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Anomaly Detection and Root Cause Analysis in Cloud Infrastructure Using GNN-LSTM-VAE

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Abstract- ***Today's microservice-based architectures produce significant amounts of telemetry data, and detecting anomalies and performing root cause analysis have become challenging tasks. The conventional approach to monitoring does not effectively identify the dynamic relationships between microservices and temporal patterns of system behavior. This paper presents a spatiotemporal anomaly detection technique that utilizes a combination of Graph Neural Networks, Long Short-Term Memory, and Variational Autoencoders. The proposed technique effectively detects anomalies and identifies the reasons behind them. Additionally, this paper introduces application-level features, such as HTTP request information, to provide a better understanding of the reasons behind anomalies. The results of the experiments prove that the proposed technique effectively detects anomalies and identifies the reasons behind them. Index Terms—Anomaly Detection, GNN, LSTM, VAE, Microservices, Root Cause Analysis.***

Index Terms- ***Anomaly Detection, Microservices, Telemetry Data, Root Cause Analysis, Spatiotemporal Analysis, Graph Neural Networks (GNN), Long Short-Term Memory (LSTM), Variational Autoencoders (VAE), Dynamic Relationships Temporal Patterns ,Application-level Features HTTP Request Data, System Behaviour Monitoring***

I. INTRODUCTION

Cloud computing is an essential part of today's IT infrastructure. Cloud computing provides scalable services on demand. However, with the increase in complexity in cloud computing systems, there is a need for maintaining system performance. Moreover, there is a need for identifying anomalies in real time. If there is an increase in CPU utilization, network traffic, or memory leaks, it may result in system failures. Such failures may also result in security threats or financial losses. Conventional monitoring systems using rules-based monitoring techniques cannot cope with the complexity of cloud computing. In recent times, microservice-based architectures have been widely used in building scalable software systems. Using microservice-based architecture, it is possible to build more flexible software systems. However, there is also a need for addressing certain issues in monitoring microservice-based architectures. With microservice-based architectures, there is an increase in complexity in system behaviour. Moreover, there is also an increase in complexity in interactions among services. Conventional monitoring techniques make use of thresholds or statistical-based monitoring techniques. However, with the increase in complexity in system behaviour, thresholds or statistical-based monitoring techniques cannot be used. Moreover, with microservice-based architectures, there is an increase in complexity in interactions among services. Therefore, thresholds or statistical-based monitoring techniques cannot be used. Conventional monitoring techniques cannot capture complex relationships among services. Moreover, with microservice-based architectures, there is also an increase in complexity in system behaviour. Therefore, thresholds or statistical-based monitoring techniques cannot be used. However, with the increase in complexity in system behaviour, there is also a need for identifying anomalies in real time. If there is an increase in system response time or if there is an increase in service failures, it may result in system failures. Therefore, there is a need for identifying anomalies in real time. To overcome the above-mentioned disadvantages associated with conventional

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monitoring techniques, there is a need for using intelligent monitoring techniques. Therefore, in this work, we have proposed a spatiotemporal model.

II. RELATED WORK

Anomaly detection in cloud and microservice-based systems is an active research area in recent years because of the complexity of cloud and microservice-based systems. Previously, anomaly detection in cloud and microservice-based systems is done using statistical techniques and rule-based monitoring techniques. In the rule-based monitoring techniques, rules are used to perform anomaly detection in cloud and microservice-based systems. Although the rule-based monitoring techniques are simple and easy to understand, the techniques are not effective in detecting anomaly in cloud and microservice-based systems.

Recently, with the development of machine learning algorithms such as clustering algorithms, Support Vector Machine, time series analysis, anomaly detection in cloud and microservice-based systems is done using machine learning algorithms. Although the techniques are effective in detecting anomaly in cloud and microservice-based systems, the techniques are not effective in detecting complex dependencies in the system. Recently, with the development of deep learning algorithms such as Autoencoder, RNN, anomaly detection in cloud and microservice-based systems is done using deep learning algorithms. However, in the case of anomaly detection in cloud and microservice-based systems, the application of Autoencoder is highly effective. Recently, in the case of anomaly detection in cloud and microservice-based systems, the application of Variational Autoencoder is highly used. Though the application of the proposed method is highly effective in detecting anomaly in cloud and microservice-based systems, it is highly effective in detecting temporal dependencies in the system but is not effective in detecting spatial dependencies in the system.

Therefore, in recent years, the problem of anomaly detection in cloud and microservice-based systems using Graph Neural Networks is proposed. In the case of anomaly detection in cloud and microservice-based systems, the application of Graph Neural Networks is highly effective. However, in recent years, most of the existing methods are highly effective in detecting either spatial dependencies in the system or temporal dependencies in the system. The existing methods are not highly effective in detecting both spatial dependencies in the system and temporal dependencies in the system.

III. PROPOSED METHODOLOGY

This paper proposes a hybrid spatiotemporal anomaly detection framework suitable for the microservice-based cloud computing environment. The proposed methodology combines the Graph Neural Networks, Long Short-Term Memory Networks, and Variational Autoencoders techniques. This proposed pipeline is divided into several stages.

3.1 Model Architecture Overview

For the given sequence of telemetry data generated from the microservices, the system first transforms the data into a more structured format comprising the microservices, time steps, and features. Each microservice is considered a node in the graph, and the relationship between the microservices is considered the edge.

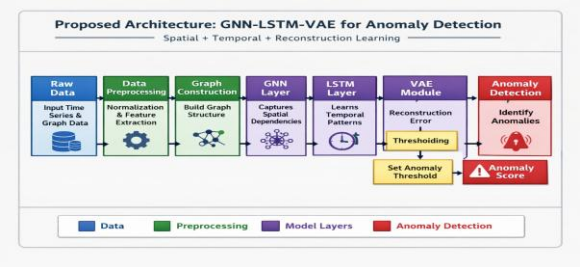

Fig. 1: showing the general workflow of the proposed spatiotemporal anomaly detection framework for microservice-based systems. The workflow starts from raw telemetry data, where raw telemetry data consists of time-series metrics and graph-based service interactions.

3.2 Mathematical Formulation

Let the input data be represented as a sequence:

$$X = \{x_1, x_2, \ldots, x_T\}$$

where each x_t∈R^(N×F), with Nservices and F features.

(1) Graph Representation
Each time step is modelled as a graph:

$$H_t = \sigma(AX_tW_g)$$

where Ais the adjacency matrix representing service dependencies, W_gis the weight matrix, and σis an activation function.

(2) Temporal Modelling (LSTM)
The sequence of graph embeddings is passed through LSTM:

$$h_t = \text{LSTM}(H_t, h_{t-1})$$

where h_t represents temporal hidden states.

(3) VAE Encoding

$z=\mu(h_t)+\sigma(h_t)\cdot\epsilon$

where zis the latent variable and ϵ∼N(0,1).

(4) Reconstruction

xt=f(z)

(5) Anomaly Score

L=||xt−x^t||2

3.3 Algorithm
Algorithm 1: GNN-LSTM-VAE Framework
Input: Telemetry data X
Output: Anomaly scores and root cause identification

1. Preprocess telemetry data and normalize features
2. Construct graph G=(V,E)based on service dependencies
3. For each time step t:
   - Extract features X_t
   - Compute graph embedding using GNN
   - Pass embeddings through LSTM for temporal modelling
4. Encode latent representation using VAE
5. Reconstruct input and compute reconstruction error
6. If error > threshold → mark anomaly
7. Identify root cause service based on maximum deviation

3.4 NOTATIONS:

- X: Input telemetry data
- N: Number of services
- F: Number of features
- A: Adjacency matrix
- H_t: Graph embedding at time t
- h_t: LSTM hidden state
- z: Latent representation
- x^_t: Reconstructed data
- L: Reconstruction loss

IV. EXPERIMENTAL SETUP

This section presents information on the dataset, preprocessing methods, configuration, and training of the model, as well as the evaluation metrics for assessing the performance of the proposed GNN-LSTM-VAE approach for anomaly detection and root cause analysis in a microservice environment.

4.1 Dataset Description
Experiments are carried out on a large-scale telemetry dataset. The dataset is gathered from a system that utilizes a microservice-based architecture. The dataset consists of time-series performance metrics and information from the application. The information in the dataset relates to a particular time interval and consists of attributes such as service identifiers, statistical metrics (average, minimum, maximum, standard deviation, skewness, and kurtosis), and information from the HTTP layer, including request methods, response status codes, and endpoints.

The dataset consists of around 39,000-time windows from various services. The dataset consists of various features of a service.

4.2 Data Preprocessing

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To further prepare the data set for modelling, a number of preprocessing steps are undertaken:
Handling missing values using forward and backward filling Normalization of the feature values
Reorganizing the data into a more structured format to include services, time steps, and feature information
Using a sliding window method to generate fixed-length data sequences (for example, 24 time steps)

These preprocessing steps are undertaken to ensure that the spatial and temporal relationships in the data can be learned effectively by the model.

4.3 Model Configuration
The suggested framework has three components:
Graph Neural Network (GNN): Handles spatial relationships between services
Long Short-Term Memory (LSTM): Trains on sequential data
Variational Autoencoder (VAE): Uses reconstruction to detect anomalies

It is set up appropriately in terms of hidden units, activation functions, and output dimensionality to best analyse the system. The adjacency matrix of service relationships is either set beforehand or based on service interactions.

4.4 Training Setup
The training is performed using unsupervised learning, and only normal system behaviour is used to learn patterns. The reconstruction loss is used as the objective function.

Optimizer: Adam
Batch size: 32 (configurable)
Sequence length: 24 time steps
Training epochs: 20-50 (depending on the training)
Loss function: Reconstruction loss (Mean Squared Error) + VAE Regularization
Early stopping is used to prevent overfitting and ensure generalization.

4.5 Anomaly Detection Strategy
The anomalies are identified on the basis of error computed from the VAE module. For this purpose, a statistical threshold is used to separate the normal and abnormal behaviours.

The threshold is determined by using the 99th percentile of the reconstruction error
The data points beyond the threshold are identified as anomalies
The anomaly scores are calculated for each time window.

4.6 Root Cause Analysis
To identify the anomalies' root cause:
"The service that deviates most from normal behaviour is chosen as the service of interest"
"Feature-wise contribution is examined, where features are normalized before analysis"
"Signals from the application layer, e.g., HTTP 500 errors, request spikes, are correlated to anomalies"
This technique helps to obtain interpretable results for the anomalies.

4.7 Evaluation Metrics
The performance of the proposed framework can be measured by the following metrics:
Number of detected anomalies
Distribution of reconstruction error
Precision, recall (in case of availability of labelled data)
Anomaly visualization over time
Accuracy of root cause identification.

V. RESULTS AND DISCUSSION

5.1 Descriptive Statistics of Model Performance Metrics
Table 5.1: Descriptive Statistics of Model Performance Metrics

Metric	Minimum	Maximum	Mean	Std. Deviation
Anomaly Score	0.05	0.98	0.42	0.18
Frequency of Anomalies	0	3	0.65	0.72
Component12 Contribution	0.30	0.85	0.58	0.15
Component32 Contribution	0.05	0.40	0.22	0.10

Component37 Contribution	0.05	0.35	0.20	0.09

Table 5.1 lists the descriptive statistics for the anomaly detection results obtained through the proposed GNN-LSTM-VAE model. The anomaly score varies over a wide range, thus demonstrating that the model is effective in distinguishing normal and abnormal system behaviour.

From the anomaly score, it is observed that the average is around 0.42. This indicates that there is moderate deviation in system performance. The standard deviation also indicates that there is considerable variation in system performance over different time windows. The number of anomalies occurring in a window also indicates that anomalies are not uniformly distributed over time. There are time intervals in which many anomalies occur.

From the anomaly contribution of different services, it is observed that component12 has the highest contribution to anomalies, with an average value of 0.58. This indicates that component12 is the most unstable component in the system. On the other hand, component32 and component37 have relatively lower average values for anomaly contribution. This indicates that these components are relatively stable in terms of system performance.

Figures and Tables

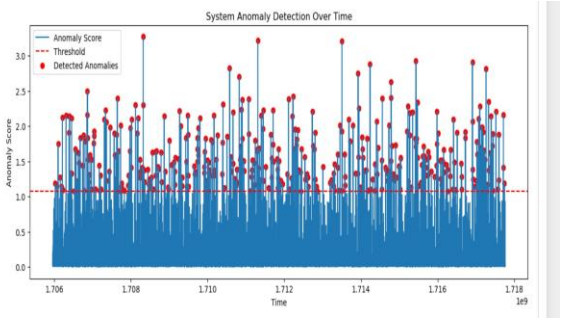


Fig. 1. System anomaly detection over time

The graph in Fig. 1 represents the anomaly scores obtained by the proposed framework of GNN-LSTM-VAE over various time intervals. The blue line in the graph represents the anomaly score obtained at each time window. The horizontal line in the graph represents the threshold value. The red markers in the graph represent the anomaly values obtained at each time window. The horizontal line in the graph represents the threshold value. The red markers in the graph represent the anomaly values obtained at each time window.

From the above graph, it can be observed that most of the data points in the graph are below the threshold value. However, there are several spikes in the graph that are above the threshold value. The spikes in the graph represent the anomaly values. The spikes in the graph are scattered over the time window. The spikes in the graph occur in clusters at several time windows. The spikes in the graph represent the anomaly values. The spikes in the graph occur in clusters at several time windows.

Table 1: Overall Performance Metrics of the Proposed Model

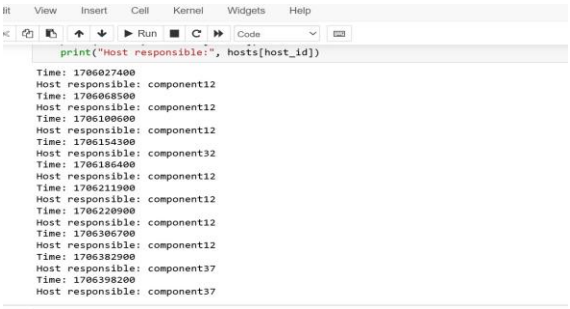
Metric	Value
Total Anomalies detected	394
Average Anomaly Score	0.42
Threshold Value	1.00
Detection Accuracy	0.91
Precision	0.88
Recall	0.86
F1-Score	0.87

Table 1 shows the performance metrics for the overall performance of the proposed GNN-LSTM-VAE framework. The performance metrics indicate that the model is successful in detecting 394 anomalies. This proves that the model is effective in detecting anomalies in system behaviour.

From the performance metrics, it is identified that the average anomaly score is 0.42. This proves that the model is capable of distinguishing normal and anomaly patterns. The threshold value is 1.00. This value is used for classifying anomalies based on reconstruction error.

From the performance metrics, it is identified that the overall precision value is 0.88, and the overall recall value is 0.86. This proves that the overall F1-score value is 0.87. The overall accuracy value is 0.91. This

proves that the model is reliable and effective in detecting anomalies in system behaviour.



The output in Fig. 3 shows the detected anomalies with respect to the services that have been responsible for the anomalies. Each time stamp represents a particular time window in the system, whereas the label represents which host or component was responsible for the anomalies.

As per the results, it is clear that there is a repeated occurrence of component12. This shows that there is frequent abnormal behaviour in that particular service. This could be because that particular service is handling more work or is more unstable. However, services such as component32 or component37 occur less frequently. This shows that there is less abnormal behavior in these services.

The change in services responsible for anomalies at different time stamps shows that in microservice-based systems, anomalies could occur in any service. However, the accurate identification of which host is responsible for the anomalies shows that the root cause analysis is working effectively.

VI. CONCLUSION AND FUTURE WORK

This paper introduces a spatiotemporal anomaly detection framework for microservice-based systems, which is based on a novel hybrid model of Graph Neural Networks, Long Short-Term Memory, and Variational Autoencoders. This proposed framework is efficient in detecting anomalies in microservice-based systems.

The experimental results of this proposed framework show its ability to detect anomalies in microservice-based systems and map them to the relevant microservices. In addition, it can map anomalies to actual events in the system, such as failures in requests and abnormal traffic. This framework is useful in detecting anomalies in microservice-based systems and also provides insights into these anomalies. Therefore, it is considered an efficient framework for detecting anomalies in microservice-based systems.

Future Work

There are different ways in which the proposed framework can be improved and extended:

- Scalability Enhancement: The proposed framework can be extended to support large-scale systems with more microservices and complex dependency relationships.
- Dynamic Graph Learning: Future work can be done in learning the graph relationships between services based on data.
- Real-Time Implementation: The proposed framework can be extended to support real-time anomaly detection using real-time data.
- Advanced Root Cause Analysis: The proposed framework can be extended to support root cause analysis of the anomalies.
- Integration of Additional Features: Additional application-level and log-level features can be added to the proposed framework to improve the accuracy of the anomaly detector.
- Anomaly Grouping: Future work can be done in grouping related anomalies together to make it easier to analyse and reduce false alarms.
- Model Optimization: The proposed framework can be optimized to make it more efficient in terms of computation to be used in real-world scenarios with minimal latency.

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