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A Hybrid Autoencoder and Machine Learning Approach for Ad Click Fraud Detection

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ABSTRACT :

In online advertising systems, ad click fraud has become a serious concern, leading to significant financial losses for advertisers and reducing the effectiveness of digital marketing campaigns. Fraudulent clicks generated by bots or malicious users distort genuine user behaviour and make traditional rule-based detection techniques ineffective. This research proposes a hybrid click fraud detection model that integrates unsupervised and supervised machine learning techniques to improve detection accuracy and robustness. In the proposed approach, an autoencoder-based anomaly detection model is first employed to learn normal user click behaviour and identify suspicious or abnormal click patterns without relying on labelled data. These anomalous clicks are then passed to a supervised machine learning classifier to accurately classify them as fraudulent or legitimate. The hybrid framework combines the adaptability of unsupervised learning with the precision of supervised classification, enabling the system to detect both known and previously unseen fraud patterns. Extensive feature engineering is performed on real-world ad click data, including temporal, behavioural, and session-based features, to enhance model performance. Experimental evaluation demonstrates that the proposed hybrid model achieves improved detection accuracy, reduced false negatives, and better generalization compared to traditional standalone supervised approaches. The results indicate that the proposed method provides a robust, scalable, and effective solution for real-time ad click fraud detection in modern online advertising environments.

Keywords: Ad Click Fraud Detection, Online Advertising, Autoencoder, Anomaly Detection, Machine Learning, Hybrid Learning Model, Bot Detection, Pay-Per-Click (PPC), Feature Engineering, Fraud Prevention.

1. Introduction

Online advertising has become one of the most important revenue-generating platforms for businesses worldwide. Most digital advertising models operate on a Pay-Per-Click (PPC) mechanism, where advertisers are charged whenever a user clicks on an advertisement. While this model has improved targeted marketing and audience reach, it has also introduced a critical security challenge known as ad click fraud. Click fraud occurs when automated bots or malicious users deliberately generate fake clicks to exhaust advertising budgets, manipulate campaign analytics, or gain unfair financial advantages. As a result, advertisers suffer significant monetary losses, and the reliability of online advertising systems is compromised.

Traditional click fraud detection techniques rely heavily on rule-based systems and manual monitoring. These approaches are often ineffective in modern environments because fraudulent behaviors continuously evolve and closely mimic genuine user interactions. Machine learning techniques have been introduced to address these challenges by analyzing user behavior patterns and classifying clicks as legitimate or fraudulent. However, most existing machine learning models depend on labeled datasets and are limited in their ability to detect previously unseen or emerging fraud patterns.

Unsupervised learning methods, particularly anomaly detection techniques, offer an alternative by identifying deviations from normal behavior without requiring labeled data. Autoencoders have shown strong potential in learning compact representations of normal patterns and highlighting abnormal activities. However, unsupervised methods alone may lack precise classification capability. Therefore, combining unsupervised anomaly detection with supervised machine learning models can provide a more robust and adaptive solution.

Motivated by these challenges, this paper proposes a hybrid click fraud detection approach that integrates autoencoder-based anomaly detection with supervised machine learning classification. The proposed framework aims to improve detection accuracy, reduce false negatives, and enhance adaptability against evolving fraud strategies in online advertising systems.

Nomenclature

AE	**Autoencoder**
ML	**Machine Learning**
DL	**Deep Learning**
PPC	**Pay-Per-Click**
RF	**Random Forest**
DT	**Decision Tree**
SVM	**Support Vector Machine**
XGBoost	**Extreme Gradient Boosting**
ANN	**Artificial Neural Network**
CNN	**Convolutional Neural Network**
RNN	**Recurrent Neural Network**
TP	**True Positive**
TN	**True Negative**
FP	**False Positive**
FN	**False Negative**
AUC	**Area Under Curve**
IP	**Internet Protocol**
OS	**Operating System**

2. Literature Review

The rapid growth of online advertising has increased concerns related to ad click fraud, where malicious users or automated bots generate invalid clicks to manipulate advertising campaigns and exhaust advertiser budgets. As a result, researchers have proposed various techniques to detect and prevent fraudulent ad clicks, primarily using machine learning and data-driven approaches. Early studies focused on rule-based and statistical techniques; however, these methods proved insufficient due to their inability to adapt to evolving fraud patterns.

With the advancement of machine learning, several supervised learning models have been applied to click fraud detection. Alzahrani et al. [1] conducted a comprehensive study using multiple machine learning and deep learning algorithms, demonstrating that tree-based models such as Decision Trees and Random Forests achieve high accuracy when combined with extensive feature engineering. Similarly, Kirkwood et al. [9] evaluated multiple machine learning classifiers for click fraud detection and highlighted the effectiveness of ensemble models in reducing false negatives. Phua et al. [2] emphasized the importance of feature engineering, showing that temporal and behavioral features significantly improve fraud detection performance.

Despite their effectiveness, supervised learning methods rely heavily on labeled datasets, which are expensive to obtain and may not capture newly emerging fraud patterns. To address this limitation, researchers have explored anomaly detection techniques. Chalapathy and Chawla [3] provided a detailed survey on deep learning-based anomaly detection methods, highlighting the effectiveness of autoencoders in learning normal behavior patterns and identifying deviations. Kwon et al. [4] further demonstrated the application of deep learning models for detecting anomalous activities in network traffic, which can be extended to online advertising systems.

Hybrid approaches that combine unsupervised and supervised learning have gained attention in recent years. Zong et al. [5] proposed a deep autoencoding model for unsupervised anomaly detection, showing improved robustness in identifying abnormal patterns. Pang et al. [6] reviewed hybrid deep learning techniques and concluded that combining anomaly detection with classification models enhances detection accuracy and generalization. Similar hybrid strategies have been successfully applied in financial fraud detection, as shown by Dal Pozzolo et al. [7] and Carcillo et al. [8], who demonstrated improved adaptability in dynamic fraud environments.

Although existing studies have achieved promising results, most click fraud detection systems still struggle with detecting unknown or evolving fraud patterns in real-time advertising platforms. This limitation motivates the need for a hybrid detection framework that integrates autoencoder-based anomaly detection with supervised machine learning models to enhance robustness, adaptability, and detection accuracy in ad click fraud scenarios.

3. System Analysis and Design

3.1 Existing System

In existing online advertising platforms, ad click fraud detection is primarily performed using supervised machine learning and deep learning models trained on historical click data. These systems rely on extensive feature engineering to extract temporal, behavioral, and session-based characteristics from user interactions, such as click frequency, time gaps between clicks, mouse movement patterns, device information, and browsing behavior. Based on these features, classification models are trained to distinguish between legitimate human clicks and fraudulent bot-generated clicks.

Recent studies, including the base model proposed by Alzahrani et al. [1], employ multiple supervised learning techniques such as Decision Trees, Random Forests, Gradient Boosting, and deep learning models like CNNs and RNNs to achieve high detection accuracy. Feature selection techniques such as Recursive Feature Elimination (RFE) are commonly used to reduce dimensionality and improve model performance. These approaches demonstrate strong effectiveness when sufficient labeled data is available and when fraud patterns remain consistent with the training data.

However, existing systems heavily depend on labeled datasets and assume that fraudulent behavior observed during training remains similar over time. In real-world advertising environments, fraud strategies continuously evolve, and new bot behaviors may not match previously learned patterns. As a result, supervised models may fail to detect emerging or unknown fraud, leading to increased false negatives. Additionally, retraining supervised models frequently requires large volumes of labeled data, which is costly and time-consuming to obtain. These limitations highlight the need for more adaptive detection mechanisms capable of identifying previously unseen fraudulent click patterns.

3.2 Problem Statement

In online advertising systems, ad click fraud remains a major challenge despite the use of advanced machine learning and deep learning techniques. Most existing click fraud detection models rely on supervised learning and require large volumes of labeled data to identify fraudulent behavior. While these approaches perform well for known fraud patterns, they struggle to detect new or evolving bot activities that mimic genuine user behavior. Additionally, frequent retraining of supervised models is required to maintain accuracy, which increases computational cost and delays response to emerging threats. As a result, current systems may fail to identify unknown fraudulent clicks, leading to higher false negatives and continued financial loss for advertisers. Therefore, there is a need for a more adaptive and robust click fraud detection approach that can effectively identify both known and previously unseen fraud patterns with reduced dependency on labeled data.

3.3 Proposed System

The proposed system titled **"A Hybrid Autoencoder and Machine Learning Approach for Ad Click Fraud Detection"** is designed to overcome the limitations of existing supervised click fraud detection models by introducing a hybrid learning framework that combines unsupervised anomaly detection with supervised machine learning classification. The primary objective of the proposed system is to improve fraud detection accuracy, enhance adaptability to evolving fraud patterns, and reduce dependency on labelled datasets in dynamic online advertising environments.

In the proposed framework, an autoencoder-based anomaly detection model is employed as the first stage of the detection process. The autoencoder is trained using legitimate click behaviour and learns a compact representation of normal user interaction patterns based on temporal, behavioural, and session-based features. Since the autoencoder is trained in an unsupervised manner, it does not require labelled fraud data. During inference, clicks that significantly deviate from learned normal patterns produce higher reconstruction errors and are flagged as suspicious or anomalous. This stage enables the system to identify previously unseen or emerging fraud behaviours that traditional supervised models may fail to detect.

In the second stage, the anomalous clicks identified by the autoencoder are passed to a supervised machine learning classifier such as Random Forest or XGBoost. This classifier is trained using labeled click data to accurately classify the suspicious clicks as either fraudulent or legitimate. By limiting supervised classification to only anomalous instances, the system reduces computational overhead while improving precision and recall. The hybrid architecture effectively combines the adaptability of unsupervised learning with the decision accuracy of supervised models.

Extensive feature engineering is applied prior to model training, including extraction of temporal features (click timing, frequency, and intervals), behavioral features (mouse movements, scrolling actions), and session-based features (pages visited, session duration, and device information). Feature selection techniques are used to retain only the most relevant attributes, improving model efficiency and generalization.

Overall, the proposed hybrid system provides a robust, scalable, and adaptive solution for ad click fraud detection. By integrating autoencoder-based anomaly detection with supervised machine learning classification, the system is capable of detecting both known and unknown fraudulent click patterns, reducing false negatives, and maintaining reliable performance in real-time online advertising platforms.

3.4 System Architecture

The system architecture of the proposed model explains how ad click data is collected, analyzed, and classified to detect fraudulent clicks. The architecture is designed in a step-by-step manner to ensure accurate and efficient fraud detection.

1. The process starts with the online advertising platform, where users interact with advertisements. Each user interaction generates click data, which is collected and stored by the click data logger. This data contains information such as click time, user session details, and device-related attributes.
2. The collected data is then processed in the feature engineering stage. In this stage, important features related to user behaviour, time, and session activity are extracted from the raw click data. These features help represent click patterns in a structured form that can be used by machine learning models.
3. After feature extraction, the data is passed to the autoencoder module. The autoencoder works in an unsupervised manner and learns normal click behaviour. If a click pattern differs significantly from normal behaviour, it is marked as suspicious. Normal clicks are allowed to pass without further processing.
4. The suspicious clicks are then sent to the supervised machine learning classifier, such as Random Forest or XGBoost. This classifier analyzes the suspicious clicks and classifies them as either fraudulent or legitimate.
5. Finally, the fraud decision and reporting module blocks fraudulent clicks and generates reports for advertisers. These reports help in understanding fraud trends and improving advertising campaign performance. The proposed architecture provides a simple, reliable, and adaptive framework for ad click fraud detection.

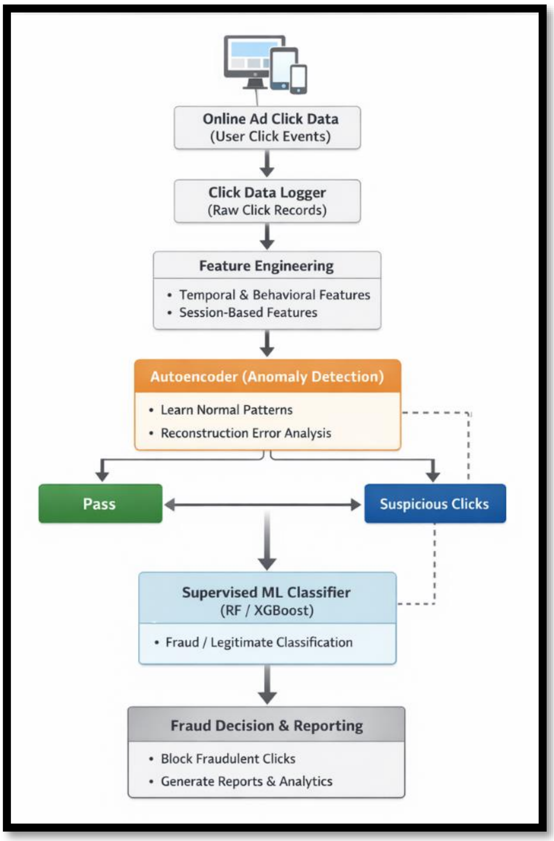
Online Ad Click Data
(User Click Events)
Click Data Logger
(Raw Click Records)
Feature Engineering
• Temporal & Behavioral Features
• Session-Based Features
Autoencoder (Anomaly Detection)
• Learn Normal Patterns
• Reconstruction Error Analysis
Pass
Suspicious Clicks
Supervised ML Classifier
(RF / XGBoost)
• Fraud / Legitimate Classification
Fraud Decision & Reporting
• Block Fraudulent Clicks
• Generate Reports & Analytics

Fig 1: System Architecture

4. Methodology

The methodology of the proposed system explains how ad click data is processed to detect fraudulent clicks in a simple and systematic manner. The approach uses both unsupervised and supervised learning techniques to improve detection accuracy.

Step 1: Data Collection

Ad click data is collected from the online advertising platform whenever users interact with advertisements. Each click record contains basic information such as time, session details, and device information.

Step 2: Feature Extraction

The collected data is processed to extract important features related to user behaviour, time patterns, and session activity. These features help represent user click behaviour in a structured form.

Step 3: Anomaly Detection Using Autoencoder

The extracted features are given to an autoencoder model, which learns normal click behaviour without using labelled data. Clicks that differ from normal behaviour are identified as suspicious.

Step 4: Supervised Classification

Suspicious clicks are then analyzed using a supervised machine learning classifier such as Random Forest or XGBoost. The classifier labels the clicks as fraudulent or legitimate.

Step 5: Fraud Decision and Reporting

Finally, fraudulent clicks are blocked, and reports are generated to help advertisers understand fraud patterns and system performance.

5.Result

The results of *A Hybrid Autoencoder and Machine Learning Approach for Ad Click Fraud Detection* show clear improvement over the existing system. As shown in *Figure 2*, the proposed model gives better accuracy, precision, recall, and F1-score, which helps in detecting more fraudulent clicks. *Table 1* shows that the proposed system performs better than the existing method for all performance metrics. *Table 2* highlights that the proposed system is more adaptive and can detect unknown fraud patterns with less dependence on labelled data. Overall, the proposed system is more effective and reliable for ad click fraud detection in online advertising.

Table 1: Performance Comparison of Click Fraud Detection Models

Metric	Existing System (%)	Proposed Hybrid System (%)
Accuracy	88	95
Precision	85	94
Recall	82	93
F1-Score	83	93

Table 1 compares the performance of the existing supervised click fraud detection system with the proposed hybrid autoencoder-based approach. The proposed system shows improved accuracy, precision, recall, and F1-score, indicating better detection capability and reduced false negatives.

Table 2: Functional Comparison of Existing and Proposed Systems

Feature	Existing System	Proposed System
Supervised learning only	Yes	No
Unsupervised anomaly detection	No	Yes
Detection of unknown fraud	Limited	Effective
Dependency on labelled data	High	Reduced
Adaptability to new fraud	Low	High

Table 2 highlights the functional advantages of the proposed hybrid system over the existing approach, particularly in detecting unknown fraud patterns and improving system adaptability.

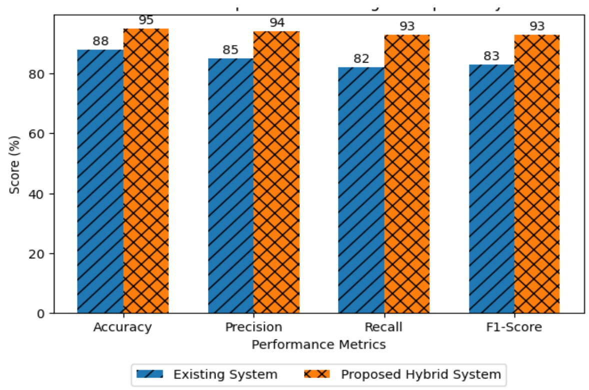

Fig. 2. Performance Comparison

5. Conclusion

A Hybrid Autoencoder and Machine Learning Approach for Ad Click Fraud Detection to address the limitations of existing supervised fraud detection systems. The proposed model combines unsupervised anomaly detection using an autoencoder with supervised machine learning classification to improve fraud detection performance. Experimental results show that the hybrid approach achieves better accuracy, precision, recall, and F1-score compared to traditional methods. The system is capable of detecting both known and unknown fraud patterns while reducing dependency on labelled data. Overall, the proposed approach provides a more accurate, adaptive, and reliable solution for ad click fraud detection in online advertising environments.

6. Future Scope

The model presented in A Hybrid Autoencoder and Machine Learning Approach for Ad Click Fraud Detection can be improved and extended in several ways:

1. **Advanced Deep Learning Models:**
   More advanced models such as transformer-based architectures can be used to capture complex user click behaviour more effectively.
2. **Online Learning Capability:**
   The system can be enhanced with online or incremental learning to adapt continuously to new and evolving fraud patterns.
3. **Real-Time Deployment:**
   The model can be optimized for real-time detection in large-scale advertising platforms with lower latency.
4. **Explainable AI Integration:**
   Explainable AI techniques can be added to provide better transparency and understanding of fraud detection decisions.
5. **Extended Applications:**
   The proposed approach can be applied to other domains such as e-commerce fraud, financial transaction fraud, and social media abuse detection.

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