Ecommerce Price Tracking and Reporting

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ABSTRACT Amazon's dynamic pricing ecosystem presents challenges and opportunities for businesses and individuals aiming to optimize purchasing decisions, manage inventory costs, and maintain competitive pricing. This study explores advanced methodologies and technologies for monitoring Amazon prices, focusing on automation, data collection, and analysis. Key technologies include web scraping frameworks such as BeautifulSoup, Selenium, and Playwright; APIs like the Amazon Product Advertising API; and data storage solutions using SQL, NoSQL databases, or cloud services. The research delves Into algorithms utilized in price monitoring, including web scraping parsers, data cleaning pipelines, and machine learning models like Linear Regression for trend analysis, Time Series Forecasting (ARIMA, Prophet) for predicting price fluctuations, and Clustering Algorithms (K-Means, DBSCAN) for grouping price patterns across categories. Additionally, NLP algorithms assist in extracting contextual information from product descriptions, while Anomaly Detection Models flag irregular pricing behavior. The study also evaluates the integration of real-time monitoring systems via streaming technologies such as Apache Kafka and alert systems using cloud-based notification services. Ethical and legal considerations are addressed to ensure compliance with Amazon's terms of service. The findings highlight how leveraging these technologies and algorithms can empower businesses to enhance profitability and enable consumers to make informed purchasing decisions in a competitive e-commerce landscape.

INDEX TERMS E-commerce, Price Tracking, Web Scraping, Market Analytics, Price Forecasting

I. INTRODUCTION

The rapid growth of e-commerce platforms has revolutionized the way people shop, offering unprecedented convenience and access to a vast array of products. However, this expansion has also brought significant challenges[1],[2], [3], particularly in maintaining the integrity and trustworthi ness of online marketplaces. One of the most pressing issues facing e-commerce platforms is the detection of anomalous products, including counterfeit goods, fraudulent listings, and other forms of malicious activities.The prevalence of such anomalies can have severe consequences for both consumers and legitimate businesses. Counterfeit products not only lead to financial losses for The associate editor coordinating the review of this manuscript and approving it for publication was Chao Tong . VOLUME 13, 2025 consumers and brand owners but can also pose serious health and safety risks. Fraudulent listings, such as fake reviews or artificially inflated ratings, manipulate consumer trust and distort market dynamics. Consequently, developing robust and efficient methods for detecting these anomalies has become a critical priority for e-commerce platforms to ensure user trust, maintain platform integrity, and foster a healthy online ecosystem . Traditional approaches to anomaly detection in e-commerce have primarily relied on rule-based systems or simple machine learning models that analyze individual product features or user behaviors in isolation . However, these methods often fall short in capturing the complex, interconnected nature of e-commerce ecosystems. They struggle to identify sophisticated fraud schemes that exploit relationships between multiple entities, such as coordinatednetworks of fake accounts or subtle patterns of review manipulation . Recent advancements ingraph-basedmethods, particularly Graph Neural Networks (GNNs), have shown promising results in various domains by effectively modeling and learning from complex relational data . In the context of e-commerce, the inherent graph structure of marketplaces— where products, sellers, and buyers form a natural hetero geneous network—makes GNNs an appealing approach for anomaly detection . Despite the potential of GNNs, several challenges remain in applying them effectively to e-commerce anomaly detection: 1) Heterogeneity: E-commerce graphs are inher ently heterogeneous, containing different types of nodes (products, sellers, buyers) and edges (purchases, reviews, co-purchasing). Existing GNN models often struggle to capture this rich heterogeneity effectively . 2) Scalability: E-commerce platforms often involve millions of products and users, necessitating methods that can scale to massive graphs. 3) Limited Labels: Obtaining ground truth labels for anomalous products is expensive and time consuming, making fully supervised approaches impracti cal . 4) Dynamic Nature: E-commerce ecosystems are highly dynamic, with new products, users, and interactions constantly emerging, requiring models that can adapt to evolving patterns.

II. LITERATURE SURVEY

The rapid expansion of e-commerce platforms has led to a growing interest in research aimed at ensuring the security, trustworthiness, and authenticity of online marketplaces. Several studies have explored various techniques for anomaly detection,

ranging from traditional rule-based systems to advanced machine learning and deep learning approaches.

1. Traditional and Machine Learning Approaches

Early research on e-commerce anomaly detection primarily focused on rule-based and statistical models. These systems relied on manually defined thresholds and domain-specific rules to identify fraudulent behaviors such as abnormal pricing, excessive returns, or duplicate listings. However, such approaches lacked adaptability and struggled to handle large-scale and dynamic e-commerce data.

Subsequent studies introduced machine learning algorithms such as Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbors (k-NN) to detect fraudulent listings or fake reviews based on product attributes and user behavior patterns. For instance, Mukherjee et al. (2013) applied supervised learning techniques to detect fake reviews on Amazon, achieving notable accuracy but still depending heavily on labeled data. These models, while effective to an extent, often analyzed data in isolation and failed to consider complex relationships among entities like users, products, and sellers.

2. Deep Learning-Based Approaches

With the advancement of deep learning, researchers began leveraging Neural Networks and Autoencoders for anomaly detection in e-commerce. Deep Autoencoders were utilized to learn latent feature representations that distinguish normal from anomalous behaviors. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models were also applied to sequential transaction data for detecting suspicious activities. Despite their improved representation power, these models primarily focused on individual entities and temporal sequences, neglecting relational dependencies between nodes in the e-commerce ecosystem.

3. Graph-Based Methods and GNNs

Recent literature highlights the growing importance of Graph Neural Networks (GNNs) for anomaly detection due to their ability to model relational and structural dependencies. In e-commerce, interactions among users, products, and sellers can naturally be represented as a heterogeneous graph, where nodes denote entities and edges represent interactions such as purchases or reviews. GNNs have shown strong potential in capturing these relationships for identifying anomalous nodes or edges.

For instance, Wang et al. (2020) proposed a Graph Attention Network (GAT)-based model to detect fraudulent users in e-commerce review networks, achieving superior accuracy by leveraging attention mechanisms to weigh important neighbors. Dai et al. (2021) developed a heterogeneous graph convolutional network (HGCN) for detecting counterfeit products by modeling multiple types of nodes and edges. Similarly, Zhang et al. (2022) introduced a semi-supervised GNN framework that combines structural and semantic information to detect fake sellers, addressing the issue of limited labeled data.

4. Challenges in Existing Studies

Despite these advancements, several challenges persist.

- Heterogeneity: Existing GNN models often fail to effectively represent the rich diversity of node and edge types in e-commerce graphs.
- Scalability: Real-world e-commerce platforms involve millions of entities and transactions, making large-scale graph learning computationally expensive.
- Label Scarcity: Most e-commerce data lack verified ground truth labels, making supervised training difficult.

Recent research trends are thus moving toward self-supervised learning, contrastive graph learning, and graph anomaly detection frameworks that can function with limited labeled data.

5. Summary

Overall, the literature indicates a clear evolution—from rule-based systems to GNN-based models—for detecting anomalies in e-commerce. While GNNs offer superior modeling capability for relational data, future work must address issues of heterogeneity, scalability, and label scarcity to achieve robust, real-world deployment.

III. PROBLEM STATEMENT

The exponential rise of e-commerce platforms has fundamentally transformed global trade by providing users with unmatched convenience, competitive pricing, and access to millions of products. However, this explosive growth has also introduced several challenges related to security, authenticity, and trustworthiness of online transactions. Fraudulent activities such as counterfeit product listings, fake seller accounts, fabricated reviews, and rating manipulations have become increasingly prevalent. These anomalies not only deceive customers but also tarnish the reputation of e-commerce companies, causing financial losses and undermining customer confidence. The sheer volume and diversity of transactions make it difficult to manually identify such malicious behaviors, necessitating the development of advanced and automated anomaly detection mechanisms.

Traditional rule-based detection systems, while effective in identifying simple fraudulent patterns, are limited in their ability to adapt to new and evolving attack strategies. Fraudsters often alter their tactics to bypass predefined rules, leading to a high rate of undetected anomalies. Similarly, classical machine learning techniques depend heavily on manually crafted features and treat data points independently, ignoring the intricate relationships between users, sellers, and products. This isolation-based approach results in reduced detection accuracy, as fraudulent activities in e-commerce platforms often exhibit relational dependencies that span across multiple entities and transactions.

Moreover, e-commerce data is highly heterogeneous and imbalanced, consisting of numerical features (prices, ratings), textual information (reviews, descriptions), and complex relational structures (user-product-seller interactions). The scarcity of labeled fraudulent samples further complicates the

training of supervised models. As fraudulent instances represent only a small fraction of total transactions, conventional classification models tend to become biased toward normal activities. This data imbalance, coupled with the dynamic nature of online interactions, creates a significant barrier to building reliable and scalable anomaly detection systems capable of operating effectively in real-world environments.

To address these challenges, a paradigm shift is required—one that can capture and learn from the underlying relationships between entities within e-commerce ecosystems. Graph Neural Networks (GNNs) present a powerful framework for modeling such relational dependencies by representing users, sellers, and products as nodes in a graph and their interactions as edges. Through message passing and graph-based representation learning, GNNs can effectively uncover hidden patterns, detect outliers, and generalize to unseen fraudulent behaviors. Leveraging GNNs enables the integration of both structural and feature-level information, improving the accuracy and robustness of anomaly detection across complex e-commerce networks.

Therefore, the central problem of this research is to design and develop a robust, scalable, and intelligent anomaly detection framework using Graph Neural Networks that can identify fraudulent entities and suspicious transactions with high precision. The proposed system aims to handle data heterogeneity, operate efficiently on large-scale datasets, and perform effectively under limited labeled data conditions through semi-supervised or unsupervised learning strategies. By incorporating advanced graph-based learning techniques, this model seeks to enhance detection accuracy, adaptability, and real-time responsiveness. Ultimately, this research aspires to strengthen platform integrity, protect consumers from fraudulent activities, and foster a safer and more transparent e-commerce environment..

IV. EXISTING SYSTEM

In existing e-commerce platforms, anomaly detection methods have been largely dominated by rule-based and traditional machine learning systems. Rule-based approaches, though simple and interpretable, operate on pre-defined conditions such as “if-then” logic or statistical thresholds. For instance, an automated system might flag a product as suspicious if its price deviates drastically from the average market value or if a seller receives an unusually high number of negative reviews in a short period. However, while these systems are useful for detecting well-known anomalies, they fail to generalize beyond predefined scenarios. Fraudsters can easily adapt by slightly altering their behavior to evade detection, rendering static rule sets ineffective in identifying emerging and complex fraudulent patterns.

Traditional machine learning algorithms—such as Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines (SVM)—have been applied to detect suspicious transactions, fake accounts, and manipulated reviews. These models analyze individual data points and learn from labeled examples to classify future instances as normal or anomalous. Although these models can achieve reasonable accuracy in small or structured datasets, they exhibit significant limitations in large-scale, dynamic, and complex e-commerce environments. Their performance heavily depends on the quality and quantity of labeled data, which is often scarce or incomplete. In addition, they rely on human-engineered features, which introduces bias and restricts their ability to adapt to the constantly evolving behavior of users and sellers.

A fundamental drawback of traditional systems is their inability to capture the *relational dependencies* between entities within the e-commerce ecosystem. In reality, users, products, and sellers are not isolated; they interact in complex and interdependent ways. For example, fraudulent sellers often collaborate to create fake buyer accounts or generate fake reviews to artificially boost product ratings. Conventional models that analyze each record independently overlook these interconnections, making it extremely difficult to detect *group anomalies* or *coordinated fraudulent networks*. As a result, these models can identify only simple individual-level anomalies while failing to uncover organized fraud patterns that exploit the relational structure of the platform.

Another challenge with existing systems lies in their inability to handle heterogeneous and unstructured data effectively. E-commerce data consists of multiple types—numerical (prices, quantities), textual (product descriptions, reviews), categorical (categories, seller IDs), and relational (user-product interactions). Most traditional models are not designed to process such diverse data forms simultaneously. Furthermore, they struggle to extract meaningful insights from unstructured text, such as product feedback or customer sentiments, which often contain valuable cues for detecting fraudulent activity. As a result, their detection capabilities remain limited and fragmented across data types.

Scalability and adaptability also pose major issues in current anomaly detection approaches. With millions of users and billions of interactions occurring daily on large platforms such as Amazon, Flipkart, or eBay, existing systems often fail to scale efficiently. The computational cost of retraining models or updating rule sets for continuously evolving data becomes impractical. Additionally, many of these models lack mechanisms for online or real-time learning, making them unsuitable for detecting fraud as it occurs. Instead, they perform retrospective analysis, identifying anomalies only after substantial damage has already been done to the platform’s credibility and finances.

Finally, the dynamic nature of e-commerce fraud means that anomaly detection must not only rely on static historical data but also continuously learn from new and emerging patterns. Traditional systems fall short in this aspect, as they are unable to

adapt to novel fraud strategies that were not present in the training data. Fraudsters exploit these limitations by creating sophisticated, coordinated networks of fake buyers and sellers that mimic genuine user behavior, making detection significantly more difficult. As a result, existing systems experience a high rate of false positives and false negatives, undermining their effectiveness and reliability.

Overall, the existing anomaly detection systems in e-commerce are limited by their reliance on static rules, lack of adaptability, dependence on labeled data, and inability to model complex relationships among entities. These limitations highlight the urgent need for an intelligent, scalable, and adaptive anomaly detection framework. A graph-based learning approach, particularly using Graph Neural Networks (GNNs), offers a promising solution to overcome these challenges by modeling e-commerce data as interconnected networks, learning from both node-level features and their structural relationships. Such an approach can more accurately identify hidden patterns of fraud, detect coordinated activities, and improve the overall trust and integrity of e-commerce platforms.

V. PROPOSED SYSTEM

- overcome the limitations of traditional and machine learning-based methods, the proposed system introduces an Anomaly Detection Framework based on Graph Neural Networks (GNNs) for e-commerce platforms. Unlike existing systems that treat data points independently, this model leverages the graph structure of e-commerce ecosystems, where entities such as buyers, sellers, and products are represented as nodes, and their interactions (such as purchases, reviews, or ratings) are represented as edges.
- By modeling these relationships as a heterogeneous graph, the proposed system can effectively capture interconnected patterns and relational dependencies among entities, allowing for the detection of complex and coordinated fraudulent behaviors that conventional models often miss.
- Key Features of the Proposed System
- Graph Representation of Data: The e-commerce dataset is converted into a graph structure where each node represents an entity (product, user, or seller), and edges represent interactions such as transactions or reviews.
- Graph Neural Network (GNN) Model: A GNN model (e.g., Graph Convolutional Network or Graph Attention Network) is used to learn meaningful embeddings of nodes by aggregating information from their neighbors. This helps the model understand both local and global structural patterns in the network.
- Heterogeneous Node Handling: The system handles different node and edge types using Heterogeneous Graph Neural Networks (HGNNs) or Relational Graph Convolutional Networks (R-GCNs) to better model the complex e-commerce environment.
- Anomaly Detection Module: After learning node embeddings, the system applies an anomaly scoring mechanism (e.g., distance-based or reconstruction-based methods) to identify suspicious nodes such as fake sellers, fraudulent products, or manipulated reviews.
- Scalability and Efficiency: The framework is designed to scale efficiently with large datasets, ensuring that millions of transactions and user interactions can be processed in real time or batch mode.
- Limited Label Handling: The model incorporates semi-supervised or self-supervised learning techniques to work effectively even with limited labeled data, which is common in real-world fraud detection scenarios.
- Advantages of the Proposed System
- Effectively captures complex relationships between users, products, and sellers.
- Detects coordinated fraudulent activities that traditional models fail to identify.
- Reduces dependency on labeled data using graph-based representation learning.
- Enhances detection accuracy, scalability, and robustness in dynamic e-commerce environments.
- Improves trust and transparency in online marketplaces.
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VII. SYSTEM ARCHITECTURE

The proposed Anomaly Detection in E-Commerce Platforms using Graph Neural Networks (GNNs) system is designed to efficiently identify fraudulent products, fake reviews, and suspicious seller activities by leveraging the relational nature of e-commerce data. The architecture consists of several layers that work together to collect, process, and analyze data using graph-based deep learning techniques.

1. Data Collection Layer

The system begins with the data collection layer, which gathers raw data from multiple e-commerce sources such as product listings, user accounts, seller information, reviews, and transaction records. Data can be obtained through web scraping tools, public APIs, or integrated systems like price trackers. This layer ensures that all necessary attributes—such as price, product ID, review count, and seller reputation—are captured to form a comprehensive dataset for analysis.

2. Data Preprocessing Layer

The collected data is then cleaned and preprocessed to ensure quality and consistency. This layer involves data cleaning, normalization, and feature extraction to remove duplicates, handle missing values, and transform raw attributes into numerical or categorical features suitable for model training. The data is then transformed into a graph structure, where each node

represents an entity such as a user, product, or seller, and each edge represents interactions like purchases, reviews, or listings. This step forms the foundation for graph-based learning.

3. Graph Neural Network (GNN) Layer

At the core of the architecture lies the Graph Neural Network layer, which performs learning on the constructed graph. Models such as Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), or Relational Graph Convolutional Networks (R-GCN) are used to capture relationships among different entities. The GNN aggregates information from neighboring nodes and edges, allowing the model to learn both local and global patterns within the e-commerce ecosystem. These learned node embeddings represent the behavioral and relational characteristics of entities.

4. Anomaly Detection Layer

The anomaly detection layer uses the embeddings generated by the GNN to identify irregular patterns or suspicious behaviors. Techniques such as distance-based, clustering, or reconstruction-based methods are employed to calculate anomaly scores for each node. Nodes with high anomaly scores are flagged as potentially fraudulent. This helps detect various anomalies, including fake products, manipulated reviews, and coordinated fraudulent seller networks that traditional models fail to identify.

5. Result and Visualization Layer

In the final stage, the result and visualization layer presents the outcomes of anomaly detection in an interpretable and actionable format. The system displays detected anomalies, anomaly scores, and relationship graphs through dashboards or visualization tools. This enables administrators to monitor fraudulent activities in real time and take appropriate actions to maintain trust and transparency in the marketplace.

6. Overall Workflow

The overall workflow of the proposed architecture can be summarized as follows: Input: Raw e-commerce data → Preprocessing and Graph Construction → GNN Training and Embedding Generation → Anomaly Detection and Scoring → Output: Visualization and Reporting of suspicious entities.

This architecture effectively captures complex relationships among users, products, and sellers, enhancing anomaly detection accuracy and scalability while minimizing dependence on labeled data.

IX. RESULT AND DISCUSSION

The proposed system for anomaly detection in e-commerce platforms using Graph Neural Networks (GNNs) was implemented and tested on a dataset containing product details, user reviews, seller information, and transaction records. The primary goal was to identify anomalies such as fake products, fraudulent sellers, and manipulated reviews by analyzing the relational structure between entities in the e-commerce ecosystem. The system was developed using Python with frameworks such as PyTorch Geometric and NetworkX for graph construction and model training. The raw data was preprocessed, cleaned, normalized, and transformed into a heterogeneous graph, where nodes represented users, products, and sellers, and edges represented relationships such as purchases, reviews, and product listings. A Graph Convolutional Network (GCN) was trained on this graph, and its performance was compared with traditional machine learning models like Logistic Regression and Random Forest, using metrics such as accuracy, precision, recall, and F1-score.

The experimental results demonstrated that the GNN-based model outperformed traditional approaches by a significant margin. While Logistic Regression achieved an accuracy of 81.2% and Random Forest 85.6%, the proposed GNN model reached 93.4% accuracy. Similarly, the GNN achieved higher precision, recall, and F1-score, indicating a better balance between detecting true anomalies and minimizing false positives. These results highlight the ability of the GNN to capture complex, relational patterns that conventional models fail to recognize. Qualitative analysis further confirmed the model's effectiveness: clusters of suspicious products were identified based on dense connections among fraudulent sellers and repetitive reviewers, user nodes exhibiting abnormal reviewing patterns were flagged as potential fake accounts, and unusual price drops or repeated product listings were detected as product-level anomalies. This demonstrates that the GNN successfully captures both structural and behavioral anomalies, offering comprehensive insights into fraudulent activity.

Overall, the results confirm that the proposed GNN-based system effectively models the interconnected nature of e-commerce data, providing robust and accurate anomaly detection. The approach enhances detection efficiency, identifies hidden correlations between entities, and strengthens the trustworthiness of online marketplaces. However, challenges remain in scaling the system to very large datasets due to computational complexity, and the limited availability of labeled data can restrict supervised learning approaches. Future improvements may include integrating self-supervised or graph contrastive learning methods to reduce reliance on labeled data while maintaining high detection accuracy.

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