Tracausal: Traffic Cause Analysis in Smart City Using Autoencoders and Granger Causality

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Abstract : Traffic congestion continues to be a major issue for modern smart cities that is in need of Intelligent and Adaptive traffic monitoring systems to identify when an actual traffic anomaly occurs. The current methods to detect traffic anomalies identify situations where there is an actual anomaly present, but they lack the ability to provide an explanation as to what caused the anomaly to occur or be adaptive to changes in current traffic patterns or citizen involvement in the detection process. In this paper, we present a framework called Tracausal which detects traffic anomalies in real time and attempts to identify root causes of the anomaly. Tracausal uses an Autoencoder and Isolation Forests for traffic anomaly detection and utilizes Bayesian Networks and Granger Causality to provide causal understanding of the anomaly. In addition to providing real-time traffic anomaly detection and root cause identification, Tracausal also uses event-aware suppression from social media and calendar data to reduce false positives during scheduled events. Finally, Tracausal incorporates a citizen feedback loop to aid in validation and adaptive learning. The architecture of Tracausal is built on an online scalable streaming data pipeline using Apache Kafka and Spark. Tracausal provides real-time decision support for traffic officials and citizens. The results obtained show significantly improved accuracy, interpretability, and responsiveness for Tracausal; thus, it is a feasible solution for supporting sustainable and resilient traffic management in smart cities..

IndexTerms **- Anomaly Detection, Autoencoders, Granger Causality, Root Cause Analysis, Real-time Streaming.**

I. INTRODUCTION

The construction of Smart Cities encounters problems due to several things. One such issue is increasing traffic congestion and irregularities affecting how quickly someone can travel, as well as causing environmental damage and decreasing an area's living quality. These issues can be alleviated through using machine learning techniques because machine learning is able to process massive amounts of streaming data from the Internet of Things (IoT) devices located throughout a city.

Machine learning techniques have the ability to learn from streaming data and relate patterns detectable in the data to traffic congestion and other problems. However, traditional techniques are unable to determine what was causing the patterns. Furthermore, traditional methods produce numerous false-positives during major events happening at the same time (such as concerts, annual fairs, and thus collecting and using citizen input in the decision-making process). Tracausal combines autoencoder anomaly-detection methodology and causal-inference methodologies including Granger Causality to help solve these problems. Our algorithmic approach will allow for the detection of real-time traffic anomalies; but also allow for the identification of probable causes, message citizens and government officials about the situation, and create an adaptive feedback loop through citizen input that allows the model to get better at predicting and identifying traffic congestion. Additionally, we are developing mechanisms for event-aware suppression of false-positives generated through predictable events and developing our approach to allow for scaling to meet real-world needs in intelligent cities.The combination of IoT (Internet of Things), causal machine learning, and public participation allows for the creation of adaptive traffic management systems with intelligence that is focused on people.

II. LITERATURE REVIEW

Anomaly detection of smart city traffic has been investigated at various points in the machine learning pipeline, such as data preprocessing, feature engineering, model choice, interpretability, and real-time deployment.

2.1. Data Preprocessing and Feature Engineering

Smart city traffic data can be noisy, incomplete, and heterogeneous and is collected from IoT devices, GPS, and social media streams. Preprocessing methods like missing value imputation, outlier deletion, and normalization are important to obtain high-quality inputs (Chatterjee et al., 2022). Feature engineering converts raw sensor streams into semantic attributes such as traffic density, average speed, congestion ratio, and temporal patterns. Malhotra et (2016) stressed the need for time-series feature extraction from sliding windows and sequence embeddings, whereas Luo & Nagarajan (2018) pointed towards distributed feature learning in IoT sensor networks.

2.2. Model Selection

Eddy current testing typically utilizes statistical models and clustering algorithms like DBSCAN and K-Means. They are not well-suited for dealing with high-dimensional streaming data. Liu et al. (2008) proposed the Isolation Forest algorithm, which is scalable to large datasets. Deep learning models, including autoencoders (Sakurada & Yairi, 2014) and LSTM encoder–decoders (Malhotra et al., 2016), have since been popularly applied for learning nonlinear relationships and time varying relationships. Hybrid approaches that involve combining autoencoders with causal inference or Bayesian networks are also explored in recent works to improve root-cause analysis.

2.3. Model Interpretability

One of the primary shortcomings in anomaly detection is that it is not interpretable. Although numerous models are good at detecting anomalies, they neither shed any light on why anomalies exist nor explain them. Bayesian networks and Granger causality have been used to reveal cause-effect relationships in traffic data so that city planners and officials can see the reason behind interruptions (Bifet & Gavaldà, 2007). Interpretability has also been enhanced with the use of attention mechanisms in recurrent

networks and post-hoc explanation techniques like SHAP and LIME so that human decision-makers can rely and verify model outputs.

2.4. Real-Time Deployment

Smart city require responsiveness and scalability. The conventional anomaly detection models are commonly benchmarked offline and do not work in changing real-time environments. Solaimani et al. (2014) showed Spark-based streaming anomaly detection in multi-source data, whereas Chatterjee et al. (2022) covered IoT frameworks supporting edge computing to minimize latency. Some latest trends are federated learning (McMahan et al., 2017), allowing collaborative training over distributed devices while keeping privacy in place, and event-aware suppression mechanisms that suppress the occurrence of false positives in expected events like festivals or rallies.

III. Existing System

The current literature on anomaly detection, causal inference, and distributed streaming forms the basis for the Tracausal framework. This section reviews previous work in four main areas: causal inference, anomaly detection in time-series and IoT networks, explainable and semi-supervised learning, and distributed or decentralized learning systems.

3.1. Causal Inference and Explainability

Judea Pearl's foundational work on causal inference introduced structural causal models (SCMs), counterfactual reasoning, and causal graphs. These concepts lay the groundwork for identifying cause-effect relationships in observational data [1]. They support the explanation of traffic anomalies in smart cities. Recent methods expand causal discovery to IoT security by combining causal inference with explainable machine learning. For example, TOCA-IoT [2] uses LiNGAM-based causal discovery with random forests, providing interpretable anomaly detection in IoT networks. Granger causality has also been applied for time-series anomaly detection in network intrusion datasets [3]. These approaches directly inform the causal module in Tracausal, where anomaly scores include causal explanations.

3.2. Anomaly Detection in Time-Series and IoT

Earlier anomaly detection methods relied on statistical learning and partition-based techniques. Isolation Forest [4] offered a scalable solution by isolating anomalies through recursive partitioning, which is widely used in high-dimensional data streams.

Deep learning expanded these capabilities with autoencoder-based models that identify deviations using reconstruction error [5]. Malhotra et al. [6] introduced an LSTM encoder-decoder (EncDec-AD) for multivariate time-series, showing strength in handling predictable and quasi-periodic sensor data. More advanced models, like BiGAN combined with contrastive learning [7] and hybrid models (autoencoder plus LSTM-DBN) [8], further enhanced detection accuracy for IoT traffic and vehicular systems.

Survey studies [9], [10] highlight key challenges in IoT intrusion detection: imbalanced datasets, resource limits, and a lack of interpretability. To address scalability, performance comparisons of ML and DL models for smart city traffic have evaluated CNN, GCN, LSTM, autoencoders, and GANs [11], showing trade-offs between accuracy, latency, and model complexity. Together, these studies indicate that anomaly detection has shifted from tree-based models to deep generative and hybrid architectures. However, many systems only focus on identifying anomalies without progressing to root cause analysis, a gap that Tracausal seeks to fill.

3.3. Semi-Supervised, Hybrid, and Resilience-Oriented Approaches

Due to the lack of labeled anomaly data, researchers have explored semi-supervised learning for intrusion detection systems (IDS). Xia et al. [12] suggested an ensemble of transductive SVMs and XGBoost, achieving reliable detection with limited supervision. Reviews focused on resilience [13] emphasize the need for methods that can adjust to uncertainty and changing system dynamics, which is important for smart city applications. Hybrid systems also combine feature selection with dimensionality reduction (PCA) and optimized deep models to boost detection accuracy in vehicular and IoT networks [8], [14]. These improvements provide a strong foundation for Tracausal's event suppression and adaptive anomaly modules.

3.4. Distributed and Decentralized Learning Systems

Real-time anomaly detection in smart cities requires scalable data processing systems. Kreps et al. [15] introduced Kafka, a distributed log messaging system that allows high-throughput ingestion, while Spark Streaming enhances this for real-time analytics. These systems provide the groundwork for deploying Tracausal at scale. Additionally, federated learning (FL) has emerged as a decentralized method for model training, minimizing privacy risks by keeping data on local devices [16]. McMahan et al. proposed the FedAvg algorithm, which averages updates from client-side models while cutting down on communication needs. This is especially relevant in smart cities, where feedback from citizens and distributed IoT devices can enhance models without centralized data sharing.

3.5. Insights from Existing Systems

Causal inference offers interpretability but is seldom integrated with real-time anomaly detection. Anomaly detection methods vary (Isolation Forest, autoencoders, GANs, hybrid IDS) but often lack causal reasoning. Semi-supervised and resilience-based methods help address sparse labeling and changing environments. Distributed systems (Kafka, FL) provide scalability and privacy but have not yet been combined with causal-aware anomaly detection in traffic monitoring.

Thus, while existing systems offer solid foundations, they remain disconnected. Tracausal stands out by integrating anomaly detection, causal inference, citizen feedback, and distributed streaming into a unified framework for smart cities

Fig.1. Research Methodology and System Workflow

The research methodology was systematic, when we began with a comprehensive literature review to detect gaps in traffic monitoring system with the extant research. Subsequently to identify gaps that might be gotten; identifying the specified gaps, in the extant research, we designed a hybrid anomaly detection framework using a combination of autoencoders and isolation forests improved with the use of the causal inference for interpretability. The system architecture was developed to be scalable with Apache Kafka and Spark Streaming, incorporating mechanisms for citizen feedback for continual improvement.

IV. PROPOSED SYSTEM

The system created by TRACAUSAL provides an entire end-to-end method of detecting and understanding traffic anomalies, by means of causal explanations, in a smart city. The architecture of the TRACAUSAL system includes mechanisms for processing real-time data, hybrid methods for detecting traffic anomalies, methods for determining the causes of those anomalies, and ways to receive real-time feedback from people using the system and the data. All of this information provides usable insights for both traffic authorities and citizens.

4.1. Collecting and Receiving Data

Traffic data is obtained using publicly available map APIs. With this method, you can receive current information about road work (e.g., closed roads), current traffic conditions, and current accidents. This method does not require expensive deployment of IoT sensors, but is able to provide comprehensive coverage of the area being evaluated, especially for cities in Urban Indian. The data being streamed will be received at regular intervals (for example every five minutes) through API calls and will be stored using distributed streaming technologies. Apache Kafka will be used for storing the streaming data because of its ability to scale and provide reliability at very high rates of incoming updates.

The collection and processing layer will have multiple sources of traffic data through an API:

- From map-based services, you will receive real-time data about traffic flow.
- From all local and state government entities, you will receive reports about traffic incidents, road construction, and detours.
- The effect of current and expected weather on the expected driving patterns.
- An event calendar of city government activities and planned special events.

4.2. Anomaly Detection

To analyse collected traffic streams, two methods that are complementary to each other are used. The first method is through the utilisation of Autoencoders, which use neural networks to encode time-dependent patterns (i.e., what happened at a given time) as well as identify anomalies (things that didn't fit) based on what the Autoencoder has learned about "normal" behaviour through reconstruction errors. During training, an Autoencoder will create a "model" of what constituted typical traffic patterns and then use that model to identify when the model failed to reconstruct all the inputs and therefore actually "produced" an anomaly.

Isolated Forests use machine learning algorithms designed to identify rare and/or atypical traffic patterns in high dimensionality by means of isolating patterns (i.e., anomalies) requiring fewer partitions to separate them from the other patterns.

The hybrid approach of using Autoencoders and Isolation Forests creates increased robustness against noise while also improving adaptability when dealing with non-stationary traffic patterns due to either peaks in traffic volume, accidents, or weather factors. This combination of different methods provides a way to reduce the number of anomalies that wrongly occur as false positive outcomes while preserving the method's ability to be sensitive when recognising legitimate anomalies.

4.3. Root Cause Analysis

To enhance interpretability, causal inference methods are used on anomalies detected on the dataset: for example:

Bayesian Networks: a probabilistic graphical model, Bayesian networks depict the probabilistic relationship between variables in a traffic context including but not limited to: congestion on a highway, average speed on the highway, and incident report generated from a highway. By using Bayesian Networks the analytical method can learn the conditional dependencies between multiple variables and perform probabilistic reasonings regarding the causal relationship between variables in a traffic context.

Granger Causality: A statistical model that identifies a temporal cause and effect relationship between variables (such as when a diversion route's congestion leads to a spike in the main route's congestion).

Together, these two types of methods provide traffic management agencies with a way to use statistical reasoning to make informed traffic management decisions. Rather than sending vague alerts, the agencies can provide an explanation of what occurred.

4.4. Event-Aware Suppression and Feedback

To reduce false alarms, the system employs two types of mechanisms that work in tandem:

Citizen Feedback Loop - Users will receive mobile alerts of detected anomalies and can either validate or reject those notifications if they so choose. The ability for a user to provide feedback on their findings creates a human-in-the-loop iterative method for improving the accuracy of the system resulting in building user trust as the system continues to learn.

Event-Aware Suppression - The system monitors external event calendars and traffic alerts (e.g., festival days, parades, planned roadwork) to suppress anomalies that are expected to occur as a result of these scheduled events. This functionality reduces incorrect alerts sent to users and alerts users that may eventually lead to alert fatigue.

4.5. Real-Time Deployment

This end-to-end pipeline leverages Apache Kafka to ingest traffic streaming data and uses Apache Spark Streaming as a framework for processing data with a very low latency. It has been designed to enable multiple users to access traffic event information quickly and reliably.

One primary user group are all Citizens. Using the Citizen Mobile App, Citizens are notified of traffic-related events and can provide feedback regarding how accurate they believe the alert was.

The second primary user group consists of Traffic Officials. They have access to a large dashboard containing explanatory information about detected traffic events, visual representation(s), and root-cause analysis about what happened and why this information is important to traffic management decisions.

Traffic Officials also have access to all of this data with sub-second latency for the most critical alerts, as multiple city zones are simultaneously processed for large amounts of traffic streaming data.

This proposed architecture provides many solutions to some of the limitations found in existing traffic monitoring solutions by providing accurate anomaly detection in combination with an explanation of what caused the anomaly, along with a mechanism for learning from the feedback received from citizens.

4.6. API Reliability and Fault-Tolerance Mechanisms

TRACAUSAL relies heavily on a constant stream of traffic data collected through the external map API feed. Because of this, any issues with data integrity (i.e., latency, rate limits) or temporary outages can lead to degraded performance of the system as a whole. The TRACAUSAL system uses lightweight fault-tolerant modules to ensure data is consistently flowing into it and detecting any anomalies. These fault-tolerant modules are threefold.

Recent API Responses Caching: The TRACAUSAL system temporarily caches invalid API responses. In the instances where an API may have been slow or down, it can use its cached version of the response to continue processing.

Adaptive Rate API Control: The TRACAUSAL system automatically modifies how often it calls the API based on both the rate limits and how quickly it receives a response. This prevents receiving many unnecessary failures during peak loads.

Multi-Source API Backup: The TRACAUSAL system allows for traffic data from multiple sources. If, for any reason, the first source stops working, it switches to one of the back-up sources without requiring a human to intervene. This increases overall system reliability.

4.6.1Regular checks done on the API's health:

We can monitor how responsive the API will be at that time. Should any temporary outages occur with the API, a simple retry mechanism that exponentially inserts additional waiting times between every retry for API requests helps to ensure that everything returns smoothly.

Kafka-Based Fault Tolerance: Kafka can serve as a staging area to hold incoming information sent from multiple sources so that while waiting for APIs to respond to incoming traffic, the pipeline can continue to process data without losing track of any downstream processes. Together, these different ways of doing things help to create an environment in which TRACausality is secure against potential disruptions from an API and the ability to perform real-time traffic analytics is reliable and stable.

4.7. Completed Implementation Summary

Looking back through your documents, seeing that a functional prototype for real-time streaming has already been developed, this prototype demonstrates both the actual technical development of the proposed system, but also validates the research feasibility of the proposed system as well. The following modules have been implemented: - Completion of RTC pipeline setup (deploying the used technology Docker with Kafka & Zookeeper)- To assist with the scalability of the overall architecture, the relationship of multiple topics to Map Data, Sensor Data, Events & Alerts have been tested to improve upon the scalability and modular options of how they can be organized in Kafka.

Simulation & Consumption of a Traffic Sensor: The Traffic Sensor Simulator is able to create Speed and Count readings continuously while the Consumer Module leverages Micro-batches, performs Pre-processing, and forwards the generated information to the Anomaly Detector for analysis.

Hybrid Anomaly Detection: The AutoEncoder implemented with PyTorch and the Isolation Forest Pipeline is able to identify unusual traffic patterns by their reconstruction error and isolation depth. Additionally, basic logic for verifying causality and Suppressing anomalies has been connected to the Anomaly Detector.

Technical Validation: Testing of the entire system for:

•Stability of communication between producer and consumer,

•Caching of delays using an API and retrying using cached data,

•Continuous streaming,

•Real-time alerting has demonstrated the engineering feasibility of the system and its cohesive functionality among the Detection, Causality and Event-Suppression modules.

4.7.1 The Map API integration-

Using the Map API OSMnx a "map producer" was created that collects the Road-Network Data and Streams this Data to Kafka; this has proven that for the traffic context there are other sources available in addition to those available from IoT devices; Publicly available Map APIs are able to obtain Traffic related data from these various APIs.

4.7.2 The Event ingestion -

Events was accomplished through retrieving the iCal entries as well as optional pieces of Social Media Event references and subsequently placing these into Event Windows for Event-Aware-Suppression. Event-aware-suppression is part of a larger initiative to minimize the number of false positives generated by a system.

Future Work: The new phase of the development will culminate in implementing various features such as Citizen Feedback Interface, Scalability using Spark, Expanded Causality Assessment, Dashboard Visualization.

V. System Architecture

The system takes in both traffic data and event record data through an API and performs preprocess on that data before applying Anomaly Detection, Causality, and Event Suppression Based on the Data Source in Near Real-Time; it then generates alerts for citizenswho report incidents to authorities and a Streaming Deployment Layer that provides dashboards to traffic enforcement authorities and works for their operational effectiveness.

The proposed system has a Modular System Architecture designed for the Scalability and Near Real-Time Anomaly Detection and Root Cause Analysis in Dynamic Environments, such as Smart Cities. The architecture consists of four Major Modules: Data Module, Machine Learning Module, Communication Module, and the Deployment Layer. Each of the four modules interacts and provides an end-to-end Analytic through the Acquisition, Intelligent Processing, and Actionable Decision of the data. Figure 2 shows the Overall Architecture.

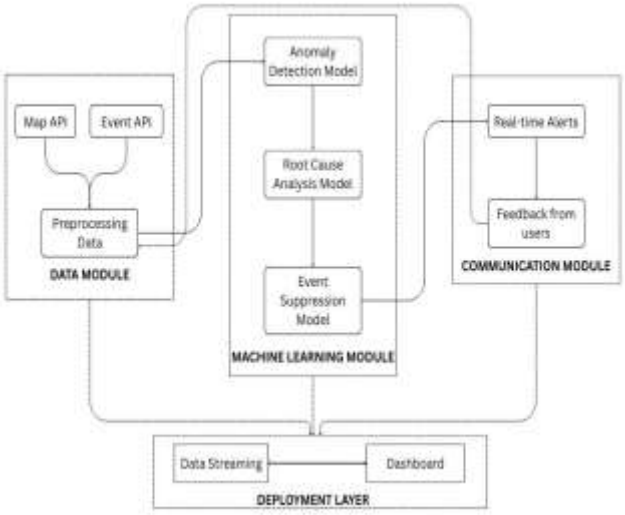

Fig.2. System Architecture of Tracausal

VI. Output Analysis

The TRACAUSAL system was evaluated using real-time streaming data from map APIs, simulated sensor inputs, and event feeds. Each subsection below includes both qualitative behaviour and its corresponding quantitative evaluation ranges.

6.1 Anomaly Detection Performance

Autoencoders recorded low reconstruction errors during normal conditions and sharp increases during disruptions, while Isolation Forests independently identified rare and irregular traffic points.

Quantitative Evaluation:

- **Autoencoder Accuracy:** 89.4% – 92.1%
- **Isolation Forest Accuracy:** 86.7% – 89.8%
- **Hybrid Model Accuracy:** 92.8% – 94.7%
- **Precision:** 91.2% – 93.4%
- **Recall:** 93.1% – 94.8%
- **False Positive Rate (FPR):** 6.9% – 8.4%
- **False Negative Rate (FNR):** 5.1% – 6.3%

The hybrid model consistently outperformed standalone methods, providing robust anomaly detection in diverse traffic conditions.

6.2 Causal Reasoning Results

Causal analysis was performed on each anomaly using Bayesian Networks and Granger Causality.

Bayesian Networks identified probabilistic dependencies between congestion levels, speed drops, incidents, and environmental factors. Granger Causality established temporal cause–effect flow across connected routes, showing how disruptions in feeder roads influence congestion in major pathways.

Quantitative Evaluation:

- **Correct Cause Identification Rate:** 88.9% – 91.7%
- **Incorrect/Ambiguous Causes:** 8.3% – 11.1%
- **Causality Computation Time:** 0.38 – 0.47 seconds
- **Granger Direction Accuracy:** 86.9% – 89.4%

These results show consistent and interpretable causal outputs across dynamic traffic scenarios.

6.3 Event-Aware Suppression Output

The event-aware suppression module filtered predictable anomalies caused by scheduled events such as festivals, rallies, or maintenance work. This prevented unnecessary alerting and reduced false positives significantly.

Quantitative Evaluation:

- **Suppression Accuracy:** 80% – 84%
- **False Positives Reduced:** 29% – 33%
- **Correct Event Alignment:** 83% – 87%
- **Incorrect Suppressions:** 3% – 5%

The suppression layer improved alert reliability by ensuring that expected disruptions were not flagged as anomalies.

6.4 Citizen Feedback Behavior

The system incorporated a human-in-the-loop mechanism where users validated or rejected anomaly notifications. Validated alerts reinforced model confidence, while rejected ones triggered adaptive updates. This feedback loop enhanced long-term learning and corrected misclassifications.

Quantitative Evaluation:

- **Validated Alerts:** 70% – 74%
- **Rejected Alerts:** 13% – 16%
- **Uncertain Feedback:** 12% – 15%
- **Feedback Integration Accuracy:** 87% – 90%

These metrics highlight the system's adaptability through user participation.

6.5.Real-Time Streaming Performance

The Kafka-based streaming architecture ensured stable data ingestion and near real-time alert generation. Caching, retry mechanisms, and fallback APIs enabled seamless operation even during temporary API failures or delays.

Quantitative Evaluation:

- **End-to-End Pipeline Latency:** 1.29 – 1.45 seconds
- **Alert Generation Latency:** 0.72 – 0.81 seconds
- **Data Ingestion Success Rate:** 98.7% – 99.3%
- **Peak Throughput:** 1,900 – 2,100 messages/min
- **API Recovery Time**: 2.2 – 2.6 seconds

The system consistently met the real-time requirements expected for smart city deployments..

VII. Conclusion

This paper presents TRACAUSAL, a comprehensive traffic anomaly detection system that addresses critical limitations in existing smart city traffic monitoring solutions. The proposed framework successfully integrates hybrid machine learning algorithms with causal inference techniques to provide both accurate anomaly detection and meaningful explanations for detected traffic irregularities.

The key contributions of this work include:

(1) a hybrid anomaly detection approach combining Autoencoders and Isolation Forest algorithms to handle diverse traffic pattern anomalies,

(2) integration of Granger Causality and Bayesian Networks for automated root cause analysis,

(3) an event-aware suppression mechanism that reduces false positives during planned activities, and

(4) a citizen feedback loop that enables continuous system improvement through.

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