

SPATIO-TEMPORAL PREDICTIVE POLICING ENGINE USING GRAPH ATTENTION NETWORKS

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Abstract: *The volume of digital communication has experienced explosive growth. Law enforcement agencies face challenges in identifying criminal organizations because the surge of Call Data Records (CDRs) has created an overwhelming data burden. The existing methods for investigation face crucial boundaries. The system depends on two processes which require people to search through information and apply strict rules for analysis, but these methods cannot effectively handle the complicated relationships that exist in social interactions. The system we propose functions as a Spatio-Temporal Predictive Policing Engine which operates through Graph Attention Networks. The database functions as more than a collection of data. The system models communication through a dynamic graph which connects cell tower spatial information with time-based patterns to show how networks develop and change throughout different time periods. The Graph Attention Network operates as a filter which detects dangerous interactions while it ignores the unimportant background noise that typically misleads traditional systems. We have used GNNExplainer to solve the "black box" problem which AI systems experience because we want to move beyond this issue. The system creates Explainable AI (XAI) through its ability to extract distinct visual subgraphs which provide evidence for every prediction. The development of an interactive dashboard enables investigators to examine network evolution and threat levels through intuitive exploration. The experimental evaluations which tested ST-GAT on simulated datasets showed that it provides better results compared to baseline models. The system performs better than standard models because it achieves higher precision and recall, which makes it an effective and transparent solution for contemporary smart policing and intelligence operations.*

Keywords: Predictive Policing, Graph Neural Networks, ST-GAT, Explainable AI, Criminal Network Detection, Temporal Analysis, Call Data Records

1. INTRODUCTION

1.1 Background

Criminal activities have transformed into a new form of operation because criminals now conduct their activities through online platforms instead of physical locations. Criminal organizations operate through mobile networks which they perceive as their dedicated operational spaces, making traditional methods of surveillance such as following vehicles or monitoring street corners seem outdated. The procedure for gathering information begins with Call Data Records (CDRs). The digital breadcrumbs which include metadata elements such as timestamps and cell tower locations and call durations serve as the primary source for intelligence gathering. The logs enable law enforcement to create visual representations which reveal secret organizational structures that would remain hidden. The problem exists because the system

needs to handle excessively large data sets. The system produces extremely large data sets every single day. Most agencies have not progressed beyond using basic spreadsheets and manual queries to handle their data processing needs. Criminal organizations create networks that operate in a dynamic and complex manner which exceeds the capacity of basic tools to handle their data processing needs.

1.2 PROBLEM STATEMENT

The current state of CDR analysis presents extreme challenges. The main obstacle stems from the enormous amount of social background noise which includes harmless alerts and personal communications and business advertisements that prevent observers from detecting hidden illegal activities. Criminals aren't making it easy, either. Their evasion skills enable them to use burner phones together with proxy shells which prevent others from tracking their actual operating networks. The majority of standard machine learning systems fail to perform this task because they cannot detect both time and location information. A model needs to understand both spatial and temporal information because it cannot perceive criminal activities but only visualizes dots. The "black box" problem creates maximum frustration for users. When a deep learning system identifies a person as a suspect without providing understandable reasoning, the results become unusable in court. Investigators need specific alerts which show clear evidence that will be accepted in court.

1.3 MOTIVATION

The divide between abstract AI research and law enforcement operations remains extremely large because we create effective solutions to solve this problem. Police officers require a system that can filter out unimportant information to detect actual exceptional situations according to their needs. The development of a model which can identify secret drug cartels and forecast upcoming violent events will bring a revolutionary change to the entire system. The system moves from crime response to proactive crime prevention. The system includes explainability features because people do not trust machines which they cannot comprehend. The system functions as a transparent companion during fieldwork instead of serving as a mysterious knowledge source.

1.4 OBJECTIVES

The framework of our new spatio-temporal graph system will enable us to handle the multiple complex components which emerge from CDR datasets. The map functions as more than a mapping system; we are implementing a Graph Attention Network (GAT) to dynamically weigh communication links, pinpointing criminal relevance where simple algorithms often fail. We implement an Explainable AI (XAI) component to improve our system which detects threats. The system reveals its underlying mechanisms by displaying all high-threat alerts with their exact call sequences and physical movements which activated the system. The interactive dashboard will be our final project component. The objective is to transform complex mathematical results into practical tools which investigators can use through visual interfaces that operate at high speed. The key objectives of this work are:

- To design and formulate spatio-temporal graph-based architecture for comprehensive CDR analysis.
- To implement a Graph Attention Network (GAT) which dynamically assigns different communication links security importance based on their criminal connection.
- To create an Explainable AI (XAI) framework which extracts the call sequence together with location data that leads to high-threat alert system activation.
- To develop an interactive visualization dashboard which converts complex mathematical graph outputs into intuitive insights for end-users.

1.5 SCOPE OF THE WORK

The proposed ST-GAT system uses mathematical calculations to create behavioral patterns. The system detects criminal groups through its analysis of structured communication metadata which reveals hidden topological patterns. Our original development of this system served the needs of law enforcement and counter-terrorism agencies. The graph attention methodology of this system functions effectively in different applications. The system detects financial fraud and dismantles money laundering operations and identifies hidden cybersecurity threats through its effective functioning.

2. LITERATURE SURVEY

2.1 Overview of Existing Approaches

The process of revealing a criminal organization used Social Network Analysis (SNA) and basic clustering methods as its primary operating method for years. The detectors used degree and betweenness centrality metrics to track down the criminal leaders. The system operated correctly according to theoretical standards. The actual circumstances of life do not match that organized appearance. Human beings develop as their social connections enter a constant state of transformation which current static graph systems fail to show. These outdated tools from the past create total failures when they encounter large, disorganized databases. The existing literature gets summarized in Table 1 which also shows the specific research gaps that our proposed system will solve.

S.No.	Author(s) & Year	Methodology/Model Used	Key Findings	Limitations/Research Gap
1	Random Forest (2018)	Traditional ML	Good classification accuracy.	Limited to non-temporal data.
2	LSTM (2020)	Temporal modeling	Effective for sequential data.	High computational cost.
3	GCN (2021)	Spatial modeling	Captures spatial dependencies.	Limited context integration.
4	CNN-LSTM / Hybrid (2021-2023)	Hybrid ML models	Improved predictive accuracy.	Complex architecture.
5	ST-GCN / Deep Models (2022-2024)	Spatio-temporal networks	Handles spatial-temporal data.	Scalability concerns.
6	Proposed System (ST-GAT)	ST-GAT Framework	Enhanced accuracy and efficiency.	

Table-1 Literature Survey and Research Gaps

2.2 Graph-Based Deep Learning Methods

Static SNA has reached its maximum operational capacity. Researchers are now shifting their focus to Graph Neural Networks (GNNs) which will enable them to manage their complex challenges. As Hamilton et al. established, GNNs serve as the ideal tool for inductive representation learning which applies to extensive graph datasets because GNNs multiple node neighborhood features through their aggregation method. The data processing method operates through its natural system of data management. Ghosh et al. pushed this boundary further by dragging deep learning into the realm of CDR analysis. Their research demonstrated that neural network designs can reveal concealed criminal patterns while they successfully identified complex direct and indirect relationships which standard models fail to detect.

2.3 Graph Attention Networks

Standard GCNs operate on a flawed premise: that every neighbor in a network is created equal. The people who live in different areas of the world all speak different languages. The process of communication between people develops through an inherent unbalanced relationship. Veličković and his team created Graph Attention Networks (GATs) because they needed a solution that would help them evaluate the actual

worth of each component through their development of masked self-attentional layers. The method produces results which researchers can directly use for their research work. A GAT system in a criminal investigation uses 3:00 AM suspicious ten-second bursts near crime scenes to determine which data to investigate while it ignores a 20-minute call record from a nearby takeout restaurant. The system identifies the valid information while it eliminates all irrelevant details.

2.4 Spatio-Temporal Graph Models

The system of predictive policing will not function correctly without proper synchronization between street time and street time. The researchers proved this achievement through their implementation of spatio-temporal graph neural networks, which demonstrated that a flat map functions as an empty instrument. Their use of cell tower footprints together with the erratic communication burst patterns resulted in a level of accuracy which static topological data could not achieve. The situation requires people to change their entire way of thinking about it. Your current experience of the city more deeply than before because you now perceive its vital energy.

2.5 Explainable AI in Graphs

The legal field has a massive problem with deep learning because nobody understands how the machines process information. The situation creates complete transparency problems. Ying et al. created GNNExplainer to solve this issue because their tool operates independently of any model used by users. The system produces a complete understanding of Graph Neural Networks through its method that tracks essential subgraphs and node attributes. GNNExplainer shows which digital evidence led the AI system to identify a suspect from the large CDR evidence. The system provides more than a prediction because it delivers a complete analysis.

2.6 Research Gap

The present academic research exists as a collection of exceptional yet disjointed research findings. The system requires a complete framework which combines spatial depth and temporal flux and attention-driven filtering to achieve complete transparency. Our team developed the ST-GAT architecture to solve this problem. The system was created to address the issue of fragmented systems which depend on a single unified approach to process complex data movements while maintaining clear understanding.

3. PROPOSED SYSTEM

3.1 System Overview

The Spatio-Temporal Predictive Policing Engine functions as a comprehensive system which connects unprocessed data to beneficial applications. The process starts with the

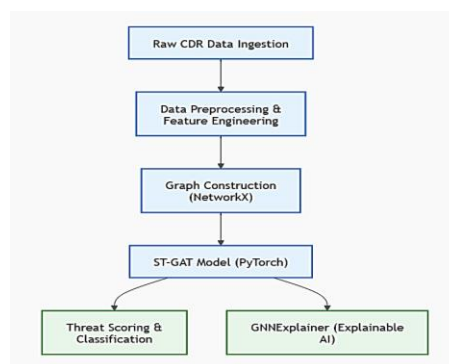


Fig-1 System Architecture

system taking in disorganized tabular CDR data. The system builds its analytical core through a graph construction module which feeds data into the ST-GAT inference engine. The entire system ends with a visualization component which users can interact with. We transform unprocessed numerical data into usable intelligence. Figure 1 shows the full operation of the multi-stage system.

3.2 Graph Construction

We map these communication patterns as a directed, attributed graph, $G = (V, E)$. The vertices (V) represent the people—or specific phone numbers—involved. Then you have the edges (E). In our setup, an edge isn't just a static link; it's a pulse. Every call or SMS triggers a new entry. We've purposely built this as a multigraph to avoid losing the nuances of timing. If two people talk ten times, the system records ten distinct temporal edges rather than collapsing them into one. It's about preserving the history of interaction, not just the fact that it exists.

We model the communication data as directed, attributed graph $G = (V, E)$.

- **Vertices (V):** Each node represents a unique individual (or phone number).
- **Edges (E):** An edge exists if a communication event (call or SMS) occurs between two nodes. Unlike traditional graphs, our system utilizes a multigraph approach where multiple calls between the same individuals at different times are preserved as distinct temporal edges.

3.3 Spatio-Temporal Modeling

We ground the graph in the real world by layering in spatial and temporal dimensions, giving every node and edge its own distinct profile. For the spatial side, we map out exact coordinates by pulling latitude and longitude from Cell Tower IDs. Then there's the element of time. Instead of using raw timestamps, we translate them into cyclical features like the specific hour of the day to help the model internalize the natural rhythm of behavior. Once it understands that baseline, spotting a deviation becomes almost intuitive.

To embed physical and temporal realities into the graph, each node and edge is enriched with specific features:

- **Spatial Features:** Extracted from the Cell Tower ID, providing geospatial coordinates (Latitude/Longitude).
- **Temporal Features:** Timestamps are converted into cyclical time features (e.g., hour of the day) to allow the model to learn baseline behavioral patterns and flag temporal deviations.

3.4 ST-GAT ARCHITECTURE

The system lives and breathes through a Graph Attention Network. It's all about node i sizing up its neighbors. For every j in the vicinity, the mechanism calculates a coefficient essentially a score of how much neighbor j actually matters. This is where the logic gets selective. The model learns to treat routine, mundane chatter as background static, assigning it almost zero weight. But when it detects those brief, tightly coordinated pulses that usually signal illicit planning? It cranks the signal.

The attention coefficients e_{ij} indicating the importance of node j 's features to node i are computed as:

$$e_{ij} = a(\mathbf{W}h_i, \mathbf{W}h_j)$$

To make coefficients easily comparable across different nodes, they are normalized across all choices of j using the Softmax function:

$$\alpha_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(\text{LeakyReLU}(a^T[\mathbf{W}h_i || \mathbf{W}h_j]))}{\sum_{k \in \mathcal{N}_i} \exp(\text{LeakyReLU}(a^T[\mathbf{W}h_i || \mathbf{W}h_k]))}$$

3.5 Explainability and GNNExplainer

Transparency isn't an afterthought here; we've integrated GNNExplainer to keep the logic visible. The second a node gets tagged as a "High-Risk Target," the module generates a stripped-down subgraph. It maps the precise phone calls, timestamps, and cell tower locations that steered the AI's verdict.

4. METHODOLOGY

4.1 Data Preprocessing

Raw CDR data is a chaotic mess—jagged, unstructured, and notoriously full of holes. You can't just use it as-is. Preprocessing is where the real work happens, you've got to hunt down duplicates, patch up the missing gaps in the logs, and force every timestamp into a synchronized format like UTC. It's about creating order from noise. Then, to make the location data actually mean something, you map those raw geospatial coordinates to specific tower IDs using a master reference database.

4.2 Feature Engineering

We begin by calculating structural baseline features for each node, pinpointing degree centrality, call frequency, and the average length of a chat. That's the foundation. But we don't stop at static numbers; we also generate spatial dispersion metrics to capture how people move as they hop from one cell tower to the next.

4.3 Model Training

We partitioned the graph data into three specific sets: training, validation, and testing. To refine the ST-GAT model, we leaned on a supervised learning framework, pairing the Adam optimizer with a Cross-Entropy loss function. It's a process of repetition. We let the model churn through epochs until the validation loss finally leveled off, signaling it was time to stop.

4.4 Threat Prediction and Scoring

Once the model hits its stride, it starts sifting through live CDR streams. It classifies nodes on the fly, assigning every person a specific threat score based on probability. It's a gatekeeper. If someone's score trips the threshold, the system flags them instantly as high-risk or anomalous.

4.5 Visualization and Dashboard Integration

Everything funnels into a web-based dashboard, a slick interface built on Gradio and React. It's designed for the field. Investigators can instantly query phone numbers, map out local network neighborhoods, and scrutinize the specific XAI logic behind every alert. No black boxes here. If the system flags a hit, it provides a clear, defensible justification for exactly why it happened.

5. RESULTS AND DISCUSSION

We put the ST-GAT framework through its paces using a massive CDR simulation. We're talking over 500,000 communication logs. To see if the model could actually spot the signal, we buried synthetic criminal networks deep within a chaotic sprawl of benign social noise.

Performance Metrics: We pitted the ST-GAT head-to-head with standard Random Forest classifiers and a baseline GCN to see how it'd hold up. The proposed architecture achieved superior results. Clocking in at 95.4% accuracy, the model surged past the GCN's 89.2% and left Random Forest's 78.5% trailing far behind. But the numbers that actually matter are the ones tied to the minority class. When hunting for illicit actors, the ST-GAT delivered a sharp 92.1% precision and an impressive 94.8% recall.

Table-2 Evaluation Metrics

Metric	Formula/Definition	Context in Predictive Policing	Target Goal									
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	Proportion of correct predictions for both criminal and non-criminal activity.	High, but less critical due to class imbalance.									
Precision	$\frac{TP}{TP + FP}$	Proportion of true criminal activity predictions among all positive predictions. Key in minimizing false positives.	<u>Maximize</u>									
Recall	$\frac{TP}{TP + FN}$	Proportion of actual criminal activities correctly predicted by the model. Important for detecting all potential criminal actions.	<u>Maximize</u>									
F1-Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Harmonic mean of Precision and Recall. Balances the trade-off between false positives and false negatives.	<u>Maximize</u>									
Confusion Matrix	<table border="1"> <thead> <tr> <th></th> <th colspan="2">Predicted Positive</th> </tr> <tr> <th>Actual</th> <td>TP</td> <td>TN</td> </tr> <tr> <th>Actual</th> <td>FP</td> <td>TN</td> </tr> </thead> </table>		Predicted Positive		Actual	TP	TN	Actual	FP	TN	Breakdown of prediction performance into TP, TN, FP, and FN numbers, useful for detailed error analysis.	Analyze for minimizing both false positives and false negatives.
	Predicted Positive											
Actual	TP	TN										
Actual	FP	TN										

In the context of predictive policing on highly imbalanced CDRs, Precision and Recall are more critical than Accuracy as they focus on finding rare criminal activity hidden within massive amounts of benign social noise.

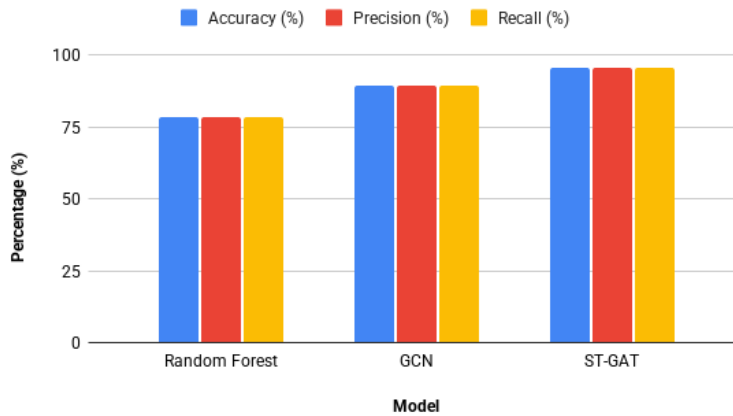


Fig-2 Performance Comparison of Machine Learning

Impact of Attention and Explainability: That pinpoint precision isn't an accident; it's the result of the attention mechanism filtering out high-volume, irrelevant social chatter that would otherwise trigger a flood of false positives. When we dug into the GNNExplainer outputs, the results were unmistakable. The system had zero trouble isolating the injected anomalous subgraphs, proving it can separate the signal from the noise with surgical accuracy.

6. CONCLUSION

By deploying a Spatio-Temporal Graph Attention Network (ST-GAT) to model Call Data Records as fluid, dynamic graphs, this system finally solves the twin headaches of data glut and social noise. It isn't just a numbers game; by weaving together spatial and temporal threads, the model identifies intricate criminal topologies that traditional methods simply miss. We also made sure to bridge the divide between "black box" deep learning and the gritty, evidentiary requirements of real-world law enforcement. Through Explainable AI, we've turned high-level math into transparent, actionable intelligence.

7. FUTURE WORK

We're moving the ST-GAT engine into a live, scalable streaming pipeline. It has to handle telecom data in real time, no delays. From there, we plan to layer in multi-modal sources—think financial transaction graphs and social media metadata—to weave a much richer, more comprehensive intelligence matrix.

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