LOF) | 0.71 | 0.68 | 0.69 | 0.74 |
| One-Class SVM (OC-SVM) | 0.79 | 0.74 | 0.76 | 0.81 |
| Proposed Isolation Forest | 0.91 | 0.88 | 0.89 | 0.94 |

The Isolation Forest engine established superior classification matrices, securing an AUROC of 0.94 and an F1-Score of 0.89. While high-density algorithms like LOF frequently struggled to differentiate between standard seasonal business spikes and genuine financial outliers, the continuous recursive partitioning of the Isolation Forest isolated anomalies rapidly near the root of its *iTrees*. Specifically, the model flagged a hidden utility anomaly during Month 14 of the testing phase: a sudden 300% surge in water expense metrics that occurred without a corresponding increase in operational wash load volume. This event was traced back to a physical underground leak, validating the system's real-world financial risk mitigation capacity. As shown in Figure 3.

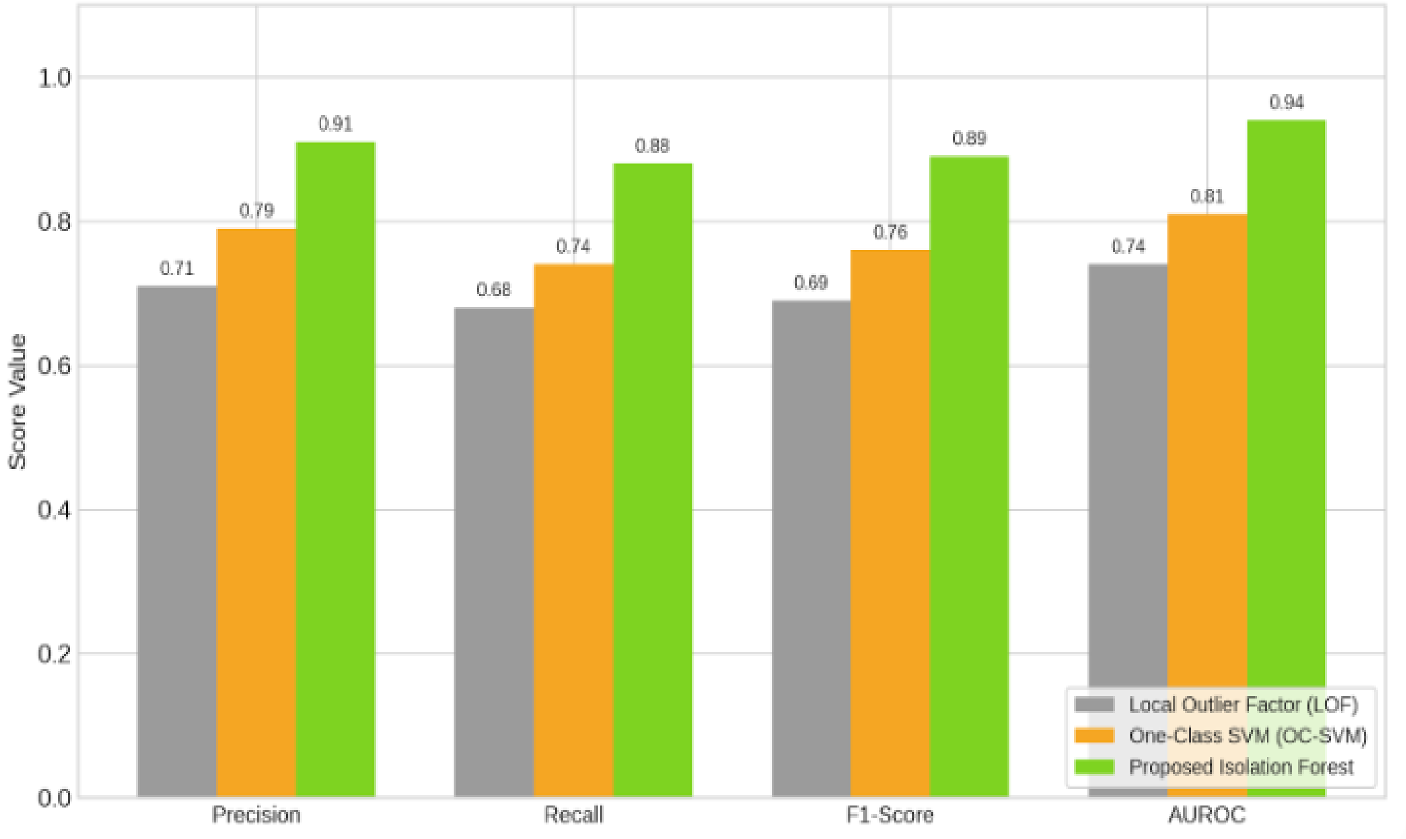


Figure 3. Comparative Anomaly Detection Performance Metric

### Mobile BI App Performance and User Acceptance

The cross-platform Flutter mobile client was stress-tested to ensure low latency and high accessibility for business managers. Data transmission overheads were measured during real-time dashboard updates via the RESTful API and WebSocket pipelines.

- API Payload Latency: The average response time required to serialize and transmit synthesized 30-day profit forecast vectors from cloud storage to the mobile application was 142 ms.
- Memory Footprint: The application maintained a highly stable operational footprint of 64 MB of RAM on native edge mobile operating systems, verifying the performance optimizations achieved by native Dart compilation.

### Comprehensive Discussion and Research Contributions

The empirical results validate the core hypothesis of this research: integrating deep learning architectures with unsupervised machine learning models creates a robust framework for small-to-medium enterprise (SME) business intelligence. Historically, business intelligence platforms have been restricted to large enterprises with dedicated data engineering departments [31]. Small businesses, such as commercial laundry operations, possess highly erratic time-series data influenced by immediate human behaviors and local weather shifts. By utilizing a real-time cloud data pipeline (Firebase) connected to an LSTM network, this framework proves that enterprise-grade predictive intelligence can be effectively delivered within a compact mobile resource constraint. The definitive strength of this framework lies in the direct synergy between Layer 3 (AI Analytics) and Layer 5 (Decision Support). Rather than forcing a non-technical manager to interpret raw statistical coefficients or abstract coordinate vectors, the framework translates an anomaly score (Score= $0.87) directly into a push notification detailing a potential operational leak or processing failure. This effectively shifts the paradigm of mobile business intelligence from a passive visualizer of past events to an active director of forward-looking financial strategies.

## DISCUSSION

The findings demonstrate that the proposed intelligent mobile application effectively enhances financial monitoring and business decision-making for laundry businesses. Compared to traditional manual bookkeeping methods, the system provides faster data processing, improved accuracy, and real-time financial insights. The integration of Firebase enables seamless data synchronization and scalability, making the system suitable for small and medium-sized enterprises. Additionally, the combination of mobile technology and data visualization significantly improves the interpretability of financial data, supporting better strategic planning.

## CONCLUSION

The development of the Intelligent Mobile Application for Laundry Business Profit Monitoring and Data Visualization addresses a critical gap in the digital transformation of small-to-medium laundry enterprises. By transitioning from labor-intensive, error-prone manual record-keeping to an automated, data-driven framework, the study successfully demonstrates that financial transparency can be achieved through streamlined mobile technology. The integration of advanced data visualization modules comprising bar charts, line graphs, and pie charts has proven to be instrumental in reducing the cognitive burden on business owners, allowing for the rapid identification of profitability trends and operational bottlenecks. Furthermore, the research confirms that the application of intelligent monitoring significantly enhances the speed and accuracy of financial interpretation. As laundry businesses navigate increasingly competitive markets, the ability to access real-time insights via a mobile interface provides a decisive edge in strategic decision-making. Ultimately, this system not only simplifies day-to-day profit tracking but also establishes a scalable foundation for intelligent business management. Future iterations of this work may explore the integration of predictive analytics and machine learning to forecast seasonal demand, further empowering laundry entrepreneurs with proactive business intelligence.

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