

FRAUD DETECTION IN SOCIAL NETWORKS

By

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BONAFIDE CERTIFICATE

This is to certify that this project work entitled “**FRAUD DETECTION IN SOCIAL NETWORKS**” is a bonafide record of work done by **Ms. TANUSHREE SARKAR** (Reg. Number **23352079**) in the partial fulfilment for the Degree of **Master of Computer Applications** in the **Department of Computer Science, School of Engineering and Technology** of Pondicherry University.

This work has not been submitted elsewhere for the award of any other degree to the best of our knowledge.

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ABSTRACT

The rapid expansion of social networking platforms has significantly transformed communication and digital interaction by allowing users to share content, build connections, and engage across global communities. These platforms, however, also provide a ground for fraudulent activities such as fake account creation, phishing, spamming, and misinformation posing risks to both users and platform integrity. Fraud detection in social networks involves analyzing user behavior, network structures, and content to identify such malicious actions. Traditional rule-based systems and classical Machine Learning (ML) models, although widely adopted, often struggle with real-time adaptability, interpretability, and handling the complex, dynamic, and highly relational data inherent in these digital environments. While prior research has explored both ML and Deep Learning (DL) methods, gaps remain in scalability, contextual understanding, and cross-platform effectiveness.

To bridge these gaps, this study proposes a hybrid fraud detection framework that integrates diverse ML algorithms Random Forest(RF), XGBoost(XGB), and Support Vector Machine(SVM) with DL models such as Convolutional Neural Networks(CNN), Long Short-Term Memory (LSTM) , and Graph Neural Networks (GNN). The system processes multi-modal data including user behavior, account attributes, and network interactions. The ensemble learning technique employed to combine the outputs of individual models, enhancing prediction robustness and reducing false positives.

Experiments were conducted on three datasets: an Instagram profile dataset, the Youtube01-Psy comment dataset, and video metadata collected via the YouTube Data API. The ensemble model achieved the highest accuracy across all datasets, with perfect scores on the Youtube01-Psy dataset. These results confirm the effectiveness of the hybrid approach in accurately detecting fraud across different types of social media data.

CHAPTER 1 – INTRODUCTION

The domain of this research is '*Fraud Detection in Social Networks*', an increasingly critical area in the age of digital communication. Social media platforms such as Instagram, Twitter, Facebook, and YouTube have revolutionized the way people connect, communicate, and share information. However, the very openness and reach of these platforms have also made them attractive targets for fraudulent activities. These include the creation of fake user accounts, spread of misinformation, engagement manipulation through bots or spam accounts, and malicious behavioral patterns like phishing and online scams. These threats not only compromise user privacy and trust but also damage the credibility and integrity of the platforms themselves.

While numerous fraud detection mechanisms have been introduced, existing systems still face major limitations in effectively identifying and mitigating fraudulent behavior. The dynamic and constantly evolving nature of online interactions—coupled with the high dimensionality, volume, and diversity of social media data—poses significant challenges. Traditional rule-based approaches lack adaptability and often become obsolete as new fraud tactics emerge. Classical machine learning (ML) models such as Naïve Bayes, Decision Trees, and even early use of Support Vector Machines (SVM) and Random Forests have shown some success but are constrained in their ability to generalize across platforms and adapt to evolving patterns.

Recent advances in deep learning (DL) have led to the use of Convolutional Neural Networks (CNN) for feature extraction and Long Short-Term Memory (LSTM) networks for temporal analysis of user behavior. Similarly, Graph Neural Networks (GNN) have shown potential in modeling the relational aspect of user interactions. However, despite their power, individual DL models often fall short in capturing the full complexity of multimodal and multi-relational fraud data. In addition, many of these models suffer from low interpretability, high computational cost, and limited precision, often resulting in increased false positives and inconsistent real-world performance.

To address these gaps, this research proposes a robust hybrid fraud detection framework that integrates the strengths of both machine learning and deep learning techniques. Specifically,

it leverages Random Forest, XGBoost, and SVM as part of the ML module to learn behavioral patterns based on user activity and engagement metrics. In parallel, CNN, LSTM, and GNN models form the DL module to uncover hidden feature interactions, sequential user patterns, and community-level fraud clusters within the network. These diverse model outputs are then fused using an ensemble learning approach, which aggregates predictions to enhance overall accuracy, reduce false positives, and provide a balanced and adaptable fraud detection mechanism.

The proposed system is evaluated using three datasets. An Instagram profile dataset, the Youtube01-Psy dataset, and a custom dataset collected via the YouTube Data API, including video metadata and user interactions.

Experimental results reveal that the ensemble model consistently outperforms individual ML and DL models, with the highest performance observed on the Youtube01-Psy dataset where the system achieved perfect accuracy, precision, and recall. These findings validate the effectiveness of the hybrid framework in detecting diverse fraud patterns across different types of social media data. Furthermore, the system demonstrates high adaptability, scalability, and potential for cross-platform deployment, making it a valuable contribution to the field of social network security and fraud analytics.

CHAPTER 2 – LITERATURE SURVEY

With the exponential rise in online interactions, social media has become a major target for fraudulent activities. Traditional rule-based systems have proven inadequate for evolving threats, leading researchers to explore intelligent solutions using ML, DL, and hybrid approaches. This review categorizes recent literature into these three domains, outlining methodologies, findings, and limitations to uncover potential areas for improvement.

2.1 Machine Learning Models

The fake profile and fraud detection in social media using ML reveals a progressive shift from traditional methods to more sophisticated, scalable, and adaptive approaches.

Austin-Gabriel et al. [1] implemented rule-based and basic ML models for small business fraud detection but failed to address sophisticated fraud strategies. Ramdas and Neenu [2] improved ML models through feature engineering for social profiles, although scalability remained an issue. Farooqui and Khan [3] applied soft computing and SVM for fake profile detection but lacked robustness with large datasets. Ahmad and Tripathi [4] reviewed RF and SVM techniques and advocated for hybrid approaches to tackle large-scale challenges. Kavin et al. [5] proposed RF and Artificial Neural Network(ANN) for secure mobile network fraud detection with scalability in mind. Pombal et al. [6] explored bias in ML models and suggested mitigation strategies. Chakraborty et al. [7] and Meshram et al. [8] used RF, XGB, CNN, and ANN to detect fake profiles, pointing out the need for models that adapt to evolving threats. Goyal et al. [9] and Singh et al. [10] used Naïve Bayes and Decision Trees, which lacked support for complex datasets.

It is deduced that ML models are efficient and interpretable, making them suitable for basic detection tasks. However, they often rely on manual feature engineering, struggle with data complexity, and lack adaptability to real-time threats. While scalable solutions are being explored, limitations in handling relational and behavioral data persist.

2.2 Deep Learning Models

Various DL strategies are employed to detect and prevent fraud, cybercrime, and misinformation, particularly across financial systems and social media platforms.

Zhang et al. [16] analyzed AI-based real-time fraud detection. Adekunle et al. [17] developed an LSTM model to handle complex and evolving cyberattacks on social media. Alharbi et al. [18] used multimodal DL combining text, image, and behavior for fake Instagram profile detection. Zioviris et al. [19] utilized LSTM for behavior-based fraud detection and suggested graph-based enhancements. Huang et al. [20] presented DGraph for large-scale financial anomaly detection. Hu et al. [21] proposed Behavioral Information Aggregation Network, a behavioral fraud model enhancing GNN performance. Shehnepoor et al. [22] found that DL models using content and metadata outperform behavior-only models for fake review detection. Zhang et al. [23] combined multiple data cues for detecting tax evasion on social media. Rossi et al. [24] introduced SIGN, a scalable GNN for large graphs. Shi et al. [25] proposed a semi-supervised message-passing model to handle sparse label issues. Monti et al. [26] employed geometric DL for language-independent fake news detection using user engagement graphs.

It is understood that DL models excel in extracting complex patterns from unstructured data and can process large volumes efficiently. However, they are resource-heavy, often lack interpretability, and may fail in low-data scenarios. Graph-based and multimodal DL approaches show promise, but scalability and transparency remain open challenges.

2.3 Hybrid Model

Hybrid approaches combine ML and DL to improve fraud detection by leveraging ML's interpretability and DL's deep feature learning. These models handle complex, multimodal data and are better suited for dynamic social platforms.

Anila et al. [27] combined K-Nearest Neighbors(KNN) and SVM to detect fake profiles, improving accuracy on the Instagram dataset but faced limitations in feature extraction and

explainability. Sharmila et al. [28] introduced PDHS for hate speech detection using tweet representation, improving accuracy but requiring better multilingual handling. Alarfaj et al. [29] applied hybrid ML-DL models for credit card fraud detection, successfully reducing false positives and boosting precision. Sansonetti et al. [30] used DL models like LSTM and CNN with traditional classifiers such as SVM and KNN to identify unreliable social media users, highlighting adaptability issues across platforms.

Hybrid models blend ML's interpretability with DL's representational power, offering better accuracy and generalization. They are especially useful for dynamic, multi-modal social media environments.

The literature survey shows substantial progress in detecting fraud and fake profiles using ML, DL, and hybrid models. ML models are interpretable but less effective with complex data. DL approaches handle complex features but face scalability and transparency issues. Hybrid models undoubtedly offer a balanced approach.

There is a clear need for a scalable, explainable, and real-time fraud detection model that combines the strengths of ML and DL. Most existing approaches either compromise on interpretability or struggle with adaptability across platforms. Additionally, they often lack the ability to fully capture complex social connections, evolving temporal behaviors, and multi-modal data that characterize modern social networks. This study addresses these research gaps by proposing a hybrid ensemble-based framework that integrates relational and behavioral features to improve detection accuracy, scalability, and adaptability for evolving social media fraud patterns.

CHAPTER 3 – RESEARCH GAP

It highlights the gaps in current fraud detection methods, focusing on where they struggle with adaptability, interpretability, and analyzing network-level data. It sets the stage for introducing our hybrid solution to address these challenges.

3.1 Problem Definition

Despite the growing use of social networks, these platforms have also become prone to fraudulent activities like fake account creation, phishing, spamming, and online scams. Detecting such activities remains a significant challenge due to the high dimensionality of social media data, which includes user behavior, interaction patterns, and network structures. Traditional fraud detection approaches—rule-based systems or conventional machine learning techniques—struggle to handle the scale, complexity, and constantly evolving tactics used by fraudsters.

Many existing methods fall short in adapting to real-time threats or understanding the intricate relationships between users in a network. Moreover, they often lack the ability to interpret contextual and behavioral cues that signal fraudulent behavior. There's a clear need for a more intelligent, flexible, and explainable system that can process multi-modal data and detect hidden fraud patterns effectively.

This project addresses this gap by proposing a robust fraud detection system that integrates both machine learning and deep learning approaches. It aims to capture not only static account attributes but also temporal behaviors and network-level interactions, ultimately improving detection accuracy while minimizing false positives.

3.2 Research Objectives

- To build a hybrid deep learning architecture that integrates graph-based and sequence-based models for enhanced fraud detection.
- To design a unified framework capable of analyzing user behavior, network interactions, and content-based features.
- To incorporate dynamic fraud tracking through temporal graph models that can identify evolving fraudulent patterns over time.
- To ensure model interpretability, making the system more transparent and practical for real-world application.

This chapter highlighted where current fraud detection methods are falling short—especially when it comes to understanding complex social network data, adapting to new fraud tactics, and providing clear, explainable results. These challenges show a real need for smarter and more flexible solutions. With this proposed hybrid approach, I aim to bridge these gaps by combining the power of DL and ML models to create a system that's not only accurate but also practical and easy to understand in real-world scenarios.

CHAPTER 4 – PROPOSED SYSTEM

The primary objective of this project is to build a hybrid architecture that integrates graph-based and sequence-based models for more effective fraud detection. The goal is to design a unified framework capable of analyzing user behavior, network interactions, and content-based features simultaneously. Additionally, the system aims to incorporate dynamic fraud tracking using temporal graph models to detect evolving fraudulent patterns over time. The model is also designed to be easy to understand, making it more useful and practical for real-world use.

4.1 Model Architecture

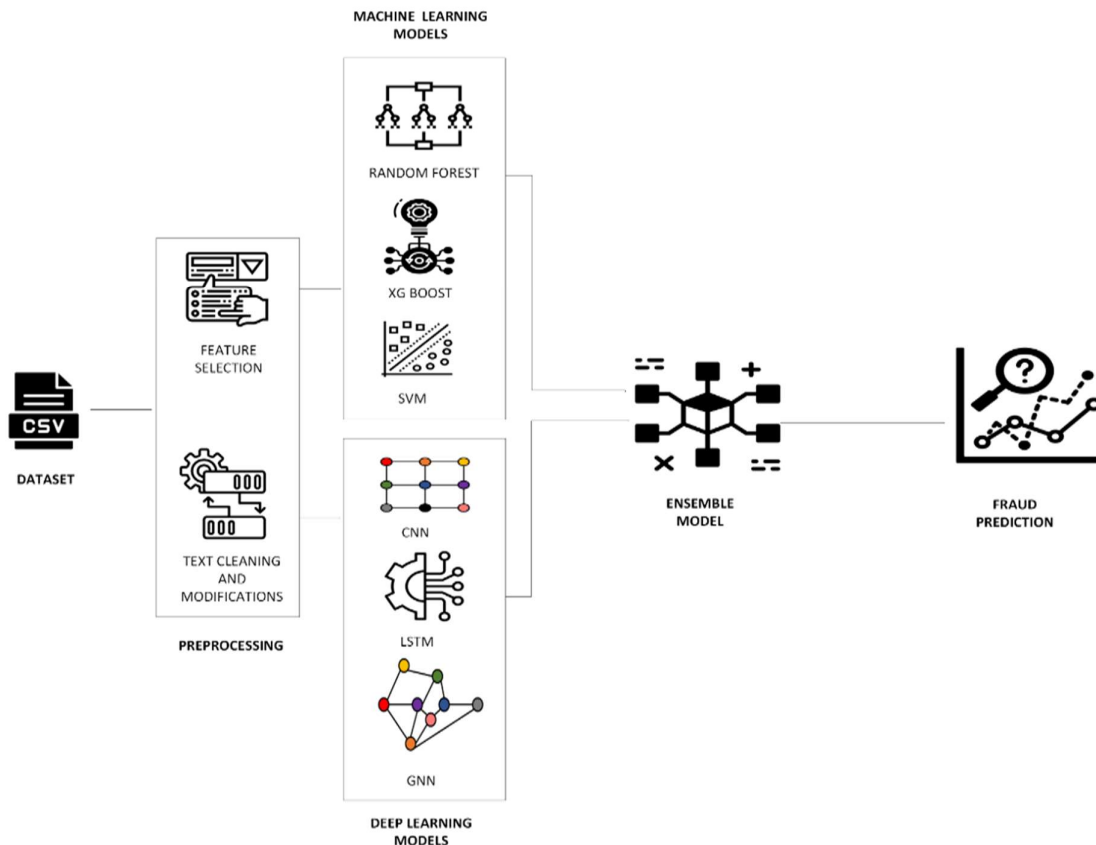


Figure 1 – Hybrid architecture of the proposed model

In figure 1 the proposed system aims to detect fraudulent activities within social networks by leveraging a hybrid framework that combines traditional machine learning (ML) models and advanced deep learning (DL) techniques. This hybrid approach is designed to effectively handle high-dimensional, complex, and dynamic social media data while improving detection accuracy and minimizing false positives.

4.2 Data Collection and Preprocessing

The process begins with the collection of social network data from structured datasets for training and test.csv for evaluation. The raw data consists of user-related attributes.

Preprocessing includes:

- **Feature Selection:** Standardization is performed to ensure all features contribute equally during model training.
- **Text Cleaning and Modifications:** Missing entries are filled using the median to preserve the distribution and reduce bias. Label Encoding is applied to transform categorical text into numerical form.

This cleaned and normalized data serves as the input for both ML and DL models.

4.3 Machine Learning Component

Three key ML algorithms are employed:

- **Random Forest (RF):** Used for its ability to handle high-dimensional data and detect patterns through an ensemble of decision trees. It evaluates account behavior and interaction frequency.
- **XGBoost (XGB):** A gradient-boosting framework that captures complex patterns in features like engagement metrics and posting frequency.
- **Support Vector Machine (SVM):** Utilized for finding a decision boundary based on numerical features such as follower ratio and interaction density.

Each model is trained to classify accounts as fraudulent or genuine, outputting probability scores for interpretation.

4.4 Deep Learning Component

To enhance pattern recognition, particularly for sequential and relational data, deep learning models are integrated:

- **Convolutional Neural Network (CNN):** Applied on structured tabular data to uncover non-linear feature interactions that correlate with fraud.
- **Long Short-Term Memory (LSTM):** Focuses on temporal behavior such as user activity trends and time-based posting patterns.
- **Graph Neural Network (GNN):** Models the social network as a graph where users are nodes and their interactions are edges. It captures relationship patterns and community-level fraud clusters.

Each model learns different aspects of fraud patterns, from individual user behavior to community-level interactions.

4.5 Ensemble Learning for Final Prediction

Outputs from the individual ML and DL models are fed into an **ensemble model**, which aggregates their predictions using weighted averaging or majority voting. This integration improves the overall robustness and accuracy of the fraud detection system by balancing the strengths of each model.

4.6 Visualization and Interpretation

To make the results interpretable, a **graph-based visualization** is generated. Users are displayed as nodes, and their relationships as edges. Fraudulent users are color-coded (e.g., red for high-risk, green for genuine), making it easier to visually identify fraud clusters within

the network. This helps not only in detection but also in communicating findings to non-technical stakeholders.

In this chapter, I outlined the structure and flow of our proposed hybrid fraud detection system. By combining the strengths of machine learning and deep learning models, and layering them with ensemble learning, the system is built to handle complex, high-dimensional social network data effectively. With dynamic fraud tracking, user-friendly visualizations, and a focus on interpretability, this approach is designed not just to boost detection accuracy but also to make insights clearer and more actionable for real-world applications.

CHAPTER 5 – IMPLEMENTATION & RESULT ANALYSIS

This chapter evaluates the performance of the hybrid fraud detection framework across multiple datasets, comparing the results of individual ML and DL models. It also highlights the improvements achieved through ensemble learning and discuss key insights from feature importance and graph visualizations to ensure model transparency and effectiveness.

5.1 Datasets Used

5.1.1 Dataset 1 – test.csv and train.csv

Column Name	Description
profile_pic	Indicates whether the user has a profile picture (Yes/No).
ratio_numlen_username	Represents the ratio of numeric characters to total characters in the username.
len_fullname	Refers to the length of the user's full name.
ratio_numlen_fullname	Denotes the ratio of numeric characters to total characters in the full name.
sim_name_username	Describes how similar the user's full name is to their username, ranging from "Full match" to "No match."
len_desc	Shows the length of the user's description or bio.
extern_url	Indicates whether the user has an external URL linked to their profile (Yes/No).
private	Represents whether the user's account is private (Yes/No).
num_posts	The number of posts the user has made.
num_followers	The number of followers the user has.
num_following	The number of users the profile is following.

5.1.2 Dataset 2 - Youtube01-Psy.csv

Column Name	Description
COMMENT_ID	A unique identifier for each comment, likely auto-generated by YouTube or the dataset provider.
AUTHOR	The username or alias of the person who posted the comment.
DATE	The timestamp (ISO 8601 format) showing when the comment was posted.
CONTENT	The actual text of the comment. This can include links, self-promotion, or general commentary.
CLASS	The label or classification of the comment(0 for genuine and 1 for fraud)

5.1.3 Dataset 3 – Dataset fetched via Youtube Data API

Column Name	Description
video_id	Unique identifier of the video on YouTube.
title	The video's title (may include special characters or symbols).
description	Full video description written by the uploader, including links and hashtags.
channel_id	Unique ID of the channel that uploaded the video.
channel_title	Name of the YouTube channel.
publish_time	Date and time when the video was published (in ISO 8601 format).
tags	A list of keywords or hashtags related to the video (in JSON-style list format).

category_id	Numerical ID representing the video's category (e.g., 25 for News & Politics, 28 for Science & Technology).
thumbnail_url	URL of the video's thumbnail image.
thumbnail	HTML tag showing the video's thumbnail (for rendering purposes).
view_count	Total number of times the video has been viewed.
like_count	Total number of likes on the video.
comment_count	Total number of user comments under the video.
duration	Length of the video (formatted in ISO 8601 duration, e.g., PT53S = 53 seconds).
definition	Video quality: sd (standard definition) or hd (high definition).
caption_status	Whether the video has captions: TRUE or FALSE.
title_clean	The title field, cleaned of symbols and special characters for analysis.
description_clean	The description field, similarly cleaned of non-standard characters and links.
label	Likely a binary label (0 or 1), used for supervised learning tasks.

5.2 Platforms for Implementation

- **Google Colab:** For training and experimentation with hybrid models, leveraging GPU/TPU resources using Python Programming.
- **Kaggle and GitHub:** For accessing datasets.
- **Youtube Data API:** To extract real-time data through web scraping.

5.3 Results

5.3.1 Dataset 1

5.3.1.1 ML models

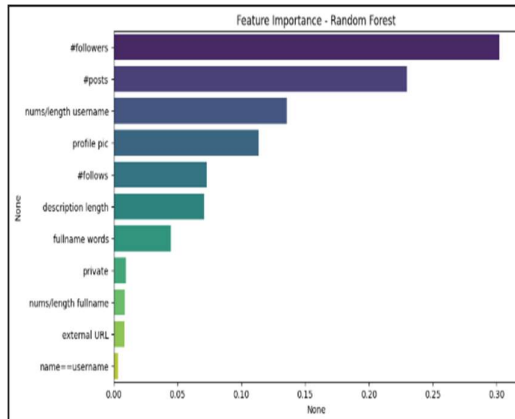


Figure 2 – Feature Importance of RF

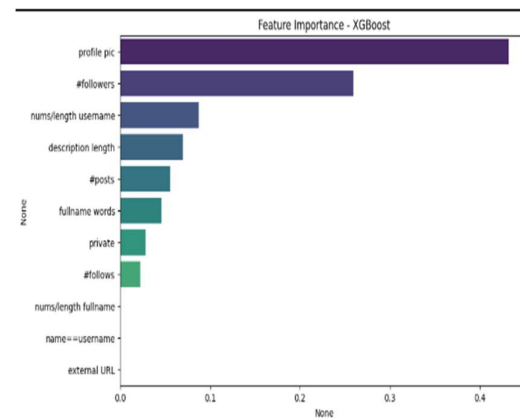


Figure 3 - Feature Importance of XGB

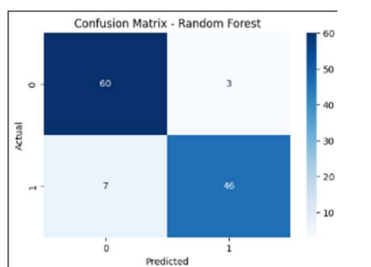


Figure 4 – Confusion matrix of RF

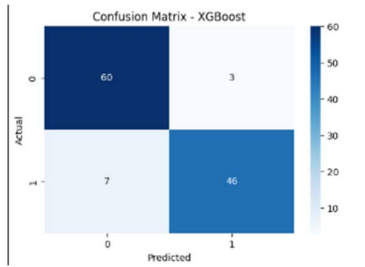


Figure 5 - Confusion matrix of XGB

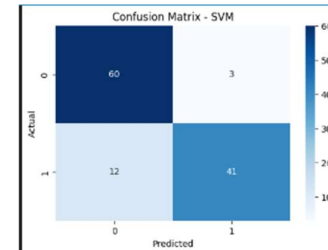


Figure 6 - Confusion matrix of SVM

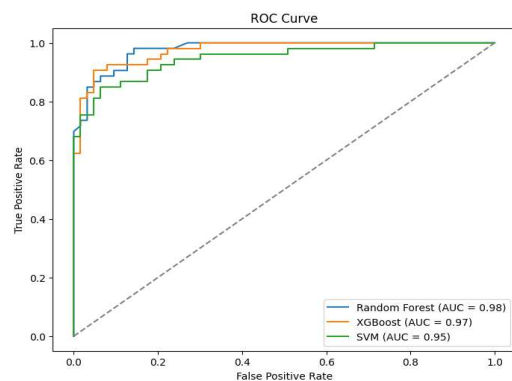


Figure 7 – ROC Curve

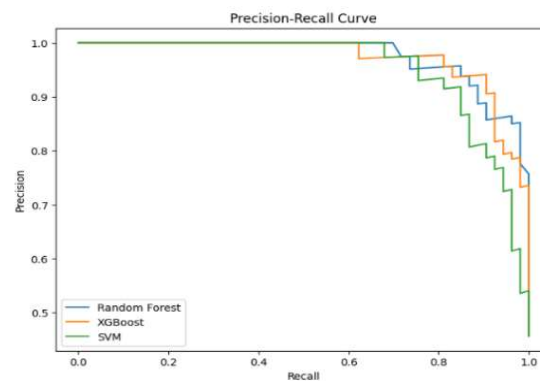
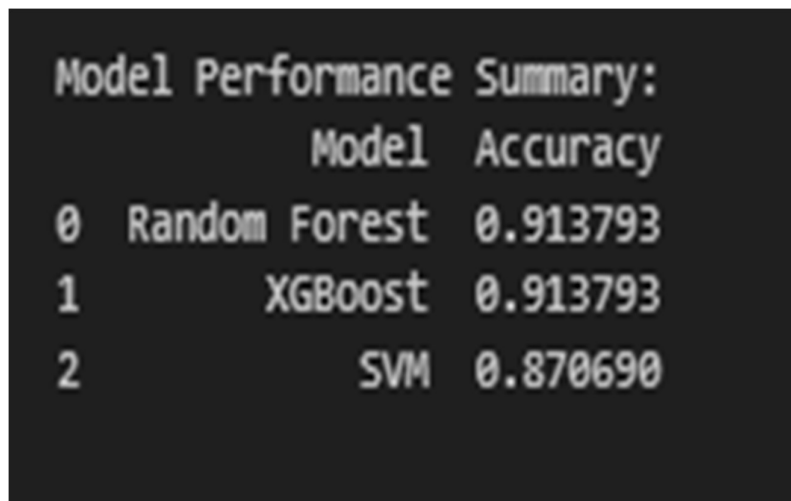


Figure 8 – Precision Recall Curve

A table with a dark background and light-colored text. The title 'Model Performance Summary:' is at the top. Below it are two columns: 'Model' and 'Accuracy'. There are three rows of data, indexed 0, 1, and 2.

Model Performance Summary:		
	Model	Accuracy
0	Random Forest	0.913793
1	XGBoost	0.913793
2	SVM	0.870690

Figure 9 – Model Performance Summary

In figure 2 Random Forest plot shows that #followers and #posts are the most important features for its predictions. Other features have less influence, with external URL and name==username being the least important.

In figure 3 XGBoost feature importance plot shows which profile characteristics are most influential in its predictions. "profile pic" and "#followers" are the top drivers, meaning they strongly affect the outcome the model is predicting. Other features like username length and description length have moderate influence, while "external URL" and "name==username" have very little impact.

Figure 4 and figure 5 shows a confusion matrix for a Random Forest and XGBoost model:

- True Negatives (actual 0, predicted 0): 60
- False Positives (actual 0, predicted 1): 3
- False Negatives (actual 1, predicted 0): 7
- True Positives (actual 1, predicted 1): 46

Figure 6 shows a confusion matrix for a SVM model:

- True Negatives (actual 0, predicted 0): 60
- False Positives (actual 0, predicted 1): 3
- False Negatives (actual 1, predicted 0): 12
- True Positives (actual 1, predicted 1): 41

In figure 7 ROC curve compares three models: Random Forest (AUC=0.98, best), XGBoost (AUC=0.97, very good), and SVM (AUC=0.95, good). Higher AUC indicates better performance in distinguishing between classes. Random Forest performs slightly better than the other two.

In figure 8 Precision-Recall curve compares three models: Random Forest (best), XGBoost (good), and SVM (worst). Random Forest maintains high precision as recall increases better than the others, indicating a better balance in its predictions.

In figure 9 Random Forest and XGBoost have the same higher accuracy (around 91.38%), while SVM has a lower accuracy (around 87.07%).

5.3.1.2 DL models

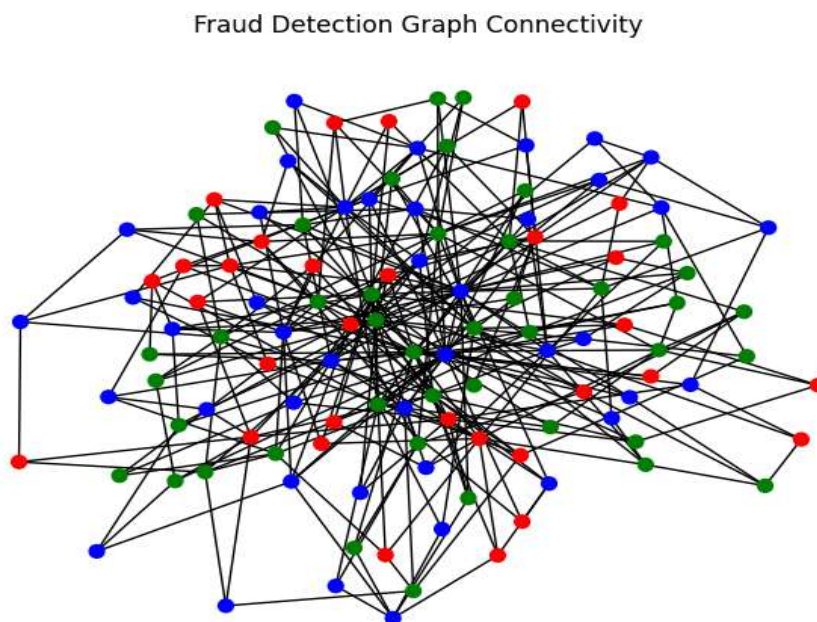


Figure 10 – Fraud Detection Graph Connectivity

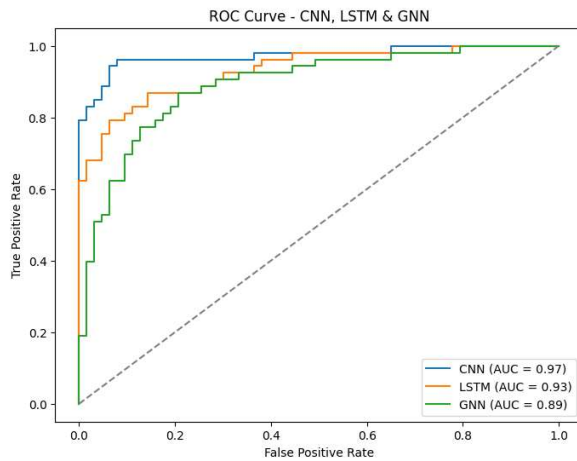


Figure 11 – ROC Curve

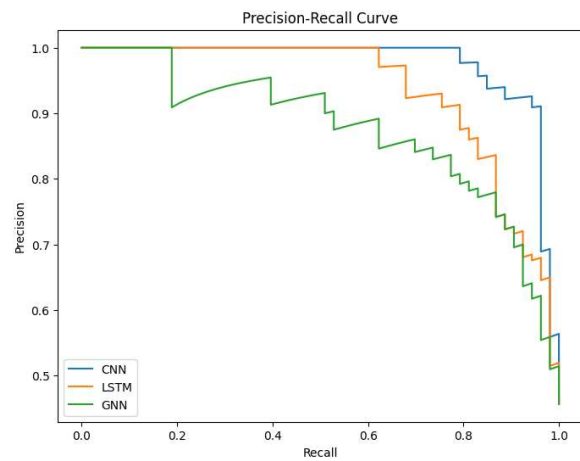


Figure 12 – Precision Recall Curve

Model Performance Summary:		
	Model	Accuracy
0	CNN	0.905172
1	LSTM	0.844828
2	GNN	0.818966

Figure 13 – Model Performance Summary

In figure 10 the graph visualizes connections between entities (colored circles) in a fraud detection system. Lines show relationships, and colors likely indicate fraud risk (red = high risk, green = genuine, blue = suspicious). Analyzing how these entities are connected can help identify fraudulent patterns.

In figure 11 CNN (AUC=0.97) performs best, followed by LSTM (AUC=0.93), and then GNN (AUC=0.89). Higher AUC means better classification.

In figure 12 Precision-Recall curve compares CNN, LSTM, and GNN models. CNN generally maintains higher precision across different recall levels, suggesting better performance in avoiding false positives while capturing true positives, especially at higher recall. LSTM performs second best, and GNN shows the weakest performance with a lower precision-recall trade-off.

In figure 13 Based on accuracy, **CNN (0.905)** performs best, followed by **LSTM (0.845)**, and then **GNN (0.819)**. CNN has the highest proportion of correctly classified instances.

5.3.1.3 Hybrid model

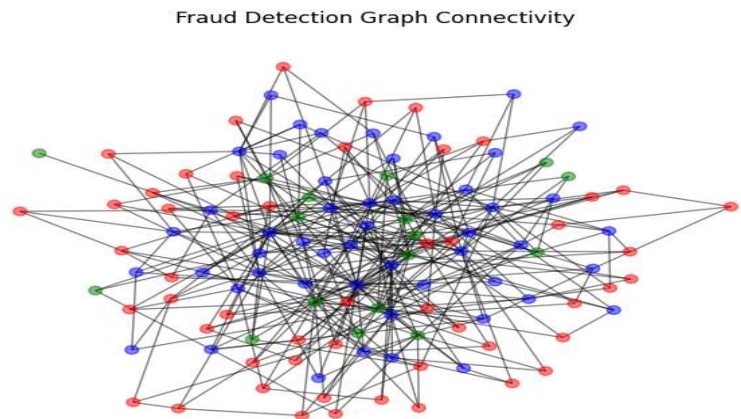


Figure 14 – Fraud Detection Graph Connectivity

Model Performance Summary:		
	Model	Accuracy
0	CNN	0.900000
1	LSTM	0.816667
2	GNN	0.741667
3	Random Forest	0.875000
4	XGBoost	0.883333
5	SVM	0.883333
6	Ensemble	0.875000

Figure 15 – Model Performance Summary

In figure 14 the graph shows connections between entities in a fraud detection system. Red nodes likely represent potential fraud, blue are likely legitimate, and green might be suspicious. The lines indicate relationships. Clusters of red nodes or specific connection patterns could signal fraudulent activity.

In figure 15 table shows the accuracy of different models. **CNN (0.900)** has the highest accuracy. **XGBoost (0.883)** and **SVM (0.883)** are next, followed by **Random Forest (0.875)** and an **Ensemble (0.875)**. **LSTM (0.817)** and **GNN (0.742)** have the lowest accuracy among the listed models.

5.3.2 Dataset 2

Classification Report (Ensemble):					
	precision	recall	f1-score	support	
0	1.00	1.00	1.00	27	
1	1.00	1.00	1.00	43	
accuracy			1.00	70	
macro avg	1.00	1.00	1.00	70	
weighted avg	1.00	1.00	1.00	70	
Accuracy Summary:					
	Model	Accuracy			
0	CNN	0.900000			
1	LSTM	0.571429			
2	Random Forest	0.957143			
3	XGBoost	0.957143			
4	SVM	0.928571			
5	GNN	0.385714			
6	Ensemble	1.000000			

Figure 16 – Classification Report of Ensemble Algorithm and Model Performance of all models

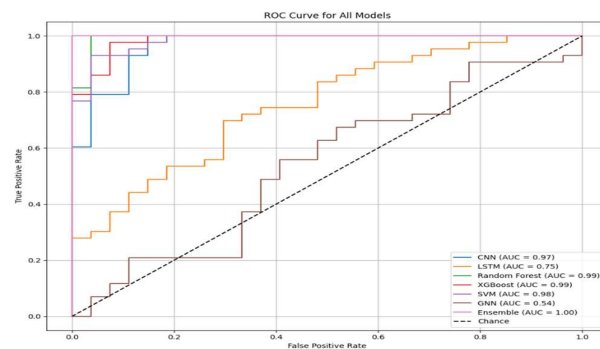


Figure 17 – ROC curve for all models

	COMMENT_ID	AUTHOR	DATE	CONTENT	label	Predicted_Prob	Predicted_Label
0	z12lg1vizm3q23oj4aqrj3dd1p	Holly	2014-11-06T13:41:30	Follow me on Twitter @mscalifornia95	1	0.795577	0
1	z13qydk5tzq1e5asx22xj3wdq3ns32f5	AmeenK Chanel	2014-11-14T11:50:02	Free my apps get 1m credits ! Just click on the...	1	0.779162	0
2	z12lg3jmlfvsthaa04chjkrply5zligbdg	Aaa Aaa	2014-11-12T05:46:27	PLEASE SUBSCRIBE ME!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!	1	0.807438	1
3	z130i3yaexrmtxyic04ccnk5hwwfs33as0c	Alucard Hellsing	2014-11-07T22:21:29	What Can i say....This Song He Just Change The...	0	0.486009	0
4	z12yinh5ks2oinqzn04cctkgvvrohbravz0k	Rancy Gaming	2014-11-06T09:41:07	What free gift cards? Go here http://www.swag...	1	0.783915	0
5	z12qfjubxk2iftnwk04chp5amsmmuvpwh5w	FaceTheFacts	2014-11-08T07:07:44	You know a song sucks click when you need to us...	0	0.395646	0
6	z13xwborhli2vdrab04chblgxvjatt4e2s0k	Luna Gamer Potter	2014-11-09T02:42:40	I hate this song!	0	0.176142	0
7	z13wj1pgwlfijjn4d04cilo5nwnhsbdavz0k	Tee Tee	2014-11-07T20:16:51	Loool nice song funny how no one understands (...)	0	0.441643	0
8	z13nw3lght2nf5wwe04cdx5iyaydznrve0	Wert Walleet	2014-11-08T09:15:22	This song is great there are 2,127,315,950 vie...	0	0.171064	0
9	z122dfb5htjxgpb0t04cdj1aikatybbjsb0	Kitts Hausman	2014-11-07T04:48:01	It's so funny it's awesomeness lol aaaaaa sex...	0	0.197357	0

Figure 18 – Updated data with predicted labels

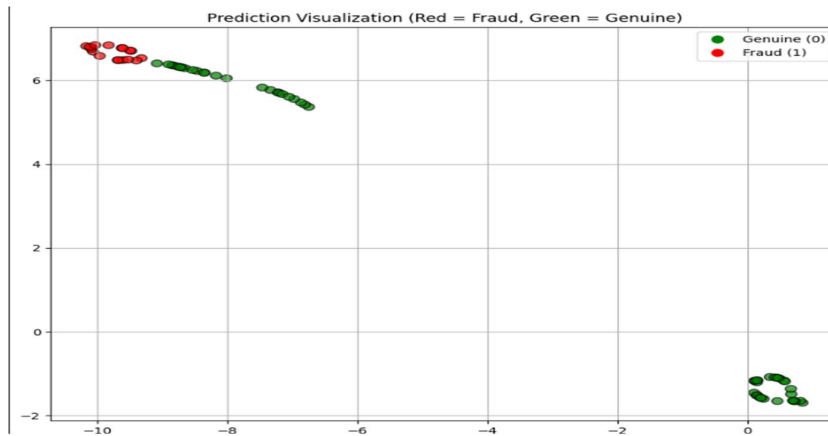


Figure 19 – Prediction Visualization

In figure 16 the Ensemble model achieved perfect scores: 1.00 for precision, recall, and F1-score for both class 0 and class 1. This means it had no false positives or false negatives for either class. The accuracy, macro average, and weighted average are also 1.00. Class 0 had 27 instances (support), and class 1 had 43. It also shows that the Ensemble model has the highest accuracy (1.00). Random Forest (0.957), XGBoost (0.957), and SVM (0.929) also show high accuracy. CNN has an accuracy of 0.900. LSTM (0.571) and GNN (0.386) have the lowest accuracy among these models.

In figure 17 the ROC curve compares several models. The **Ensemble** model has a perfect AUC of 1.00, indicating ideal performance. **Random Forest** and **XGBoost** are very close with AUCs of 0.99 and 0.99 respectively. **CNN** (AUC=0.97) and **SVM** (AUC=0.98) also perform well. **LSTM** (AUC=0.75) is moderate, while **GNN** (AUC=0.54) performs only slightly better than chance. Higher AUC means better classification.

In figure 18 table shows the results of a classification model on social media comments. Each row represents a comment with its ID, author, date, content, true label (1 for spam, 0 for not spam), predicted probability of being spam, and the predicted label (based on a threshold, likely 0.5). For example, the first comment was actually spam (label 1), the model predicted it

with a high probability (0.796), and correctly classified it as spam (Predicted Label 1). The second comment was also spam and was incorrectly predicted as not spam (Predicted Label 0).

In figure 19 scatter plot visualizes model predictions for fraud detection. Red points represent instances predicted as fraud (label 1), and green points represent instances predicted as genuine (label 0). The plot shows how the model separates the two classes in a 2D space after some dimensionality reduction. Ideally, red and green points would be in distinct clusters, indicating good separation by the model. Here, there's some overlap, especially in the top-left cluster, suggesting some misclassifications.

5.3.3 Dataset 3

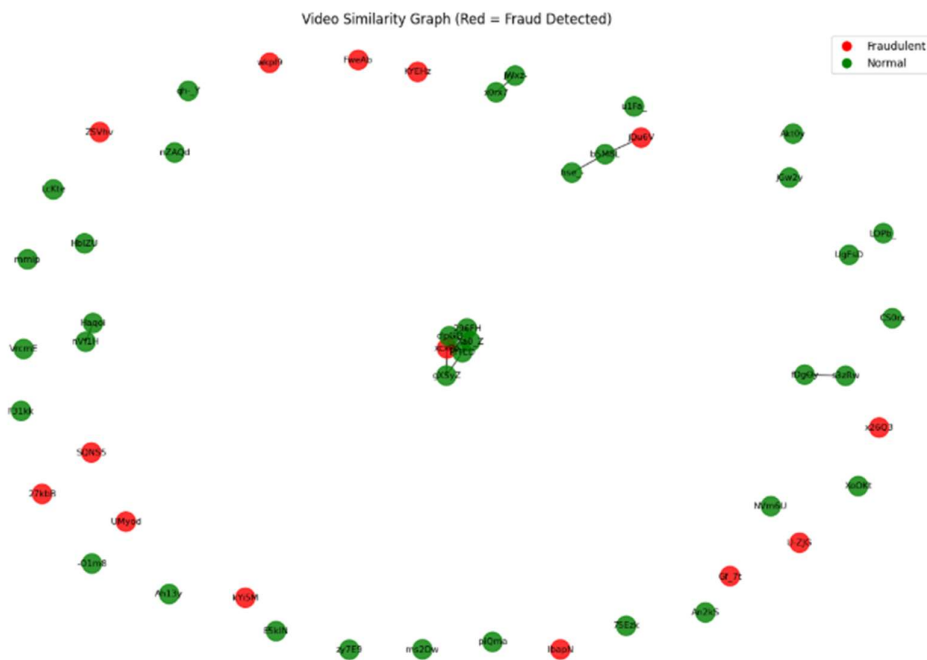


Figure 20 – Video Similarity Graph based on LSTM

In figure 20 the video similarity graph, derived from YouTube data API web scraping, visualizes video relationships. Although YouTube's own fraud detection deemed the initial data genuine, applying an LSTM model identified certain videos as potentially fraudulent (red nodes), while others are considered normal (green nodes). Connections show video similarity, and clusters of red nodes might indicate patterns flagged by the LSTM.

The comprehensive evaluation of the hybrid fraud detection framework across diverse datasets has demonstrated the effectiveness of combining machine learning and deep learning techniques. The performance metrics, confusion matrices, and ROC-AUC analyses clearly highlight the superiority of ensemble models in achieving higher accuracy, precision, and recall. Among the individual models, Random Forest and XGBoost consistently performed well, while CNN led the deep learning approaches with strong classification capabilities. The hybrid approach, supported by graph visualizations and feature importance analyses, proved instrumental in enhancing detection transparency and understanding model behavior. Through real-time data analysis using the YouTube Data API, the framework also showcased adaptability to dynamic, real-world environments. These results validate the robustness and reliability of the proposed system in detecting fraudulent behavior across varied social network platforms.

CHAPTER 6 – CONCLUSION & FUTURE ENHANCEMENT

This chapter gives us an overview of the whole project work on '*Fraud Detection in Social Networks*'. It summarizes how efficiently the hybrid model has performed across the three datasets and also discusses the scope of improvement in the near future.

6.1 Conclusion

This project delved into the domain of fraud detection in social network data using a blend of machine learning (ML), deep learning (DL), and hybrid modeling approaches across three diverse datasets. Each dataset represented different characteristics and challenges, allowing for a robust evaluation of multiple algorithms and modeling strategies.

In Dataset 1, traditional ML models such as Random Forest and XGBoost demonstrated superior performance, with Random Forest achieving the highest AUC (0.98). Feature importance analysis revealed that attributes like the number of followers, posts, and presence of a profile picture were the most influential in identifying fraudulent behavior. In contrast, features such as external URLs and name matching with usernames had minimal impact. Among the DL models applied, CNN outperformed LSTM and GNN in terms of accuracy and AUC, suggesting that convolutional architectures are better suited for pattern recognition in user profile data. Additionally, graph visualizations generated through GNN provided valuable insights into the network structure and helped visualize fraud clusters in the data.

Dataset 2 focused on a more refined scenario, where the ensemble model—combining the strengths of several classifiers—delivered perfect results with 1.00 scores for precision, recall, F1-score, and AUC. This clearly demonstrates the power of hybrid approaches, especially when incorporating both probabilistic and structure-based insights. Traditional models like Random Forest and XGBoost also performed well, with high accuracy and AUC close to 0.99.

However, models like LSTM and GNN showed relatively weaker standalone performance. The scatter plots of model predictions visually reinforced these outcomes, showing a good separation between genuine and fraudulent instances, although minor overlaps were present.

In Dataset 3, which involved YouTube video data, an LSTM model was used to detect fraudulent patterns. Despite YouTube's own fraud detection labeling the data as genuine, the LSTM model identified certain videos as potentially fraudulent. This indicates the model's ability to uncover deeper temporal patterns in user behavior that traditional filters might overlook. Furthermore, graph-based visualizations helped in identifying communities of suspicious content, offering a visual understanding of video similarity and potential risk zones within the network.

The project shows that integrating diverse models—ranging from classical tree-based algorithms to sequence and graph-based neural networks—can significantly enhance fraud detection systems. It underscores the importance of model diversity, feature relevance, and structural understanding in identifying fraudulent activities in complex social networks.

6.2 Future Enhancement

It explores potential future enhancements to the proposed fraud detection framework, focusing on areas for improvement and further development to adapt to evolving challenges and technologies.

- **Use on Other Social Media Platforms:** This project focused only on YouTube data. In the future, the same idea can be used on other platforms like Instagram, Twitter, or Facebook to catch fraud there too.
- **Add Blockchain for Security:** Blockchain can be added to make the system more secure. It helps in keeping data safe and makes sure no one can change the information secretly.

- **Better Cybersecurity Features:** Extra safety tools like two-step login (2FA), alert systems for strange behavior, and stronger checks can be added to protect user accounts and data.
- **Privacy-Friendly Learning:** In the future, learning methods can be used where data stays on the user's device. This way, models can learn without needing to share private data.

This chapter summarizes the outcomes of the 'Fraud Detection in Social Networks' project, highlighting the effectiveness of the hybrid model in detecting fraudulent behavior across diverse datasets. It underscores the value of integrating traditional machine learning, deep learning, and hybrid approaches to enhance fraud detection systems. The future enhancements discussed will further strengthen the framework, enabling its application across various platforms, improving security, and ensuring privacy. With continued development, this project has the potential to evolve into a robust, adaptable solution for combating fraud in dynamic social network environments.

APPENDIX

Coding

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import networkx as nx
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Conv1D, Flatten
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from torch_geometric.data import Data
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, auc, precision_recall_curve

# Load datasets
train_path = "train.csv"
test_path = "test.csv"
df_train = pd.read_csv(train_path)
df_test = pd.read_csv(test_path)
df_train.fillna(df_train.median(), inplace=True)
df_test.fillna(df_test.median(), inplace=True)
df_train = df_train.apply(LabelEncoder().fit_transform)
df_test = df_test.apply(LabelEncoder().fit_transform)

# Split features and target
X_train = df_train.drop(columns=['fake'])
y_train = df_train['fake']
X_test = df_test.drop(columns=['fake'])
y_test = df_test['fake']

# Standardization
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Reshape for DL models
X_train_d1 = X_train_scaled.reshape((X_train_scaled.shape[0], X_train_scaled.shape[1], 1))
X_test_d1 = X_test_scaled.reshape((X_test_scaled.shape[0], X_test_scaled.shape[1], 1))

# CNN Model
cnn_model = Sequential([
    Conv1D(64, kernel_size=3, activation='relu', input_shape=(X_train_d1.shape[1], 1)),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(1, activation='sigmoid')
])
cnn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
cnn_model.fit(X_train_d1, y_train, validation_data=(X_test_d1, y_test), epochs=10, batch_size=32)
y_prob_cnn = cnn_model.predict(X_test_d1).flatten()

# LSTM Model
lstm_model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(X_train_d1.shape[1], 1)),
    LSTM(32),
    Dense(1, activation='sigmoid')
])
lstm_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

```

cnn_model.fit(X_train_d1, y_train, validation_data=(X_test_d1, y_test), epochs=10, batch_size=32)
y_prob_cnn = cnn_model.predict(X_test_d1).flatten()

# LSTM Model
lstm_model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(X_train_d1.shape[1], 1)),
    LSTM(32),
    Dense(1, activation='sigmoid')
])
lstm_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
lstm_model.fit(X_train_d1, y_train, validation_data=(X_test_d1, y_test), epochs=10, batch_size=32)
y_prob_lstm = lstm_model.predict(X_test_d1).flatten()

# GNN Model
Qodo Gen: Options | Test this class
class GCN(torch.nn.Module):
    Tabnine | Edit | Test | Explain | Document | Qodo Gen: Options | Test this method
    def __init__(self, num_features):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_features, 16)
        self.conv2 = GCNConv(16, 1)

    Tabnine | Edit | Test | Explain | Document | Qodo Gen: Options | Test this method
    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        return torch.sigmoid(x)

num_features = X_train.shape[1]
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long)
X_train_gnn = torch.tensor(X_train_scaled, dtype=torch.float)
y_train_gnn = torch.tensor(y_train.values, dtype=torch.float)
gnn_model = GCN(num_features)
optimizer = torch.optim.Adam(gnn_model.parameters(), lr=0.01)
for epoch in range(10):
    optimizer.zero_grad()
    out = gnn_model(X_train_gnn, edge_index).squeeze()
    loss = F.binary_cross_entropy(out, y_train_gnn)
    loss.backward()
    optimizer.step()

# Convert GNN predictions
X_test_gnn = torch.tensor(X_test_scaled, dtype=torch.float)
y_prob_gnn = gnn_model(X_test_gnn, edge_index).detach().numpy().flatten()

# ML Models
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train_scaled, y_train)
y_prob_rf = rf.predict_proba(X_test_scaled)[: , 1]

xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss')
xgb.fit(X_train_scaled, y_train)
y_prob_xgb = xgb.predict_proba(X_test_scaled)[: , 1]

svm = SVC(kernel='linear', probability=True)
svm.fit(X_train_scaled, y_train)
y_prob_svm = svm.predict_proba(X_test_scaled)[: , 1]

# Ensemble Model
ensemble_probs = (y_prob_cnn + y_prob_lstm + y_prob_gnn + y_prob_rf + y_prob_xgb + y_prob_svm) / 6
y_pred_ensemble = (ensemble_probs > 0.5).astype(int)

```

```

# Save Predictions to CSV with Original Test Data
df_results = df_test.copy()
df_results['Predicted'] = y_pred_ensemble
df_results['Probability'] = ensemble_probs
df_results.to_csv("fraud_predictions.csv", index=False)

# Graph Visualization
G = nx.random_graphs.barabasi_albert_graph(len(y_test), 3)
colors = ['red' if p > 0.8 else 'green' if p < 0.2 else 'blue' for p in ensemble_probs]
nx.draw(G, with_labels=False, node_color=colors, node_size=50, alpha=0.5)
plt.title("Fraud Detection Graph Connectivity")
plt.show()

# Model Performance Summary
results_df = pd.DataFrame({
    "Model": ["CNN", "LSTM", "GNN", "Random Forest", "XGBoost", "SVM", "Ensemble"],
    "Accuracy": [accuracy_score(y_test, (y_prob_cnn > 0.5)),
                 accuracy_score(y_test, (y_prob_lstm > 0.5)),
                 accuracy_score(y_test, (y_prob_gnn > 0.5)),
                 accuracy_score(y_test, (y_prob_rf > 0.5)),
                 accuracy_score(y_test, (y_prob_xgb > 0.5)),
                 accuracy_score(y_test, (y_prob_svm > 0.5)),
                 accuracy_score(y_test, y_pred_ensemble)]
})
print("\nModel Performance Summary:")
print(results_df)

```

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