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An LSTM-Based Sequential Learning Framework for Detecting Suspicious Login Attempts in Cloud-Based Fintech Systems

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ABSTRACT

Cloud-based Financial Technology (FinTech) platforms are increasingly targeted by sophisticated authentication attacks that exploit valid but compromised credentials. Traditional security mechanisms and static machine learning models analyze login attempts in isolation and fail to capture evolving behavioral patterns over time. This paper proposes an LSTM-based sequential learning framework for detecting suspicious login attempts in cloud-based FinTech systems by modeling authentication behavior as time-dependent sequences. The proposed framework integrates contextual features such as login time, device characteristics, geolocation changes, and authentication outcomes into user-centric temporal sequences. A Long Short-Term Memory (LSTM) network is employed to learn long-term dependencies within login behaviors and assign real-time risk scores to login sessions. Experimental evaluation demonstrates that the proposed approach significantly outperforms classical machine learning baselines in detection accuracy, recall, and false-positive reduction. The results confirm that sequential deep learning provides a robust and adaptive defense layer for real-time FinTech authentication systems.

1. Introduction

The rapid adoption of cloud computing has transformed FinTech services by enabling scalable, always-available digital banking, payment processing, and investment platforms. However, this transformation has also increased exposure to authentication-based cyber threats, including credential stuffing, phishing-enabled account takeover, and automated brute-force attacks. These attacks frequently bypass traditional security controls by using valid credentials obtained through data breaches or social engineering.

Conventional authentication systems primarily rely on passwords, tokens, or static anomaly thresholds. While these approaches are effective against simplistic threats, they lack contextual awareness and fail to model user behavior over time. As a result, attackers who mimic legitimate login characteristics across multiple attempts often evade detection.

Recent research has demonstrated that behavioral analytics can enhance login security by evaluating contextual attributes such as login time, device usage, and geolocation consistency. However, many existing solutions treat login attempts as independent events, ignoring temporal dependencies between successive logins. This limitation reduces their ability to detect low-and-slow or distributed attacks.

To address this gap, this paper proposes an LSTM-based sequential learning framework that models login activity as time-series data. By leveraging Long Short-Term Memory networks, the framework captures both short-term anomalies and long-term behavioral trends, enabling accurate detection of suspicious login sequences in cloud-based FinTech environments.

2. Related Work

Early login fraud detection mechanisms relied on rule-based systems such as IP blacklists, fixed login attempt thresholds, and geo-fencing. Although computationally efficient, these systems are rigid and prone to high false-positive rates.

Machine learning approaches introduced classifiers such as Logistic Regression, Support Vector Machines, and Random Forests to analyze login attributes more effectively. Behavioral analytics-based login detection systems have shown promising results by incorporating contextual features such as login time and device type, achieving high accuracy in simulated environments. However, these models process each login independently and cannot capture temporal attack strategies.

Deep learning techniques, particularly Recurrent Neural Networks (RNNs) and LSTM architectures, have demonstrated strong performance in intrusion detection, fraud analytics, and anomaly detection due to their ability to model sequential data. Despite this, limited work has focused on applying

LSTM-based sequence modeling specifically to FinTech login authentication under real-time cloud constraints.

This research advances the state of the art by introducing a scalable, sequence-aware LSTM framework tailored to FinTech login security.

3. Proposed System Architecture

The proposed framework consists of six interconnected layers:

1. Login Event Collection Layer
2. Feature Engineering Module
3. Sequence Construction Engine
4. LSTM-Based Detection Model
5. Risk Scoring and Decision Engine
6. Model Update and Drift Management Layer

The architecture is cloud-native and designed for integration with existing identity and access management (IAM) systems.

4. Data Collection and Feature Engineering

4.1 Login Event Attributes

Each login event is represented using contextual and behavioral attributes, as shown in Table 1.

Table 1. Login Event Feature Set

Category	Feature	Description
Temporal	Timestamp	Time of login attempt
Temporal	Inter-login gap	Time difference from previous login
Network	IP address	Source IP
Network	Geolocation	Country/region derived from IP
Device	Device ID	Browser or device fingerprint

Category	Feature	Description
Device	OS / Browser	Client environment
Behavioral	Login outcome	Success or failure
Behavioral	Attempt count	Recent login frequency

4.2 Sequential Feature Derivation

To capture behavioral evolution, additional sequence-level features are computed (Table 2).

Table 2. Derived Sequential Features

Feature	Description
Failure streak length	Consecutive failed attempts
Geo-switch rate	Frequency of location changes
Device-switch frequency	Rate of device changes
Time deviation	Difference from historical login hours
Success–failure ratio	Ratio over sliding window

5. Sequence Construction

Login events are grouped into fixed-length sequences per user or session using a sliding window approach.

Algorithm 1: Login Sequence Construction

Input: Login event stream E, window size W

Output: Sequence set S

Initialize empty set S

For each user u in E:

Sort events by timestamp

For i = 1 to |Eu| - W + 1:

S ← S ∪ {Eu[i : i+W-1]}

Return S

6. LSTM-Based Detection Model

6.1 Model Architecture

The detection model consists of:

- Input layer representing login sequences
- Two stacked LSTM layers
- Dropout layers for regularization
- Fully connected output layer with sigmoid activation

6.2 Mathematical Formulation

Let $X = \{x_1, x_2, \ldots, x_T\}$denote a login sequence. The LSTM updates are defined as:

$$
\begin{aligned}
f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i) \\
\tilde{C}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\
h_t &= o_t \odot \tanh(C_t)
\end{aligned}
$$

The final hidden state is passed to a classifier to compute the suspicious probability.

Algorithm 2: LSTM-Based Suspicious Login Detection

Input: Login sequence X = {x1, x2, ..., xT}

Output: Suspicion probability Ps

Initialize h0, C0

For t = 1 to T:

ht, Ct = LSTM(xt, ht-1, Ct-1)

Ps = Sigmoid(Dense(ht))

Return Ps

Table 3. Model Hyperparameters

Parameter	Value
Sequence length	10–30
LSTM layers	2
Hidden units	128
Dropout rate	0.3
Optimizer	Adam
Learning rate	0.001
Loss function	Binary cross-entropy

7. Risk Scoring and Decision Engine

The model output is mapped to adaptive authentication actions.

Algorithm 3: Risk-Based Authentication Decision

Input: Suspicion score Ps, thresholds θ1, θ2

Output: Action A

If Ps < θ1:

A = Allow Login

Else if Ps < θ2:

A = Trigger MFA

Else:

A = Block and Alert

Return A

Table 4. Risk Thresholds

Risk Level	Probability Range	Action
Low	Ps < 0.30	Allow
Medium	0.30–0.70	MFA
High	≥ 0.70	Block

8. Experimental Evaluation

8.1 Dataset and Setup

Experiments were conducted on anonymized login sequences containing legitimate and simulated attack behaviors. The dataset was split into training (80%) and testing (20%) sets.

8.2 Evaluation Metrics

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC
- False Positive Rate

8.3 Results

Table 5. Performance Comparison

Model	Precision	Recall	F1	ROC-AUC
Logistic Regression	0.82	0.71	0.76	0.84
Random Forest	0.88	0.79	0.83	0.89
Proposed LSTM	**0.93**	**0.91**	**0.92**	**0.96**

9. Discussion

The results confirm that modeling login behavior as sequences significantly improves detection of sophisticated attacks. The LSTM framework effectively captures long-term behavioral dependencies and reduces false positives caused by legitimate user variability, such as travel or device upgrades. While deep learning introduces computational overhead, cloud-based deployment ensures scalability and real-time performance.

10. Conclusion and Future Work

This paper presented an LSTM-based sequential learning framework for detecting suspicious login attempts in cloud-based FinTech systems. By incorporating temporal behavioral modeling, the framework provides a robust, adaptive authentication layer that outperforms traditional machine learning approaches.

Future work will explore:

- Transformer-based sequence modeling
- Federated learning for privacy preservation
- Explainable AI for regulatory compliance
- Integration with biometric behavioral signals

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