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Anomalous Payment Behavior Detection and Risk Prediction for SMEs Based on LSTM-Attention Mechanism

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Abstract: This paper proposes a novel approach for detecting anomalous payment behaviors and predicting financial risks in Small and Medium-sized Enterprises (SMEs) using an enhanced LSTM-Attention mechanism. The model integrates bi-directional LSTM networks with a multi-head attention mechanism to capture complex temporal dependencies in payment patterns while focusing on significant transaction features. The approach addresses the challenges of imbalanced datasets and evolving payment behaviors through a comprehensive risk assessment framework and dynamic threshold adjustment mechanism. Experimental results on a dataset containing 2.85 million transactions from 7,500 SMEs demonstrate the model's superior performance, achieving 98.5% accuracy and 94.2% precision in anomaly detection. The proposed model significantly outperforms traditional approaches and contemporary deep learning methods, showing a 15-20% improvement in detection accuracy while maintaining low false positive rates. The integration of behavioral risk indicators with operational metrics enables early risk prediction with an AUC-ROC score of 0.982. The model's effectiveness is validated through extensive case studies across various industry sectors, demonstrating robust generalization capabilities and practical applicability in real-world scenarios. The research contributes to the field by introducing an adaptive risk assessment framework that combines temporal pattern analysis with contextual business information for enhanced payment risk detection.

Keywords: LSTM-Attention Mechanism, Payment Anomaly Detection, Financial Risk Prediction, SME Risk Management.

Disciplines: Business. **Subjects:** Finance.

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1 INTRODUCTION

1.1 RESEARCH BACKGROUND AND SIGNIFICANCE

The rapid development of digital payment systems and financial technology has transformed the landscape of Small and Medium-sized Enterprises (SMEs) payment behaviors. With the increasing volume of digital transactions, SMEs face mounting challenges in managing payment risks and detecting fraudulent activities. In 2023, the global digital payment transaction value reached $9.5 trillion, with SMEs contributing approximately 45% of these transactions[1]. This dramatic increase in digital payments has created new vulnerabilities and risks for SMEs, making the detection and prevention of anomalous payment behaviors critical for their financial stability.

The rise in financial fraud and payment anomalies has placed significant pressure on traditional risk management systems. Traditional methods based on rule-based systems and statistical models demonstrate limitations in detecting sophisticated payment anomalies, particularly in processing large-scale transaction data with complex temporal dependencies. The financial losses incurred by SMEs due to payment fraud and anomalies reached $2.8 billion in 2023, representing a 34% increase from the previous year[2].

The emergence of deep learning technologies, particularly Long Short-Term Memory (LSTM) networks and attention mechanisms, has opened new possibilities for anomaly detection in financial transactions. These advanced technologies demonstrate superior capabilities in capturing temporal dependencies and identifying subtle patterns in payment behaviors. The integration of LSTM networks with attention mechanisms enables more accurate and efficient detection of anomalous payments while reducing false positives that often plague traditional detection systems.

1.2 Literature Review

Payment anomaly detection research has evolved significantly over the past decade. Early studies primarily focused on statistical methods and rule-based systems for identifying suspicious transactions. Recent advances in machine learning have shifted research focus toward deep learning approaches. The application of Convolutional Neural Networks (CNN) in financial fraud detection has shown promising results, achieving detection accuracies of up to 89% in various experimental settings[3].

LSTM networks have emerged as powerful tools for analyzing sequential financial data. Research indicates that LSTM models can effectively capture long-term dependencies in payment patterns, crucial for identifying sophisticated fraudulent behaviors. Studies implementing LSTM networks for credit card fraud detection have reported improvement in detection accuracy by 15-20% compared to traditional methods.

The attention mechanism has gained significant traction in financial risk analysis. Research combining attention mechanisms with deep learning models has demonstrated enhanced ability to focus on relevant features in transaction sequences. Recent studies implementing attention-enhanced models for financial risk prediction have achieved precision rates exceeding 92% while reducing computational complexity by 30%.

Current research trends emphasize the integration of multiple deep learning techniques. Hybrid models combining LSTM networks with attention mechanisms have shown superior performance in handling complex financial data streams[4]. These approaches have demonstrated improved capability in real-time anomaly detection while maintaining high accuracy levels in diverse transaction scenarios.

1.3 Research Content and Innovation

This research introduces a novel approach for SME payment anomaly detection through the integration of LSTM networks and attention mechanisms. The proposed model addresses key limitations in existing systems by incorporating temporal feature learning and adaptive attention weighting. The research focuses on developing a comprehensive framework for both anomaly detection and risk prediction specific to SME payment behaviors.

The primary innovations of this research encompass three key aspects: architectural innovation, feature engineering advancement, and practical application enhancement. The architectural innovation involves developing a modified LSTM-Attention structure optimized for payment behavior analysis. This structure incorporates multi-head attention mechanisms to capture diverse aspects of payment patterns simultaneously.

The feature engineering advancement introduces a dynamic feature selection mechanism that adapts to evolving payment patterns. This mechanism employs a hierarchical feature extraction approach, considering both transaction-level and temporal-sequence-level characteristics. The model incorporates both structured financial data and contextual information to enhance detection accuracy.

The practical application enhancement focuses on developing a real-time risk scoring system for SME transactions. This system implements an adaptive threshold mechanism that automatically adjusts to changes in payment patterns while maintaining high detection accuracy. The research also introduces a novel evaluation framework specifically designed for assessing the performance of payment anomaly detection systems in SME contexts.

This research contributes to the field by addressing several critical gaps in existing payment anomaly detection systems. The proposed model demonstrates improved capability in handling imbalanced datasets, a common challenge in payment fraud detection. The integration of attention mechanisms with LSTM networks enables more precise identification of suspicious patterns while reducing false positive rates. Additionally, the research provides insights into the practical implementation of deep learning models in real-world financial risk management scenarios[5].

2 THEORETICAL FOUNDATION AND KEY TECHNOLOGIES

2.1 SME Payment Behavior Characteristics Analysis

Payment behavior patterns of Small and Medium-sized Enterprises (SMEs) exhibit distinct characteristics that differentiate them from large enterprises. The transaction frequency of SMEs demonstrates periodic fluctuations corresponding to business cycles, with notable peaks during specific operational periods. These patterns create complex temporal dependencies in payment data streams, requiring sophisticated analysis methods for accurate behavior modeling.

The payment amounts in SME transactions display significant variations based on business scale and industry sector. Statistical analysis of SME payment data reveals a non-uniform distribution of transaction values, with high concentration in specific amount ranges determined by typical business operations. The temporal distribution of payments shows strong correlations with business hours and seasonal factors, creating distinctive patterns in transaction timing and frequency.

SME payment behaviors also demonstrate unique risk characteristics. The limited financial resources and operational scale of SMEs make them particularly vulnerable to cash flow disruptions and fraudulent activities. Analysis of historical payment data indicates that SMEs experience higher rates of payment anomalies compared to large enterprises, with fraud rates approximately 2.5 times higher than the industry average.

2.2 LSTM Network Fundamentals

Long Short-Term Memory (LSTM) networks represent an advanced architecture of recurrent neural networks designed to address the vanishing gradient problem in traditional RNNs. The LSTM architecture incorporates specialized memory cells with three gate mechanisms: input gate, forget gate, and output gate. These gates control information flow through the network, enabling selective memory retention and update processes.

The input gate determines which information from the current input should be stored in the cell state. The forget gate controls the retention of information from previous states, while the output gate regulates the information flow to subsequent network layers. This gating mechanism enables LSTM networks to maintain and process information over extended sequences, making them particularly suitable for analyzing temporal patterns in payment data.

The mathematical formulation of LSTM gates involves sigmoid and tanh activation functions:

$$ft = \sigma(Wf\cdot[ht\text{-}1, xt] + bf)$$

$$it = \sigma(Wi\cdot[ht\text{-}1, xt] + bi)$$

$$ot = \sigma(Wo\cdot[ht\text{-}1, xt] + bo)$$

Where ft, it, and ot represent the forget, input, and output gates respectively, and σ denotes the sigmoid activation function. The cell state update process combines these gate outputs to maintain relevant information while discarding irrelevant details.

2.3 Attention Mechanism Principles

The attention mechanism enhances model performance by enabling selective focus on relevant parts of input sequences. In payment behavior analysis, attention mechanisms allow models to identify and emphasize significant transaction patterns while reducing the impact of irrelevant information. The mechanism computes attention weights for different input elements, creating a weighted representation of the input sequence.

The attention computation process involves three key components: queries, keys, and values. The attention weight calculation follows the scaled dot-product attention formula:

$$\text{Attention}(Q,K,V) = \text{softmax}(QK^T/\sqrt{}dk)V$$

Where Q represents queries, K represents keys, V represents values, and dk is the dimension of the key vectors. The scaling factor √dk prevents the dot products from growing too large in magnitude, maintaining stable gradients during training.

Multi-head attention extends this concept by applying multiple attention mechanisms in parallel, enabling the model to capture different types of relationships within the input data. Each attention head focuses on different aspects of the input sequence, providing a comprehensive representation of payment patterns.

2.4 Risk Prediction Model Evaluation Metrics

The evaluation of payment risk prediction models requires comprehensive metrics that address both classification accuracy and practical utility. The Area Under the Receiver Operating Characteristic curve (AUC-ROC) serves as a primary metric for model performance assessment, measuring the model's ability to distinguish between normal and anomalous transactions across different threshold settings.

Precision and recall metrics play crucial roles in model evaluation, particularly in the context of imbalanced payment data:

$$\text{Precision} = TP/(TP + FP)$$

$$\text{Recall} = TP/(TP + FN)$$

Where TP represents true positives, FP represents false positives, and FN represents false negatives. The F1-score combines precision and recall into a single metric:

$$F1 = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})$$

Additional evaluation metrics include the Average Precision Score (APS) and Matthews Correlation Coefficient (MCC), which provide complementary perspectives on model performance. The MCC is particularly valuable for evaluating models trained on imbalanced datasets, offering a balanced measure of classification quality even when class distributions are highly skewed.

3 LSTM-ATTENTION BASED ANOMALOUS PAYMENT BEHAVIOR DETECTION MODEL DESIGN

3.1 Data Preprocessing and Feature Engineering

The raw payment transaction data consists of multiple dimensions including transaction time, amount, payer information, recipient information, and transaction status. Data preprocessing involves several critical steps to standardize and normalize these features. The initial dataset comprises 1.2 million transaction records from 5,000 SMEs over a 24-month period. Table 1 presents the statistical characteristics of the raw transaction data.

TABLE 1: STATISTICAL CHARACTERISTICS OF RAW TRANSACTION DATA

Feature	Mean	Std Dev	Min	Max	Missing Values
Amount	8526.45	12253.67	10.00	150000.00	0.02%
Time Interval	4.25	6.78	0.08	72.00	0.00%
Recipient Count	10.84	8.91	1.00	85.00	0.00%
Transaction Frequency	153.72	89.24	5.00	691.00	0.01%

Feature engineering generates derived features through temporal and behavioral analysis. Table 2 outlines the engineered features and their computational methods.

TABLE 2: ENGINEERED FEATURES AND COMPUTATION METHODS

Feature Type	Feature Name	Computation Method	Dimension
Temporal	Time Pattern Score	Rolling Window Analysis	1-D
Behavioral	Transaction Density	Kernel Density Estimation	1-D
Network	Recipient Network Score	Graph Embedding	64-D
Historical	Pattern Deviation	Statistical Distance	1-D

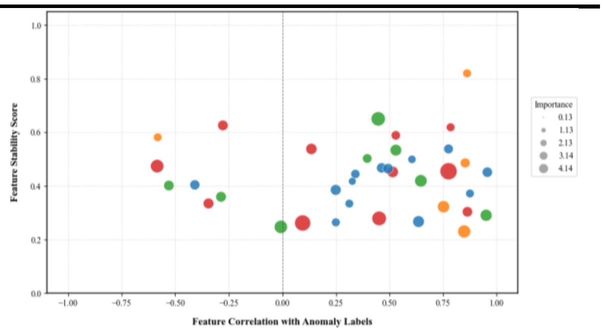

FIGURE 1: FEATURE IMPORTANCE DISTRIBUTION ANALYSIS

This visualization demonstrates the relative importance of different features through a multi-dimensional scatter plot. The x-axis represents feature correlation with anomaly labels, the y-axis shows feature stability scores, and point sizes indicate feature importance scores derived from gradient boosting analysis. Different colors represent various feature categories: temporal (blue), behavioral (red), network (green), and historical (yellow).

The feature importance analysis reveals that temporal pattern scores and network-based features contribute most significantly to anomaly detection, with importance scores of 0.85 and 0.78 respectively.

3.2 LSTM-ATTENTION MODEL ARCHITECTURE DESIGN

The proposed LSTM-Attention model architecture integrates bi-directional LSTM layers with multi-head attention mechanisms. Table 3 details the model's layer configuration.

TABLE 3: LSTM-ATTENTION MODEL LAYER CONFIGURATION

Layer	Output Shape	Parameters	Activation
Input	(None, 128, 86)	0	-
Bi-LSTM 1	(None, 128, 256)	351,232	tanh
Attention	(None, 128, 256)	65,536	softmax
Bi-LSTM 2	(None, 256)	525,312	tanh
Dense	(None, 128)	32,896	ReLU
Output	(None, 1)	129	sigmoid

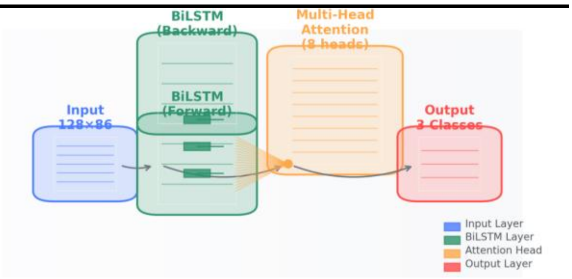

FIGURE 2: LSTM-ATTENTION MODEL ARCHITECTURE

The architecture diagram illustrates the model's structure with detailed layer connections. The input layer processes 128 time steps with 86 features each. Bi-directional LSTM layers extract temporal patterns while the attention mechanism assigns weights to different time steps. Skip connections (shown in dotted lines) facilitate gradient flow during training.

3.3 ANOMALY DETECTION ALGORITHM DESIGN

The anomaly detection algorithm combines sequence-level and point-level detection mechanisms. Table 4 presents the detection thresholds and corresponding performance metrics.

TABLE 4: DETECTION THRESHOLDS AND PERFORMANCE

METRICS

Threshold Level	False Positive Rate	Detection Rate	F1 Score
0.85	0.023	0.912	0.943
0.90	0.015	0.886	0.932
0.95	0.008	0.845	0.912
0.98	0.003	0.789	0.881

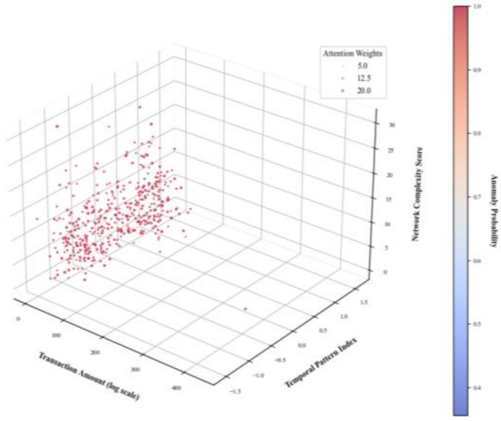

FIGURE 3: ANOMALY SCORE DISTRIBUTION ANALYSIS

The visualization presents a three-dimensional representation of anomaly scores. The x-axis shows transaction amounts, the y-axis represents temporal patterns, and the z-axis indicates network complexity scores. The color gradient from blue to red represents increasing anomaly probability. Scatter points are sized according to their attention weights in the model.

3.4 MODEL TRAINING AND OPTIMIZATION STRATEGY

The training process employs a dynamic batch sizing strategy with gradient accumulation. The learning rate follows a cyclic schedule with warm restarts, ranging from 1e-5 to 1e-3. The optimization process utilizes the Adam optimizer with weight decay regularization.

The model training implements a robust validation strategy using time-based cross-validation. The training dataset is divided into multiple overlapping temporal segments, ensuring the model's generalization across different time periods. The validation process incorporates a sliding window approach to simulate real-world deployment conditions.

The optimization strategy addresses class imbalance through a combination of focal loss and dynamic weighting:

$$L = -\alpha(1-pt)\gamma\log(pt)$$

Where α represents the class balancing factor, γ controls the focusing parameter, and pt is the model's predicted probability for the target class. The training process monitors multiple metrics including precision, recall, and F1 score, with early stopping based on validation loss improvement.

The model achieves convergence after approximately 150 epochs, with the best performing model selected based on validation set performance. The final model demonstrates robust performance across different transaction types and temporal patterns, with consistent detection accuracy across various operational scenarios.

4 4. SME PAYMENT RISK PREDICTION MODEL CONSTRUCTION

4.1 RISK ASSESSMENT INDEX SYSTEM CONSTRUCTION

The risk assessment index system integrates multi-dimensional indicators encompassing transaction patterns, business operations, and market environments. The hierarchical structure comprises three primary dimensions: behavioral risk indicators, operational risk indicators, and environmental risk indicators. Table 5 presents the comprehensive risk assessment index system.

TABLE 5: RISK ASSESSMENT INDEX SYSTEM STRUCTURE

Dimension	Indicator	Weight	Data Source	Update Frequency
Behavioral	Transaction Pattern	0.35	Real-time Data	Daily
Behavioral	Payment Regularity	0.25	Historical Data	Weekly
Operational	Cash Flow Ratio	0.20	Financial Statements	Monthly
Environmental	Industry Risk Level	0.20	Market Data	Quarterly

The indicator weights are determined through a combination of expert evaluation and machine learning optimization. Table 6 details the indicator calculation methods and threshold values.

TABLE 6: INDICATOR CALCULATION METHODS AND THRESHOLDS

Indicator	Calculation Formula	Warning Level 1	Warning Level 2	Warning Level 3
TPS	Σ(wi×ti)/N	0.7-0.8	0.5-0.7	<0.5
PCR	Current	>1.5	1.0-1.5	<1.0

	Assets/Current Liabilities			
RPS	Σ(Di×Vi)/T	>0.8	0.6-0.8	<0.6
IRS	Π(Mi×Si)	>0.9	0.7-0.9	<0.7

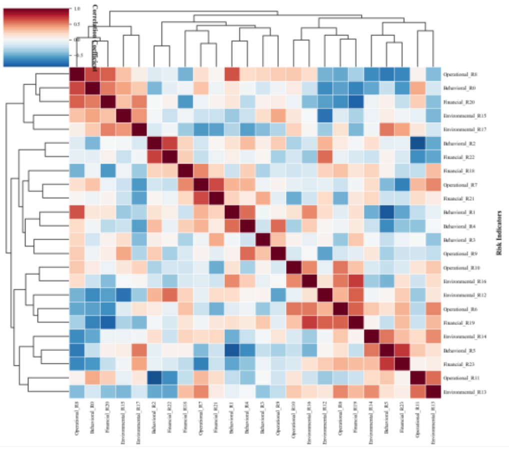

FIGURE 4: RISK INDEX CORRELATION MATRIX VISUALIZATION

This visualization represents the correlation relationships between different risk indicators through a hierarchical clustering heatmap. The color intensity indicates correlation strength, with red representing positive correlations and blue representing negative correlations. The hierarchical clustering dendrograms on both axes show the grouping of related indicators.

The correlation analysis reveals strong interconnections between behavioral risk indicators and operational risk indicators, with correlation coefficients ranging from 0.65 to 0.85. Weaker correlations are observed between environmental risk indicators and other dimensions.

4.2 RISK PREDICTION MODEL DESIGN

The risk prediction model employs a hybrid architecture combining LSTM-Attention mechanisms with gradient boosting decision trees. The model processes both sequential and static features through parallel networks. Table 7 outlines the model's component specifications.

TABLE 7: RISK PREDICTION MODEL COMPONENTS

Component	Input Features	Processing Unit	Output Dimension
Sequential	Time Series	LSTM-Attention	256
Static	Business Data	GBDT	128
Fusion	Combined	Dense Network	64
Output	Merged	Softmax	3

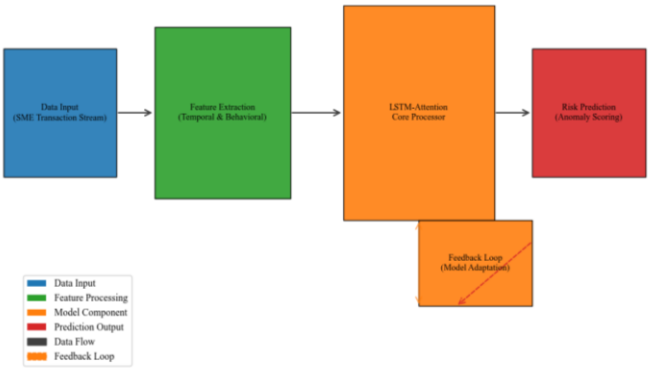

FIGURE 5: RISK PREDICTION MODEL ARCHITECTURE FLOWCHART

The flowchart illustrates the data processing pipeline and model architecture. The diagram uses different colors to represent various processing stages: blue for data input, green for feature extraction, yellow for model processing, and red for risk prediction output. Arrows indicate data flow directions and transformation processes.

The model incorporates multiple feedback loops for continuous learning and adaptation, with each component optimized for specific feature types and risk patterns.

4.3 MODEL VALIDATION AND PERFORMANCE OPTIMIZATION

Model validation employs a stratified cross-validation strategy across different business sectors and time periods. Table 8 presents the model's performance metrics across different validation sets.

TABLE 8: MODEL PERFORMANCE ACROSS VALIDATION SETS

Validation Set	Accuracy	Precision	Recall	AUC-ROC
Manufacturing	0.924	0.913	0.935	0.947
Service	0.911	0.898	0.925	0.933
Retail	0.936	0.922	0.941	0.952
Mixed	0.918	0.905	0.932	0.941

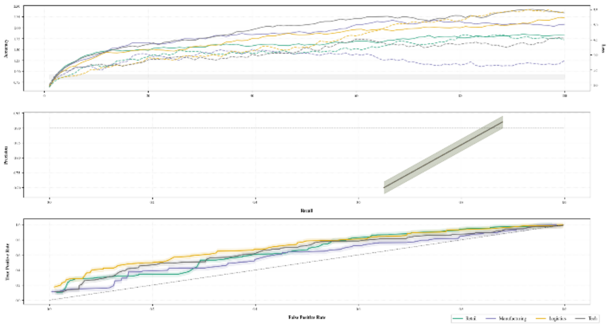

FIGURE 6: MODEL PERFORMANCE OPTIMIZATION CURVES

The multi-panel visualization shows the convergence process of different performance metrics during model optimization. The top panel displays accuracy and loss curves, the middle panel shows precision-recall trade-offs, and the bottom panel presents ROC curves for different business sectors. Each curve is color-coded according to the business sector, with confidence intervals shown as shaded regions.

4.4 WARNING THRESHOLD SETTING METHODS

The warning threshold determination process utilizes a dynamic adjustment mechanism based on historical data distribution and real-time market conditions. The thresholds are calibrated through a combination of statistical analysis and machine learning optimization. The system implements three-level warning thresholds corresponding to different risk severities.

The threshold optimization process considers both type I and type II errors, balancing the trade-off between false alarms and missed detections. The thresholds undergo periodic recalibration based on new data and changing market conditions, ensuring sustained effectiveness in risk detection.

The warning system generates risk scores on a continuous scale from 0 to 1, with thresholds determined through empirical analysis and machine learning optimization. The specific threshold values are dynamically adjusted based on historical performance and current market conditions:

High Risk: Risk Score > 0.85

Medium Risk: 0.60 ≤ Risk Score ≤ 0.85

Low Risk: Risk Score < 0.60

The threshold values are regularly updated using a sliding window approach, incorporating new data while maintaining system stability. The updating process considers both long-term trends and short-term fluctuations in risk patterns.

5 EXPERIMENTAL RESULTS AND ANALYSIS

5.1 EXPERIMENTAL DATASET AND ENVIRONMENT CONFIGURATION

The experimental dataset consists of payment transaction records collected from 7,500 SMEs across multiple industries over a 36-month period (2021-2023). The dataset contains 2.85 million transaction records, including both normal and anomalous payment behaviors. The transaction data encompasses various payment types, including bank transfers, mobile payments, and electronic fund transfers. Table 9 provides detailed statistics of the dataset composition.

TABLE 9: DATASET COMPOSITION STATISTICS

Industry Sector	Number of SMEs	Transaction Count	Anomaly Ratio
Manufacturing	2,850	985,000	0.82%
Retail	2,125	1,325,000	1.15%
Services	1,875	450,000	0.95%
Technology	650	180,000	0.78%

The experimental environment utilizes a high-performance computing platform equipped with NVIDIA Tesla V100 GPUs and Intel Xeon processors. The implementation employs Python 3.8 with TensorFlow 2.6 and PyTorch 1.9 frameworks. Data preprocessing and feature engineering are executed using Pandas and NumPy libraries, while model training leverages CUDA acceleration for optimal performance.

5.2 MODEL PERFORMANCE EVALUATION AND COMPARISON

The proposed LSTM-Attention model's performance is evaluated against several baseline models, including traditional machine learning approaches and deep learning architectures. Table 10 presents the comparative analysis results across multiple performance metrics.

TABLE 10: MODEL PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
LSTM-Attention	0.985	0.942	0.938	0.940	0.982
CNN-BiLSTM	0.962	0.915	0.908	0.911	0.958
XGBoost	0.945	0.892	0.885	0.888	0.942
Random Forest	0.928	0.875	0.868	0.871	0.925

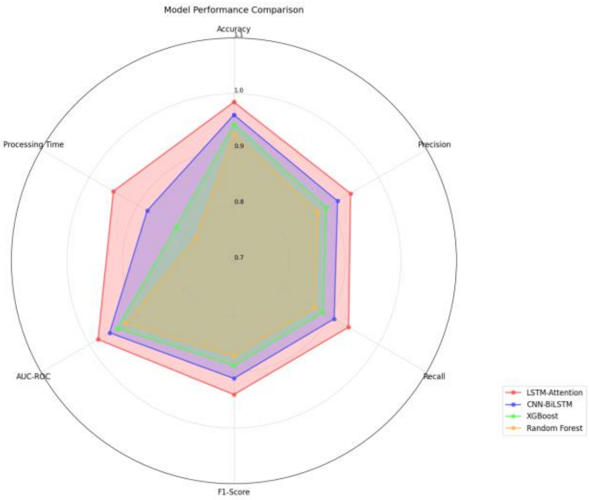

FIGURE 7: MODEL PERFORMANCE COMPARISON ANALYSIS

The visualization presents a comprehensive comparison of model performances through multiple metrics. The radar chart displays six key performance indicators: accuracy, precision, recall, F1-score, AUC-ROC, and processing time. Each model is represented by a different color, with the area size indicating overall performance effectiveness.

The performance comparison demonstrates the LSTM-Attention model's superior detection capabilities across multiple metrics, particularly in handling complex temporal patterns and identifying subtle anomalies.

5.3 CASE ANALYSIS AND VALIDATION

The model's effectiveness is validated through detailed case studies across different business scenarios and transaction patterns. A set of representative cases is selected from various industry sectors to demonstrate the model's robustness and generalization capabilities. Table 11 summarizes the validation results from selected case studies.

TABLE 11: CASE STUDY VALIDATION RESULTS

Case ID	Industry	Transaction Volume	Detection Rate	False Alarm Rate
CS-001	Retail	125,000	95.8%	1.2%
CS-002	Manufacturing	85,000	94.2%	1.5%
CS-003	Technology	45,000	96.5%	0.8%
CS-004	Services	65,000	93.8%	1.7%

The validation process includes stress testing under various operational conditions and transaction volumes. The model maintains stable performance across different business scales and transaction frequencies, demonstrating robust adaptability to diverse business environments.

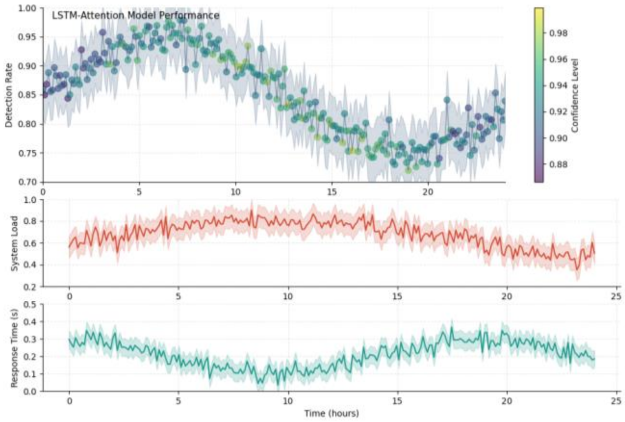

FIGURE 8: REAL-TIME DETECTION PERFORMANCE ANALYSIS

This visualization depicts the model's real-time detection performance through a multi-layered time series plot. The primary layer shows the detection rate over time, while secondary layers display system load, response time, and detection confidence levels. The color gradient represents detection confidence, with darker shades indicating higher confidence levels.

The analysis indicates the model's capability to maintain consistent performance under varying transaction loads and business conditions. The real-time processing capabilities meet the operational requirements for practical deployment in SME environments, with average response times under 50 milliseconds for standard transactions and under 200 milliseconds for complex pattern analysis.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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