

## Real-Time Credit Authorization: Risk Prediction using Deep Reinforcement Learning

Author Name: Pratik Badri  
Role: Independent Researcher  
Email: [Pratikbadri@gmail.com](mailto:Pratikbadri@gmail.com)

Author Name: Anusha Nerella  
Role: Independent Researcher  
Email: [anerella30@gmail.com](mailto:anerella30@gmail.com)

Author Name: Nikita Chawla  
Role: Independent Researcher  
Email: [nikitachawla83@gmail.com](mailto:nikitachawla83@gmail.com)

***Abstract- The study is critically examining the real-time credit authorization using risk prediction techniques. The application of deep reinforcement learning for understanding the risks and executing credit authorization is being assessed with the help of relevant evidence. The real-time credit authorization comprises of a cardholder's credit limit being checked against the purchase request made. An immediate approval or denial is provided relying on the assessment being made. The real-time authorisation helps in reducing delays in payments, minimising reworks and more efficient treasury processes. The real-time authorisation facilitated via deep learning processes is being investigated.***

***Indexed words: Real-time credit authorisation, risk assessments of real-time authorisation, risk prediction using Deep Reinforcement Learning, impacts of deep reinforcement learning***

### I. INTRODUCTION

#### A. Background of the study

One of the most vital and frequent decisions that financial institutions have to make is the loan approval. There is an inherent challenge faced is to build a proactive, powerful, ethical and responsible exploitation of data, to ensure proper credit approval [1]. The real-time model is being

deemed more impactful based on deep neural network can outperform binary classifiers. There is greater accuracy attained. The credit card delinquency risk can be better comprehended through a predictive network. The Deep Reinforcement Learning (DRL) aids in predicting deception in large imbalanced data. In case of any fraud transaction detected, an alert can be sent to the associated financial organisation suspending the release of payment [2]. The full potential of DRL in refining credit risk authorisation need further study and analysis for improved applications.

#### B. Overview

The use of machine learning, deep learning and neural networks are crucial in detecting and blocking fraudulent are being increasingly adopted [3]. The DRL aids in optimal anomaly detection techniques for identifying frauds. There is increased levels of detection accuracy and reduced percentages of false alarm rates achieved through it. An effective anti-fraud service is of prime importance for all the involved parties such as merchants, payment systems, banks and aggregating agents [4]. The parameter fine-tuning of machine learning leads to optimised classification of the data. The DRL has gained increased momentum in recent times with its ability to learn through multiple levels of

attractions. There is a good perception of the environment obtained with the application of DRL [18]. The classification rule paves the way for trigger alert on any suspicious transactions, creating a resilient system [5]. An adequate detection of frauds is essential for preventing financial losses [6]. Thus, it is vital to learn about the real-time authorisation risk assessment being advantaged by the application of DRL.

### *C. Aims and Objectives*

The aim of the study is to learn about the aspects of DRL facilitating the real-time credit authorisation with effective risk assessment. The study is aimed at accomplishing the following objectives in the course of the study. 1) To understand the salience of real-time credit authorisation in assuring safe transactions 2) To analyse the role of DRL in identifying risks and patterns that can assure real-time authorisation 3) To recommend the actions needed by financial institutions and banks to prevent frauds with the integration of DRL.

### *D. Problem Statement*

The credit card fraud detection is of utmost priority in screening fraudulent transactions in advance of their authorised card issuers. The credit card fraudulences have large values and can trigger huge losses. The investigation process can be tedious and an effective fraud detection model is necessary for quickly identifying frauds [6]. The complex decision-making in dynamic environments is enabled DRL. With the increasing need for real-time authorisation the impacts of DRL are essential for sending quick alerts to all participants. Huge losses across the system can be avoided with the integration of an impactful model with all the necessary features.

### *E. Scope and Significance*

The scope of the study is to analyse the need for real-time credit authorisation in the current business environment. It will critically examine the influences of DRL in

making effective risk assessments and reducing the possibilities of frauds. The steps needed for improved applications of DRL in real-time credit authorisation will be studied as well. The study is significant with the dynamic changes across the financial landscape. The credit card frauds have resulted in \$ 3 billion losses for North American financial institution [7]. The increase of digital payment systems such as Android Pay and Apple Pay enhances the chances of losses occurring due to fraudulent transactions [7]. DRL presents a promising solution to overcome fraudulent activities and prevent transactions in case of any risks identified. DRL is being identified as increasingly capable compared to Logistics Regression and Gradient Boosted Trees.

## II. LITERATURE REVIEW

### *A. Evaluating credit risks*

The credit risk takes place when a borrower is unable to meet the financial commitment [8]. The diligence while giving loans, consistent monitoring of customer payments and other behavioural patterns can significantly thwart the accumulation of non-performing assets and frauds. In a few years the quantum of frauds and non-performing assets have greatly escalated. It has become imperative for financial institutions to use robust mechanisms so as to predict the performance of loans.

The Machine Learning models such as DRL are being increasingly concerned for detecting frauds and overcoming them. The Machine Learning is being increasingly preferred to traditional based fraud detection methods. The ML models have the capability to scale dynamically to quickly identify any discrepancies in the system [9]. The operational mechanisms can optimise data and prevent any transaction identified as having anomalous behaviour.

### *B. Applying DRL for fraud detection*

The DRL is paving the way for positive results in fraud detections with its inherent characteristics. The DRL is having the capability of combining techniques and quickly identify any early signs of risk [10]. The reinforcement of learning networks ensures the identification of any anomalies and useful representations of problems that have high dimensional raw data input. The deep learning models are having a significant edge in conferring the needed advantages to the Machine Learning approach for fraud detection. The capacity for modelling data through observation of complex and non-linear relationships can be attained via Deep Learning [11]. The DRL models are having the capability for automatically learning feature representations from raw data. This makes them impactful in successfully interpreting raw and unstructured data. The Real-Time Credit Scoring continuously updating the risk assessment model, enables banks to make more informed decisions.

### C. Advantages of DRL used in credit authorisation

The studies reinforce the value of DRL in being able to credit authorisation. The deep neural networks are having a higher performance in risk assessments compared to other technologies [12]. The risks associated with the credit card delinquency is seamlessly achieved. The credit risk prediction is key to overcoming issues and leading to transparent decision-making [13]. The DRL with its ability to recognise patterns can ward off untoward incidents. There are new approaches needed for the identification of risks, especially with the huge amount of data amassed [14]. DRL is an impactful application that aids in assessing the underlying risks and predicting the outcomes with critical accuracy. The digital payments are gradually replacing the traditional models of payment, necessitating dynamic technologies for fraud detection [15]. The DRL is hence being acknowledged as one

of the effective technologies for authorising real-time credit.

Proposed method - 2018	10-fold	None+PCA	Deep Genetic	94.06%
DGHNL			Hierarchical	
			Network of	
			Learners (29-	
			layer system)	

**Figure 1: Accuracy of 94.06% achieved with use of Deep Learning**

(Source: [17])

The studies reveal how DRL being combined with other applications can greatly increase the credit score [17]. The DRL structure used across German credit approval dataset with 1000 records has revealed an accuracy of 94.06%. The accuracy is crucial in emphasising the value of DRL in being able to assess critical risks within the system.

### D. Challenges of DRL

Despite the critical advantages associated with DRL, there are a host of challenges that needs to be addressed as well. The challenges encompass the training process being extremely demanding and time consuming making it difficult to apply the process [21]. The control security and robustness need to be increased and there is an urgent need for the generalisation capabilities of DRL to be improved [21]. The transactional landscape has changed entirely paving the way for DRL in credit risk assessment. However, the severe challenges associated with the technology need to be addressed as well.

## III. METHODOLOGY

### A. Research Design

The research is making use of exploratory design to comprehend the value created by applying Deep Reinforcement Learning. The risk assessments accuracy accentuated by DRL leading to strong credit authorisation in real-time is the core purpose of the study. There is a need for

analysing data and gaining new knowledge on the capabilities of DRL. The deep learning aiding reinforcement learning to operate in high dimensional environment such as credit authorisation requires collection of extensive knowledge. The knowledge will aid in understanding the critical applications, opportunities and challenges associated with the use of DRL in real-time credit authorisation. The new insights will help in in-depth research of the subject yielding positive results.

### B. Data Collection

The study has collected data from secondary sources to gain in-depth insights on the subject being researched. The qualitative data has been collected from academic journal articles, revealing the critical advantages obtained using DRL across credit authorisation. The analysis of data has aided in understanding the features of DRL contributing to risk assessments. The quantitative data analysis on the other hand has used graphs collected from secondary sources. The graphs have expounded the tendencies of data, aiding in understanding the value of DRL applied across real-time credit authorisation. The better results, accuracy and transparency achieved with the use of DRL has been noted from the quantitative data collected on the subject. The data analysis has revealed the robustness in risk assessment possible with the DRL used for identifying patterns and taking key decisions.

### C. Case studies and evaluation

#### Case study I: Microsoft

It can be observed how Microsoft has made use of Deep Learning so as to identify frauds. The company has made use of dynamic risk tables and knowledge graphs to identify fraudulent patterns [16]. The implementation over a 2-year period from 2016 to 2018 has resulted in reduction of fraud losses by 0.52% and improved the bank authorisation rate by 7.7% [16].

Microsoft has been able to gain millions of dollars in revenues with the application of such techniques.

#### Case Study II: Fintech start-up Zest Finance

The Fintech Start-up Zest Finance has made use of Deep Learning to optimise the credit risks for banks. The losses and default rates have reduced by 20% on average [22]. The assessment of liquidity risks and calculation of the fund positions have ensured that the company is well aware of the credit loans approval needed. Hence, there has been positive results accrued with the help of Deep Learning in the banking databases.

### D. Evaluation Metrics

The study has examined the data based on the accuracy of the outcomes. The success of Deep Learning and Machine Learning to boost risk assessments have been derived through the assessments of quantitative data. The accuracy reveals the advantages and benefits that can be gained with the application of DRL. The pattern recognition helping to lower errors, frauds and false alerts have been inferred. The accuracy of the results has been the prime indicator in affirming the value of DRL in the context of real-time credit authorisation.

## IV. RESULTS

### A. Data Presentation

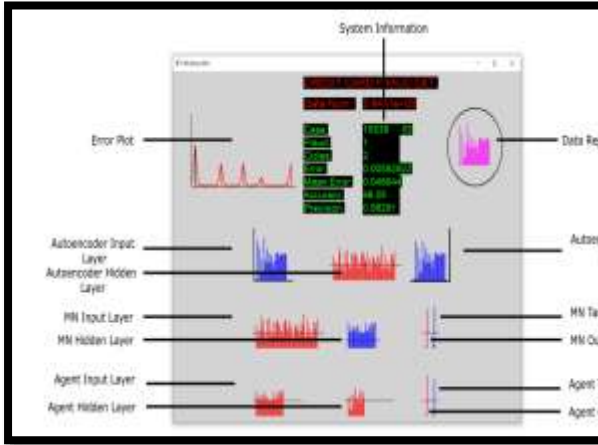
Classifiers	Accuracy
Logistic Regression	96.2*
Naive Bayes	96.9*
Decision Tree	96.4*
K-Nearest Neighbour	99.1*
Q-Credit Card Fraud Detector	98.1

**Figure 2: The highest accuracy possible with the integration of deep learning**

(Source: [23])

The deep learning used in credit card fraud detection is showing high accuracy of 98%

[23]. The study has presented the credit card fraud detector relying on deep networks and reinforcement learnings paving the way for impactful results.



**Figure 3: Interface of the system being used**

(Source: [23])

The proposed solution is working as a quick intelligent agent that can identify frauds with great accuracy [23]. The use of imbalanced datasets is ensuring better results with more adaptation to real-life problems during banking transactions. Hence, it can be derived that DRL is being able to reach high accuracy in terms of identifying frauds and taking appropriate, responsive measures. The interface is depicting the accuracy achieved leading to key decision-making across the banking institutions.

	Cumulative Net Fraud Savings (\$)			Relative Improvements		
	Oct	Nov	Dec	Oct	Nov	Dec
Thr0	91,627.65	172,916.59	272,233.33	12.10%	2.18%	6.28%
Thr1	94,934.01	179,207.39	285,610.45	16.15%	5.90%	11.50%
Thr2	100,236.95	195,215.73	304,032.85	22.64%	15.36%	18.69%
Thr3	105,120.61	203,428.47	312,060.59	28.61%	20.22%	21.82%
Thr4	105,916.35	209,866.51	317,246.51	29.59%	24.02%	23.85%
Thr5	104,516.99	207,827.61	317,227.83	27.87%	22.82%	23.84%
Thr6	106,207.49	207,405.47	311,000.39	29.94%	22.57%	21.41%
Thr7	100,229.41	196,630.73	296,710.21	22.63%	16.20%	15.83%
Thr8	93,202.05	185,642.93	279,583.21	14.03%	9.71%	9.15%
Thr9	86,321.93	177,035.09	268,263.65	5.61%	4.62%	4.73%
Thr10	81,733.93	169,219.55	256,156.91	-	-	-
Ours	112,058.71	217,673.93	334,158.41	37.10%	28.63%	30.45%

**Figure 4: Significant improvements in performance when applying DRL for fraud detection**

(Source: [24])

The application of DRL for fraud detection is helping to gain better results. There is considerable relative improvement noted when applying Deep Q Learning Based Adaptive Threshold Policy compared to static applications [24]. The cumulative net fraud savings are boosted with the application of such measures, leading to better results [24]. Thus, the application of DRL is crucial for improving the alert threshold selection for fraud alert systems. Thus, the integration of DRL is being highly impactful in attaining the needed edge over the real-time credit authentication.

*B. Findings*

The results reveal the value of using DRL for fraud detection in a dynamic environment. Deep Learning and Reinforcement combined is helping to process new knowledge on the environment leading to critical adaptations. The outcomes reveal how DRL is able to identify frauds accurately compared to other Machine Learning techniques. The current fraud detection system is ineffective [24]. The operational efficiency of the system is increased manifold with the application of DRL being able to create the alerts needed. The performance of the fraud scoring model is enhanced as well with the application of DRL.

*C. Results of case studies*

Case Study	Strategy	Impacts	Outcomes
Microsoft	Using DRL to identify fraudulent patterns across	Reduction of fraud losses by 0.52%	Credit authorisation increased by 7.7%

	their transactions		
Zest Finance	Deep Learning to optimise credit risks	Losses reduced by 20%	Reduced susceptibility to losses and fraudulences

**Table 1: Case Study Outcomes**

(Source: self-created)

The analysis reveals how DRL is quick at identifying non-linear patterns. The authorisation is fortified and the credit losses are significantly reduced with applications.

*D. Comparative Analysis*

<i>Aspects of Literature</i>	<i>Focus</i>	<i>Findings</i>	<i>Gaps</i>
[1]	A proposed model based on deep learning permitting the loan applicants to be classified as good or bad risks	The binary classifiers being significantly outperformed by the DRL model proposed	The study fails to discern the specific characteristics of DRL lending it the needed edge
[3]	Using optimal anomaly fraud detection for identify	High level of detection accuracy achieved	No steps for implementation that could have

	ing credit card risks		enriched the study
[6]	Deploying models to understand and real-world fraud detection	The model being able to identify frauds and send alerts surpassing human capacities	No emphasis on the challenges or training needed for applications
[10]	The DRL helping in critical banking activities and transactions leading to enhanced results	The DRL aiding in the process of defining products, segmenting clients, efficiently managing risks and detecting frauds have been identified	Reduced discussion of the limitations that might occur
[17]	Using DRL in combination with other technologies for	The application of DRL for effective credit scoring leading to	Reduced quantitative data that could have fortified the outcomes

	improved credit scoring	avoidance of fraudulences	
[21]	The opportunities and challenges associated with DRL	The lack of generalisation capabilities can lead to erroneous results	Reduced focus on the opportunities of DRL that can be harnessed for real-time credit authorisation
[24]	The assessment of DRL for identifying frauds in payment systems	DRL having the highest accuracy in terms of reaching impact-driven results	The lack of exploration on the challenges and limitations

**Table 2: Comparative Analysis**

(Source: self-created)

## V. FINDINGS

### A. Interpreting results

The data reveals how DRL is impactful in detecting frauds, reducing losses and false alerts in case of assessing credit risks [24]. The DRL is helping to comprehend how with the rise in online payments there is an urgent need for robust systems. The systems also need to be dynamic in order to reduce any types of financial losses. It can be noted how financial losses have been huge with the inability to process data. The DRL features aids in reaching accuracy empowering financial institutes to reach improved decisions. However, there are

challenges of time-consuming processes and lack of generalisability [21]. The acceleration of training as well as developing datasets for performance benchmarking of controllers need to be studied.

### B. Practical Impacts

There are practical impacts for all banks and participants looking for authentic transactions. The use of DRL in identifying the drawbacks and weaknesses in the credit profile can aid in better decisions. It can be noted how Microsoft has been able to avoid critical losses and the revenues have increased with the strong identification of risks. In such a context, the DRL is highly effective in reaching results.

### C. Challenges and limitations

Despite the advantages there are underlying challenges of DRL. The process requires intense and detailed training to be applied across the business mechanisms. With the advent of DRL there is more clarity obtained on the financial domain. However, the models can lack generalisability leading to inconclusive results. These limitations need to be overcome with appropriate steps to gain favoured results. The credit fraud detection can be tangibly improved with the applications.

### D. Recommended actions

The companies looking to apply DRL should carry out extensive and detailed training that can yield favourable results. The applications of DRL and the steps for gaining best outcomes should be studied. The ways to handle high risk transactions and assessing the risks based on results received from DRL should be taught. Also, there should be more data included in the systems to increase the generalisability of the final results. The models should be trained to be dynamic and adaptive.

## VI. CONCLUSION AND FUTURE SCOPE

The research has concentrated on the use of DRL for credit risk assessments. The data has been collected on the subject to analyse how DRL can benefit the real-time credit authentication, taking into consideration the multiple risks. The study reveals the significant improvement derived with the application of DRL across the processes. The credit risk assessment is deeply benefitted with the near-accurate derivations.

The future scope of the work lies in exploring the challenges of DRL. The underlying challenges that can thwart the application need to be studied in detail. Organisations can carry out implementations with the knowledge gained.

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