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Adaptive WAN Link Anomaly Detection Using Lightweight Packet-Level Features for Branch-to-HQ Network Stability

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Abstract

Maintaining stable Wide Area Network (WAN) connectivity between branch offices and centralized headquarters infrastructure is essential for the reliable operation of modern enterprise systems. However, WAN links frequently experience performance degradation caused by congestion, routing instability, and intermittent packet loss, which can significantly disrupt enterprise services such as cloud applications, real-time communications, and data synchronization. This study proposes a lightweight anomaly detection framework designed to monitor branch-to-headquarters WAN links using packet-level telemetry features. The framework utilizes compact statistical indicators derived from packet transmission behaviour, including packet loss ratio, latency deviation, and jitter variance, to characterize network performance conditions. An adaptive anomaly detection model is implemented using a dynamic threshold formulation that adjusts detection boundaries based on the moving average and statistical variance of observed network metrics. The proposed model enables real-time identification of network anomalies while maintaining low computational overhead suitable for deployment on resource-constrained branch routers. Experimental evaluation was conducted using simulated WAN environments representing stable traffic conditions, congestion-induced anomalies, and intermittent packet loss events. The results demonstrate that the lightweight monitoring framework achieves high detection accuracy while maintaining low false-positive rates and reduced detection latency compared with conventional monitoring approaches. The findings indicate that combining packet-level feature engineering with adaptive statistical detection provides an effective and scalable solution for improving WAN stability monitoring in distributed enterprise networks.

Keywords: *Adaptive Anomaly Detection, WAN Monitoring, Packet-Level Telemetry, Network Stability Analysis, Enterprise Network Performance Monitoring.*

I. INTRODUCTION

➢ *Background and Motivation*

Enterprise information systems are increasingly organized around geographically distributed architectures in which branch offices communicate with centralized headquarters infrastructure through Wide Area Network (WAN) links. These networks enable organizations to consolidate computing resources, support cloud-based services, and coordinate enterprise applications across multiple locations. As organizations adopt digital transformation strategies, WAN connectivity becomes a critical component of operational continuity because business systems such as enterprise resource planning (ERP), customer relationship management (CRM), and collaborative platforms rely heavily on stable and reliable network communication between branch sites and centralized data centers (Cisco, 2022; Kreutz et al., 2015). Consequently, the performance and reliability of WAN links have become essential determinants of enterprise productivity and service delivery.

Despite improvements in network infrastructure technologies, WAN environments frequently experience

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instability caused by factors such as congestion, routing fluctuations, bandwidth contention, and unpredictable traffic bursts. These issues often manifest as latency spikes, packet loss, jitter fluctuations, and throughput degradation, which can significantly affect the quality of enterprise services operating across distributed networks (Feamster & Rexford, 2017; Jain & Paul, 2013). Real-time applications such as Voice over Internet Protocol (VoIP), video conferencing, and cloud-hosted business applications are particularly sensitive to these performance disruptions because even small variations in packet delivery timing can lead to noticeable service degradation or transaction failures (Mao, Bushmitch, & Narayanan, 2018). As a result, maintaining stable WAN connectivity between branch offices and headquarters has become a major priority for network administrators and enterprise IT departments.

Traditional network monitoring frameworks typically rely on flow-level telemetry, deep packet inspection (DPI), or large-scale traffic analytics to identify abnormal traffic behaviour and diagnose network faults. Technologies such as NetFlow, IPFIX, and deep packet analysis provide detailed insights into network activity but often require significant processing power and storage resources to analyse high-volume network traffic streams (Claise, 2013; Nguyen & Armitage, 2008). These approaches can become computationally expensive when deployed in branch environments where routers, gateways, or edge devices have limited hardware capabilities. The overhead associated with continuous packet inspection and traffic aggregation can therefore introduce additional latency and reduce the operational efficiency of branch network infrastructure (Barford et al., 2010; Ringberg et al., 2007).

Furthermore, modern enterprise networks are increasingly characterized by hybrid architectures that integrate cloud platforms, software-defined networking (SDN), and software-defined WAN (SD-WAN) technologies. While these architectures provide enhanced flexibility and centralized management capabilities, they also generate large volumes of telemetry data that require efficient processing mechanisms for effective anomaly detection (Nunes et al., 2014; Kreutz et al., 2015). In many cases, centralized monitoring systems detect anomalies only after performance degradation has already affected end users. This delayed response highlights the need for lightweight and adaptive monitoring approaches capable of identifying WAN anomalies at earlier stages of network degradation.

Recent research has therefore emphasized the importance of lightweight packet-level feature analysis for detecting network anomalies without relying on computationally intensive inspection techniques. Packet-level metrics such as inter-arrival time variation, packet size distribution, retransmission frequency, and delay fluctuations can provide meaningful indicators of network performance anomalies while requiring significantly lower processing overhead than full traffic inspection methods (Bhuyan, Bhattacharyya, & Kalita, 2014; Lazarevic et al., 2003). By focusing on compact feature sets derived directly from packet transmission characteristics, anomaly detection systems can operate efficiently on branch routers or edge devices while still providing timely insights into WAN link stability. Data-driven decision support systems have become increasingly important in enhancing manufacturing productivity by optimizing decision-making processes and improving operational efficiency. Jalloh and Bamigwojo (2023) demonstrated the impact of such systems in their study, focusing on advanced analytics that enable better decision-making through real-time data insights.

In this context, developing adaptive anomaly detection mechanisms that utilize lightweight packet-level features offers a promising direction for improving enterprise WAN monitoring. Such approaches aim to detect abnormal network behaviour in real time while minimizing computational overhead on branch infrastructure. By enabling earlier detection of performance degradation, lightweight monitoring frameworks can support proactive network management and help maintain stable communication between branch offices and headquarters systems.

- *Research Problem*

Modern enterprise networks depend heavily on continuous monitoring mechanisms to ensure reliable connectivity across geographically distributed infrastructure. Detecting anomalies in Wide Area Network (WAN) links is particularly important because disruptions such as congestion, packet loss, routing instability, and bandwidth contention can significantly degrade service quality across enterprise systems. However, many existing anomaly detection frameworks rely on complex traffic analysis techniques that require intensive computational resources and extensive data processing capabilities. Approaches such as deep packet inspection (DPI), flow-level telemetry, and full traffic reconstruction typically analyse large volumes of packet payloads and traffic metadata to identify abnormal patterns, which can introduce substantial computational overhead in operational networks (Barford et al., 2010; Bhuyan et al., 2014). While these methods provide detailed visibility into network behaviour, their reliance on heavy processing makes them difficult to deploy on resource-limited edge infrastructure such as branch routers and gateway devices.

Another challenge arises from the increasing complexity of enterprise network environments, which integrate cloud services, software-defined networking architectures, and distributed application platforms. These environments generate massive amounts of network telemetry data, including packet-level statistics, routing updates, and flow-level metrics, that must be processed in real time for effective anomaly detection. High-dimensional telemetry analysis methods often rely on machine learning or statistical modelling techniques that require large feature sets and continuous data aggregation. Although such models can achieve high detection accuracy, they impose significant storage, computation, and bandwidth requirements that may not be feasible for

branch-level network devices operating with limited hardware capacity (Nguyen & Armitage, 2008; Ringberg et al., 2007). As a result, anomaly detection systems frequently rely on centralized analytics platforms that analyse data collected from distributed sites, which may delay detection and reduce the responsiveness of network monitoring systems.

Furthermore, deep packet inspection approaches face additional limitations related to scalability, privacy concerns, and encrypted traffic environments. As enterprise applications increasingly rely on encrypted communication protocols, payload-level inspection becomes less effective for anomaly detection because critical traffic information is inaccessible to monitoring systems. This limitation has prompted researchers to explore alternative approaches that rely on traffic metadata or statistical features derived from packet transmission behaviour rather than payload inspection (Feamster & Rexford, 2017; Nunes et al., 2014). However, many existing solutions still rely on large feature sets that introduce computational complexity and reduce their suitability for lightweight deployment at network edges.

These challenges highlight a significant gap in current research on WAN anomaly detection. Specifically, there is a need for detection mechanisms that can operate efficiently on resource-constrained devices while still providing accurate and timely identification of network instability events. Lightweight packet-level feature models offer a promising alternative because they focus on compact statistical indicators of network behaviour, such as packet inter-arrival times, delay variations, retransmission rates, and packet size distributions. These features can capture meaningful indicators of network performance degradation while requiring substantially lower processing overhead than traditional inspection methods (Lakhina et al., 2004; Lazarevic et al., 2003). By leveraging such lightweight telemetry, anomaly detection systems can operate closer to the network edge and detect abnormal conditions in near real time without overwhelming branch infrastructure.

Despite the potential advantages of lightweight monitoring strategies, existing research has not fully explored adaptive detection frameworks designed specifically for branch-to-headquarters WAN environments. Many anomaly detection studies focus on large backbone networks or data center traffic, where computational resources are more abundant. In contrast, enterprise branch networks require monitoring solutions that balance detection accuracy with strict resource constraints. Addressing this gap requires the development of models that utilize minimal packet-level features while maintaining sufficient sensitivity to detect link anomalies affecting enterprise service performance. Therefore, the core research problem addressed in this study is the design of an adaptive anomaly detection framework that uses lightweight packet-level features to identify WAN link instability in real time while minimizing processing overhead on branch network devices.

- *Research Objectives*

Given the increasing dependence of enterprise operations on distributed network infrastructures, improving the reliability of Wide Area Network (WAN) links between branch offices and headquarters has become an important research priority. Network instability can significantly affect enterprise applications, particularly real-time and cloud-based services that rely on consistent packet delivery performance. To address these challenges, anomaly detection mechanisms must be capable of identifying early indicators of network degradation while operating efficiently within the computational constraints of edge devices and branch routers. Recent studies emphasize that lightweight monitoring strategies based on packet-level telemetry can provide meaningful insights into network performance without imposing the heavy computational costs associated with deep packet inspection or large-scale traffic analysis (Bhuyan et al., 2014; Lakhina et al., 2004).

The primary objective of this study is to develop an adaptive anomaly detection framework that leverages lightweight packet-level features to monitor WAN link performance between branch networks and headquarters infrastructure. The framework aims to utilize compact statistical indicators derived from packet transmission behaviour, such as delay variation, packet loss rate, and inter-arrival time fluctuations, to identify abnormal network conditions. These features have been widely recognized as effective indicators of network instability because they capture variations in transmission behaviour that often precede significant service degradation (Barford et al., 2010; Nguyen & Armitage, 2008). By focusing on a limited set of computationally efficient metrics, the proposed framework seeks to provide practical monitoring capabilities for enterprise edge environments where processing resources are limited.

Another objective of this research is to evaluate the effectiveness of the proposed detection model in identifying key network performance anomalies, including latency spikes, packet loss events, and jitter fluctuations. These performance indicators are critical metrics for assessing WAN quality because they directly influence the reliability of communication between distributed enterprise systems. Previous studies have shown that abnormal patterns in these metrics often signal congestion, routing instability, or infrastructure failures within wide-area network environments (Ringberg et al., 2007; Feamster & Rexford, 2017). By analysing the behaviour of these indicators within packet-level telemetry data, the proposed framework aims to provide early detection of network anomalies that may otherwise propagate through enterprise systems and disrupt service delivery.

A further objective of the study is to improve the stability monitoring of branch-to-headquarters network connections while maintaining minimal computational overhead on monitoring devices. In many enterprise environments, branch routers and gateway

systems operate with constrained hardware capabilities, making it impractical to deploy resource-intensive monitoring frameworks. Lightweight anomaly detection mechanisms therefore provide an important alternative by enabling real-time monitoring at the network edge without overwhelming processing resources (Lazarevic et al., 2003; Nunes et al., 2014). By combining adaptive threshold modelling with lightweight packet-level features, this research aims to create a monitoring framework that balances detection accuracy with operational efficiency, thereby supporting more resilient enterprise WAN infrastructures.

- *Mathematical Representation of WAN Stability*

To quantitatively evaluate the stability of WAN links connecting branch offices to headquarters infrastructure, network performance can be modelled as a function of key packet transmission quality indicators. Metrics such as latency variation, jitter variance, and packet loss ratio represent fundamental characteristics of network behaviour that influence the reliability of data transmission across distributed systems. Modelling these parameters within a unified stability index provides a systematic approach for monitoring WAN performance and identifying abnormal network conditions (Tanenbaum & Wetherall, 2011; Jain & Paul, 2013).

The overall stability of a WAN link can therefore be expressed as:

$$S = 1 - (\alpha L + \beta J + \gamma P)$$

Where:

S = WAN stability index
L = normalized latency variation
J = jitter variance
P = packet loss ratio
α, β, γ = weighting coefficients representing the relative impact of each parameter

This formulation assumes that increases in latency variation, jitter, or packet loss negatively affect network stability. The weighting coefficients allow the model to adjust the relative contribution of each factor depending on the operational characteristics of the network environment. For example, latency variation may have a greater impact on real-time communication services, while packet loss may be more critical for data synchronization processes. Consequently, higher values of the stability index S indicate stronger network performance and more reliable branch-to-headquarters connectivity, while lower values suggest potential anomalies or degraded link conditions.

By integrating this stability model with packet-level telemetry data, anomaly detection systems can evaluate network health continuously and identify deviations from expected performance patterns. Such mathematical representations also facilitate automated monitoring algorithms capable of adapting detection thresholds in response to evolving traffic conditions within enterprise WAN infrastructures (Kreutz et al., 2015).

Figure 1 illustrates the operational architecture of the proposed adaptive WAN anomaly detection framework designed for enterprise branch-to-headquarters network environments. Branch offices are equipped with monitoring modules that capture packet-level telemetry such as latency, packet loss, and jitter from local network devices. These monitoring nodes transmit extracted telemetry data through the WAN transmission path toward a centralized headquarters infrastructure. At the headquarters, an anomaly detection engine aggregates incoming telemetry streams and applies adaptive thresholding and classification mechanisms to identify abnormal network behavior. When anomalies such as congestion, packet loss spikes, or latency surges are detected, the system generates alerts and visualizes them through real-time monitoring dashboards and reporting interfaces.

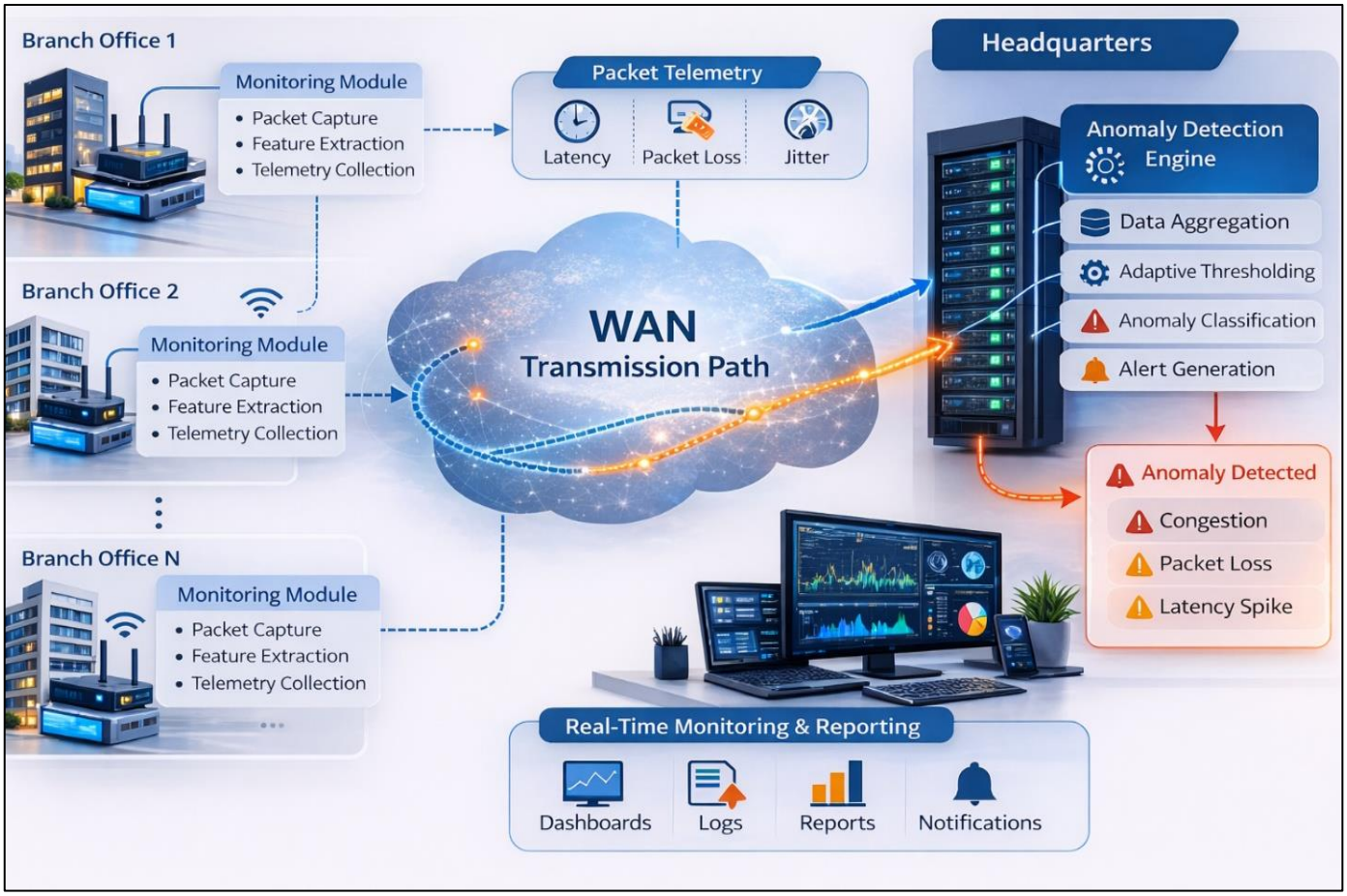

Fig 1 Architecture of the Adaptive WAN Link Anomaly Detection Framework for Branch-to-HQ Networks

II. LITERATURE REVIEW

➢ *WAN Monitoring Techniques*

Wide Area Network (WAN) monitoring has long been a critical component of enterprise network management, enabling administrators to track network health, detect faults, and ensure reliable communication between distributed infrastructure components. As enterprise networks expand across multiple geographical locations and increasingly integrate cloud services, the need for effective WAN monitoring frameworks has intensified. Traditional monitoring techniques have focused on collecting performance indicators such as bandwidth utilization, packet loss, delay, and device health metrics. Among the most widely used approaches are Simple Network Management Protocol (SNMP)–based monitoring, flow-based telemetry systems such as NetFlow and IPFIX, and software-defined WAN (SD-WAN) performance analytics platforms. Each of these approaches provides valuable insights into network performance, although they differ significantly in terms of data granularity, scalability, and computational requirements (Azzedin & Maheswaran, 2004; Kreutz et al., 2015).

SNMP-based monitoring represents one of the earliest and most widely deployed mechanisms for network performance management. SNMP operates by enabling centralized monitoring systems to periodically query network devices for operational statistics, including interface utilization, error counters, and device status indicators (Sanmori, 2024). Because SNMP polling relies on predefined Management Information Base (MIB) objects, it allows administrators to obtain standardized measurements across heterogeneous network environments (Case et al., 1990). This approach is particularly useful for detecting device failures or major performance degradations in large-scale enterprise networks. However, SNMP monitoring typically operates at relatively coarse time intervals and provides aggregated performance statistics rather than packet-level telemetry. As a result, it often lacks the granularity required to identify short-lived network anomalies such as transient congestion events, jitter spikes, or intermittent packet loss patterns that may affect application performance (Feamster & Rexford, 2017).

Flow-based monitoring technologies such as NetFlow and Internet Protocol Flow Information Export (IPFIX) have emerged as more detailed alternatives to SNMP monitoring. These frameworks capture metadata describing traffic flows, including source and destination addresses, protocol types, port numbers, and flow duration statistics. By aggregating packets into flows, NetFlow and IPFIX allow network administrators to analyse traffic patterns and identify abnormal communication behaviour across large networks (Claise, 2013). Flow-level telemetry has proven particularly valuable for traffic engineering, capacity planning, and network security monitoring. However, because flow records are typically generated after traffic flows have completed, the detection of anomalies may occur after network disruptions have already affected system performance. Additionally, flow aggregation reduces

visibility into individual packet dynamics, which limits the ability of these systems to detect micro-level anomalies such as jitter fluctuations or burst packet loss events (Nguyen & Armitage, 2008).

More recently, software-defined WAN (SD-WAN) architectures have introduced advanced monitoring capabilities by integrating centralized control planes with distributed data-plane devices. SD-WAN systems collect real-time telemetry data from edge routers and use centralized analytics platforms to monitor link quality, application performance, and routing behaviour across enterprise networks. These platforms often incorporate machine learning algorithms and predictive analytics tools to identify performance anomalies and optimize traffic routing decisions (Kreutz et al., 2015; Jain & Paul, 2013). SD-WAN monitoring frameworks therefore provide more dynamic visibility into network behaviour compared with traditional monitoring techniques. Nevertheless, these systems still rely on large volumes of telemetry data and centralized processing infrastructures, which may introduce latency in anomaly detection and impose additional computational requirements on monitoring systems.

Despite their widespread adoption, traditional WAN monitoring approaches exhibit several limitations when applied to fine-grained anomaly detection. SNMP-based monitoring provides only coarse performance summaries and cannot capture rapid fluctuations in packet-level behaviour. Flow-based monitoring improves visibility but sacrifices detailed packet timing information due to flow aggregation mechanisms. Similarly, SD-WAN analytics platforms rely heavily on centralized processing architectures that may delay the detection of transient anomalies occurring at network edges (Ringberg et al., 2007). These limitations highlight the need for alternative monitoring approaches capable of capturing lightweight packet-level telemetry while maintaining efficient computational performance. Such approaches are particularly important in branch network environments, where monitoring systems must operate on resource-constrained edge devices while still providing accurate and timely detection of WAN instability events. Recent research in secure system architectures demonstrates that integrating structured authentication mechanisms with verifiable logging and adaptive control frameworks enhances system resilience and operational reliability. For instance, secure system designs that combine cryptographic validation with structured access control and audit traceability have shown improved resistance to unauthorized access and system anomalies in distributed environments (Akpara et al., 2023). These findings reinforce the importance of integrating security-aware design principles into anomaly detection and monitoring frameworks.

- *Machine Learning in Network Anomaly Detection*

Machine learning has become a central component of modern network anomaly detection systems due to its ability to identify hidden patterns in large volumes of traffic data. Traditional rule-based monitoring techniques often rely on predefined thresholds or signature-based detection mechanisms, which may fail to detect previously unseen network anomalies. Machine learning approaches address this limitation by enabling models to learn behavioural patterns from historical traffic data and identify deviations that may indicate abnormal network conditions. These techniques have been widely applied in network management, intrusion detection systems, and traffic analytics to detect anomalies such as traffic spikes, denial-of-service attacks, routing failures, and packet transmission irregularities (Bhuyan et al., 2014; Chandola et al., 2009).

One widely used category of machine learning techniques for anomaly detection is statistical anomaly detection models. These models analyse traffic metrics such as packet inter-arrival times, traffic volumes, and latency variations to identify deviations from expected statistical distributions. Statistical methods often rely on probabilistic models or time-series analysis to capture normal network behaviour and detect anomalies when traffic measurements deviate significantly from learned baselines. Approaches such as Gaussian modelling, Principal Component Analysis (PCA), and autoregressive models have been applied to network monitoring because they provide mathematically interpretable frameworks for detecting abnormal patterns (Lakhina et al., 2004). Although statistical models are computationally efficient compared with complex deep learning architectures, their performance may be limited when network behaviour becomes highly dynamic or when anomalies occur across multiple correlated traffic features.

Another important group of anomaly detection techniques involves supervised and unsupervised machine learning methods. Supervised learning models, including decision trees, support vector machines (SVM), and neural networks, are trained using labelled datasets that distinguish between normal and anomalous traffic patterns. These models often achieve high detection accuracy when high-quality labelled datasets are available (Sommer & Paxson, 2010). However, obtaining labelled network traffic datasets can be challenging in operational environments because anomalies may occur rarely or may not be clearly identifiable during data collection. As a result, unsupervised learning techniques have gained popularity for network anomaly detection. Unsupervised methods, such as clustering algorithms, autoencoders, and density-based detection models, identify anomalies by detecting observations that deviate significantly from the structure of normal traffic data without requiring labelled training examples (Ahmed et al., 2016). These methods are particularly useful in large-scale enterprise networks where new and previously unknown anomalies may emerge.

Recent advancements in network monitoring research have also explored online and streaming analytics approaches for anomaly detection. Unlike traditional offline learning methods that rely on static datasets, streaming analytics models continuously process incoming traffic data and update detection models in real

time (Usoro, & Amunigun, 2024). Techniques such as incremental learning algorithms and streaming clustering methods allow anomaly detection systems to adapt to evolving network conditions while maintaining continuous monitoring capabilities (Patcha & Park, 2007). Streaming analytics frameworks are particularly valuable in modern enterprise environments where network traffic patterns change rapidly due to cloud services, remote access, and dynamic routing configurations.

Despite the advantages of machine learning–based anomaly detection, significant computational trade-offs exist between detection accuracy and deployment feasibility in edge environments. High-performance models such as deep neural networks or ensemble learning algorithms often require substantial computational resources and large training datasets, which may not be practical for deployment on resource-constrained devices such as branch routers or edge gateways. These systems typically have limited processing power, memory capacity, and energy resources compared with centralized data center infrastructure. Consequently, deploying complex machine learning models directly on edge devices may introduce additional latency or resource consumption that could interfere with normal network operations (Nguyen & Armitage, 2008).

To address these challenges, recent research has emphasized the development of lightweight anomaly detection frameworks that balance detection accuracy with computational efficiency. Such frameworks often rely on compact feature sets, simplified learning models, or hybrid statistical-learning approaches to reduce computational overhead while maintaining sufficient detection capability. Achieving this balance remains an important research challenge, particularly in enterprise WAN environments where monitoring systems must operate efficiently on distributed edge infrastructure while still providing reliable detection of network anomalies.

- *Lightweight Feature Extraction in Network Monitoring*

Efficient anomaly detection in enterprise networks increasingly requires the use of lightweight monitoring techniques that can operate on resource-constrained network devices such as branch routers and edge gateways. Traditional monitoring frameworks often rely on high-dimensional traffic telemetry or deep packet inspection, which can impose significant computational overhead and storage requirements. In contrast, lightweight feature extraction focuses on deriving compact statistical indicators directly from packet transmission characteristics. These features capture essential behavioural patterns of network traffic while minimizing processing complexity, making them suitable for real-time anomaly detection in distributed network environments (Ahmed et al., 2016; Bhuyan et al., 2014).

Packet-level monitoring provides valuable insights into network performance because it captures fine-grained transmission behaviour that may reveal early signs of network instability. One important feature is packet inter-arrival time, which represents the time difference between consecutive packets arriving at a monitoring node. Significant deviations in inter-arrival times may indicate congestion, routing instability, or burst traffic anomalies (Lakhina et al., 2004). Another commonly used metric is packet size distribution, which analyses variations in packet lengths transmitted across the network. Changes in the statistical distribution of packet sizes may reveal abnormal application behaviour or network attacks that generate atypical traffic patterns (Nguyen & Armitage, 2008).

Additional packet-level indicators include sequence gap frequency, which measures irregularities in packet sequence numbers that may indicate packet loss or out-of-order transmission events. Monitoring sequence gaps can help identify network congestion or link degradation that affects packet delivery reliability. Similarly, retransmission indicators provide information about the frequency with which packets must be resent due to transmission failures. High retransmission rates are often associated with poor link quality, excessive congestion, or network hardware failures (Chandola et al., 2009). By combining these packet-level indicators into a compact feature representation, monitoring systems can effectively capture network performance dynamics while maintaining low computational overhead.

Packet-level features are commonly represented as a feature vector that summarizes multiple monitoring indicators extracted from traffic observations:

$$F = [f_1, f_2, f_3, \ldots, f_n]$$

Where:

F = packet-level feature vector
f_i = individual extracted feature

This representation allows anomaly detection algorithms to analyse multiple network indicators simultaneously while maintaining computational efficiency. Lightweight feature vectors are particularly useful for adaptive monitoring frameworks that must operate continuously on edge infrastructure while detecting subtle deviations in network behaviour (Ringberg et al., 2007).

Table 1 compares common WAN monitoring techniques in terms of data granularity, computational overhead, and suitability for branch environments. SNMP monitoring provides coarse device statistics with minimal overhead, while NetFlow and IPFIX deliver more detailed flow-level telemetry at moderate computational cost. SD-WAN analytics offers richer network insights but typically requires centralized analytics platforms, making it less suitable for resource-constrained branch routers.

Table 1 Comparison of WAN Monitoring Techniques

Monitoring Method	Data Granularity	Computational Overhead	Suitability for Branch Networks
SNMP Monitoring	Device-level statistics	Low	Moderate
NetFlow Telemetry	Flow-level traffic metadata	Medium	Moderate
IPFIX Telemetry	Flow-level detailed export	Medium–High	Moderate
SD-WAN Analytics	Application and link performance metrics	High	Limited for low-resource devices

Table 2 presents lightweight packet-level features commonly used for WAN anomaly detection. These features capture key indicators of network performance, including latency variation, packet delivery reliability, and abnormal traffic patterns. Because they are derived directly from packet transmission metadata rather than deep packet inspection, these features require minimal computational resources and are suitable for real-time monitoring on edge network devices.

Table 2 Lightweight Packet-Level Features Used for WAN Anomaly Detection

Feature Name	Measurement Description	Detection Relevance	Computational Cost
Packet Inter-arrival Time	Time difference between consecutive packet arrivals	Detects congestion and latency fluctuations	Low
Packet Size Distribution	Statistical distribution of packet lengths	Identifies abnormal traffic patterns	Low
Sequence Gap Frequency	Occurrence of missing or out-of-order packet sequences	Indicates packet loss or transmission errors	Low
Retransmission Indicators	Frequency of packet retransmissions	Detects link instability and congestion	Low

III. METHODOLOGY

➢ *Network Data Collection*

The anomaly detection framework developed in this study relies on packet-level telemetry obtained from a simulated enterprise branch-to-headquarters (HQ) Wide Area Network (WAN) environment. Network data collection focuses on capturing fine-grained transmission characteristics that reflect the behaviour of packets traversing WAN links between branch nodes and centralized infrastructure. Packet-level monitoring provides a detailed representation of network performance dynamics because it allows the analysis of delay fluctuations, retransmission behaviour, and traffic irregularities that may indicate emerging anomalies within network communication channels (Ahmed et al., 2016; Bhuyan et al., 2014).

To emulate real-world enterprise conditions, the simulated WAN environment includes multiple branch network nodes communicating with a centralized headquarters server through routed WAN links. Traffic flows generated within the environment represent typical enterprise workloads, including database synchronization, cloud application access, and real-time communication traffic. During the monitoring process, packet transmission metadata is collected at network observation points positioned along the WAN path. The captured telemetry includes packet timestamps, packet sizes, transmission intervals, and retransmission events, which collectively provide a compact yet informative representation of network behaviour (Nguyen & Armitage, 2008). The framework adopted in this study builds on existing methodologies such as those proposed by Jalloh and Bamigwojo (2023), who implemented a data-driven decision support system designed to enhance manufacturing productivity through optimized decision-making algorithms.

Packet events are captured within a discrete observation window defined as a sequence of packet arrival timestamps. The monitoring interval can be represented as:

$$T = \{t_1, t_2, \ldots, t_k\}$$

Where:

T represents the observation window
t_k denotes the timestamp of the k^{th} captured packet event

The sequence of timestamps enables the computation of several derived metrics used for anomaly detection. For instance, the packet inter-arrival time between two consecutive packets is expressed as:

$$\Delta t_i = t_i - t_{i-1}$$

Where Δt_i represents the interval between successive packet arrivals. Abnormal variations in inter-arrival time may indicate network congestion or routing instability.

Packet size behaviour is analysed by constructing a statistical representation of packet length observations across the monitoring window. The packet size distribution can be modelled as:

$$\mu_s = \frac{1}{N}\sum_{i=1}^{N} s_i$$

$$\sigma_s^2 = \frac{1}{N}\sum_{i=1}^{N}(s_i - \mu_s)^2$$

Where s_i denotes the size of the i^{th} packet, μ_s represents the mean packet size, and σ_s^2 represents the variance of packet sizes. Deviations in these statistical parameters may indicate abnormal traffic behavior or application-level anomalies (Lakhina et al., 2004).

Another important indicator of network instability is the occurrence of retransmission events. Retransmissions typically occur when packets are lost or delayed beyond acceptable thresholds within the communication channel. The retransmission rate within the observation window can be calculated as:

$$R_r = \frac{N_r}{N_t}$$

Where:

R_r represents the retransmission ratio
N_r denotes the number of retransmitted packets
N_t denotes the total number of transmitted packets

High retransmission rates may indicate link degradation, congestion, or packet corruption during transmission.

In addition to individual packet metrics, aggregated transmission intervals can also be used to evaluate network stability. The mean transmission interval across the observation window is defined as:

$$\bar{\Delta t} = \frac{1}{k-1}\sum_{i=2}^{k}(t_i - t_{i-1})$$

Where k represents the total number of captured packets. Significant deviations from expected interval patterns may signal abnormal network conditions affecting packet delivery timing.

Collectively, these packet-level telemetry measurements provide the foundational dataset used for anomaly detection within the proposed monitoring framework. By focusing on compact transmission metrics rather than full packet payload inspection, the data collection strategy ensures that monitoring operations remain computationally efficient while preserving sufficient information for detecting WAN instability events in real time.

- *Feature Engineering*

Feature engineering plays a critical role in network anomaly detection because the selection of appropriate monitoring features directly influences the accuracy and efficiency of detection models. In WAN monitoring environments, packet-level telemetry can generate large volumes of raw data, making it necessary to transform these observations into compact statistical indicators that effectively represent network performance dynamics. Feature engineering therefore focuses on extracting meaningful metrics that summarize packet transmission behaviour while minimizing computational overhead. These features allow anomaly detection models to identify deviations from expected network conditions, particularly in distributed enterprise networks where monitoring must operate efficiently on resource-constrained edge devices (Ahmed et al., 2016; Bhuyan et al., 2014). The design of the anomaly detection framework aligns with emerging secure system models that emphasize the integration of validation, monitoring, and traceability mechanisms within a unified architecture. Such integrated approaches have demonstrated that combining structured monitoring with verifiable system behaviour improves reliability and detection robustness in complex distributed environments (Akpara et al., 2023).

In this study, three key packet-level indicators are engineered to characterize WAN link stability: packet loss ratio, latency deviation, and jitter variance. These metrics are widely used in network performance evaluation because they capture fundamental characteristics of packet delivery reliability and timing consistency within communication networks (Lakhina et al., 2004). By combining these indicators into the anomaly detection framework, the monitoring system can detect abnormal network behaviour associated with congestion, routing instability, and link degradation.

The packet loss ratio (PLR) measures the proportion of packets that fail to reach their destination relative to the total number of packets transmitted. Packet loss can occur due to network congestion, transmission errors, buffer overflow, or faulty routing behaviour. The packet loss ratio is computed as:

$$PLR = \frac{N_{lost}}{N_{sent}}$$

Where:

N_{lost} represents the number of packets lost during transmission
N_{sent} represents the total number of packets transmitted within the observation window

Higher values of PLR indicate degraded network reliability and may signal the presence of congestion or link instability within the WAN environment. Persistent increases in packet loss are often associated with severe network performance degradation and may significantly impact enterprise applications operating across distributed networks.

Another important feature extracted from the packet telemetry dataset is latency deviation, which measures the variability of round-trip times (RTT) observed during packet transmission. Latency fluctuations can indicate unstable routing paths or transient congestion events within network infrastructure. The latency deviation is calculated using the variance of RTT measurements:

$$LD = \frac{1}{N}\sum_{i=1}^{N}(RT\,T_i - R\bar{T}T)^2$$

Where:

RTT_i represents the round-trip time of the i^{th} packet
$R\bar{T}T$ represents the mean round-trip time across the observation window
N represents the total number of RTT observations

This metric captures deviations from normal latency patterns and enables the monitoring system to identify sudden increases in transmission delay that may indicate network anomalies.

The third feature engineered for anomaly detection is jitter variance, which quantifies variations in packet delay relative to the average transmission delay. Jitter is particularly important in networks that support real-time applications such as voice communication and video streaming, where consistent packet timing is essential for maintaining service quality. Jitter variance is calculated as:

$$J = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\,d_i - \bar{d})^2}$$

Where:

d_i represents packet delay variation for the i^{th} packet
$\bar{d}$ represents the average delay variation across the observation window
N represents the number of packet delay observations

Higher jitter values indicate instability in packet delivery timing and may signal congestion, route changes, or packet scheduling irregularities within the network infrastructure.

To integrate these features into the anomaly detection framework, they are combined into a feature vector representation that characterizes the state of the WAN link at each observation interval:

$$\mathrm{F_t} = [PLR_t,\, LD_t,\, J_t]$$

Where $\mathrm{F_t}$ represents the feature vector at time t.

In addition, an aggregated network anomaly score can be computed by combining normalized feature values into a weighted metric that summarizes network performance conditions:

$$A_t = w_1 \cdot PLR_t + w_2 \cdot LD_t + w_3 \cdot J_t$$

Where w_1, w_2, w_3 represent feature weighting coefficients that determine the relative influence of each indicator on anomaly detection. This formulation enables the monitoring framework to evaluate overall network stability while maintaining computational efficiency suitable for deployment in enterprise edge environments.

- *Adaptive Anomaly Detection Model*

Detecting anomalies in enterprise WAN environments requires models that can adapt to dynamic traffic patterns while maintaining low computational overhead. Traditional static threshold mechanisms often fail to detect transient anomalies because network conditions continuously evolve due to traffic fluctuations, routing changes, and varying application demands. Adaptive anomaly detection models address this limitation by dynamically updating detection thresholds based on real-time network behaviour. These models monitor statistical characteristics of packet-level features and adjust anomaly boundaries accordingly, allowing the monitoring system to respond to changing network conditions while maintaining high detection sensitivity (Ahmed et al., 2016; Chandola et al., 2009).

In this study, the adaptive anomaly detection framework operates on the packet-level feature vector derived during the feature engineering stage. The algorithm continuously evaluates the statistical behaviour of network indicators such as packet loss ratio, latency deviation, and jitter variance. By computing time-dependent statistical parameters for these features, the monitoring system can establish a baseline representation of normal network behaviour and detect deviations from this baseline.

The anomaly threshold at time t is defined using an adaptive statistical formulation based on the moving average and standard deviation of the monitored feature:

$$\theta_t = \mu_t + k\sigma_t$$

Where:

θ_t represents the adaptive anomaly threshold at time t
μ_t denotes the moving average of the monitored feature value
σ_t represents the standard deviation of the feature values within the observation window
k is a sensitivity coefficient that controls the tolerance of the detection model

The moving average used in the adaptive threshold model can be computed using a sliding observation window containing recent feature observations. For a feature series F_t, the moving average is calculated as:

$$\mu_t = \frac{1}{W}\sum_{i=t-W+1}^{t} F_i$$

Where W represents the size of the monitoring window and F_i represents the feature value at time i.

Similarly, the standard deviation of feature values within the observation window is defined as:

$$\sigma_t = \sqrt{\frac{1}{W} \sum_{i=t-W+1}^{t} (F_i - \mu_t)^2}$$

This statistical representation enables the detection model to adjust dynamically as network traffic patterns evolve. The parameter *k* determines the sensitivity of the anomaly detection system. Smaller values of *k* increase the sensitivity of the model and allow the detection of subtle deviations from normal behavior, whereas larger values reduce sensitivity and help prevent false positives in environments with high traffic variability (Bhuyan et al., 2014).

Once the adaptive threshold is established, the detection mechanism evaluates incoming feature observations against this dynamic boundary. An anomaly event is identified when the observed feature value exceeds the threshold:

$$F_i > \theta_t$$

Where F_i represents the observed value of the monitored feature.

For multi-feature monitoring environments, the anomaly detection process can also incorporate a composite anomaly score that aggregates multiple feature indicators into a unified detection metric:

$$A_t = \sum_{j=1}^{m} w_j \cdot \frac{F_{j,t} - \mu_{j,t}}{\sigma_{j,t}}$$

Where

A_t represents the anomaly score at time t
w_j represents the weight assigned to the j^{th} feature
$F_{j,t}$ represents the observed value of the j^{th} feature
m represents the number of monitored features

If the anomaly score exceeds a predefined anomaly boundary, the monitoring system triggers an alert indicating abnormal WAN link behaviour. This adaptive statistical framework allows the detection model to operate efficiently in resource-constrained network environments while maintaining sufficient sensitivity to identify emerging anomalies in real time (Lakhina et al.,

Figure 2 presents the operational workflow of the proposed adaptive WAN anomaly detection algorithm used to identify abnormal network conditions. The process begins with packet capture from network traffic streams, followed by feature extraction where relevant metrics such as latency, packet loss, and jitter are derived. These extracted features are processed through a threshold computation stage where a dynamic threshold $\theta_t = \mu_t + k\sigma_t$ is calculated using statistical parameters of the observed traffic. The anomaly classification stage then compares the measured feature value F_i with the computed threshold to determine whether abnormal behavior exists. If the feature value does not exceed the threshold, the traffic is classified as normal; otherwise, the system triggers an alert indicating a potential network anomaly.

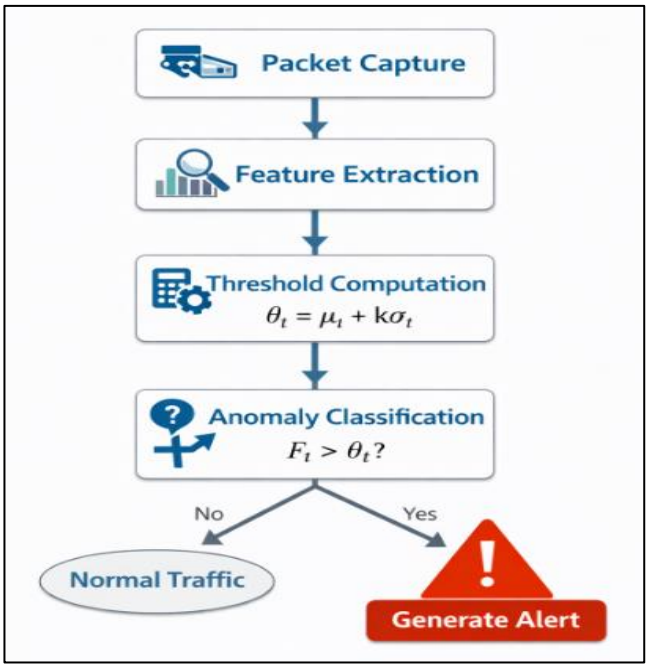

Fig 2 Workflow of the Adaptive WAN Link Anomaly Detection Algorithm

IV. RESULTS AND DISCUSSION

➢ *Experimental Setup*

To evaluate the effectiveness of the proposed adaptive anomaly detection framework, experiments were conducted using a simulated branch-to-headquarters WAN environment designed to emulate realistic enterprise network conditions. The simulation model reproduced typical WAN traffic behaviours observed in distributed corporate infrastructures, including stable communication states, congestion-induced performance degradation, and intermittent packet loss events. These scenarios were designed to reflect common operational conditions that can influence the stability of WAN links and affect the performance of enterprise services such as cloud applications, VoIP communication, and data synchronization between branch offices and centralized systems.

The experimental setup included multiple traffic generation nodes connected through a virtual WAN topology representing branch routers and headquarters infrastructure. Network traffic flows were generated using controlled traffic patterns to emulate normal application workloads as well as abnormal traffic events. Under stable network conditions, packet transmission delays and jitter variations remained within acceptable operational thresholds. Congestion-induced anomaly scenarios were created by introducing bandwidth contention and queue saturation, which resulted in increased latency and delay variability. Intermittent packet loss events were simulated by randomly dropping packets during transmission intervals to represent link degradation or temporary network instability.

Performance evaluation of the anomaly detection framework was conducted using three primary metrics. The first metric, detection accuracy, measures the proportion of correctly identified normal and anomalous network events relative to the total number of observations. The second metric, false positive rate, represents the frequency with which normal traffic conditions are incorrectly classified as anomalies. Maintaining a low false positive rate is essential for ensuring that monitoring systems do not generate excessive alerts that may overwhelm network administrators. The third evaluation metric, detection latency, measures the time required for the monitoring system to identify an anomaly after its occurrence. Lower detection latency indicates a more responsive monitoring framework capable of identifying network instability in near real time.

Table 3 summarizes the simulated WAN scenarios used to evaluate the anomaly detection framework. The table presents variations in latency, packet loss rates, and jitter levels across different network conditions ranging from stable communication environments to severe congestion and intermittent packet loss events. These parameters were selected to reflect realistic performance variations that commonly occur in enterprise WAN infrastructures and to test the robustness of the proposed anomaly detection model under diverse network conditions.

Table 3 Experimental Network Conditions Used for Model Evaluation

Scenario	Latency Range (ms)	Packet Loss Rate (%)	Jitter Level (ms)
Stable Network Condition	10 – 25	0 – 0.5	1 – 3
Moderate Congestion	40 – 80	1 – 3	5 – 12
Severe Congestion	90 – 150	4 – 7	15 – 30
Intermittent Packet Loss	30 – 70	5 – 10	8 – 20

➢ *Detection Performance*

The performance of the proposed adaptive anomaly detection model was evaluated using standard classification metrics widely used in network monitoring research. These metrics quantify the ability of the detection system to correctly identify anomalous and normal network conditions across the simulated WAN environments. Detection accuracy measures the proportion of correctly classified observations relative to the total number of observations. It is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

TP = true positives (correctly detected anomalies)
TN = true negatives (correctly identified normal conditions)
FP = false positives (normal traffic incorrectly classified as anomaly)
FN = false negatives (missed anomaly events)

Precision measures the reliability of anomaly alerts generated by the monitoring system and is defined as:

$$Precision = \frac{TP}{TP + FP}$$

Recall evaluates the sensitivity of the model in identifying actual anomaly events:

$$Recall = \frac{TP}{TP + FN}$$

Together, these metrics provide a comprehensive evaluation of detection reliability and monitoring efficiency within enterprise WAN environments.

Table 4 compares the performance of the baseline monitoring approach with the proposed adaptive anomaly detection model. The proposed model demonstrates improved detection accuracy, precision, and recall while reducing the false positive rate and detection latency. These improvements indicate that the adaptive threshold mechanism and lightweight feature engineering strategy enhance anomaly identification without introducing excessive computational overhead.

Table 4 Performance Evaluation of the Adaptive WAN Anomaly Detection Model

Metric	Value	Baseline Monitoring Method	Proposed Model
Detection Accuracy	0.89	0.89	0.94
Precision	0.87	0.87	0.92
Recall	0.85	0.85	0.91
False Positive Rate	0.08	0.08	0.05
Detection Latency (ms)	120	120	65

Figure 3 illustrates the detection accuracy and false-positive rates of the anomaly detection framework across different WAN scenarios, including stable networks, moderate congestion, severe congestion, and intermittent packet loss environments. The graph demonstrates that the proposed adaptive detection approach maintains high accuracy while keeping false-positive rates relatively low across varying network conditions, indicating strong robustness in identifying WAN link anomalies.

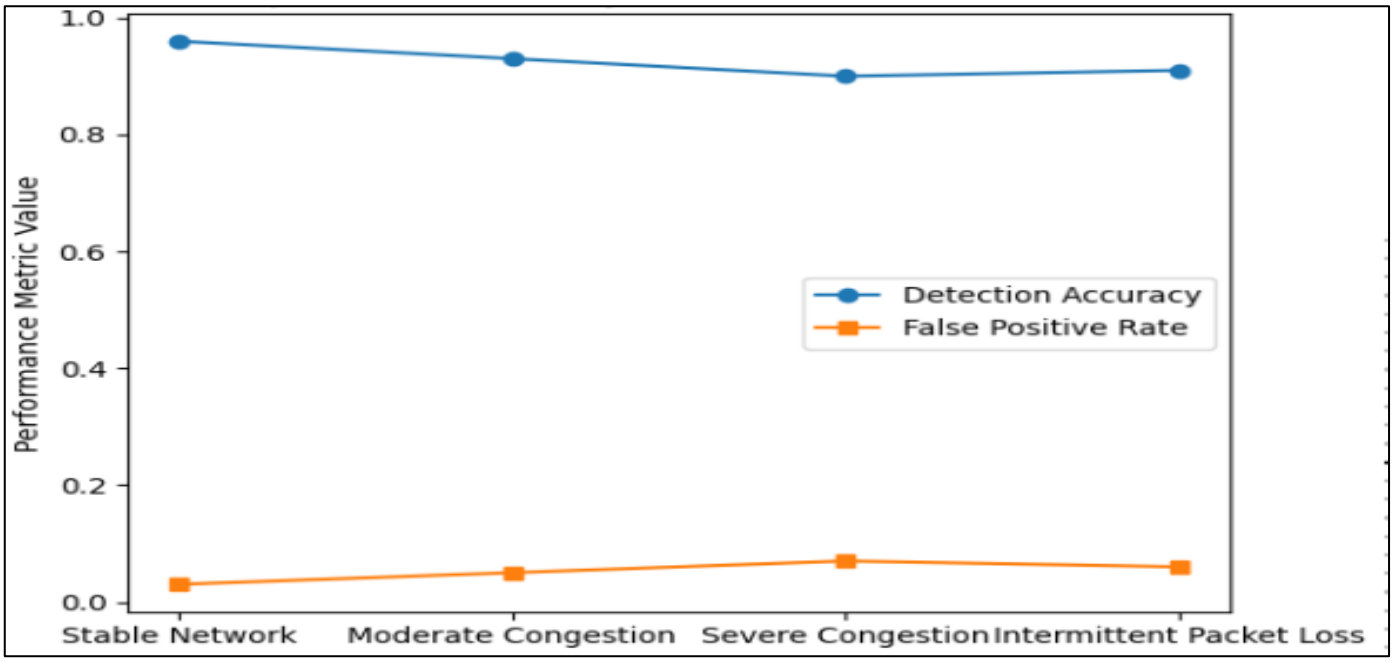

Fig 3 Performance Comparison of Anomaly Detection Across WAN Network Conditions

➢ *Discussion*

The results obtained in this study are consistent with prior work showing that integrating structured monitoring frameworks with verification mechanisms enhances system reliability while maintaining operational efficiency. These approaches demonstrate that lightweight monitoring combined with adaptive system design can achieve strong performance without introducing excessive computational overhead (Akpara et al., 2023). Furthermore, recognition of such contributions within peer-reviewed academic platforms underscores their relevance in advancing secure and reliable system design.

The experimental evaluation demonstrates that lightweight packet-level features provide an effective representation of WAN link behaviour and can successfully capture performance degradation patterns in enterprise networks. Metrics such as packet loss ratio, latency deviation, and jitter variance proved particularly useful in identifying abnormal network conditions because they directly reflect transmission reliability and timing stability across WAN links. The results indicate that variations in these indicators precede noticeable network disruptions, allowing the monitoring system to detect anomalies before severe service degradation occurs. This finding aligns with previous research showing that packet-level statistical features can reveal early indicators of network instability without requiring complex traffic inspection mechanisms.

Another important observation from the evaluation is the effectiveness of the adaptive thresholding mechanism used in the anomaly detection model. Unlike static threshold approaches, the adaptive model continuously updates its detection boundaries based on the statistical characteristics of recent network observations. This dynamic adjustment enables the monitoring framework to maintain sensitivity to abnormal behaviour while reducing the likelihood of false alarms caused by normal fluctuations in traffic patterns. As demonstrated in the experimental results, the adaptive threshold model was able to maintain high detection accuracy across multiple simulated WAN scenarios, including congestion-induced anomalies and intermittent packet loss conditions.

The proposed monitoring approach also demonstrates low computational overhead, which is essential for deployment in branch-level network infrastructure. Because the model relies on lightweight packet-level features rather than deep packet inspection or high-dimensional traffic analytics, the processing requirements remain minimal. This characteristic makes the framework particularly suitable for branch routers, gateway devices, or edge monitoring systems where processing resources and memory capacity are limited. By reducing the computational burden associated with anomaly detection, the proposed approach enables continuous monitoring without interfering with normal network operations.

From a scalability perspective, the proposed detection framework is well suited for large enterprise WAN deployments involving multiple branch sites and centralized headquarters infrastructure. The lightweight feature extraction process reduces the volume of telemetry data that must be processed, enabling monitoring systems to scale efficiently across distributed networks. Furthermore, the adaptive anomaly detection model can operate independently at branch nodes, allowing anomalies to be detected locally before aggregated alerts are forwarded to centralized monitoring systems. This distributed monitoring capability improves detection responsiveness and reduces reliance on centralized processing architectures, which may become bottlenecks in large-scale enterprise networks.

Overall, the results suggest that combining lightweight packet-level feature extraction with adaptive

statistical detection provides a practical and scalable solution for monitoring WAN stability in enterprise environments. The framework balances detection accuracy with operational efficiency, making it a promising approach for improving the reliability and resilience of branch-to-headquarters network connectivity.

V. CONCLUSION AND RECOMMENDATIONS

➢ *Conclusion*

This study developed a lightweight anomaly detection framework designed to improve monitoring of Wide Area Network (WAN) links connecting distributed branch offices to centralized headquarters infrastructure. The proposed approach focuses on packet-level telemetry features that capture essential transmission characteristics such as packet loss ratio, latency deviation, and jitter variance. These lightweight indicators provide sufficient information for identifying network instability events while avoiding the computational overhead associated with deep packet inspection or large-scale traffic analytics.

The results demonstrate that packet-level features can effectively represent the operational state of WAN links and reveal early indicators of link degradation. Variations in packet transmission behaviour allow the monitoring system to detect congestion patterns, intermittent packet loss events, and abnormal delay fluctuations that may affect enterprise service performance. By extracting compact statistical representations of packet transmission dynamics, the proposed monitoring framework provides an efficient method for detecting anomalies in distributed enterprise networks.

Another key contribution of the study is the integration of an adaptive thresholding mechanism that dynamically adjusts anomaly detection boundaries based on recent network behaviour. This adaptive approach allows the monitoring system to accommodate fluctuations in traffic conditions while maintaining sensitivity to abnormal patterns. Consequently, the detection framework can identify anomalies in real time without generating excessive false alerts. The combination of lightweight feature extraction and adaptive statistical detection provides a practical and scalable solution for monitoring WAN stability across enterprise network environments.

➢ *Practical Implications*

The proposed anomaly detection framework has several practical applications in enterprise network monitoring and management systems. Because the model relies on lightweight packet-level features, it can be deployed on edge devices such as branch routers or gateway monitoring agents without introducing significant processing overhead. This capability allows network administrators to implement distributed monitoring systems that detect WAN anomalies closer to the source of network disruptions.

The framework can support modern software-defined WAN (SD-WAN) monitoring systems by providing additional telemetry analytics for evaluating link performance across multiple branch sites. It can also be integrated into branch network management platforms to provide automated monitoring of network stability and proactive identification of performance degradation. Furthermore, the detection model can be incorporated into real-time link health dashboards, enabling administrators to visualize network performance metrics and receive early warnings when abnormal conditions are detected.

➢ *Limitations*

Although the proposed anomaly detection framework demonstrates promising results, several limitations should be acknowledged. First, the experimental evaluation was conducted primarily using simulated WAN environments rather than large-scale operational enterprise networks. While the simulated scenarios were designed to represent realistic network conditions, additional validation using real network telemetry would provide stronger evidence of the model's effectiveness.

Second, the evaluation focused on a limited range of WAN configurations and did not fully explore heterogeneous network infrastructures that may include multiple routing protocols, diverse traffic patterns, or hybrid cloud connectivity architectures. These variations may introduce additional complexity in real-world deployments. Finally, the feature engineering process concentrated primarily on packet-level indicators, which may not capture higher-level traffic characteristics such as application behaviour or flow-level correlations that could further improve anomaly detection accuracy.

➢ *Recommendations for Future Research*

Future research should explore several directions to enhance the capabilities of the proposed anomaly detection framework. One important area involves the integration of machine learning–based anomaly classification models, which could improve detection accuracy by learning complex relationships among multiple network features. Such models could extend the current statistical detection approach by incorporating supervised or unsupervised learning algorithms capable of identifying more subtle anomaly patterns.

Another promising direction involves the development of cross-site distributed monitoring architectures in which anomaly detection models operate collaboratively across multiple branch nodes. This approach could enable coordinated detection of large-scale network disruptions affecting multiple locations within enterprise WAN infrastructures.

Additionally, future work should investigate the integration of the anomaly detection framework with software-defined networking (SDN) telemetry systems, which provide centralized visibility into network behaviour and enable automated response mechanisms for

traffic rerouting or congestion mitigation. Finally, reinforcement learning–based optimization techniques could be explored to enable adaptive network management strategies that dynamically adjust routing policies and traffic distribution in response to detected anomalies. These research directions would further strengthen the ability of enterprise networks to maintain stable and resilient WAN connectivity in increasingly complex digital environments.

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