A PREDICTIVE ANOMALY ALGORITHMS ON SPATIO-TEMPORAL TRAFFIC FLOW-ENABLED INTERNET OF THINGS

Agboi Joy, *Edje E. Abel, Omede U. Edith, Akazue I. Maureen, Ogeh Clement, Atonuji O. Ephraim, Fasanmi A. Ezekiel

Department of Computer Science, Faculty of Science, Delta State University, Abraka, Delta State, Nigeria

*Corresponding Author Email Address: edjeabel@delsu.edu.ng

ABSTRACT

The transportation infrastructure has advanced significantly in the last few decades, yet traffic issues persist since more people are living in metropolitan areas, necessitating the usage of various modes of transportation. Due to this, there are now more challenges with traffic control that directly affect the public, such as air pollution, traffic rule violations, and accidents. In this regard, intelligent transport systems integrate intelligent algorithms and the internet of things as an alternative for improving the traffic environment. In this study, a thorough analysis of traffic anomaly prediction involving the transition from spatiotemporal data flow is presented. It consists of a comprehensive analysis of various techniques applied for anomaly prediction on spatiotemporal data traffic. The various benchmark algorithms and models adopted to validate the performance of the proposed techniques are presented. Metrics adopted to evaluate the performance of proposed techniques are highlighted and briefly discussed. Limitations of the proposed techniques during and after the prediction phase are documented. The outcome of this study shows that Convolutional Neural Network techniques were majorly proposed and applied to predict anomalies in spatiotemporal data traffic flow, while Classification algorithms were mostly adopted as benchmarks for performance validation of the proposed techniques. It was also observed that Root Mean Squared Error (RMSE) was majorly adopted to evaluate the performance of the proposed techniques. Also, Computation Complexity was discovered as the most prevalent challenge bedeviling the proposed techniques, paving the way for future research directions in this field.

Keywords: Internet of Things, Data Traffic, Prediction Techniques, Spatiotemporal, Performance Metrics

INTRODUCTION

Internet of Things (IoT) has emerged as a new field of study in Information and Communication Technologies (ITS) in recent years. IoT technology connects smart devices and sensors that are available over the Internet. Bluetooth, Wireless Fidelity (Wi-Fi), Radio Frequency Identification (RFID), Wireless Sensor Network (WSN) and other communication channels are only a few of the ways that internet-connected IoT items send and receive data (Swarnamugi and Chinnaiyan, 2018). IoT is thriving because of its interoperability, dependability, and real-time interconnection for smart grid applications. Moreover, as the number of connected devices increases, so does the amount of data that they collect. Models for traffic analysis are being developed more and more to take use of this great potential for the applications that comprise these systems, as smart algorithms are integrated with the growing amount of spatiotemporal traffic data captured by IoT devices (Majumdar *et al.,* 2021).

Using spatiotemporal data for traffic anomaly detection is one of the fundamental principle to obtain vital information to resolve traffic problems. Consequently, the traffic anomaly identification topic has attracted a lot of interest from both academia and industry (Kalair and Connaughton, 2020). Furthermore, big data and artificial intelligence have been used to facilitate a wide range of studies on the traffic anomaly detection problem. The increased use of Global Positioning System (GPS) and IoT devices over the last few decades have drawn greater attention to urban traffic flow studies. Hao et al. (2022) appraised temporal and spatial data mining techniques. Sub-trajectories were categorized, outlier and anomalous flow were detected, segments and groups were created, and regular and periodic sequential patterns were identified from trajectory clusters.

One of the main applications of urban traffic analysis is to identify anomalies in the traffic flow data. The goal is to identify flow values that, when considering the spatial and temporal features of urban traffic data, deviate considerably from other flow values. One useful strategy for detecting abnormalities in traffic flow is the adoption of anomaly identification tools. An anomaly is an observation (or a collection of observations) that appear unusual compared to the rest of the data set (Shu et al., 2023). A lot of research has been done on anomaly detection during the last 20 years. These studies fall into one of the following categories: density-based, deviationbased, statistical-based, distance-based, and clustering-based methods. The purpose of the anomalous urban traffic flow data is to detect anomalous behaviors, which are represented by anomalous flow values originating from different traffic actors, such as cars, trucks, buses, and bikes. These anomalous behaviors include oversaturated conditions, traffic congestion, and bottlenecks (Wang et al., 2020; Khan et al., 2023).

Several literature surveys have investigated the dynamics in anomaly detection in spatiotemporal urban traffic flow over last seven years. For example, Boris et al., (2022) classified the smart techniques that are used to analyze mobility data to predict traffic flow in urban area. It further presented the outcomes of applying said techniques and describe the procedures adopted to comprehend the advantages and disadvantage of these smart techniques. Hamdi et al., (2022) presents the challenges related to data properties, discretization, interdisciplinary, and spatiotemporal interactions. Additionally, the gaps in the literature and unresolved research issues with modeling and visualization, spatiotemporal data formats are discussed. Classification, clustering, hotspot identification and pattern mining were also presented.

Gawali and Deore (2023), investigated variety of studies and spatiotemporal graph-based model developed for predicting the likelihood of future traffic accidents. Also, deep convolution networks for the purpose of recognizing and measuring traffic accidents, as well as adopting hybrid technique to enhance both recurrent and non-recurrent traffic situations. A state-of-art deep

learning based algorithms for identifying anomalies in traffic data flow is presented (Nayak et al., 2021). Additionally, compared the approaches in terms of datasets, processing capacity, and performance indicators for qualitative and quantitative analysis. Also, outline the challenges and positive pathways for future study. Fahrmann et al., (2024), presented the basic principles of anomaly detection in addition to highlighting a variety of cutting-edge techniques, such as proximity-based, statistical, and deep learning approaches. These elements include of the classification of anomalies, scenarios for detection and related challenges in spatiotemporal data traffic flow.

The existing research surveys majorly focuses on deep learning techniques, with minimum or without considering other techniques deployed for anomaly detection on spatiotemporal urban traffic flow-enable IoT. Therefore, this research studies the adoption and deployment of various types of techniques or algorithms for the prediction of anomalies on spatiotemporal urban data traffic flowenabled IoT. The contributions of this study are highlighted as follows.

- i. A comprehensive analysis of different types of techniques used for anomaly prediction on spatiotemporal traffic data flow in IoT ecosystem.
- ii. The benchmark algorithms used to validate the performance of the current diverse techniques.
- iii. The performance metrics adopted to evaluates the performance of the said techniques.
- iv. The limitations of the existing techniques while in active state, paving the way for future research directions.

The rest of this paper comprises research methodology adopted to accomplish the research contributions, research results presenting the analysis diverse techniques deployed, algorithms adopted to validates the performance of said techniques, metrics used for evaluating the performance of the techniques and their limitations in active state and ends with a concluding remark.

MATERIALS AND METHODS

A systematic framework known as research methodology is used to solve a research problem by selecting the most effective and practical ways to carry out the study while keeping the goals and purposes of the study in mind. The research methodology used by Dhanvijay *et al.,* (2019) and adigwe *et al.,* (2024) was adopted to conduct this research. It aids to facilitate the understanding of diverse existing techniques/algorithms, their limitations, and how they were evaluated based on performance measurement for predicting anomalies on spatiotemporal data traffic flow in the Internet of Things (IoT) ecosystem. The following are the primary Research Questions (RQ) that are developed to investigate and conduct this research.

- i. What features and attributes do the algorithms in the IoT device(s)-generated spatiotemporal data traffic flow?
- ii. What benchmark algorithms or techniques used for the performance validation of the algorithms for anomaly detection in spatiotemporal data traffic flow?
- iii. What performance metrics adopted to evaluate the performance of the algorithms in predicting anomaly on spatiotemporal data traffic flow?
- iv. What are the limitations of the said algorithms during anomaly detection operation on spatiotemporal data traffic flow?

To search for relevant existing articles, six major electronic research repositories were investigated namely, IEEE Xplore,

ACM, Taylor & Francis, Science Direct, Wiley Online Library, and Springer. Nonetheless, this study also includes a few publications from MDPI that are somewhat related to the current study.

In the context of this study, the following keywords are defined for the search process: "anomaly detection," "algorithms," "spatiotemporal data traffic flow," and "internet of things ecosystem." By using both manual and search engine screening, we conducted an automated in-depth text search using these keywords. Conversely, Boolean operators were applied with the stipulated keywords, within the scope of the established research questions to retrieve and classify relevant papers (Edje and Ureigho, 2015). In accordance with the inclusion criteria (the relevance of the paper to the application of anomaly detection algorithms on spatiotemporal data traffic flow in IoT, articles published between 2016 and 2023, should be written in English, electing exclusively primary studies from relevant research), a time restriction was set for the search process so that all relevant papers would be found and gathered with an emphasis on the predetermined keywords. The selected research articles' paragraphs were further filtered out using keywords in order to minimize their size and make them more manageable.

During the first phase, an estimated 221 articles were collected for the years 2018–2023. The second phase involved employing screening based on keywords and titles to remove a total of 167 articles. In the final step, the remaining articles were filtered according to the abstract using the predefined search research questions and the Boolean AND operator. The final 25 papers were selected by the authors, who considered all the predetermined research questions with the inclusion criteria for further investigation and analysis, which is shown in figure 1 from the first to the last phase.

Figure 1: Research Methodology Structure (adigwe *et al.,* 2024)

A table and statistical charting tools will be used to facilitate the evaluation of the research results obtained based on the research questions (RQ) as stated above. The table will list and illustrate the several algorithms/techniques currently in use, benchmark algorithms used foe validating current approaches, metrics adopted for performance evaluation as well as their drawbacks. Tools such as statistical charts will be used to graphically compare results and visually display findings.

RESULTS AND DISCUSSION

There are numerous types of existing techniques applied for the detection of anomalies on spatiotemporal data traffic flow in urban smart cities. Some of these techniques are extensively discussed as follows.

Analysis of the various types of techniques

Adapted k Nearest Neighbors for Detecting Anomalies on Spatio-Temporal Traffic Flow by Djenouri et al. (2019). The authors delve into the realm of outlier detection within the context of spatiotemporal urban traffic flow. The authors explore the field of outlier detection in the setting of urban traffic flow that is spatiotemporal. This study tackles an important field of research that has applications in many different fields, including medical diagnostics, biological sciences, surveillance, and traffic anomaly detection. The authors provide a cutting-edge method that is centered on how traffic flows are distributed over a specified amount of time (Edje, 2015). Building flow distribution probability (FDP) databases with temporal and spatial information is part of the process. Then, an approach for distance-based outlier detection using k-Nearest Neighbors (kNN) is investigated and modified to find abnormalities in flow distribution probabilities.

Detecting Urban Anomalies Using Multiple Spatio-Temporal Data Sources is presented by Zhang et al., (2018). They tackle the crucial problem of identifying urban anomalies, which, if missed, can have detrimental effects on property and human life. Timely detection of urban abnormalities, including unusual population movements or accidents, is a major difficulty. The main goal of the project is to present a technique that uses several spatiotemporal data sources to identify anomalies in metropolitan areas. The suggested two-step approach uses a one-class Support Vector Machine algorithm to integrate anomaly scores across several data sources, neighboring locations, and time slots, and a similaritybased methodology to estimate anomaly scores for specific data sources. There are two steps in the methodology. Using previously related locations into consideration, a similarity-based algorithm initially predicts anomaly scores for each unique data source in each region and time frame (Edje and Ekebua, 2015). To provide a final integrated anomaly score for each location, an algorithm based on one-class Support Vector Machines is used in the second stage to identify rare patterns that appear across several data sources, surrounding regions, or time windows.

Joint Static-Dynamic Spatio-Temporal Evolutionary Learning is proposed by Liu *et al.*, (2023). The authors address the difficulty of accurately predicting traffic anomalies, highlighting the vital chance it provides for prompt intervention to prevent fatalities. Both static and dynamic elements contribute to the complexity of traffic anomalies, and the authors use evolving representation learning to understand this complicated process. Creating spatio-temporal encoders to convert data into a vector space that shows their inherent relationships is a key component of the suggested spatiotemporal evolution model. Then, to concentrate on uncommon traffic anomalies, a temporally dynamic evolving embedding technique is used. In addition, an attention-based multiple graph convolutional network is employed to capture spatial mutual influence from various angles. To aggregate heterogeneous characteristics while taking spatiotemporal impacts into account, FC-LSTM is used. Ultimately, the unbalanced data issue is resolved and "over-smoothing" is addressed by a well-designed loss approach.

To estimate short-term traffic flow while taking spatiotemporal correlation into account, a hybrid model made up of Type-2 Fuzzy C-Means (FCM) and Artificial Neural Network was proposed (Tang et al., 2019). The model takes on the crucial duty of short-term traffic flow to improve the forecast of future traffic patterns. First, taking into account both time correlation and spatial equivalent

distance, it assesses the spatiotemporal correlation of data samples obtained from various loop detectors. The membership function is then unambiguously identified using a type-2 FCM, which improves the classification accuracy and consistency of anomalous data samples. After that, different traffic flow patterns are predicted using a combination of neural network approach and classification algorithm. Further modifications to the results are made using quantized spatio-temporal correlation. Conversely A study on conformal anomaly detection on spatiotemporal observations with missing data was carried out by Xu and Xie in 2021. In order to find anomalies without assuming data exchangeability, a distribution-free, unsupervised anomaly detection technique called ECAD was created. It was then smoothly integrated with a regression algorithm. The simulation findings indicate that ECAD uses ensemble predictors for increased statistical power instead of data-splitting, demonstrating computational efficiency.

Zhang et al. (2019) looked at a short-term traffic flow prediction based on spatiotemporal analysis and CNN deep learning. The authors tackle the important problem of precise short-term traffic flow prediction with the goal of improving trip planning and active traffic control. Current models of traffic flow frequently fail to properly utilize the geographical and temporal information present in traffic data. A short-term traffic flow prediction model built on a deep learning framework for Convolutional Neural Networks (CNNs) was used to get around this restriction. STFSA, or the spatio-temporal feature selection algorithm, is used to find the best spatial data amounts and time lags for input data. A twodimensional matrix containing the selected features is fed into the CNN in order for it to build a prediction model.

GeoTraPredict: Li et al. (2021) used a machine learning algorithm to forecast anomalies in Web Spatio-Temporal Traffic Flow data. The model learns the spatiotemporal patterns of traffic flow using a computer platform, and then it makes predictions about trends in both temporal and geographical dimensions. GeoTraPredict integrates cloud-based compute capabilities and a data aggregation portal to handle the volume of online traffic flow log data and the complexity of spatial data structures. It highlights the vital connection between population patterns and web traffic flow and solves the drawbacks of conventional forecast techniques. GeoTraPredict is a noteworthy addition to the traffic prediction area, demonstrating potential applicability in a range of real-world scenarios through its machine learning platform, data gathering portal, and cloud-based compute functionalities. In contrast, Priyadharsini and Chitra (2021) introduced a novel method of employing Kernel Support Vector Machines (KSVM) based on spatio-temporal motion pattern models for anomaly identification in excessively congested settings. Using threshold values, the methodology first segments the video. Next, it segments moving objects using Extended Kalman Filters (EKF) to improve classification accuracy. Finally, texture features are removed to differentiate between foreground and background objects. Finally, artifacts are labeled using improved Learning Vector Quantization (LVQ) to efficiently identify anomalies. Finally, Kernel Support Vector Machine (KSVM) based on spatio-temporal movement pattern models is effectively classified. The comparison with SVM and Hidden Markov Model (HMM) shows that KSVM is very useful for precisely tracking objects in busy environments.

Li et al. (2022) present a spatio-temporal graph neural network approach for traffic flow prediction. It tackles the problem of shortterm traffic flow prediction, highlighting how important it is to

forecast traffic conditions precisely in order to construct smart cities and reduce traffic congestion. During the deep learning portion of the process, a dynamic perceptual graph neural network model is adopted in order to reveal hidden links in space-time. Graphs are used to aggregate and represent geographical and temporal elements, making it easier to understand possible linkages. Graphs are used to aggregate and represent geographical and temporal elements, making it easier to understand possible linkages. Real datasets were used for experimental validation, and the suggested approach's effectiveness was evaluated by comparing it to other benchmark models already in use. By capturing the subtle interactions between temporal and spatial dimensions in traffic flow data, the suggested method successfully addresses the issues of variability under various road conditions. Thus, Predicting Citywide Crowd Flows Using Deep Spatio-Temporal Residual Networks is the focus of Zhang et al.'s (2018) study. It tackled the difficult problem of predicting metropolitan crowd flows, which is essential to traffic control and public safety. The process entails creating a deep learning model called ST-ResNet specifically for predicting crowd movements in urban areas. The model addresses temporal aspects including closeness, period, and trend using a residual neural network structure. To capture spatial properties, a branch of residual convolutional units complements each temporal property. Based on data, the model progressively aggregates these branches' outputs, giving various branches and geographical areas distinct weights. To increase the precision of crowd flow forecasts, additional outside variables are included to the aggregation process, such as the day of the week and the weather.

An investigation was conducted on HUAD, or Hierarchical Urban Anomaly Detection Based on Spatio-Temporal Data (Kong et al., 2020). Introducing HUAD, a framework for identifying urban anomalies based on spatiotemporal data, is the main goal of the study. The structure of the framework is hierarchical. Building approximate anomaly characteristics using traffic flow data—which includes taxi and subway data—is the first step in the process. The next steps are to find other abnormal regions, and generate refined anomaly characteristics from neighboring regions. The Long Short-Term Memory (LSTM) network was used for traffic prediction on historical anomaly scores, and then use the One-Class Support Vector Machine (OC-SVM) approach to detect abnormal regions. As a result, Chen et al. (2019) used traffic state analysis and prediction to address the crucial problem of traffic congestion in urban road networks. The main goal is to reduce traffic congestion and increase the traffic capacity of urban road networks by utilizing spatiotemporal correlation characteristics to distinguish between different traffic congestion situations. There are two steps in the methodology. Using the available floating automobile data, analyze and investigate the spatiotemporal correlation properties of traffic conditions first. This analysis covers the entire worldwide road network, not just interactions upstream and downstream. Second, a Mixed Forest Prediction method is developed, using the local Moran's I traffic jam aggregation and diffusion properties. By taking spatiotemporal correlation characteristics into account, this technique enhances the current Random Forest algorithm.

A novel deep learning framework named Deep Spatio-Temporal Multiple Domain Fusion Network for Urban Anomalies Detection is introduced by Liu et al. in 2020. Creating the Deep Spatio-Temporal Multiple Domain Fusion Network is one of the methodology's tasks. To obtain spatiotemporal characteristics, a temporal convolution model and weighted adaptive graph were constructed. Furthermore, a cross-domain convolution network is

utilized to create links among several domains. The end-to-end deep learning architecture makes it possible to gather the effects of urban anomalies on various datasets, which makes it easier to find anomalies in the city's various regions when the next time period rolls around. With the help of temporal convolution, crossdomain convolution, and adaptive graph convolution, the suggested end-to-end deep learning strategy demonstrates improvements in spatiotemporal feature extraction and achieves a 10% improvement over the most advanced techniques for detecting urban abnormalities.

In the field of data mining and knowledge discovery, Wang (2018) tackled the important topic of spatio-temporal anomaly detection in traffic data. Developing a thorough method for spatiotemporal anomaly detection in traffic data is the main goal of the study. The writers begin by examining several kinds of traffic data and identifying unique characteristics within each kind. Next, in order to identify anomalous data points, a grid-based Local Outlier Factor (LOF) algorithm is presented in conjunction with grid partitioning. Subsequently, a comprehensive set of experiments is conducted on real-world trip data, comprising both taxi and bus data, to assess the effectiveness of the suggested approach in anomaly detection. On the other hand, Asadi and Regan (2019) suggest using the Deep Embedded Clustering technique to anticipate abnormalities in the spatiotemporal data traffic flow. In order to train traffic flow data, it entails defining temporal and spatial clusters, establishing a spatio-temporal clustering problem, and putting forth a method based on a deep embedded clustering model. The useful connections between temporal and spatial clusters and the associated patterns in traffic data are also emphasized, underscoring the clustering method's efficiency in identifying commonalities.

An Inter-Fused Auto-encoder deep learning technique is introduced for the detection of anomalies on spatiotemporal traffic data flow **(**Aslam and Kolekar, 2022). It tackles the difficult problem of automatically identifying and deciphering unusual events in sequences of videos. For effective extraction of spatial and temporal data, it consists of an Inter-Fused Auto-encoder (IFA) that is built using layers of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN). Through the application of deep neural network advances, specifically CNN and LSTM, an end-to-end trainable Inter-Fused Auto-encoder (IFA) was shown that can identify anomalous events by taking use of temporal and spatial variances in video data. For testing videos, the reconstruction error is calculated using both Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). A comparison is then made to determine which method is most appropriate for reconstructing the video sequence. To decide whether to classify testing occurrences as uncommon or normal, an optimal threshold is computed. Xia et al. (2020) have proposed STAP: A Spatio-Temporal Correlative Estimating Model for Improving Quality of Traffic Data. It tackles the problems that Intelligent Transportation Systems (ITS) face from poor quality traffic data. To find anomalous data, an enhanced Random Forest model-based anomalies detection system is first presented. The model then isolates spatial and temporal data separately and classifies conventional features. Lastly, an XGboost-based data estimation technique is suggested to correct anomalous data, hence enhancing the traffic data's overall quality. Consequently, to handle the critical problem of traffic flow forecasting in intelligent transportation system management, Attention-Based Spatio-Temporal Graph Convolutional Networks were presented for the prediction of

anomalies on traffic data flow (Lu et al., 2021). A spatio-temporal graph convolutional network based on attention is at the center of the suggested methodology. This model, in contrast to conventional methods, makes use of several channels to integrate various information sources on traffic conditions and maintenance events. The model attempts to improve traffic flow predictions during maintenance downtime by explicitly addressing spatiotemporal interdependence and relationships within roadway networks. Furthermore, the practical implementation of the proposed model's computational complexity and scalability should be taken into account for future research directions. According to Xiao et al. (2020), a dual-stage attention-based Conv-LSTM network model is suggested for multivariate time series prediction and anomaly detection on spatiotemporal correlation. The focus of deep learning-based approaches is frequently on extracting temporal features, hence ignoring the complex spatial and temporal dynamic connections found in MTS. As a result, a dualstage attention-based Conv-LSTM network is used in the suggested model. Convolution operations are optimized at the outset of the process using a novel MTS preprocessing technique. After that, temporal correlations are captured by the LSTM model, and spatial correlations are extracted by the convolution layer. Insufficient temporal dependency in MTS prediction is effectively addressed by integrating attention processes with LSTM. By further removing unimportant data, the dual-stage attention process raises the significance of exogenous sequences and raises prediction accuracy overall.

Xie et al. presented Deep Graph Convolutional Networks for Incident-Driven Traffic Speed Prediction (2020). It happens in three main steps. First, in order to find high-impact traffic occurrences, a critical incident finding method is presented. Second, latent incident impact features are extracted by a binary classifier that uses deep learning techniques. Lastly, a system for robust traffic speed prediction that effectively combines incident, spatiotemporal, periodic, and context information is introduced: the Deep Incident-Aware Graph Convolutional Net (DIGC-Net). Experiments using real-world traffic datasets from New York City and San Francisco are used to assess the framework and show its superiority over rival benchmarks.

Singh and Mohan (2018) proposed the use of the stacked autoencoder technique in conjunction with deep spatio-temporal representation to detect road accidents. It deals with the difficult but important problem of vision-based traffic accident identification in traffic surveillance footage. In contrast to conventional hand-crafted features, the authors' innovative system automatically learns feature representation from spatiotemporal volumes through the use of deep learning techniques. This opens the door to more accurate accident detection. To extract deep representations, the proposed methodology involves training denoising auto-encoders using regular traffic movies. Next, reconstruction error assessment and an unsupervised one-class support vector machine model are used to estimate the probability of an accident. Vehicle trajectory intersection points serve to reduce false alerts and improve system reliability in general. For a thorough assessment, actual accident recordings from Hyderabad, India's CCTV camera network are used. The suggested structure demonstrates effectiveness in actual accident situations. Trajectory crossing points are incorporated to further improve dependability, highlighting the potential of this method to advance automated accident detection systems in urban settings.

Dokuz (2022) proposed the concept of social velocity based

spatiotemporal anomalous daily activity discovery among social media users. It tackles the difficult problem of spotting unusual daily activities among social media users' typical behavior. Accurate information dissemination and user protection from hazardous content depend on the recognition of such activities. The intricacy of anomalous actions, the difficulty in identifying bot applications, and the large data aspect of social media databases all contribute to the complexity. The core of the suggested methodology is the creation of an interest metric called "social velocity" to identify unusual everyday activities based on temporal and spatial variations between subsequent posts.

An approach to road accident identification and localization based on deep learning is presented (Pawar and Attar, 2022). The main idea is to frame the issue as anomaly identification in actual traffic cam footage. Using spatiotemporal auto-encoder and sequenceto-sequence long short-term memory auto-encoder, a one-class classification strategy is used. Road accident localization and identification are made possible by the efficient modeling of temporal and spatial representations in the video data made possible by these components. To evaluate the method's qualitative and quantitative performance, real-world video traffic surveillance datasets are used to conduct a thorough execution and evaluation. Xie et al. (2019) present a Deep Graph Convolutional Network for incident-driven traffic speed prediction. The study's main goal is to increase traffic speed prediction accuracy by using data on urban traffic occurrences. A three-step incident-driven prediction paradigm is presented by the authors. They first provide a way to find important urban traffic events. Second, a deep learning approach is used in the building of a binary classifier to extract latent incident impact features. Lastly, for improved traffic speed prediction, the authors presented the Deep Incident-Aware Graph Convolutional Network (DIGC-Net), which successfully integrates urban traffic incident, spatiotemporal, periodic, and context information. Furthermore, Wang et al. (2021) also suggested using dynamic hypergraph convolution networks to precisely estimate metro passenger flow. Although Graph Convolutional Neural Networks (GCN) are extensively used for predicting traffic flow, they are not very good at capturing highorder correlations between stations and travel patterns of passengers. The dynamic spatio-temporal hypergraph neural network was developed in order to get around this restriction. The main hypergraph is built using the topology of the metro system and is enhanced with sophisticated hyper-edges that are obtained from pedestrian traffic patterns over a variety of time periods. Nodelevel prediction is then made possible by extracting spatial and temporal characteristics using hypergraph convolution and spatiotemporal blocks.

RESULTS

Table 1 (Appendix part) displays the findings of a thorough analysis and discussion of the research survey data. Statistical tools were used to further examine these data in order to provide more insight and better representations. The algorithms used, the challenged resolved, the outcome after the challenges were solved, benchmark algorithms used for validating the performance of the said algorithms, metrics adopted evaluate the performance of the said algorithms, and lingering limitations of the aforementioned algorithms are all highlighted in the table.

Algorithms adopted for the Prediction of anomalies on Spatiotemporal Data Traffic Flow

After exhaustive investigation conducted on novel literatures, it was discovered that Machine Learning and Convolution Neural Network algorithms, were majorly adopted for anomaly detection on spatiotemporal data traffic flow in Internet of Things ecosystem, as denoted in table 1. However, Convolution Neural Network (CNN) algorithms were mostly deployed on average 70% as compared to 50% Machine Learning algorithms, denoted in Figure 2.

An artificial intelligence (AI) system uses a set of mathematical procedures or methods called machine learning (ML) algorithms are methods used by artificial intelligence system to predicts output values from a given input data. These include using raw data that the algorithm has been trained on to extract significant insights, trends, and future events. On the other hand, CNN is regarded as deep learning algorithm that works especially well for tasks involving picture recognition and processing. Convolutional, pooling, and fully connected layers are some of the layers that make it up. CNN architecture is influenced by how the human brain processes images.

Figure 2. comparison of Algorithms for anomaly detection on Spatiotemporal data traffic Flow

Benchmark Algorithms adopted for Performance Validation

The algorithms adopted for the prediction of anomalies on spatiotemporal data traffic flow were validated to checkmate the genuineness by comparing their performance outcome to existing related algorithms. Investigation shows that classification, clustering and deep learning algorithms were majorly used as benchmark for the validation of the said algorithms, as captured in Table 1. However, classification algorithms were mostly deployed on average 55% as compared to that of clustering and deep learning as shown in figure 3.

Figure 3. Benchmark Algorithms

Clustering algorithms are unsupervised learning techniques, that do not have prior knowledge of any variable outcome, but instead seeks to extract insights from unlabeled data points. Examples of clustering algorithms as captured in table 1, include local factor (LOF), Support Vector Machine, Principle Component Analyses (PCA) etc. Classification is a supervised machine learning algorithm that attempts to predict the correct label of a given input set of data. Prior to being utilized to make predictions on raw dataset, unobserved data, it is thoroughly trained utilizing the training set and then assessed using test data. Examples of such algorithms as denoted in table 1, are the Random forest (RF), Knearest neighbor (KNN), Isolation forest (IF) etc.

Metrics Adopted for Performance Evaluation of the Algorithms

The performance of the proposed existing algorithms was evaluated using diverse metrics during experimentation and simulation operations. It was observed that Root Mean Squared Error (RMSE), Accuracy, Execution time, FI-Score, Receiver Operations Characteristics (ROC), Area Under Curve (AUC) and Mean Absolute Percentage Error (MAPE), were majorly adopted to evaluates the said algorithms as captured in table 1. However, RMSE was mostly used with an average of 22% as compared to other metrics. This can be verified as illustrated in figure 4.

Figure 4. Performance Metrics Adopted

MAPE measures the accuracy as a percentage, which is computed as the average absolute percent error for each time period with exclusion of actual values divisible by actual values.

ROC curve is a graph known that displays a classification model's performance across all categorization thresholds.

AUC measures the performance across all potential classification thresholds, by using the all-inclusive two-dimensional area beneath the entire ROC curve.

RMSE measures the average difference between the anticipated and actual values of a statistical model.

FI-score computes the accuracy of a binary classification algorithm, by integrating recall and precision values of the algorithm into a single metric.

Accuracy is the frequency with which a model or algorithm accurately predicts the result. It is computed by dividing the number of correct predictions by the total number of predictions.

Execution Time is the amount of time required for all computations, including data splitting, preprocessing, and model evaluation.

Limitations of the existing algorithms that leads to Future Researches

Even though the current models' performance has improved, as shown in Table 1, they are still susceptible to certain drawbacks that may guide future study. These problems include missing data, over-fitting, computational complexity and under-fitting. It was discovered that computational complexity is the most prevailing challenges with an average score of 40% as compared to other

challenges as illustrated in figure 5.

Figure 5. Limitations of the proposed algorithms

Overfitting occurs when a model tends to shield more data points than necessary or all of the data points in the dataset. Consequently, noise and incorrect values from the dataset are collected by the model, minimizing its accuracy and efficiency.

Under-fitting occurs when a model is unable to identify the underlying trend in the data. To avoid overfitting, which could lead to the model learning inefficiently from the training data, the training data stream can be terminated beforehand. As a result, it may not be able to assess how well the data matches the dominant pattern. **Computational Complexity** It tends to find the computational resources needed to address problems involving time, memory space, or communication as well as the potential and constraints of algorithmic efficiency.

Missing Data is when any of the observations in a dataset are missing, this is known as missing data or values. Furthermore, if an observation contains missing data for a variable, it is deemed odd. Therefore, any research that assumes the missing value fits nicely into the rest of the data is faulty.

Conclusion

In this study, the intelligent strategies for the anomaly prediction on spatiotemporal traffic data flow in metropolitan areas was conducted. The proposed techniques employed in the literature were identified and analyzed. In addition to examining the various benchmark algorithms adopted to validate the performance of the proposed techniques and the metrics used to evaluate the performance of the techniques. Highlighting the lingering challenges of the proposed techniques during predictive active state. Observations shows that convolution neural network algorithms were majorly applied in predicting anomalies on spatiotemporal data traffic flow, while classification algorithms were adopted mostly as benchmarking performance validation of the proposed techniques. Furthermore, root mean squared error was majorly adopted to evaluate the performance of the proposed techniques, coupled with computation complexity as the prevalent challenge that still needs to be addressed. Future work intends to implements a potential technique for detecting anomalies in spatiotemporal data traffic flow in the internet of things ecosystem.

REFERENCES

- Adigwe A.R., Abel Edje, Omede G., Atonuje O. E. Akazue M. I., Apanapudor J. S. (2024). Application of Algorithms for anomaly Detection in Health-enabled Sensor-Cloud Infrastructure, *FUDMA Journal of Sciences*, 8(3), pp. 283-296
- [Ali Hamdi,](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Ali-Hamdi-Aff1), [Khaled Shaban,](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Khaled-Shaban-Aff2) [Abdelkarim Erradi,](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Abdelkarim-Erradi-Aff2) [Amr Mohamed,](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Amr-Mohamed-Aff2)

[Shakila Khan Rumi,](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Shakila_Khan-Rumi-Aff1) [Flora D. Salim](https://link.springer.com/article/10.1007/s10462-021-09994-y#auth-Flora_D_-Salim-Aff1) (2022). Spatiotemporal data mining: a survey on challenges and open problems, *Artificial Intelligence Review (Springer),* 55, 1441-1488

- Ansari, M. Y., Ahmad, A., Khan, S. S., Bhushan, G., & Mainuddin. (2020). Spatiotemporal clustering: a review. Artificial Intelligence Review, 53(4), 2381–2423. https://doi.org/10.1007/s10462-019-09736-1
- Asadi, R., & Regan, A. (2019). Spatio-temporal clustering of traffic data with deep embedded clustering. In *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Prediction of Human Mobility* (pp. 45-52).
- Aslam, N., & Kolekar, M. H. (2022). Unsupervised anomalous event detection in videos using spatio-temporal interfused autoencoder. *Multimedia Tools and Applications*, *81*(29), 42457-42482.
- Boris Medina-Salgado, Eddy Sánchez-DelaCruz, Pilar Pozos-Parra, Javier E. Sierra (2022). Urban traffic flow prediction techniques: A review, *Sustainable Computing: Informatics and Systems (Elsevier),* 35, 2- 16
- Boukerche, A., & Wang, J. (2020). Machine Learning-based traffic prediction models for Intelligent Transportation Systems. Computer Networks, 181, 107530. https://doi.org/10.1016/j.comnet.2020.107530
- Chen, Z., Jiang, Y., & Sun, D. (2019). Discrimination and prediction of traffic congestion states of urban road network based on spatio-temporal correlation. *IEEE Access*, *8*, 3330- 3342.
- [Daniel Fährmann,](https://ieeexplore.ieee.org/author/37088646102) [Laura Martín,](https://ieeexplore.ieee.org/author/37090011230) [Luis Sánchez,](https://ieeexplore.ieee.org/author/37300583600) [Naser Damer](https://ieeexplore.ieee.org/author/38469012000) (2024). Anomaly Detection in Smart Environments: A Comprehensive Survey*, IEEE Access,* 12, 64006- 64049.
- Djenouri, Y., Belhadi, A., Lin, J. C. W., & Cano, A. (2019). Adapted k-nearest neighbors for detecting anomalies on spatio– temporal traffic flow. *IEEE Access*, *7*, 10015-10027.
- Dokuz, A. S. (2022). Social velocity based spatio-temporal anomalous daily activity discovery of social media users. *Applied Intelligence*, *52*(3), 2745-2762.
- Edje E., A., & Ekabua O., (2015). Funding E-Health in Nigeria by NGOS/Multinational Organization: Overview and Perspectives, *International Journal of Computer Applications*, 111(11), 37 – 41.
- Edje, E., A., & Ureigho, R., J., (2015). Information Systems: The Prospects of Bi-directional Counter System in the Hotel Industry, *Communications on Applied Electronics (CAE)*, 2(9), 36-41.
- Edje, E., A., (2015). An Overview and Perspective of Desktop Grid Middleware to Speed up Smul8 Process by Predicting Child Mortality Birth and Death Rate in West African Countries, *Communications on Applied Electronics (CAE)*, 2(3), 38-43.
- Hao, Y., Li, J., Wang, N., Wang, X., & Gao, X. (2022). Spatiotemporal consistency-enhanced network for video anomaly detection. Pattern Recognition, 121, 108232.

https://doi.org/10.1016/J.PATCOG.2021.108232

Kalair, K., & Connaughton, C. (2021). Anomaly detection and classification in traffic flow data from fluctuations in the flow–density relationship. Transportation Research Part C: Emerging Technologies, 127, 103178.

784

https://doi.org/10.1016/J.TRC.2021.103178

- Khan, N., al Hafiz Khan, M. A., & Roy, N. (2023). Unsupervised Spatio-Temporal Anomalous Thermal Behavior Monitoring of Inside-Built Environments. 2023 19th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT), 55–64. https://doi.org/10.1109/DCOSS-IoT58021.2023.00017
- Kong, X., Gao, H., Alfarraj, O., Ni, Q., Zheng, C., & Shen, G. (2020). Huad: Hierarchical urban anomaly detection based on spatio-temporal data. *IEEE Access*, *8*, 26573-26582.
- Li, J., Li, J., Jia, N., Li, X., Ma, W., & Shi, S. (2021). GeoTraPredict: a machine learning system of web spatio-temporal traffic flow. *Neurocomputing*, *428*, 317-324.
- Li, Y., Zhao, W., & Fan, H. (2022). A spatio-temporal graph neural network approach for traffic flow prediction. *Mathematics*, *10*(10), 1754.
- Liu, R., Zhao, S., Cheng, B., Yang, H., Tang, H., & Li, T. (2020). Deep spatio-temporal multiple domain fusion network for urban anomalies detection. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* (pp. 905-914).
- Liu, X., Zhang, Z., Lyu, L., Zhang, Z., Xiao, S., Shen, C., & Philip, S. Y. (2023). Traffic anomaly prediction based on joint static-dynamic spatio-temporal evolutionary learning. *IEEE Transactions on Knowledge and Data Engineering*, *35*(5), 5356-5370.
- Lu, Y., Kamranfar, P., Lattanzi, D., & Shehu, A. (2021). Traffic Flow Forecasting with Maintenance Downtime via Multi-Channel Attention-Based Spatio-Temporal Graph Convolutional Networks. *arXiv preprint arXiv:2110.01535*.
- Majumdar, S., Subhani, M. M., Roullier, B., Anjum, A., & Zhu, R. (2021). Congestion prediction for smart sustainable cities using IoT and machine learning approaches. *Sustainable Cities and Society*, *64*, 102500.
- Mrinai M. Dhanvijay, Shailaja C. Patil (2019). Internet of Things: A survey of enabling technologies in healthcare and its applications, *Computer Networks (Elsevier)*, 153, 113- 131
- Pawar, K., & Attar, V. (2022). Deep learning based detection and localization of road accidents from traffic surveillance videos. *ICT Express*, *8*(3), 379-387.
- Priyadharsini, N. K., & Chitra, D. (2021). A kernel support vector machine based anomaly detection using spatiotemporal motion pattern models in extremely crowded scenes. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 5225-5234.
- Rashmiranjan Nayak, Umesh Chandra Pati, Santos Kumar Das (2021). A comprehensive review on deep learningbased methods for video anomaly detection, *Image and Vision Computing (Elsevier),* 106, 78-104
- Shu, X., Bao, T., Zhou, Y., Xu, R., Li, Y., & Zhang, K. (2023). Unsupervised dam anomaly detection with spatial– temporal variational autoencoder. Structural Health Monitoring, 22(1), 39–55. https://doi.org/10.1177/14759217211073301
- Singh, D., & Mohan, C. K. (2018). Deep spatio-temporal representation for detection of road accidents using stacked autoencoder. *IEEE Transactions on Intelligent Transportation Systems*, *20*(3), 879-887.
- Swarnamugi, M., & Chinnaiyan, R. (2018). IoT Hybrid Computing Model for Intelligent Transportation System (ITS). 2018 Second International Conference on Computing Methodologies and Communication (ICCMC), 802–806. https://doi.org/10.1109/ICCMC.2018.8487843
- Tang, J., Li, L., Hu, Z., & Liu, F. (2019). Short-term traffic flow prediction considering spatio-temporal correlation: A hybrid model combing type-2 fuzzy C-means and artificial neural network. *IEEE Access*, *7*, 101009- 101018.
- Tukaram K. Gawali1, Shailesh S. Deore (2023). Survey on Spatio-Temporal Transportation Using Deep Convolution Network for Traffic Flow, *Journal of Data Acquisition and Processing*, 38(2), 10-20.
- Wang, J., Zhang, Y., Wei, Y., Hu, Y., Piao, X., & Yin, B. (2021). Metro passenger flow prediction via dynamic hypergraph convolution networks. *IEEE Transactions on Intelligent Transportation Systems*, *22*(12), 7891- 7903.
- Wang, Q., Lv, W., & Du, B. (2018, September). Spatio-temporal anomaly detection in traffic data. In *Proceedings of the 2nd International Symposium on Computer Science and Intelligent Control* (pp. 1-5).
- Xia, Y., Zhang, F., & Ou, J. (2020). Stap: A spatio-temporal correlative estimating model for improving quality of traffic data. *IEEE transactions on intelligent transportation systems*, *23*(3), 1746-1754.
- Xiao, Y., Yin, H., Zhang, Y., Qi, H., Zhang, Y., & Liu, Z. (2021). A dual‐stage attention‐based Conv‐LSTM network for spatio-temporal correlation and multivariate time series prediction. *International Journal of Intelligent Systems*, *36*(5), 2036-2057.
- Xie, Q., Guo, T., Chen, Y., Xiao, Y., Wang, X., & Zhao, B. Y. (2020). Deep graph convolutional networks for incident-driven traffic speed prediction. In *Proceedings of the 29th ACM international conference on information & knowledge management* (pp. 1665-1674).
- Xu, C., & Xie, Y. (2021). Conformal anomaly detection on spatiotemporal observations with missing data. *arXiv preprint arXiv:2105.11886*.
- Zhang, H., Zheng, Y., & Yu, Y. (2018). Detecting urban anomalies using multiple spatio-temporal data sources. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, *2*(1), 1- 18.
- Zhang, J., Zheng, Y., Qi, D., Li, R., Yi, X., & Li, T. (2018). Predicting citywide crowd flows using deep spatio-temporal residual networks. *Artificial Intelligence*, *259*, 147-166.
- Zhang, W., Yu, Y., Qi, Y., Shu, F., & Wang, Y. (2019). Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning. *Transportmetrica A: Transport Science*, *15*(2), 1688-1711.

APPENDICES

Table 1: Results of the research highlighting solutions to key research questions (RQ)

