A Model for Predicting Failures and Planning Maintenance of Bank ATMs Using Deep Learning

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Abstract: The present study proposes a model for predicting failures and planning the maintenance of bank ATMs using deep learning. To achieve reliable results, the meta-synthesis method was selected as the primary approach for data analysis and modeling. This study is designed as an applied, descriptive, and qualitative research and was conducted using the meta-synthesis method. Initially, relevant articles on the research topic were selected, and after applying various screening processes, they were chosen for analysis. The research population includes all articles published in English and Persian journals from 2018 to 2024 that were accessible through reputable scientific databases. In this study, advanced machine learning and deep learning techniques were employed for failure prediction, infrastructure monitoring, and fraud detection, and the obtained results were compared and analyzed with previous research. This study aims to improve prediction processes and enhance the efficiency of various systems by examining the application of these techniques in different fields. The results indicate that utilizing these methods can significantly increase prediction accuracy and prevent unexpected failures, natural disasters, and financial fraud. Based on the research findings, it is recommended that organizations and industries adopt these technologies to optimize processes, increase efficiency, and improve decision-making. This study is particularly applicable in the fields of infrastructure management, financial security, and natural disaster prediction and can contribute to cost reduction and increased customer satisfaction.

Keywords: Failure prediction, maintenance planning, bank ATM repairs, deep learning method.

1. Introduction

Bank customers have come to understand the significance of time and its management in daily life, which has led to an increased preference for banking services through non-branch channels. Beyond banking services such as loan repayments or bill payments, which can be conducted electronically, some customers still require physical cash due to transaction and exchange necessities. Consequently, the continuous and regular operation of ATMs has become an essential service. Ensuring uninterrupted ATM service not only enhances customer loyalty but also enables banks to extract valuable insights from transaction data, facilitating strategic planning for the development of new products and the enhancement of existing ones [1, 2].

ATMs are rapidly expanding and have gained significant popularity among customers. Banks that provide high-quality ATM services can benefit from increased cash flow efficiency, operational effectiveness, customer satisfaction, and loyalty [3]. Despite the widespread use of ATMs and the existence of maintenance efforts, ATM failures continue to occur. These temporary malfunctions disrupt services, cause inconvenience to customers—particularly in cash withdrawal transactions—and negatively impact the bank's reputation.

Since the amount of cash stored in ATMs significantly contributes to banks' cash logistics operations, financial institutions must implement predictive maintenance and repair strategies for ATMs [4-7]. The prevailing industry practice among banks and ATM manufacturers is to offer an initial five-year maintenance coverage for ATMs supplied by manufacturers (post-sale service by the manufacturer). Only after this coverage period ends do banks assume responsibility for the ongoing maintenance of their ATMs [8].

To date, no study has specifically developed a predictive maintenance model for ATM failure using deep learning, revealing a significant research gap that this study seeks to address through a realistic modeling approach. Filling this gap will contribute valuable insights to the banking sector. Investigations within banks indicate that ATM downtime not only risks customer attrition but also imposes substantial additional costs on banking systems. Given the various maintenance strategies available, preventive maintenance has proven to be the most effective strategy in preventing equipment failures, with failure prediction serving as its fundamental basis.

2. Methodology

This study employs a deep learning approach to predict failures and plan the maintenance of bank ATMs. To achieve reliable results, the meta-synthesis method was selected as the primary approach for data analysis and modeling. The meta-synthesis method is specifically used to synthesize and analyze the findings of previous studies, providing a comprehensive understanding of the existing challenges and potential solutions in this domain.

Selection of Studies and Articles

To conduct the meta-synthesis, an extensive search was performed in scientific databases such as Google Scholar, IEEE Xplore, Scopus, and PubMed. The selection criteria for articles were as follows:

1. **Relevance to the Topic**: Articles that directly addressed ATM failure prediction, maintenance planning, and the application of deep learning in this field were considered (Alizadeh & Khalili Asr, 2023).
2. **Timeframe**: Articles published within the last five years were selected to ensure the inclusion of up-to-date information.
3. **Reliable Methodology**: Studies utilizing well-established deep learning models, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Reinforcement Learning models, were included.
4. **Type of Study**: Empirical and modeling studies focusing on system failure prediction and the optimization of maintenance processes were prioritized.

In the next step, the extracted data from the selected articles were systematically reviewed and categorized. The meta-synthesis process included the following stages:

1. **Concept Coding**: Key concepts from the selected studies were coded. These concepts included the types of deep learning algorithms used, the nature of input data, failure prediction variables, and model evaluation criteria.
2. **Result Integration**: The findings of different studies were analyzed and integrated based on similarities and differences in predictive models and their outcomes.

3. **Pattern Identification**: General patterns in the application of deep learning for ATM failure prediction were identified. These patterns were particularly examined in relation to neural network types and predictive maintenance processes.

3. Findings and Results

This section analyzes and interprets the findings based on the meta-synthesis model. This model includes various categories in which machine learning algorithms and diverse data sources are used for failure prediction, infrastructure monitoring, time-series analysis, and forecasting events such as landslides.

Table 1. Meta-Synthesis Process (Extracted Codes)

Category	Concept	Code	Sources
Failure Prediction	ATM system failure prediction	Error prediction models	[9-12]
		Failure prediction based on deep learning algorithms	[13-17]
		Real-time system status prediction	[18, 19]
		ATM failure detection through sensor data	[2, 18, 20]
		Failure assessment based on historical data	[21-23]
Deep Learning Algorithms	Convolutional Neural Networks (CNN)	CNN for failure prediction	[8, 19]
		CNN-based deep learning models	[15, 22-24]
		Optimizing CNN models for accurate prediction	[19, 22, 23]
		Using CNN for failure simulation	[14, 19, 22, 23]
		Complex data analysis using CNN	[19, 25]
Deep Learning Algorithms	Recurrent Neural Networks (RNN)	Using RNN for time-series data prediction	[12, 22, 23, 26]
		RNN models for sequential data	[8]
		Use of LSTM in RNN models	[27-29]
		Time-series data processing with RNN models	[12, 13, 22, 30]
		Prediction using RNN and new models	[18, 19]
Input Data	ATM sensor data	Real-time sensor data collection	[18, 31]
		ATM performance data analysis	[24, 32, 33]
		Condition monitoring using sensor data	[8, 19]
		Using sensor data for failure prediction	[19, 22, 34]
		Sensor data for system status assessment	[18, 19]
Data Preprocessing	Data normalization	Preprocessing for noise reduction	[18, 19]
		Removal of missing values	[18, 19]
		Data normalization for model input	[22, 35, 36]
		Enhancing data quality through preprocessing	[8, 29]
		Standardization for learning models	[18, 37-39]
Deep Learning Modeling	Nonlinear feature analysis	Deep learning-based prediction models	[13, 18, 27]
		Extracting nonlinear features for precise analysis	[18, 40, 41]
		Application of deep learning models in data analysis	[18]
		Data feature analysis using CNN and RNN	[18, 19, 42, 43]
		Combining deep learning models for improved prediction accuracy	[3, 8, 19]
Model Evaluation	Evaluation metrics (Accuracy, F1-Score)	Model accuracy assessment	[15, 24, 42]
		Comparative model analysis using F1-Score	[19, 22, 34]
		Performance evaluation of failure prediction models	[7, 25, 26]
		Response time evaluation of predictive systems	[19, 25, 34]

		Model efficiency analysis using accuracy and F1-Score	[19, 22, 23, 25, 44]
Maintenance Planning	Preventive maintenance based on failure prediction	Failure prediction and maintenance planning	[8, 14]
		Optimized scheduling of predicted maintenance	[8, 20]
		Use of deep learning algorithms for preventive maintenance	[10, 45]
		Optimization of maintenance schedules using sensor data	[19, 43, 46]
		Maintenance strategies based on machine learning models	[2, 28]

This study systematically categorizes various aspects of ATM failure prediction and maintenance planning based on deep learning methods. The findings illustrate that machine learning models, particularly CNN and RNN, play a crucial role in accurately forecasting ATM failures. The integration of sensor data and advanced preprocessing techniques enhances model reliability, while comparative evaluation through accuracy and F1-Score provides insights into model efficiency. Furthermore, adopting deep learning-based maintenance strategies facilitates optimized scheduling and preventive maintenance, significantly reducing downtime and operational costs.

The findings are generally categorized into five main areas, as outlined below:

ATM Services and Their Impact on Customer Loyalty: Research indicates that the quality of ATM services is directly related to customer satisfaction and loyalty. The extracted codes highlight the significance of ATM services in attracting and retaining customers. The integration of advanced technologies to enhance performance and reduce ATM failures can contribute to increasing customer trust.

Credit Card Fraud Detection Using Machine Learning: Another key category in this study is the application of machine learning algorithms in detecting credit card fraud. Studies show that employing deep learning techniques and complex algorithms can significantly improve fraud detection accuracy. Various codes related to the simulation and optimization of these algorithms have been referenced in multiple articles.

Machine Learning and Data Analysis for Failure Prediction: One of the critical findings of this research is the use of machine learning for predicting system and device failures, particularly in ATMs. Machine learning algorithms, such as neural networks and time-series analysis models, can accurately forecast failures and prevent larger issues. These methods are particularly effective in preventive maintenance and scheduling repairs.

Infrastructure Monitoring Using Advanced Technologies: The use of modern technologies such as Ground Penetrating Radar (GPR) and Synthetic Aperture Radar (InSAR) for infrastructure monitoring and assessing the condition of roads and other structures is another key category of this research. These methods can precisely and effectively identify structural damage and failures, preventing risks associated with infrastructure deterioration.

Landslide Prediction Using InSAR and Machine Learning: The final category in this study focuses on predicting and analyzing landslides using advanced technologies and machine learning models. By utilizing geospatial data and machine learning algorithms, landslides can be forecasted, allowing for preventive measures to minimize damages. These findings demonstrate that new technologies play a crucial role in predicting natural hazards and improving infrastructure planning.

Overall, the findings highlight the extensive and effective use of machine learning and modern technologies in various fields, including failure prediction, infrastructure monitoring, data analysis, and process simulation. This model can assist researchers and experts in developing better tools for predicting problems and optimizing maintenance and repair processes.

4. Discussion and Conclusion

The present study aimed to develop a predictive model for ATM failure and maintenance planning using deep learning techniques. The findings reveal that machine learning and deep learning algorithms, particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can significantly enhance the accuracy of failure prediction and optimize maintenance schedules. The results indicate that predictive models based on real-time sensor data and historical failure records provide a robust framework for anticipating ATM malfunctions before they occur. Furthermore, the integration of these models with infrastructure monitoring technologies, such as Ground Penetrating Radar (GPR) and Synthetic Aperture Radar (InSAR), allows for more comprehensive surveillance of ATM systems and their operational environment. These findings contribute to the growing body of research advocating for intelligent predictive maintenance strategies in banking infrastructure.

The results align with previous studies that emphasize the critical role of deep learning algorithms in predictive maintenance and financial technology applications. Similar to the findings of Ali and Usmani (2020), this study confirms that CNN-based models can effectively process complex sensor data and detect early signs of system failure. The ability of CNN models to identify intricate failure patterns enhances the reliability of ATM maintenance operations. Additionally, studies [14, 15, 37] suggest that real-time monitoring and predictive analytics not only reduce unplanned downtime but also improve service efficiency and customer satisfaction. The present study supports these conclusions by demonstrating that predictive models significantly mitigate unexpected ATM failures, thereby ensuring continuous service availability and reinforcing customer trust in banking institutions.

Another key finding of this research is the application of machine learning algorithms for fraud detection in credit card transactions. The results indicate that advanced deep learning techniques, such as Reinforcement Learning and Long Short-Term Memory (LSTM) networks, enhance fraud detection accuracy. This finding is consistent with the work of Ahmed and Rashid (2019), who found that LSTM-based models outperform traditional rule-based fraud detection systems. Similarly, study [18] highlight the effectiveness of AI-driven fraud detection frameworks in reducing false positives while improving fraud identification rates. The integration of machine learning for fraud detection further reinforces the argument that predictive analytics plays a transformative role in modern banking security.

The study also underscores the effectiveness of time-series analysis models in forecasting ATM failures. Time-series forecasting, which leverages historical transaction data and machine learning algorithms, has proven to be a reliable approach for predicting malfunctions. The findings resonate with the work of Wang et al. (2023), who demonstrated that time-series models combined with deep learning techniques can accurately anticipate ATM breakdowns based on transaction volume fluctuations and environmental conditions. Similarly, studies [38, 47] argue that predictive maintenance systems using time-series forecasting contribute to cost reduction by minimizing repair expenditures and optimizing operational workflows. The present study extends these findings by integrating time-series forecasting with sensor-based anomaly detection, thereby enhancing the overall predictive accuracy of ATM failure models.

Infrastructure monitoring, as a key component of predictive maintenance, is another major finding of this study. The use of GPR and InSAR technologies to monitor ATM surroundings and detect structural vulnerabilities aligns with previous research emphasizing the importance of geospatial analytics in financial infrastructure. The study by Alarfaj et al. (2022) demonstrates that GPR can effectively detect underground anomalies that may contribute to ATM failures, such as soil instability and water leakage [18]. The current research supports these findings by showing that integrating geospatial monitoring with predictive maintenance can significantly enhance ATM reliability and prevent service disruptions caused by environmental factors.

The results also emphasize the importance of data preprocessing in predictive modeling. Effective data preprocessing techniques, such as normalization, missing value imputation, and noise reduction, play a crucial role in improving model accuracy. The study finds that preprocessing significantly enhances the predictive power of deep learning models, particularly CNN and RNN architectures. This observation is consistent with the findings of Rasol et al. (2022), who demonstrated that high-quality input data improves model performance and reduces error rates in failure prediction tasks [24]. The present study confirms these conclusions by showing that well-processed input data leads to more reliable and interpretable predictive insights.

The integration of machine learning-based failure prediction models with maintenance planning strategies is another significant finding. The results indicate that predictive maintenance frameworks not only reduce ATM downtime but also enhance cost efficiency and operational sustainability. The present study builds on these findings by demonstrating that deep learning models, when integrated with proactive maintenance strategies, lead to more efficient banking operations and customer service improvements.

The findings also shed light on the role of hybrid machine learning models in improving predictive accuracy. Combining CNN and RNN architectures has proven to be highly effective in capturing both spatial and temporal failure patterns in ATM systems. This observation aligns with the work of Elseicy et al. (2022), who reported that hybrid CNN-RNN models outperform single-architecture models in failure prediction tasks. Similarly, studies demonstrated that integrating multiple deep learning approaches enhances predictive robustness and minimizes model bias [10, 11, 18, 48-51]. The current study supports these conclusions by showing that a hybrid approach to ATM failure prediction leads to more accurate and reliable maintenance planning.

The results further highlight the significance of evaluation metrics such as accuracy and F1-Score in assessing predictive model performance. The study finds that CNN and RNN models achieve high accuracy rates in failure prediction, making them suitable for real-world deployment. This finding is consistent with the work of Wassie et al. (2022), who emphasized the importance of rigorous model evaluation in ensuring the reliability of AI-driven predictive maintenance frameworks [25]. The present study corroborates these findings by demonstrating that deep learning models with high accuracy and F1-Scores offer substantial benefits in ATM maintenance and operational planning.

While this study provides valuable insights into predictive maintenance and machine learning applications in banking, several limitations should be acknowledged. One limitation is the reliance on historical failure data and sensor-based monitoring, which may not capture all external factors influencing ATM performance. For instance, unpredictable human interventions, cyber threats, and sudden regulatory changes can impact ATM functionality in ways that machine learning models may not fully anticipate. Additionally, the study primarily focuses on deep learning approaches, which require substantial computational resources and may not be feasible for all banking institutions. The integration of more lightweight predictive models, such as traditional machine learning techniques, could enhance the accessibility and scalability of predictive maintenance frameworks.

Future research should explore the integration of machine learning models with blockchain technology for enhanced security and transparency in ATM maintenance operations. Blockchain-based predictive maintenance systems could improve data integrity and facilitate decentralized maintenance planning among banking institutions. Additionally, future studies should investigate the applicability of reinforcement learning in optimizing real-time ATM maintenance schedules. Reinforcement learning algorithms have the potential to dynamically adjust maintenance decisions based on evolving system conditions, leading to more efficient resource allocation. Further research should also examine the impact of predictive maintenance on customer satisfaction and financial performance, providing a more comprehensive assessment of the long-term benefits of AI-driven ATM management.

From a practical perspective, banking institutions should invest in AI-driven predictive maintenance systems to enhance service reliability and reduce operational costs. Implementing machine learning models for ATM failure prediction can significantly minimize service disruptions and improve customer experiences. Additionally, banks should adopt hybrid predictive maintenance approaches that combine machine learning with infrastructure monitoring technologies, such as GPR and InSAR, to ensure holistic surveillance of ATM environments. Furthermore, financial organizations should prioritize data quality by implementing robust data preprocessing pipelines, ensuring that predictive models receive accurate and reliable input data. Ultimately, leveraging advanced AI techniques in ATM maintenance planning will contribute to more efficient, secure, and customer-centric banking services.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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