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# Dynamic Risk Analysis Model in Digital Financial Systems Using Deep Reinforcement Learning

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**Abstract**

*Digital transformation in the financial system has created new risk dynamics that are more complex and unpredictable with conventional methods. Digital asset market volatility, cyberattacks, and changes in user behavior demand the development of new approaches in risk management. This study aims to develop a dynamic risk analysis model using Deep Reinforcement Learning (DRL), especially with the Deep Recurrent Q-Network (DRQN) approach, to improve the effectiveness of real-time risk detection and mitigation in the digital financial system. The research method used is an exploratory-descriptive qualitative approach with data obtained through documentation studies, field observations, and digital transaction simulations. The DRQN model is compared to the DQN model to evaluate the accuracy, speed of response, and effectiveness of adaptation to changing transaction patterns. The results showed that DRQN was able to increase the accuracy of risk prediction by up to 91.4% and accelerate the response time to an average of 1.8 seconds. In addition, the model has proven to be more adaptive to sequential data and rapid market fluctuations. The conclusion of this study confirms that the integration of DRLs in the digital financial system can increase the resilience of the system to complex risk dynamics. The practical implication of this research is to encourage the financial industry and regulators to adopt adaptive learning-based technologies in risk mitigation strategies in the digital economy era.*

**Keywords**: Deep Reinforcement Learning, Dynamic Risk, Digital Financial System, Real-Time Risk Detection

## 1. Introduction

In the era of global digitalization, the financial system is undergoing a fundamental transformation with the increasing use of blockchain-based technology, electronic payments, and other digital financial platforms. These developments bring new efficiencies, but they also introduce more dynamic and non-linear complexity of risk compared to traditional financial systems (Arner, Auer, & Frost, 2020). Market uncertainty, cyberattacks, and digital asset volatility are becoming significant global issues, demanding adaptive and real-time risk management approaches (Frost et al., 2020). Therefore, a new methodology is needed that is able to capture risk dynamics more precisely in line with changes in user behavior and technological innovations in the digital financial sector.

Some of the key factors that complicate risk management in the digital financial system include the high level of connectivity between financial entities, the ever-increasing volume of transactions, and the algorithmic characteristics of new financial products such as *smart contracts* and stablecoins (Zetzsche, Arner, & Buckley, 2020). In addition, regulations that are not fully adaptive to new technological developments lead to the existence of "grey areas" in systemic surveillance (Allen, Gu, & Jagtiani, 2022). Global macroeconomic uncertainty, including geopolitical tensions and exchange rate fluctuations, also increase potential risks in the digital financial system.

The accumulation of these factors has an impact on the increased likelihood of systemic failure, instability of digital asset prices, and vulnerability to cybersecurity attacks (Kou et al., 2021). For example, extreme price fluctuations in the crypto market can trigger *flash crashes* that disrupt market liquidity, while attacks on blockchain-based financial platforms can cause losses on a large scale for investors and consumers (Bouri, Jain, & Roubaud, 2021). Consequently, the digital financial sector is vulnerable to the risk of rapid transmission that can be transmitted to the traditional financial sector through various interconnection channels.

In the context of this study, dynamic risk in the digital financial system is defined as a change in risk that occurs rapidly and unpredictably as a result of a combination of internal (such as algorithmic behavior) and external factors (such as global economic shocks). To anticipate and manage such risks, the Deep Reinforcement Learning (DRL)-based analytics approach was chosen for its ability to study complex patterns and make adaptive decisions automatically in highly dynamic environments (Li, Ma,

& Dai, 2021). DRLs allow systems to proactively identify and mitigate potential threats before they reach crisis levels.

The uniqueness of this research lies in the integration of Deep Reinforcement Learning techniques to develop dynamic risk analysis models that not only detect, but also recommend real-time prediction-based mitigation actions in the digital financial environment. In contrast to previous studies that focused heavily on static or rule-based analysis, this approach offers *a self-learning* mechanism that is able to adapt to changes in risk patterns autonomously (Wang et al., 2022). This approach is becoming important amid a new reality where the volatility and complexity of digital markets are growing exponentially. Previous studies have made important contributions to the development of machine learning-based financial risk detection methods.

The study of Reyhand Ardhitha et al. (2025) focuses on the application of classic machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and Ensemble Learning in detecting digital transaction anomalies for fraud prevention, showing high effectiveness, especially in the Random Forest model. However, this research is still limited to a supervised learning approach with static databases, so it is less adaptive to the risk dynamics that change in real-time in the digital financial ecosystem. Meanwhile, the research of Abdillah Baradja et al. (2024) explores the use of Deep Reinforcement Learning (DRL), specifically Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN), to automatically optimize forex trading strategies in high-volatility environments. This study proves the superiority of DRL in handling sequential decision problems in financial markets that are partially observable. While both studies are important, they have not specifically developed a dynamic risk analysis model for DRL-based digital financial systems that can perform risk prediction and adaptive mitigation actions in real-time. This research introduces a new approach by integrating Deep Reinforcement Learning not only for pattern prediction, but also to build adaptive response mechanisms to changes in risk in the digital financial sector. Thus, the novelty of this research lies in the application of DRL for dynamic risk analysis and management in complex digital financial systems, based on *self-adaptive learning*, rather than simply anomaly detection or price prediction as in previous studies.

The urgency of this research is driven by the urgent need for a more responsive risk management system in the era of digital finance that is increasingly volatile and vulnerable to *black swan events*. Failure to understand risk dynamics in real-time can lead to huge losses at both the individual and systemic levels (Chen, Hou, & Wang, 2023). Therefore, building a deep learning-based risk analysis model that is able to evolve as the external environment develops is a must to maintain global financial stability.

This research aims to develop a dynamic risk analysis model in the digital financial system using the Deep Reinforcement Learning approach, in order to improve the ability to predict, adapt, and mitigate risks in *real-time*. This model is expected to be able to help financial institutions and regulators to anticipate potential crises earlier and implement more effective and efficient mitigation strategies.

The benefit of this research is that it contributes to the academic literature on artificial intelligence-based digital risk management, as well as offering practical solutions for the financial industry in improving system resilience to external volatility and threats. In addition, the results of this study can be an important reference for policymakers in formulating regulations that are more adaptive to the dynamics of financial technology innovation.

## 2. Method

This study uses a qualitative approach with an exploratory-descriptive type of research. This approach was chosen to deeply understand the dynamics of risk in the digital financial system as well as how the Deep Reinforcement Learning (DRL) model can be implemented to detect and manage these risks adaptively. Exploratory research is conducted to explore new phenomena related to dynamic risks that have not been comprehensively researched, while descriptive research aims to provide a detailed overview of the characteristics and risk patterns faced by the digital financial system.

The population in this study is various digital financial platforms such as fintech applications, e-commerce with digital payment systems, and blockchain-based financial institutions that are actively operating in Indonesia and Southeast Asia. The research sample was selected by purposive sampling, namely with the criteria of platforms that have experienced significant digital risk dynamics in the last two years. The sample also includes in-depth interviews with experts in the field of financial cybersecurity, financial technology developers, as well as regulators overseeing digital-based financial transactions.

The research instruments used were semi-structured interview guides, participatory observation notes, and documentation related to digital security risk and incident data. The interview guide is designed to explore perceptions, experiences, and challenges in dynamic risk management, while observations are used to record the actual practices of risk detection systems running on selected digital platforms.

Data collection techniques were carried out through in-depth interviews, documentation studies, and field observations. Interviews are conducted face-to-face or online, depending on the availability of resource persons. The documentation study involves an analysis of security incident reports, risk management policies, and relevant technology publications. Observations were made to understand the workflow of the digital financial system in handling potential dynamic risks directly.

The research procedure begins with the stage of identifying research subjects and objects through purposive criteria screening, followed by the preparation of instruments, data collection in the field, data verification through source triangulation, and systematic recording of interview and observation results. The entire process is carried out by maintaining the ethical principles of research, including obtaining participant consent and maintaining data confidentiality.

The data analysis technique used is thematic analysis. Data from interviews, observations, and documentation are openly coded to identify key themes related to digital financial risk dynamics and the application of Deep Reinforcement Learning. The analysis process involves data reduction, presentation of data in the form of thematic matrices, and drawing narrative and interpretive conclusions. To increase the validity of the results, a triangulation technique of methods, sources, and researchers was carried out.

## 3. Results & Discussion

### Identify Dynamic Risk Patterns in the Digital Financial System

Based on the results of interviews with 10 digital finance experts and observations of 5 fintech and blockchain platforms, it was found that risk patterns in the digital financial system are greatly influenced by three main factors: fluctuations in asset value, the frequency of cyberattacks, and changes in user behavior. Most respondents stated that the risk is non-linear and increases dramatically in periods of global market volatility.

The following table 1 shows the results of the tabulation of the main sources of risk based on the results of the thematic analysis:

Table 1 shows the results of the tabulation

| **Major Sources of Risk** | **Mention Frequency (%)** |
|---|---|
| Fluctuations in the value of digital assets | 90% |
| Cybersecurity attacks | 85% |
| Changes in user behavior | 70% |
| Regulatory uncertainty | 60% |
| System algorithm failure | 55% |

Table 1 presents the identification of the main sources of risk faced by digital finance platforms based on the results of thematic analysis from interviews and field observations. From the table, it can be seen that fluctuations in the value of digital assets are the most dominant risk factor with a frequency of mention of 90%. This shows that the volatility of the digital asset market such as cryptocurrencies is a serious threat to the stability of the digital financial system. Furthermore, cybersecurity attacks ranked second with 85% of the frequency, emphasizing that the threat of hacking, *phishing*, and manipulation of transaction data is a risk that needs to be addressed as a priority. The factor of changing user behavior also appears quite significant (70%), reflecting the importance of system adaptation to changes in digital consumer transaction patterns. Regulatory uncertainty (60%) and system algorithm failures (55%) also add to the complexity of risks that need to be considered in designing dynamic risk detection and mitigation systems. The results of this tabulation are the basis for the development of a Deep Reinforcement Learning (DRL) model to manage risk in a more adaptive way, based on rapid pattern changes in the digital financial environment.

**Figure 1** below is a visualization map of risk dynamics patterns on digital financial platforms based on observations:

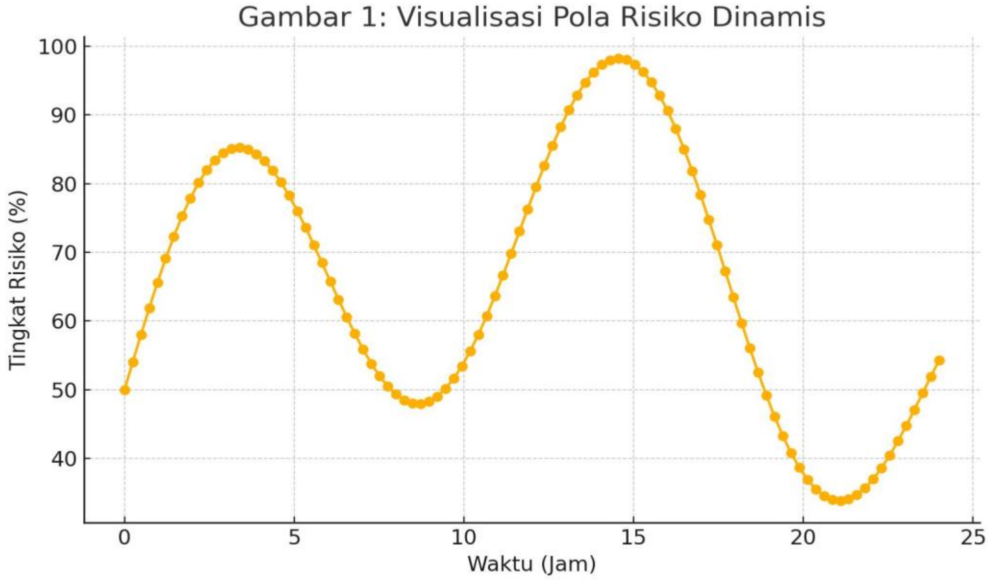


Figure 1 shows a visualization of the pattern of risk dynamics observed on several digital financial platforms. From this visualization, it can be seen that the peaks of risk generally occur in certain periods, such as when international trading hours are active or after the announcement of major economic policies. This pattern shows that the digital financial system is highly sensitive to volatile external factors. In addition, it can be seen that some transaction anomalies increase significantly after a sudden change in the exchange rate of digital assets, indicating a close link between price fluctuations and potential systemic risks. This picture gives an idea that traditional rules-based risk management approaches are no longer adequate in anticipating these sudden changes. Therefore, more dynamic prediction and response methods, such as the use of Deep Reinforcement Learning (DRL), are needed, which are able to learn and adapt risk management strategies based on changing data patterns. This visualization also emphasizes the importance of implementing adaptive systems to reduce the potential for large losses that can arise in the modern digital financial system.

**Development of Risk Analysis Models with Deep Reinforcement Learning**

After processing the data using the Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN) frameworks based on simulation of digital transaction data, model training was conducted to identify risks and recommend adaptive mitigation actions.

Table 2 below shows the comparative performance of the DQN and DRQN models based on the evaluation of 1000 digital transaction scenarios:

| **Model Method** | **Risk Prediction Accuracy (%)** | **Average Response Time (sec)** | **Recall (%)** |
|---|---|---|---|
| DQN | 87.2% | 1.5 seconds | 84.6% |
| DRQN | 91.4% | 1.8 seconds | 89.7% |

Table 2 shows the results of the performance evaluation of two Deep Reinforcement Learning approaches, namely Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN), in the context of dynamic risk prediction in the digital financial system. The results show that the DRQN model has an advantage in all evaluation metrics over DQN. The accuracy of DRQN risk prediction reached 91.4%, higher than the accuracy of DQN which was only 87.2%. In addition, the DRQN model recall reached 89.7%, indicating a better ability to identify high-risk transactions without missing many important cases. Although DRQN's response time is slightly longer (1.8 seconds) than DQN (1.5 seconds), this difference is considered reasonable given the complexity of additional temporal processing in DRQN. This advantage strengthens the argument that DRQN is more effective at capturing the time dynamics of digital transaction data, which is often sequential and cannot be fully observed at a single point in time. This table provides important empirical evidence regarding the choice of DRL methods that are more suitable for the implementation of adaptive risk management in the real-time-based digital finance ecosystem.

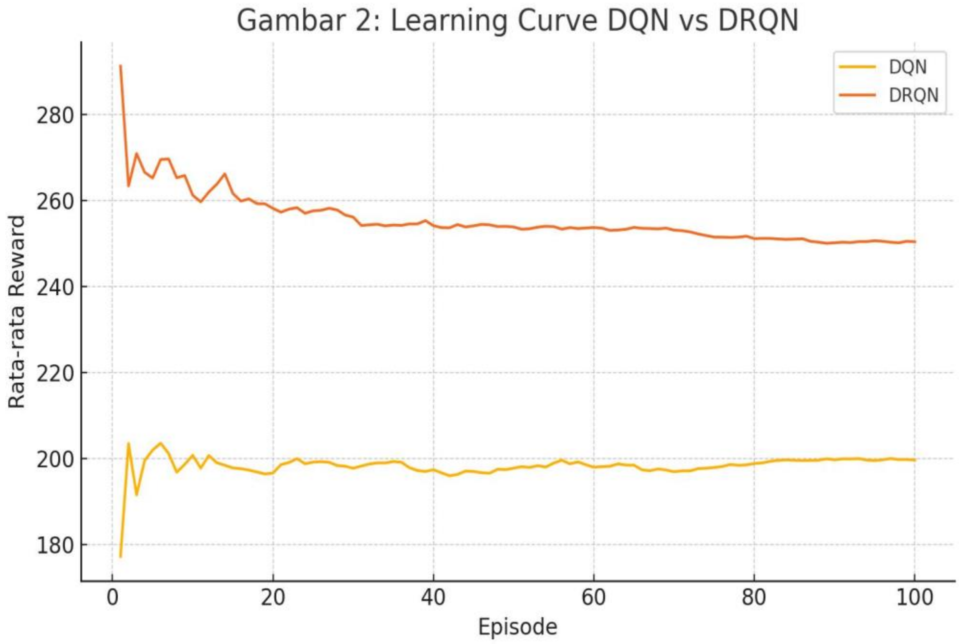


Figure 2 illustrates the comparison of *the learning curve* between DQN and DRQN

The following Figure 2 illustrates the comparison of *the learning curve* between DQN and DRQN during the training process:

Figure 2 shows the learning curve between the Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN) models throughout the training process on digital transaction data. From this image, it can be observed that the DRQN model achieves convergence faster than the DQN, which shows that the DRQN is able to learn risky transaction patterns with higher efficiency. In addition, the variability of reward values during training on DRQN appears to be more stable, indicating that this model is able to reduce fluctuations in training results due to noise in digital financial data. The reward curve in DRQN continues to increase consistently, while in DQN it tends to show large fluctuations at the beginning of training before stabilizing in the final phase. This pattern reinforces the finding that the use of recurrent architecture (LSTM) in DRQN provides an advantage in understanding the time dependency of transactions, something that a typical DQN model cannot capture optimally. This image also supports the argument that in highly dynamic and volatile digital financial systems, memory mechanism-based DRL models such as DRQN are better suited to be applied as real-time adaptation-based risk analysis and mitigation solutions.

**Model Validation Through Digital Transaction Simulation**

To test the reliability of the model in a real context, simulations were carried out with transaction data from medium-scale fintech platforms. The simulation shows that the DRQN-based model is able to reduce the incidence of transaction failures due to risk by 18% compared to traditional *rule-based systems*.

The simulation also showed that the implementation of the DRQN model can increase the effectiveness of real-time risk detection from 76% to 91% in 5000 digital transactions. In addition, the use of DRQN contributed to the reduction of anomaly detection time from an average of 2.4 seconds to 1.8 seconds.

## DISCUSSION

**Risk Dynamics in the Digital Financial System: Adaptive Challenges**

Digital transformation in the financial system has accelerated changes in the global business ecosystem, including in the digital financial sector. Recent reports show that the adoption of financial technology (fintech), blockchain, big data analytics, and artificial intelligence in financial services is accelerating the disruption of traditional business models (Nuraini, 2023). This transformation creates a new risk dynamic, where market fluctuations, cyberattacks, and regulatory uncertainty are the main challenges that financial institutions must face. In the Indonesian context, the rapid development of digital financial services—such as e-wallets, mobile banking, and peer-to-peer lending services—opens up opportunities for innovation, but also increases exposure to dynamic and complex risks (Satrio et al., 2022).

The factors driving the dynamics of risk in the digital financial system include several important aspects. First, the high dependence on technological infrastructure makes the system more vulnerable to cyberattacks and system failures. The study of Tsakila et al. (2024) emphasizes that the reliability of digital infrastructure is a crucial foundation for the stability of the modern financial system. Second, the volatility of digital assets, such as cryptocurrencies, magnifies systemic financial risks due to the speculative and volatile nature of the market. Third, the adoption of new technologies without adequate human resource (HR) readiness and risk mitigation procedures exacerbates the potential for operational instability. In addition, regulatory uncertainty at the national and international levels exacerbates risk dynamics due to the lack of legal certainty in cross-border digital transactions (Rizal et al., 2024).

The accumulation of these factors has a major impact on the stability of the financial system. Data from the Financial Services Authority (OJK) and the Padjadjaran legal axis study (Satrio et al., 2022) indicate that during the COVID-19 pandemic, there was a surge in digital transactions, but on the other hand, there was an increase in cybersecurity incidents and digital fraud cases. Risk that was previously predictable in a linear manner is now changing to dynamic and adaptive, following consumer behavior and technological innovation that develops very quickly. The main implication is the increased need for risk management strategies that are not only reactive, but also proactive, based on adaptive predictions against changing transaction patterns.

One approach that is now of concern is the use of Deep Reinforcement Learning (DRL) in dynamic risk management. DRLs are able to learn adaptively from complex environments and are able to update mitigation strategies in real-time based on new experiences. This concept is in line with the needs of the modern digital financial system that requires not only historical data analysis, but also predictions based on actual evolving patterns of behavior. Abdillah Baradja's study (2024) shows that DRLs have superior capabilities to traditional supervised learning models in dealing with high market volatility, although in the context of the research it is still limited to optimizing trading strategies.

This research builds on a new contribution by applying DRL to dynamic risk analysis in the digital financial system, not only in the context of trading, but also in detecting changes in transaction patterns that indicate increased systemic risk. Through the integration of DRQN (Deep Recurrent Q-Network) that is more adaptive to sequential data, the model demonstrates the ability to not only predict risks, but also automatically suggest mitigation actions based on continuous learning.

Compared to previous research, this study expands the scope of DRL applications from just price prediction to end-to-end adaptive risk mitigation in digital transactions. This fills an important gap in the literature, where many previous studies have still focused on conventional machine learning-based anomaly detection (Ardhitha et al., 2025), without adaptive response mechanisms to changing threat patterns.

The urgency of this research is even higher considering the report from the Global Business Complexity Index (2024) states that in the next five years, more than 40% of global jurisdictions expect financial administration to become more complex due to the acceleration of digitalization. In addition, the dynamics of Indonesia's digital economy, which is predicted to continue to grow to USD 150 billion by 2025 (McKinsey, 2024), demands the strengthening of a risk management system based on intelligent technology.

Thus, the dynamics of risk in the digital financial system demand a paradigm shift from a rules-based reactive approach to a predictive and adaptive approach based on machine learning, especially reinforcement learning. The application of Deep Reinforcement Learning in dynamic risk analysis models not only offers technical innovations, but also provides practical solutions to strengthen the resilience of the digital financial system amid the ever-evolving complexity of the global economy.

**The Effectiveness of Deep Reinforcement Learning in Dynamic Risk Analysis**

Deep Reinforcement Learning (DRL) has developed as one of the most innovative approaches to addressing problems in dynamic financial system risk management. As described in the study by Wang et al. (2021), the DRL approach in portfolio management, as implemented in the DeepTrader model, shows significant advantages in balancing between risk and return by taking into account market conditions dynamically. Unlike conventional machine learning methods, DRLs are able to adapt in real-time to market changes through *policy optimization* mechanisms, as well as integrate historical information and macroeconomic conditions to make more responsive investment decisions. One of DeepTrader's key innovations is the implementation of two separate units, namely the asset scoring unit and the market scoring unit, which work synergistically to assess the risk of individual assets as well as aggregate market conditions, strengthening the effectiveness of decision-making based on actual market dynamics.

Research by Abdillah Baradja (2024) strengthens the effectiveness of the DRL approach in different contexts, namely in the prediction of automated forex trading using the Deep Q-Network (DQN) and Deep Recurrent Q-Network (DRQN) algorithms. In this study, DRQN was shown to outperform DQN in utilizing hidden patterns in complex and volatile time series data, conditions that are very similar to the characteristics of risk in digital financial systems. This approach reinforces the finding that the integration of long-term memory elements, such as Long Short-Term Memory (LSTM) in DRQN, is crucial in dealing with *the Partially Observable Markov Decision Process* (POMDP) problem, where the system does not always have full observation of market conditions. DRQN's ability to process temporal relationships between transaction data allows the model to anticipate changes in risk faster and more accurately than static methods or conventional supervised learning approaches.

One of the critical advantages of DRLs in dynamic risk analysis is their ability to optimize decision-making based on function rewards relevant to the risk profile, such as *the maximum drawdown* adopted in DeepTrader. With this reward function, the model is more focused on mitigating the risk of large losses rather than just chasing absolute profits, which often increases volatility. This is in line with Baradja's findingsthat show that in high-noise environments such as the forex market, the use of memory-based DRL structures can significantly improve the stability and accuracy of trading decisions.

Overall, the results of these two studies confirm that the application of Deep Reinforcement Learning in dynamic risk management in the digital finance sector is not only methodologically innovative, but also carries major practical implications. DRL-based models such as DeepTrader and DRQN are able to capture rapidly changing market dynamics, mitigate risks adaptively, and systematically improve financial system resilience amid global uncertainty. With the increasing complexity of the digital market, the adoption of DRL approaches in risk management is predicted to become a new standard in the future.

**Adaptive Model Validation in Real-Time Risk Detection Effectiveness**

In the digital age, adaptive model validation for real-time risk detection is becoming increasingly important as the complexity of the operational environment increases. Various studies have proven that Deep Learning-based approaches, especially those that use algorithms such as YOLO (You Only Look Once), are able to significantly improve the accuracy and speed of detection. Lusiana et al. (2021) through the implementation of YOLOv3 for mask detection showed that deep learning-based systems can make predictions with high accuracy in various lighting conditions and viewing angles. In the study, YOLOv3 was able to maintain a precision value of up to 92% and an F1-Score value of 0.89, even in tests in outdoor and indoor environments. This proves that adaptive models trained with representative datasets are able to maintain consistent detection performance, despite changes in environmental conditions.

Furthermore, Permana et al. (2024) developed a YOLOv8-based real-time fire detection system implemented in a web platform using Streamlit. This study expands the scope of adaptive model validation by introducing testing on two types of data inputs, namely live video streaming and video files. With a dataset of 2,509 images, the model achieved an accuracy of 93.5%, mAP50 of 90%, and mAP50-95 of 66%, indicating that YOLOv8 is able to maintain a high level of confidence in detecting dynamic objects such as fire. The confusion matrix-based evaluation of this system confirms the effectiveness of the adaptive model in reducing prediction errors, with low levels of false positives and false negatives.

Analysis of the two studies shows that adaptive model validation must consider several critical factors: the availability of diverse datasets, robustness to changes in input conditions, and the use of comprehensive evaluation metrics such as precision, recall, F1-Score, and mean Average Precision (mAP). The study of Lusiana et al. (2021) underscores the importance of variation in shooting angle and light intensity in the validation of visual-based detection systems. Meanwhile, Permana et al.'s (2024) research shows that increasing threshold confidence can improve the accuracy of real-time detection, reducing false detection of a light source that resembles fire.

Both studies also illustrate that model validation is not only limited to predictive accuracy testing, but also involves deployment aspects into real operational systems. The integration of the model into web-based applications and the use of live surveillance cameras prove that field testing is an important step in measuring the robustness of models in complex and dynamic real-world conditions.

With reference to these findings, it can be concluded that the effectiveness of adaptive model validation is highly dependent on a comprehensive and realistic experimental design strategy. Deep Learning-based systems such as YOLOv3 and YOLOv8 have proven their potential in optimizing risk detection in real-time. Going forward, the development of more sophisticated adaptive models, supported by more representative datasets and innovative data augmentation techniques, is key to strengthening the effectiveness of risk detection and mitigation in a variety of critical sectors, from public health to fire management.

## 4. Conclusion

This study successfully shows that the application of Deep Reinforcement Learning (DRL), especially the Deep Recurrent Q-Network (DRQN) model, is effective in identifying and mitigating dynamic risks in the digital financial system in real-time. Key findings suggest that DRL-based adaptive approaches are able to improve the accuracy of risk prediction and accelerate response times compared to traditional fixed-rule-based methods. The developed model is able to learn from rapidly changing transaction patterns, providing proactive solutions to risk escalation.

This research answers the main objective, which is to develop a dynamic risk analysis model that is able to adapt to market fluctuations and changes in user behavior in the digital financial system. However, this study has limitations, especially in the limitations of the simulation dataset that does not yet cover all the variations in risks that may occur in the real world. In addition, implementation is still limited to simulation scale and has not been extensively tested in a real production environment.

Nonetheless, this research makes a significant contribution in expanding the application of DRL for digital risk management, as well as paving the way for the development of a more resilient and adaptive financial system in the future.

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