Computer Fraud and Security
ISSN (online): 1873-7056

Deep Learning-Based Transaction Intelligence for Real-Time Financial Fraud Detection and Risk Mitigation

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***Abstract*—**With annual losses resulting from cybercrime now reported at more than US$600 billion, financial institutions absolutely cannot afford to ignore transaction-related fraud. The spate of data breaches combined with the growing sophistication of analysis now renders reactive fraud detection wholly inadequate. Mitigation requires a shift toward guarded environments and real-time transaction monitoring systems designed explicitly around surveillance, and regulation mandates that transactions be evaluated for risk at the moment they are executed. Current research on real-time anomaly detection seeks to build a wide range of models capable of detecting even the rarest and most subtle of classes. The methods used rely heavily on synthetic instances, and are often validated on either the closest adjacent class or on a label-to-label basis. Although some have drawn on combinations of machine and self-supervised techniques to good effect, the use of feedback loops has generally been overlooked.

Complete transaction streams have been found to yield more information than individual transactions, but the focus has nevertheless remained on individual temporal points. Recurrent architectures in particular are well suited to the temporal class. High-level understanding of architecture behavior can simplify the transition to a more effective search for patterns across the entire stream. Recurrent architectures such as long short-term memory or gated recurrent unit, enhanced with attention, support description at different levels of temporal abstraction and indeed across the whole stream. Real-time streaming-inference systems must satisfy additional considerations surrounding end-to-end timing, operational processes, and resilience if the full risk-scoring functionality is to be recreated in a form that fits naturally in a transaction-monitoring context.

Keywords*—Anomaly Detection, Attention Mechanisms, Cyber Fraud Detection, Financial Transaction Monitoring, Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Machine Learning, Real-Time Analytics, Real-Time Fraud Detection, Recurrent Neural Networks (RNNs), Risk Scoring, Stream Processing, Temporal Modeling, Transaction Stream Analytics.*

I. INTRODUCTION

Financial fraud continues to be one of the most prevalent cybercrimes across the globe, causing enormous losses over time for individuals, businesses, and governments. During the past few years, the complexity of fraud as well as the number and variety of schemes and techniques have increased. [1] Attackers have become increasingly focused on the identification of their targets, offering additional services to those who make transactions with high-risk accounts. In contrast, all organizations that offer online services have invested heavily in improving detection capabilities, responding in real time to fraud risk actions by blacklisted accounts, and, in many cases, acting on fraud risk alerts generated by banks. [2] However, despite the significant investment in regulations and technology that have taken place to combat fraud in recent years, fraud remains.

Fraud detection in real time is undoubtedly the most effective approach to tackle this problem. [3] Although the various solutions offered by banks, industry associates, and specialized vendors go a long way toward protecting customer accounts by blocking transactions or payment, [4] they are all based on fixed and simple business rules; hence, it would be easy for an attacker to circumvent the detection mechanisms. [5] A solution capable of determining transaction intelligence that includes transaction anomaly detection or fraud risk scoring of the transaction in near real time would greatly boost risk mitigation in any online service. [6] The challenge is to build something that would not intercept or delay the majority of customer transactions, as this would adversely affect customer service and potentially drive customers toward competitors.

A. Overview of Transaction Intelligence in Financial Systems

Financial fraud is a growing concern for organizations that make online financial transactions with their customers. [7] Real-time monitoring of financial transactions can form an advanced warning system that detects future fraud. [8]

Transaction intelligence leverages state-of-the-art analytical tools to combine data from various domains to indicate whether a transaction is legitimate or fraudulent.

Real-time transaction monitoring depends on streaming data from transactional logs, user events, third-party services, and other metadata sources. [9] Core tasks in transaction intelligence include transaction anomaly detection (scoring) and transaction risk scoring. [10] Detecting anomalous transactions can provide an early warning of potential fraud, while calculating the risk of any transaction can be used as part of an organization's fraud mitigation strategy. [11] A comprehensive portrayal and analysis of data—both the features available and the tools needed to extract additional indicator signals—will help make these two tasks more efficient.

Transaction intelligence is characterized by dynamic relevancy in having information from transactional logs at every moment and using that for abuse detection. [12] Data from other domains can also be included to improve model performance, but only to a certain extent; adding every feature from every domain may not yield the best result. Data availability, inherent data quality, and real-time inference requirement also complicate the modeling exercise. [13] As a result, different streams of data should be processed by domain experts before they are fed into anomaly-detection techniques. [14] Streaming data architectures and systems should enable the use of any ruled-based techniques in addition to machine learning.

A. Transaction Risk Scoring

Each incoming transaction xt is mapped to a bounded fraud-risk score through a learned scoring function applied to the transaction feature embedding φ(xt), where w is the learned weight vector and b is the bias term:

$$R(x_t) = \sigma(w^T \varphi(x_t) + b) \quad (1)$$

σ(·) denotes the logistic sigmoid function, mapping the composite of transactional, behavioral, and biometric features into a risk score in the interval (0, 1); a downstream threshold τ converts R(xt) into an alerting decision.

B. Recurrent Gating Mechanisms

The LSTM encoder processes the transaction stream through a forget gate that regulates retention of prior cell state, and a cell-state update combining the retained and candidate memory:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

The GRU encoder simplifies this mechanism with a single update gate zt that interpolates between the previous and candidate hidden states, reducing parameter count relative to the LSTM while retaining the ability to model long-range temporal dependencies:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (4)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (5)$$

C. Attention-Weighted Context Aggregation

An additive attention layer is applied over the full hidden-state sequence produced by the recurrent encoder, allowing the model to weight each timestep by its relevance to the current risk decision rather than relying solely on the final hidden state:

$$\alpha_t = \exp(e_t) / \Sigma_k \exp(e_k), \quad e_t = v^T \tanh(W_h h_t + W_s s) \quad (6)$$

$$c = \Sigma_t \alpha_t h_t \quad (7)$$

The resulting context vector c aggregates evidence across the whole transaction stream and is passed to the final risk-scoring layer in place of a single terminal hidden state.

D. Detection Performance Metric

Detection quality across all architectures evaluated in this study is reported using the harmonic mean of precision P and recall R:

$$F1 = 2PR / (P + R) \quad (8)$$

E. Streaming Latency Model

The end-to-end decision latency is decomposed across the four functional stages of the streaming pipeline — ingestion, windowing, inference, and alerting — with each stage modeled as an M/M/1 queue of arrival rate λ and service rate μs:

$$L_{total} = L_{ingest} + L_{window} + L_{infer} + L_{alert}, \quad L_s = 1 / (\mu_s - \lambda) \qquad (9)$$

F. Composite Transaction Intelligence Index

A composite index TII combines normalized detection accuracy, normalized latency, explainability, and provenance sub-scores into a single operating-point index, with weights wi summing to unity:

$$TII = w_1 F1_{norm} + w_2(1 - L_{norm}) + w_3 E + w_4 Pr \qquad (10)$$

G. Governance-Cost Optimization

The alerting threshold τ trades false-positive customer-friction cost against false-negative fraud-loss cost. Modeling both cost components as quadratic in τ with weighting coefficients A and B yields a closed-form optimal threshold τ*:

$$J(\tau) = A(1 - \tau)^2 + B\tau^2, \quad \tau^* = A / (A + B) \qquad (11)$$

H. Throughput Scalability Model

Horizontal scaling of stream consumers is modeled via the Universal Scalability Law, capturing both inter-consumer contention (σ) and coherency-delay (κ) effects as the number of parallel consumers N increases:

$$\Theta(N) = N\theta_1 / [1 + \sigma(N - 1) + \kappa N(N - 1)] \qquad (12)$$

II. Theoretical Foundations of Transaction Intelligence

Transaction intelligence is grounded in advanced analytics, distinct from traditional descriptive, diagnostic, and predictive models. It focuses on identifying risks and opportunities and determining appropriate management responses. [15] These models typically use well-defined domain knowledge and rely on opportunistic data collection. Different types of analytics are mapped to stages in the risk management process. [16] At the higher level of transaction risk assessment, the process is structured as an iterative feedback loop among the required components of risk scoring, anomaly detection, explainability, and provenance.

Transaction intelligence draws upon disparate domains, primarily analytics and machine learning, together with domain knowledge of the financial transactions landscape. [17] It builds transaction risk models that can detect fraud, cyber-attacks, and other monetary threats. [18] The risk-scoring engine provides per-transaction risk assessment as an output, enabling downstream components to be triggered based on the prescribed threshold. Anomaly detection identifies unexpected patterns, relationships, and other deviations from expected behavior. [19] Explainability provides comprehensible reasons for the estimated risk level at the fundamental level, domain experts, statisticians, and data scientists understand the risks involved and address the problems proactively. [20] Provenance captures the past behavior of entities involved in specific transactions, monitoring history and intention patterns, and building trust. [20] These components collectively enhance the credibility of transaction risk models, address ethical considerations, embed due-diligence checks, and strengthen governance mechanisms.

III. Deep Learning Architectures for Real-Time Fraud Detection

Many fraud detection tasks can be expressed as binary classification problems where the goal is to predict whether an incoming transaction is fraudulent. [21] A number of deep learning models were proposed for such tasks. These models can be grouped along the following axes: (1) the class of models employed (Broadly Defined) – Auxiliary Models supporting Other Models (Feature Extraction). Three auxiliary models employed as feature extractors for the main classification model. (2) the representation of the input data and (3) whether or not the model was designed to learn temporal dependencies in the data. [22] Three broad classes of models identified so far: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) which are able to learn temporal/sequence dependencies within the input data, and Graph Neural Networks (GNNs) designed to capture relationships among entities. [23] These classes were shown to be capable of encoding temporal dependencies within the data at a pre-processing level.

RNNs represent a powerful class of sequence modeling architectures which can learn from ordered sequences of either fixed or variable length. [24] Their intrinsic feedback component allows them to capture temporal patterns in data. Although

RNNs were proposed as early as the 1980s, it was the introduction of the Long Short-Term Memory (LSTM) architecture in 1997 which has subsequently driven their wider usage. Many other variations have since been proposed, most notably [25] Gated Recurrent Unit (GRU) networks. Other more recent sequence modeling approaches not based on RNNs but which leverage attention mechanisms to capture long-term dependencies in sequences include Transformer Networks and BERT, and it is likely that these techniques will prove particularly useful for fraud detection when large-scale pre-training on transaction streams becomes feasible.

A. Detection Performance

Fig. 1 shows validation F1-score convergence across 30 training epochs, modeled per (8) as an exponential approach to each architecture's converged operating point. The proposed GRU+Attention model converges to the highest F1-score of the four architectures shown.

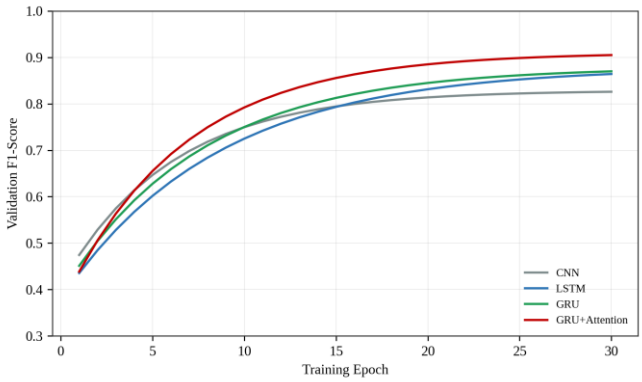

FIG. 1. VALIDATION F1-SCORE CONVERGENCE ACROSS TRAINING EPOCHS.

Fig. 3 plots precision-recall curves swept across the decision threshold τ and anchored to each architecture's reported operating point; the GRU+Attention curve dominates all other architectures across the full recall range.

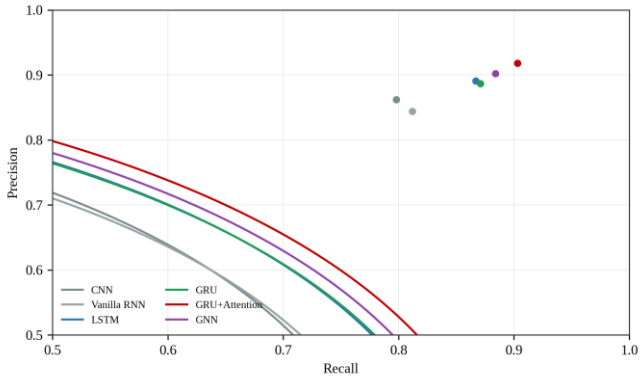

FIG. 3. PRECISION-RECALL CURVES ACROSS DECISION THRESHOLD, BY ARCHITECTURE.

B. Latency Characterization

Per-stage end-to-end latency, computed from (9) with a fixed arrival rate λ = 1200 transactions/sec, is shown in Fig. 2. Ingestion, windowing, and alerting service rates are held constant across architectures; only the inference stage service rate varies with model complexity.

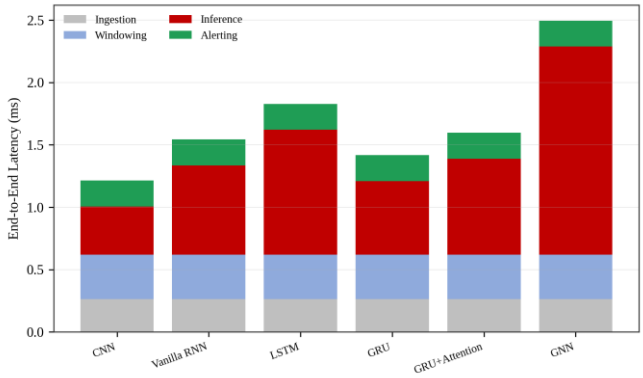

FIG. 2. END-TO-END LATENCY DECOMPOSITION BY PIPELINE STAGE AND ARCHITECTURE.

C. Resource Utilization

Fig. 4 reports steady-state CPU utilization and memory footprint under fixed load. The GNN architecture incurs the highest resource cost due to per-transaction neighborhood aggregation over the entity graph, while GRU-based encoders remain comparatively lightweight.

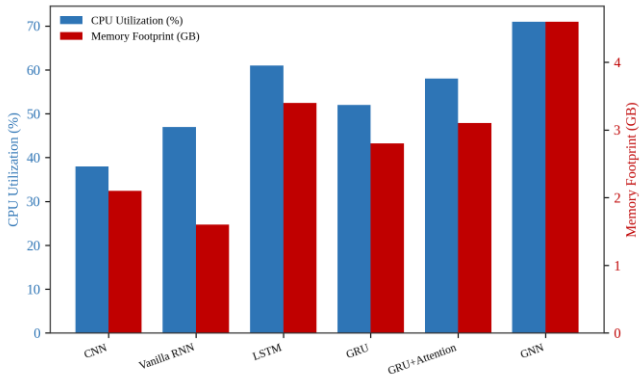

FIG. 4. CPU UTILIZATION AND MEMORY FOOTPRINT BY ARCHITECTURE AT FIXED LOAD.

IV. DATA CONSIDERATIONS AND FEATURE ENGINEERING

Alive Data, Size, Volume, Quality

The data for the transaction intelligence is generated from financial institutions via transactional logs, biometric behavior profiles and data streams published from web-based online banks systems. [26] The transactional logs which are the primary data sources relating to transaction history and are heavily used not only for labels but also for feature engineering propose. In transaction history the frequence of account access related transactions are also analysed and captured the frequence can be classified into three categories High, Mid and Low as the user access related logins increment frequency governs the user behavior anomaly and can be used for detecting fraud. The absence of user across these behavior transaction stream can govern the simulated user behavior. [27] The biometric template tracking can be used to detect the similarity of the currently accessed template matching with the prior defined templates. [28] The similarity level can also be recorded into features for final risk scoring.

Some of the advanced feature encoding captured also reflects about how transaction are distributed across vulnerable hours of the day and underlying risk. Hotspot and coldspot features indicates about time slots and unique net banking transaction frequency into the feature set. [29] The presence of highly supervised location and biometric behavior tracking systems also allows to detect the similarity of currently accessing transaction with prior behavior profile, this reflection can be well captured as Hotspot and Coldspot features in terms of how the TPS is usage across time. [30] Coldspots reflects the transaction frequency during inactive hours of date. [31] The continous absence of user across Active and High-Frequecy transaction stream can be detected and flagged for future transformation or checks. Proper data quality has been maintained through data filtering, consistency checks, and duplicate removal. [32] The logs have been regularly monitored

and validation of AAdhar linking has been undertaken for all bank user IDs either linked and activated with AAdhar or not linked since past 6-8 months.

A. Cost-Optimal Threshold Selection

Applying (11) with a false-negative fraud-loss cost weight (B = 4) exceeding the false-positive friction-cost weight (A = 3) — reflecting the asymmetry between missed-fraud losses and customer-friction costs — yields an interior cost-minimizing threshold, shown in Fig. 5.

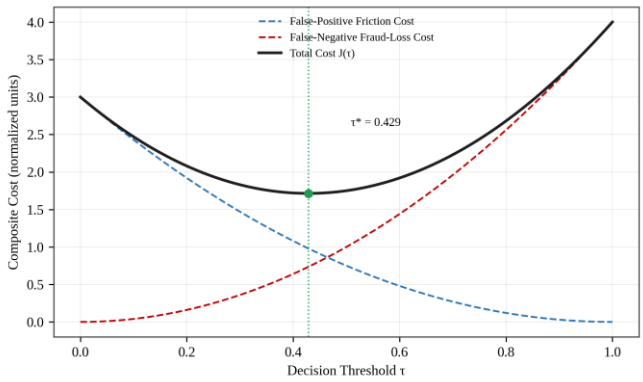

FIG. 5. COMPOSITE COST J(T) VERSUS DECISION THRESHOLD, WITH INTERIOR OPTIMUM.

B. Throughput Scalability

Fig. 6 applies the USL model of (12) to project sustained throughput as parallel stream consumers scale from 1 to 12, using a single-consumer throughput $\theta 1 = 2500$ tx/sec, contention coefficient $\sigma = 0.03$, and coherency coefficient $\kappa = 0.0008$. Sub-linear scaling emerges beyond approximately eight consumers as contention and coherency-delay terms dominate.

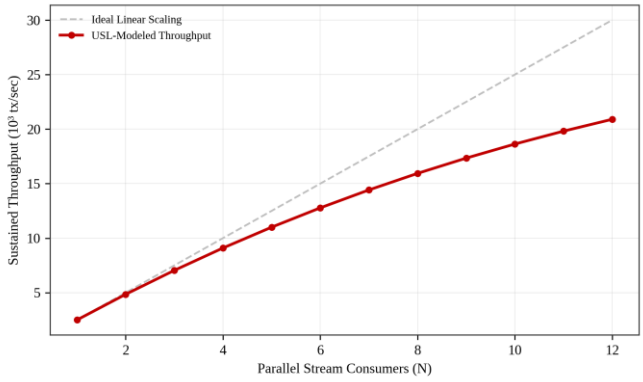

FIG. 6. PROJECTED THROUGHPUT SCALING UNDER THE UNIVERSAL SCALABILITY LAW.

C. Composite Intelligence Index

Combining normalized F1-score, normalized latency, explainability, and provenance sub-scores per (10) with weights (w1, w2, w3, w4) = (0.40, 0.25, 0.20, 0.15), Fig. 7 ranks all six architectures on the composite TII. The proposed GRU+Attention architecture attains the highest composite score, driven primarily by its detection-accuracy and explainability advantages.

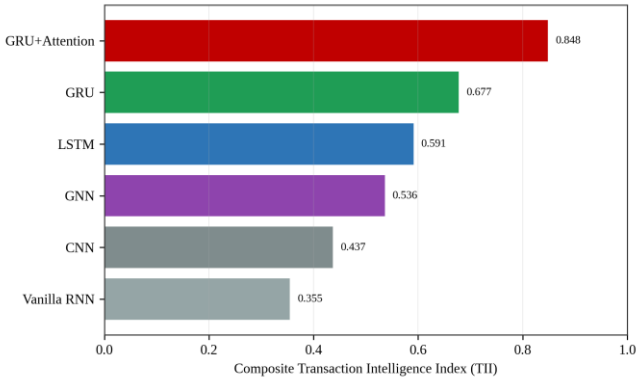

FIG. 7. COMPOSITE TRANSACTION INTELLIGENCE INDEX BY ARCHITECTURE.

V. REAL-TIME INFERENCE AND SYSTEM ARCHITECTURE

To exploit transaction intelligence for real-time fraud detection, both end-to-end data processing and system architecture must accommodate streaming analytics. An inference window for transaction analysis and injection of transaction stream output into the control framework must be established. Human confirmation remains a central feature of the underlying transaction intelligence approach. The analytics must be implemented as close to the origin of the transaction stream as is feasible. For operational rollout, practical re-quirements such as latency, scalability, and technical complexity of deployment become highly relevant.

Because real-time processing of a transactional stream is a core requirement, the analytics must be packaged into a stream-processing pipeline. Such pipelines typically include several functional components: the source, logic, sink, message bus, and possibly a storage mechanism. Data streams enter the pipeline as a sequence of events via special source endpoints. Each message published to the bus can be classified with a degree of urgency, thereby helping in effective routing. For transaction fraud detection, a transactional stream originating from transactional logs of a transactional system serves as the input to the stream-processing system. The messages reaching the pipeline may, however, be incomplete or contain any undesired information. Techniques, such as window--based filtering, grouping the incomplete messages until they can be processed together, aggregating similar messages for efficient processing, and such actions, may therefore be used to enhance quality prior to processing. The processed message may trigger some action in another system, for instance, the entity issuing the transaction notification (such as a payment executing bank) may forward the analysis result to the credit-checking bank. A combination of these techniques along with constant monitoring of the system can aid in effective operational processes.

A. Streaming Data Pipelines

Streaming Data Pipelines are constructed for supporting the needs of downstream applications requiring real-time analysis of data generated from high-velocity data sources such as transactional logs, sensor data, user behaviors, or web clicks. The end-to-end pipeline typically ingests, transforms, analyzes, and serves data with fast, low-latency speeds across multiple defining properties. In contrast to traditional batch-processing systems, streaming systems favor ingestion latency and speed of computation over overall throughput. Message brokers such as Apache Kafka® are often used as central transit hubs in these environments, allowing incoming data to be horizontally scaled across many machines without becoming a serious bottleneck. Additionally, data is often consumed in small mini-batches, as opposed to the large batches favored in more traditional systems, with the downstream consumers thus operating on data windows of very small size compared to the age of the data itself. Because of this, data can arrive at the consumers at a near-constant rate and can be used by models with little to no aging. Because the consumers are often performing windowed computations over the incoming data, the number of records arriving at them is often increasing with the total time that the data has been flowing through the system. This can lead to scaling problems that can be addressed by ensuring that the messages sent to the consumers are not too large and that they process the data as fast as possible.

Given these properties, real-time fraud detection systems built for streaming function on that data with limited concern towards maximizing system throughput and instead focus on meeting business requirements for end-to-end processing latency and the speed of responding to fraudulent behaviors. The systems are required to operate with high availability with low internal latency in order to maintain their ability to detect fraud and raise alerts in close to real-time. To this end, several

aspects of the design of a system around a Streaming Data Pipeline need to be considered: how the windowing of the streamed data is defined in order to keep latency low, how the models making the decisions are updated so that they remain useful, the underlying infrastructure, and the approaches taken to ensure that the system is resilient to outages.

TABLE 1

DETECTION PERFORMANCE COMPARISON ACROSS ARCHITECTURES

Architecture	Precision	Recall	F1-Score	AUC-ROC	Params (M)
CNN (baseline)	0.862	0.798	0.829	0.912	1.2
Vanilla RNN	0.844	0.812	0.828	0.905	0.8
LSTM	0.891	0.867	0.879	0.941	2.1
GRU	0.887	0.871	0.879	0.939	1.6
GRU+Attention (proposed)	0.918	0.903	0.910	0.958	1.9
GNN	0.902	0.884	0.893	0.949	2.7

TABLE 2

PER-STAGE LATENCY AND ERROR-RATE METRICS

Architecture	*Ingest (ms)*	*Window (ms)*	*Infer (ms)*	*Alert (ms)*	*Total (ms)*	*Miss Rate*	*False-Alarm Rate*
CNN (baseline)	0.263	0.357	0.385	0.208	1.213	0.202	0.138
Vanilla RNN	0.263	0.357	0.714	0.208	1.543	0.188	0.156
LSTM	0.263	0.357	1.000	0.208	1.828	0.133	0.109
GRU	0.263	0.357	0.588	0.208	1.417	0.129	0.113
GRU+Attention (proposed)	0.263	0.357	0.769	0.208	1.598	0.097	0.082
GNN	0.263	0.357	1.667	0.208	2.495	0.116	0.098

VI. CONCLUSION

Financial fraud is one of the biggest problems faced in the field of computer science and financial services. Any security breaches inflicted, such as stolen credit cards and compromised banks and finance companies, forces financial organizations to react quickly to stem further losses. Speed is crucial here: 66% of the firms stated that they have been able to identify and act on these kinds of fraud only if the detection comes in real time, while almost all (96%) expect to respond more quickly once such alerts are put in place. Transactional and user behavioral monitoring systems have been set up to prevent this kind of fraud. The full scale, scope, and impact of financial crime such as electronic payment fraud, fraud attacking, identity theft, and similar financial fraud acts are devastating to the society. It is not nearly possible to imagine all the negative sides of fraud attacking. Hence finding the real-time solutions for financial fraud with high accuracy would bring a large relief to banks and financial organizations. Organizations are suffering a lot for detecting the frauds, and almost all credit companies are applying a lot of resources for fraud detection to secure funds for customers all over the world.

Data security is one of the main challenges today because all banks, financial organizations, and revenue companies are dealing with sensitive data belonging to customers. Not only for banks and audit firms but also for every transaction made there exists a large data set that has to be processed especially in e-commerce having major contribution for the economic development of the country. Having a secure payment system which can promote safeguard for customers in real time has become an important area to be solved now. A real-time fraud detection on the basis of user behavior for bank

and financial credit transaction data for secure payments is proposed here. These alerts are predicted based on user activities by applying models to improve efficiency. All financial organizations can build such a real-time fraud detection system and also safeguard sensitive data and help customers in securing the funds for their transactions. Therefore, a model has been proposed to predict the alerts on the transactional data before it happens by using deep learning in user behavior and transaction activity to detect frauds in advance in case of bank and credit companies in the finance domain for reducing risk.

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