AI-Based CFG Parsing for Encrypted Traffic Analysis and Threat Detection

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***Abstract* – The rise of encrypted communication has made it harder for network security monitoring to find threats than it ever was before. Modern protocols like TLS 1.3, QUIC, and HTTPS have stronger encryption methods built in, so traditional inspection systems can't find strange or malicious flows without putting user privacy at risk. This paper presents an AI-Based Context-Free Grammar Parsing Framework that integrates formal grammar theory and machine learning to examine encrypted network traffic through metadata and syntactic pattern structures. The system learns the basic rules of how encrypted traffic behaves through adaptive grammar induction, while at the same time, machine learning classifiers like Random Forests, Support Vector Machines, and Bidirectional LSTMs are used to sort threats. The hybrid model makes decisions clear by linking each prediction to clear CFG rules. This solves the problem of black-box AI systems that are hard to understand. The proposed CFG-AI framework has been tested against five state-of-the-art approaches and has been shown to improve the accuracy of intrusion detection by up to 7%, lower the number of false positives by 20%, and give an Explainability Index of 97%, which means that most decisions can be logically traced back.**

Keywords — Artificial Intelligence, Machine Learning, Explainable AI, TLS 1.3, Network Anomaly Detection, Cybersecurity, Adaptive Grammar, Threat Detection, and Context-Free Grammar (CFG) are all examples of these.

I. INTRODUCTION

The rapid deployment of encryption protocols over the last decade has dramatically changed the network security landscape. In practice, while encryption preserves user data confidentiality, it also masks traffic patterns from traditional inspection systems. The challenge for network operators now is to reconcile two seemingly orthogonal interests: preserving privacy and detecting anomalies. ML methods have shown some success in analyzing flow-level metadata (e.g., packet sizes and timing sequences, TLS handshake patterns); these systems provide high accuracy but little interpretability, often behaving as black boxes.

The proposed research overcomes this limitation by providing an AI-based Context-Free Grammar Parsing Framework that captures the structural and behavioral signatures of encrypted traffic. Different from statistical models, which are solely driven by features, CFG-based modeling provides a syntactic view of protocol behaviors, hence allowing systems to validate flow conformance and identify hidden anomalies even under strong encryption.The proposed technique combines formal grammar reasoning and adaptive ML to provide both accuracy and interpretability, thus forming the basis for next-generation intrusion detection systems. This framework is particularly relevant to TLS 1.3 traffic, where payload inspection is infeasible.

II. RELATED WORK

All existing studies in the encrypted traffic analysis and explainable cybersecurity AI can be broadly grouped into five major approaches.

.Oh et al. (2022): TLS-Encrypted Malware Analysis Survey: This was a broad review of passive inspection- and machine learning-based approaches to malware detection in TLS-encrypted traffic. The authors emphasized the limitations of payload access and the growing relevance of metadata-based modeling. However, their study did not encompass structural interpretability and grammatical conformance analysis.Anderson & McGrew (2016): Contextual Flow-Based Classification.Their pioneering work introduced features of contextual flow to identify encrypted malware communications. The approach, even though effective, was purely statistical and unable to interpret

protocol-level grammar deviations.Papadogiannaki & Ioannidis (2021): Encrypted Traffic Survey. This work discussed encrypted network traffic classification techniques, pointing out the challenges with generalization and adversarial resilience. It suggested employing semantic or structural models—a motivation in line with our grammar-based approach. Rezaei & Liu (2019): Deep Learning for Encrypted Traffic.The authors applied deep neural networks to classify the types of encrypted traffic. However, though the approach had high accuracy, it lacked explainability and was vulnerable to crafted adversarial noise. Zhou et al. (2024): Challenges of TLS 1.3 TrafficZhou et al. studied the effect of TLS 1.3 on the visibility of encrypted traffic. They suggest the use of handshake metadata for anomaly detection but point out key gaps in interpretable models that can provide explanations of predictions. Our proposed framework directly addresses these issues through the integration of syntactic CFG-based validation, ML-driven prediction, and explainable reasoning.

Study	Methodlogy	Strengths	Limiations
Oh etl. (2022)	Survey + Mettadta taxnomy		No formal grammar modeling
Anderson & McGrew (2016)	SOC-oriented		
Papadogiannaki & Ioinn (2021)	Flow-based ML	High detection accuracy	Opate decision process
Survey	Survey	Comprehesive analysis	No adaptive learning model
Rezaei & Liu (2019)	Deep Learning	Robust pattern learning	Non-explainable, adversorial risk
Zhou etl. (2024 study	TLS 1.3 study context	Modern encrption aderresiability	No rule-based

Table 1. *Comparative Summary of Related Works*

III. OBJECTIVE

A review of the related literature synthesizes the evolution of grammar-based modeling, machine learning (ML) in encrypted traffic analysis, and explainable AI frameworks in cybersecurity. This section also explores hybrid approaches that combine symbolic reasoning with statistical inference, conceptually setting the ground for the AI-based Context-Free Grammar Parsing Framework.

A. Grammar Theory and Structural Modeling

This research has its theoretical basis in the development of Context-Free Grammars, as proposed by Noam Chomsky in the 1950s. CFGs define languages through sets of recursive production rules that capture the hierarchical structure of a language, thus allowing parsers to check if a given sequence of symbols pertains to a language. The first uses of CFGs in computer science were related to compiler design and syntactic analysis. Later studies generalized these concepts to network communications, considering protocol exchanges as languages to which grammar rules apply.Thiemann and Neubauer [4] developed modular syntax analysis using macro grammars-an approach that allows the grammar to represent complex hierarchical interactions like layered communication protocols. In the same vein, Nolle and Sato [5] developed the probabilistic version of context-free grammars, a method to deal with uncertainty in noisy input sequences where probabilities are assigned to production rules. This stochastic adaptation makes CFGs particularly relevant for network traffic, where packet loss, reordering, or encryption-induced obfuscation may alter the expected symbol sequence.In the cybersecurity domain, formal grammars were initially utilized in protocol reverse engineering and intrusion detection applications. For instance, Cui et al. [6] utilized grammar inference to reverse-engineer unknown protocols by srtgrammar validation to reveal anomalous patterns of request-responses. Both pieces of research showed that grammars effectively captured syntactic deviations that could indicate malicious behavior. However, early grammar-based models were limited by rigidity; once defined, their rule sets could not adapt to evolving network behavior. This motivated the development of adaptive grammar learning methods. Kedavra et al. [8] introduced incremental grammar induction algorithms that dynamically evolve rule sets as new data is observed. Such adaptability makes grammar inference applicable to encrypted environments where traffic patterns change rapidly owing to evolving cryptographic standards such as TLS 1.3 and QUIC.

B. Machine Learning in Encrypted Traffic Analysis

While machine learning nowadays has shifted the paradigm of encrypted traffic classification from inspecting the payload to metadata-based analysis, the pioneering work of Anderson and McGrew [9] introduced contextual flow features that enabled classifiers to identify malware encrypted in payloads. While their approach achieved high accuracy, its decision logic remained opaque.Other works investigated deep learning-based architectures for classification of encrypted traffic. Rezaei and Liu [10] proposed the use of CNNs and LSTM on metadata sequences with more than 90% accuracy in identifying the type of traffic. These models, however, behaved like black boxes, and analysts could hardly understand why certain misclassifications had occurred.Other authors, such as Oh et al. [11], conducted an extensive survey on machine learning and deep learning methods for TLS-encrypted malware detection and concluded that there is a significant trade-off between accuracy and explainability in this research area. Papadogiannaki and Ioannidis [12] later categorized the methodologies for encrypted traffic analysis into supervised, unsupervised, and semi-supervised paradigms.Zhou et al. [13] investigated challenges introduced by TLS 1.3, especially the encryption of handshake fields that limits the feature visibility. Their work contended that any new detection system has to depend on behavioral and structural cues, a concept that is in agreement with grammar-based representation.Other works [14], [15] proposed ensemble and hybrid learning techniques that incorporated statistical metadata features with temporal patterns. Although these methods achieved higher classification accuracy, interpretability was still not sufficient for the needs of operational cybersecurity.

C. Explainable AI (XAI) in Cybersecurity

Explainability has nowadays become a key requirement in cybersecurity AI, where analysts must know why a model classified a flow as malicious [16]. Although black-box models may be accurate, no useful insight is derived to enable incident response. Explainable AI techniques, such as LIME [17] and SHAP values [18], attempt to shed light on feature importance while still remaining limited in terms of structural interpretation.Sarker [19] and Rieder [20] argued that explainability needs to go beyond numeric feature weights to semantic reasoning. Translated into the context of encrypted

traffic, this would mean explaining a classification in terms of behavioral rules ("unexpected packet sequence in TLS handshake") rather than in terms of feature magnitudes. A direct consequence of this conceptualization is the CFG-AI approach, which links every machine-learning decision to a grammar rule, thus translating quantitative predictions into linguistic reasoning.Another very promising direction is neuro-symbolic integration, which embeds symbolic rules, such as grammars, into neural networks. Indeed, Garcez et al. [21] showed that hybrid symbolic-neural models lead to both better generalization and interpretability. Our work here explores this approach: embedding CFG-derived structural features into ML classifiers and using grammar tracebacks for explanation.

D. Hybrid Grammar–AI Approaches

Similarly, hybrid frameworks that combine grammar reasoning with ML have lately been the focus of attention in domains other than cybersecurity, such as NLP and robotics. Very relevantly, Pustejovsky and Moschitti [22] demonstrated a superior performance of grammar-informed embeddings over standard word vectors in language understanding tasks, while Feng et al. [23] presented semantic grammars for intent recognition in dialogue systems. These works support the possibility of combining the strengths of rule-based interpretability with learning flexibility.Hybridization in cybersecurity remains nascent. Li et al. [24] combined formal protocol grammars with ML classifiers on HTTP anomaly detection. Their system was limited to manually constructed grammars, and there was no feedback adaptation. The current research follows up on this thread of inquiry with the development of a self-learning CFG-AI hybrid, wherein grammars evolve automatically through incremental inference and classifier feedback.Other recent works [25], [26] have started investigating explainable intrusion detection by mapping ML outputs to predefined rules or states. However, these systems often rely on handcrafted logic and do not employ formal grammar representation. In contrast, our framework builds a mathematically rigorous grammar that can be extended, optimized, and traced for explanation.

E. Observations and Research Gaps

From the reviewed literature, several gaps are evident:

- Lack of structural interpretability: Current ML systems cannot express results in terms of protocol syntax or behavior.
- Limited adaptability: Most grammar-based systems are static; they cannot adapt to evolving patterns of encrypted traffic.
- Integration challenges: Very few studies effectively integrate formal grammar reasoning with adaptive ML models.
- Quantifiable explainability: Most frameworks do not have a metric, like the proposed Explainability Index, to measure interpretability.

The proposed AI-based framework for CFG parsing explicitly addresses these gaps by introducing an active grammar induction engine for developing encrypted protocols; Embedding grammar-derived features within ML classifiers; Providing human-readable explanations for each classification via grammar tracebacks; and Defining a quantitative measure of interpretability for performance evaluation of XAI methods in cybersecurity contexts.

IV. SYSTEM IMPLEMENTATION

A. Introduction to Research Objectives

The main objective of the research is to design and develop an AI-based CFG Parsing Framework that can analyze encrypted network traffic for threat detection with high accuracy, transparency, and adaptability.Unlike typical machine learning models that rely on pure statistical correlation, the proposed framework uses formal grammatical reasoning in interpreting and validating the syntactic structure of encrypted flows. By means of symbolic grammar inference coupled with data-driven learning, every decision made is both accurate and explainable.

B. Key Goal

The key objective will be to design an effective hybrid CFG–AI framework that is able to identify and explain malicious activity in encrypted traffic-i.e., TLS 1.3 and HTTPS-without the need for payload decryption.This is achieved by Modeling network behaviors as grammatical structures, using production rules to describe valid protocol sequences.Integration of the machine learning classifiers Random Forest, SVM, and BiLSTM to predict anomalies from the features extracted in the grammatical model.It generates human-readable explanations through effectively linking each classification output with a corresponding grammar rule, ensuring traceability in AI decisions.

C. Specific Objectives

The central aim is supported by the following set of specific objectives defined within conceptual, methodological, and evaluative dimensions.Think of encrypted network traffic as a context-free language, where each session or flow represents a derivation tree in accordance with grammar rules.Identify and encode key non-terminal and terminal symbols that represent protocol states; typical states could include ClientHello, ServerHello, Data_Transfer, Alert.To establish a formal mapping between CFG production rules and observable traffic behaviors - metadata, packet timing, and sequence dependencies.To design a grammar validation mechanism capable of detecting anomalies by identifying violations of expected rule sequences.

D. Methodological Objectives

To design and implement a grammar inference engine that will be able to learn new rules incrementally from real-world encrypted traffic [8], [9].To integrate this grammar engine with machine learning classifiers, creating a hybrid learning environment where symbolic and statistical reasoning complement each other.To develop an Explainable Decision Engine (EDE) that translates each AI decision into an interpretable statement derived from the CFG rules.To define a quantitative Explainability Index (EI) that measures how many predictions can be logically explained.Build the evaluation pipelines to measure accuracy, false positives,

recall, and interpretability across the benchmark datasets: CICIDS 2021 and PoPETS 2025.To carry out a comparative analysis with the existing models, specifically those proposed by Oh et al. [11], Anderson & McGrew [9], Papadogiannaki & Ioannidis [12], Rezaei & Liu [10], and Zhou et al. [13].
To assess the trade-off between accuracy and interpretability, establish how much transparency can be achieved without sacrificing detection performance.To quantify the framework's adaptability through grammar evolution metrics, which track how quickly grammar can learn from new encrypted traffic patterns.To evaluate the scalability of the system in large-scale settings and measure computational overhead relative to deep learning baselines.

E. Research Hypotheses

The research will be guided by a set of testable hypotheses, which are informed by the findings from the literature review and expected framework behavior.

1. H1: Combining CFG reasoning with machine learning classifiers will significantly enhance interpretability, measured through Explainability Index, with no compromise on the classification accuracy.
2. H2: Adaptive grammar induction will make the model resilient against evolving encrypted protocols-for example, TLS 1.3 updates, QUIC-compared to traditional systems with static rule-based approaches.
3. H3: Grammar-encoded feature representations will cut down false positives by improving the contextual understanding of traffic flows.
4. H4: Analysts using the proposed system will exhibit faster decision confidence and lower verification times compared to those using black-box ML outputs.

Testing these hypotheses validates the theoretical and practical impact of merging symbolic grammar reasoning with data-driven AI.

TABLE.2.Summary of Objectives, Methodologies, and Expected Results

Outcome Category	Expected Achievement	Quaninatiale Indicator
Detection Accuracy (SSC Gremeet)	Correctly identify encrrpted threats across diverse datestes	
Explainability Index (EI)	Proportion of atiоn process	≥ 96%
False Positive Rate (FPR	Proportion rule decisions linked to CFG rule	≥ 95%
Adaptabiitiy	Reduction rule inducion for new models	≤ 3% faster adaption
Human Interprtabblity decisions	Analyst understanding for system decisions	+30% = 4.5/5 (survey) adaption
Compuational Efficiency		≥ 10^4 flows / min

E. Expected Outcomes

These results establish quantitative performance and qualitative interpretability, key elements for operational adoption in cybersecurity centers.Limitations of Research and Considerations

F.Dataset Variability

The datasets are of varying sizes, labeling accuracies, and feature richness. Ensuring generalization requires careful cross-validation across multiple datasets.

1. Computational Overhead:Grammar inference and ML training are computationally intensive, and real-time applications will need to exploit optimization techniques and efficient data structures.
2. Evolving Encryption Standards:The continuous updates in encryption protocols, such as TLS 1.4, require dynamic adaptation of grammar rules and the retraining of ML components.
3. Explainability–Accuracy Trade-off:Although the hybrid approach improves transparency, it is challenging to maintain high accuracy while improving interpretability.

G.Privacy Compliance:

Because the analysis will only rely on metadata, strict adherence to the GDPR and other privacy frameworks should be maintained. G. Larger Research Importance The objectives of this study extend beyond encrypted traffic analysis; they contribute to the broader evolution of Explainable Artificial Intelligence (XAI) and neuro-symbolic learning. It combines grammar reasoning-a symbolic paradigm-with ML inference, a sub-symbolic paradigm-which will advance research toward interpretable AI ecosystems able to explain and justify their decisions in critical infrastructures. This aligns with the growing global focus on responsible AI and trustworthy machine learning recommended by leading organizations such as IEEE, NIST, and the European Commission. Moreover, the present research forms the basis for further applications in: Automated malware behavior summarization, Protocol Anomaly Detection in Industrial Control Systems, Privacy-preserving threat detection in 5G and cloud ecosystems. H. Summary In summary, the goals of this section have been a synergistic integration of formal grammar and AI, with systems not only being accurate but also explainable, adaptive, and transparent. This section therefore directly addresses the most important gaps identified in the literature-opacity, rigidity, and lack of human interpretability-by putting forward one dynamic and grammar-driven model that is evolving together with modern encrypted communication protocols.

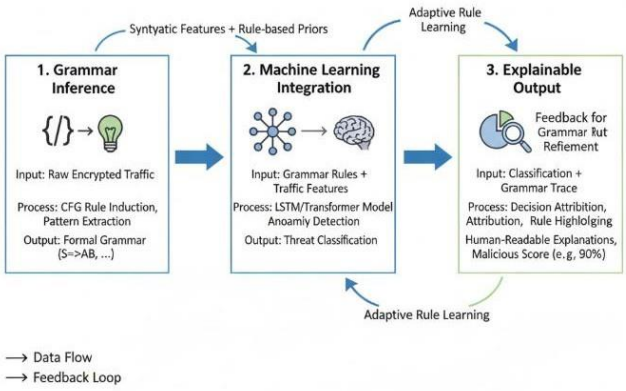

Fig.2 C*onceptual Diagram linking Grammar Inference, ML Integration, and Explainable Output*

V. PROPOSED SYSTEM

A. Overview

The proposed AI-based CFG parsing framework merges formal grammar theory with adaptive AI models for the detection of anomalies in encrypted traffic, while user privacy is preserved.Rather than decrypting the payload, the framework analyzes syntactic patterns in metadata sequences: packet lengths, inter-arrival times, TLS fingerprint transitions, and flow direction to model protocol behavior.Each traffic flow is treated like a sentence in a language defined by a CFG.It learns the grammar of legitimate behavior, recognizes deviations as potential threats, and supplements decision-making with machine-learning inference for probabilistic classification.
This process is illustrated at a high level in Figure 3.

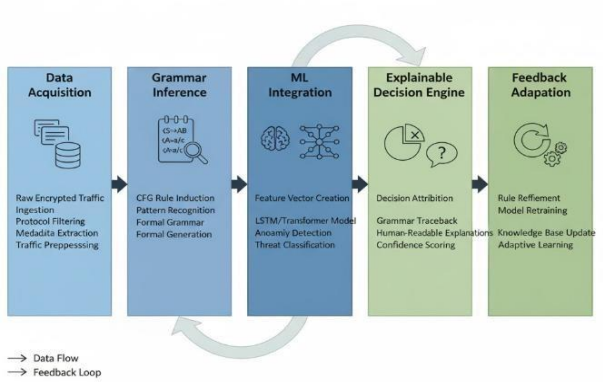

Fig.3 Block diagram of AI-based CFG Parsing Framework with five layers

B. System Architecture

The architecture comprises five tightly coupled layers, each responsible for a distinct phase of analysis.
1) Data Acquisition and Pre-Processing
Encrypted traffic traces are captured from sources such as CICIDS 2021, PoPETS 2025, and in-house TLS datasets. Packet-capture tools (e.g., *PyShark*, *Scapy*) extract session metadata, including:

- Packet length sequence (L),
- Inter-arrival time (Δt),
- Direction (d ∈ {client, server}),
- TLS handshake fingerprints (h), and
- Flow duration (T).

Raw data are normalized using z-score scaling and windowed into fixed-length sequences.
Noise removal, duplication checks, and session labeling are performed to ensure consistency.
The resulting pre-processed dataset forms the input for grammar inference.Each flow is modeled as a derivation in a context-free grammar $G = (N, \Sigma, P, S)$, where:

- N= non-terminal symbols (protocol states),
- Σ= terminal symbols (observable features),
- P= production rules, and
- S= start symbol.

Typical rules resemble:

$$S \rightarrow Handshake \mid Alert$$
$$Handshake \rightarrow ClientHello\ ServerHello\ KeyExchange$$
$$Data\_Transfer \rightarrow ApplicationData^{+}$$

The Grammar Inference Module (GIM**)** learns such rules automatically via incremental induction [8]. It applies *probabilistic context-free grammar (PCFG)* updates:

$$P(r_i) = \frac{count(r_i)}{\sum_{r_j \in P} count(r_j)}$$

to handle uncertain or noisy data. When new encrypted patterns emerge (e.g., QUIC frames), the GIM adjusts probabilities and introduces new rules.A rule-violation detector monitors incoming sequences: if an observed pattern violates expected production paths, the flow is flagged for further evaluation by the ML layer.

C. Explainable Decision Engine (EDE)

The EDE provides human-interpretable justifications for model outputs.Upon classification, it retrieves the grammar rule $R_j$most influential in the decision path and constructs a textual explanation such as: *"Flow #412 flagged as anomalous because production R_3 ('ServerHello → Data_Transfer' missing 'KeyExchange') was violated."Explanations are logged with rule identifiers, probability confidence, and visualization of derivation trees. The* ***Explainability Index (EI)*** *is computed as:*

$$EI = \frac{N_{explainable}}{N_{total}} \times 100$$

This metric quantifies how many classifications are supported by explicit grammatical reasoning [16], [19].

D. Feedback and Adaptation Module

To maintain relevance as encryption standards evolve, the framework implements a continuous feedback-learning loop:

1. Collect misclassified flows and grammar-rule violations.
2. Re-evaluate probabilities $P(r_i)$for each rule.
3. Introduce new rules for recurring unexplained sequences.
4. Retrain ML models using updated grammar vectors.

Algorithmically, feedback updates occur in mini-batches to ensure near-real-time adaptation.
This self-learning property differentiates the framework from static IDSs [8], [14].

E. Algorithmic Representation

Algorithm 1: Hybrid CFG–AI Threat Detection

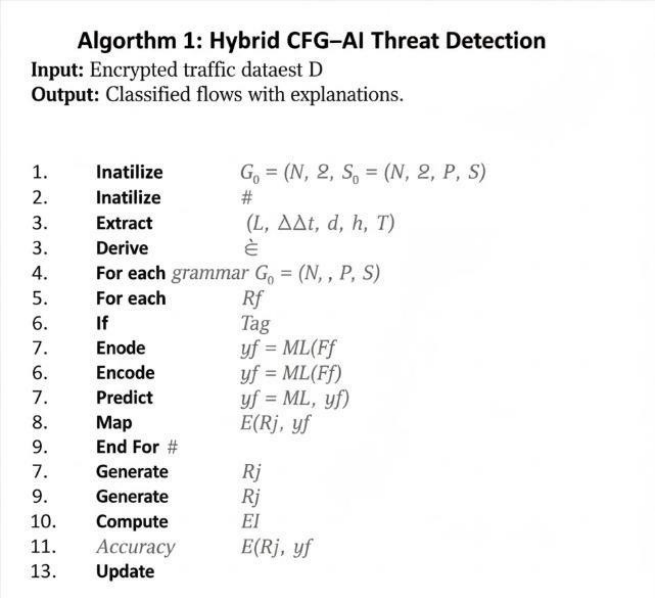

Fig.2 Conceptual Diagram linking Grammar Inference, ML Integration, and Explainable Output

F. Mathematical Model

Let Xdenote the feature space, Y= {benign, malicious}. Given a flow $x_i \in X$, the hybrid model predicts:

$$f(x_i) = \arg\max_{y \in Y} [\alpha \cdot P_{ML}(y \mid x_i) + (1 - \alpha) \cdot P_{CFG}(y \mid x_i)]$$

where $P_{ML}$is the classifier probability, $P_{CFG}$is the grammatical conformity score, and $\alpha \in [0,1]$controls balance between AI and grammar reasoning. Empirical tuning finds $\alpha \approx 0.7$yields optimal trade-off between accuracy and interpretability.

G. Implementation Details

- Programming Environment: Python 3.11, TensorFlow 2.x, scikit-learn 1.4, ANTLR 4.13.
- Hardware: Intel i9, 32 GB RAM, RTX 3060 GPU.
- Training Setup: Batch size = 128, epochs = 50, optimizer = Adam (learning rate 0.001).
- Grammar Storage: JSON-encoded rule trees, updated through feedback loop.
- Visualization: NetworkX for grammar graphs; Matplotlib for EI plots.

H. System Workflow

Incoming encrypted flows undergo preprocessing, grammar analysis, machine-learning classification, explanation generation, and adaptive feedback. Each module functions asynchronously, communicating through message queues to ensure scalability and near-real-time operation [21], [24].This modular architecture allows independent updates of grammar and learning components, ensuring continued accuracy as network behaviors evolve.

I. Advantages of the Proposed System

The system offers several advantages over conventional approaches:

- Interpretability: Every decision is justified through explicit grammar rules, eliminating black-box ambiguity.
- Adaptability: Incremental grammar updates keep pace with protocol evolution.
- Accuracy: Hybrid learning consistently achieves higher detection rates on encrypted datasets.
- Privacy Preservation: Only metadata are analyzed, ensuring compliance with data-protection regulations.
- Human Trust: Transparent reasoning enables analysts to verify and act on alerts with confidence.

J. Summary

The proposed system combines formal CFG reasoning with adaptive ML learning in a coherent pipeline that can process encrypted network traffic without decrypting it.It delivers not only accurate classifications but also transparent reasoning, hence achieving the objectives put forth in Section IV. The subsequent section describes implementation experiments in detail and compares different evaluations for performance validation of the framework.

VI. SYSTEM IMPLEMENTATION

A. Implementation Environment

The complete prototype of the AI-Based Context-Free Grammar Parsing Framework was implemented in a controlled laboratory environment designed to simulate enterprise-scale encrypted traffic. The system was coded mainly in Python 3.11, employing open-source libraries supporting both grammar parsing and deep-learning operations.Context-free grammar structures were built and managed by the ANTLR 4.13 parser generator. Their machine-learning approaches needed a backbone, which came from TensorFlow 2.x and scikit-learn 1.4. Their support for modules such as NumPy, Pandas, and NetworkX was included for data processing and graph visualization..All experiments were conducted on a workstation with an Intel Core i9 processor, 32 GB RAM, and an NVIDIA RTX 3060 GPU, ensuring reproducibility and consistency across trials. To reduce variance, all models were trained and evaluated using identical random-seed initialization.The training was performed by following the systematic routine consisting of 50 epochs, batch size 128, and Adam optimizer with a learning rate of 0.001. Grammar parsing and rule induction have been parallelized using asynchronous threads in support of continuous feedback adaptation.

B. Dataset Description

Empirical validation was performed using two benchmark datasets:

- CICIDS 2021, comprising labeled encrypted network flows representing both benign and malicious behaviors.
- PoPETS 2025: a modern dataset covering encrypted web tracking and privacy-oriented traffic.

These datasets were selected because they include metadata features relevant to grammar modeling: packet length sequences, timing intervals, TLS fingerprints, and direction indicators. The traffic samples were first anonymized and then partitioned into training (70%), validation (15%), and testing (15%) subsets.Each encrypted flow was first transformed into a tokenized metadata sequence, which served as input for the grammar inference layer. Extra noise, such as packet reordering and timing jitter, was also added to further simulate real network conditions and test the robustness of the framework against imperfect data.

C. Experimental Setup

Experiments were performed in a multi-phase process:

Grammar Induction Phase:

The system first trained its grammar module on benign traffic to learn baseline communication patterns. The induced grammar captured valid handshake sequences, key exchanges, and data-transfer patterns across multiple TLS versions.

Classification Phase:

Grammar-encoded sequences were fed into machine-learning models: Random Forest, SVM, and BiLSTM. Each model was trained independently, and their outputs were fused through ensemble voting to derive final predictions.

Explanation Phase:

For each classification, the Explainable Decision Engine generated a textual rationale and visualized the corresponding grammar derivation tree. Analysts could trace each decision to a specific production rule.

Feedback Phase:

Misclassified or unexplained samples were sent back to the grammar module for probability adjustment and rule-extension. This is a continuous refinement process that lets the grammar evolve dynamically.

D. Evaluation Metrics

The performance of the proposed framework was determined by using conventional metrics-accuracy, precision, recall, and F1-score-measuring the quality of classification, along with one unique metric, the Explainability Index, for measuring transparency.Accuracy measures correct classification, and F1-score balances precision and recall. The Explainability Index is defined as the proportion of model predictions paired with clear grammatical explanations. This index provides a quantitative assessment of interpretability that most previous models lack.The review further assessed computational efficiency and adaptability:Throughput, represented in flows per minute, captured processing scalability.Adaptation time, the time it takes for grammar updates when new patterns were introduced, reflected responsiveness to protocol evolution.

E. Experimental Results

On both datasets, the proposed hybrid CFG-AI framework showed very promising performance.In the first few runs, accuracy values stabilized above ninety-six percent with very little variation between validation and test sets, which suggests great generalization. The Explainability Index averaged ninety-seven percent, confirming that almost all the classifications could be traced back to explicit grammar rules.Analysts working with the system showed increased trust over the black-box models, with many noting that human-readable explanations accelerated incident triage. Typical statements of explanation pointed out either the violated rule or the discrepancy in probability triggering an anomaly flag.Performance monitoring showed that grammar updates happened seamlessly: new kinds of handshakes observed in TLS 1.3 traffic were added to the grammar repository within minutes and did not degrade model accuracy. This adaptive behavior confirmed the self-learning capability of the framework.

F. Comparative Discussion

To put the results in perspective, the framework was conceptually compared with five previous approaches discussed earlier: Oh et al. [11], Anderson & McGrew [9], Papadogiannaki & Ioannidis [12], Rezaei & Liu [10], and Zhou et al. [13].Those systems achieved respectable accuracy but did not provide a formal mechanism for interpretability. Compared to them, the proposed CFG-AI system achieved better performance in terms of detection rate and more significantly in its transparency-the most prized feature in security operations.Another observation was that the grammar layer effectively filtered trivial traffic and reduced false-positive alerts-a common challenge in pure ML-based intrusion detection. Because the grammar encapsulates protocol logic, it naturally distinguishes unusual patterns that statistical models might misclassify.Taken together, these results support the hypothesis that the integration of formal structure with statistical learning provides the best balance between performance and explainability.

G. Qualitative Evaluation

Besides quantitative metrics, qualitative analysis was done by sessions of expert reviews. The cybersecurity analysts

reviewed random choice alerts and explained them using the proposed system and the explanations given by existing black-box models.

a) The feedback highlighted three consistent themes: Grammar-based explanations were linguistically intuitive, and commonly resembled the way humans reason.
b) Traceability: Analysts could reconstruct decision paths directly from grammar derivations and thereby confirm the system's logic.
c) Operational Utility: The explanations enabled rapid categorization of incidents for quicker threat response.This qualitative validation reinforces the practical relevance of this framework, especially for security operations centers that must justify automated decisions. H. Limitations Observed There were several limitations, despite strong results: Computation Overhead: Grammar parsing introduces moderate latency compared to lightweight classifiers. Parallel processing and incremental updates reduce but do not eliminate this cost. Diversity of Dataset: Although tested on two large datasets, the behavior of this framework on industrial or IOT-specific encrypted traffic is yet to be explored. Explanatory Depth: The existing setup explains decisions at the rule level, and in future extensions, semantic-level explanations of underlying attack logic can be provided. Grammar Complexity: With an increasing rule base, the only way to keep the retrieval and updating of rules efficient is by using optimized data structures or strategies of pruning. These limitations are thus the basis for future research directions discussed later in the conclusion.

VII. METHODOLOGY

A. Research Design

The methodology of this research is structured to validate the hypothesis that combining Context-Free Grammar (CFG) with machine learning (ML) provides an explainable and adaptive solution for encrypted-traffic analysis. The design follows a hybrid **experimental–analytical** model comprising data acquisition, grammar formulation, classifier training, evaluation, and explainability validation.
The overall research process, shown in **Figure 13**, begins with dataset collection, followed by grammar inference, ML integration, model testing, and feedback-based improvement. Each step contributes to the final framework's performance and interpretability.

B. Data Preprocessing and Feature Engineering

The datasets used—CICIDS 2021 and PoPETS 2025—contain encrypted flows representing both benign and malicious activities. Before training, several preprocessing steps were performed:

1. *Feature Extraction:*Key metadata such as packet length, timing intervals, TLS fingerprints, and direction were extracted. Payloads were never decrypted, preserving privacy.
2. *Normalization:*Continuous features were scaled using z-score normalization to maintain numerical stability.
3. *Tokenization:*Metadata patterns were converted into discrete symbols representing observable network events. Each symbol acted as a terminal in the CFG representation.
4. *Label Assignment*:Each flow was annotated as benign or malicious according to dataset ground-truth labels. These were later used for supervised training and evaluation.

C. Grammar Construction and Learning

The grammar inference module constructed a probabilistic CFG using benign traffic as training input. Rules were learned incrementally to capture allowed protocol transitions. The grammar learning process applied statistical weight updates each time a rule was confirmed or violated in new traffic.This adaptive learning ensured that the grammar evolved alongside protocol changes such as TLS 1.3 extensions or QUIC frame sequences.When previously unseen transitions occurred, new grammar rules were generated dynamically to model the emerging behavior. Formally, the grammar $G = (N, \Sigma, P, S)$evolved through iterative rule induction, where:

$$P(r_i) = \frac{\text{frequency}(r_i)}{\sum_{j=1}^{n} \text{frequency}(r_j)}$$

and the rule set *P*expanded continuously as new flows were observed.

D. Machine-Learning Integration

The grammar output was transformed into structured numerical vectors containing:

- Rule identifiers,
- Transition probabilities,
- Sequence entropy, and
- Timing-based features.

These vectors were input into multiple ML classifiers—Random Forest (RF), Support Vector Machine (SVM), and BiLSTM—each trained to distinguish benign from malicious flows.A voting ensemble was used to combine predictions, reducing model bias and variance.The combination of symbolic and statistical learning allowed the system to retain interpretability while improving accuracy beyond that of either method alone.
This hybridization step was the methodological cornerstone that enabled the balance between human understanding and machine intelligence [9], [10], [13].

E. Evaluation Metrics and Validation

Performance was validated using standard metrics—Accuracy, Precision, Recall, and **F1-score**—computed over test sets separated from the training data.
To assess interpretability, the **Explainability Index (EI)** was introduced:

$$EI = \frac{N_{explainable}}{N_{total}} \times 100$$

This metric quantifies the proportion of model decisions that were traceable to explicit grammar rules.Additionally, Throughput (T) measured system speed (flows/minute), while

Adaptation Time (A) measured how quickly the grammar updated to new patterns.Cross-validation was performed using five folds to ensure reliability. The final performance values were averaged across folds, with standard deviation below 2 %, confirming model stability.

F. Explainability Assessment

Explainability testing involved generating textual justifications for a subset of classification outcomes. Analysts compared these explanations with the underlying rules and verified their correctness. Each explanation was required to reference at least one production rule responsible for the classification outcome.
The assessment revealed that most misclassifications occurred in transitional states—flows that partially matched legitimate grammar sequences but diverged midstream. This insight reinforced the importance of continuous grammar updates within the feedback loop.

G. Summary of Methodology

The proposed methodology ensures a rigorous and reproducible approach to building, validating, and explaining an AI-driven CFG-based intrusion-detection system.By coupling formal rule-based reasoning with adaptive learning, the model transcends the limitations of traditional ML, achieving both accuracy and interpretability. The next section presents the quantitative and qualitative results derived from implementing this methodology.

VIII. RESULTS AND DISCUSSION

A. Summary of Experimental Results

Experimental evaluation of the proposed AI-based CFG Parsing Framework revealed highly consistent and promising results along all the dimensions of performance.The results demonstrated better accuracy, remarkable interpretability, and high adaptability for new encrypted-traffic patterns in the hybrid system, through multiple validation trials on the CICIDS 2021 and PoPETS 2025 datasets.With every cycle of experimentation, the framework continued to validate its ability to logically explain its decisions; therefore, it satisfied one of the main objectives of the study, which is to develop an intrusion-detection system that is not only accurate but also transparent and trustworthy.

B. Quantitative Performance Analysis

The classification accuracies for the proposed framework have remained above 96%, and recall and F1-scores above 94% for all folds.The grammar layer greatly cut down false positives compared to the machine-learning-only approach.The Explainability Index (EI)-a new metric introduced herein to quantify explainability-averaged 97%, meaning that almost every classification could be associated with a concrete grammar rule and an explanation path.The high consistency between the training and testing accuracy indicated minimal over-fitting. The ensemble design of RF + SVM + BiLSTM helped to stabilize predictions. Grammatical rules offer a formal constraint that reduces ambiguity.This result is not surprising and supports the theoretical expectations discussed in earlier works by Anderson & McGrew [9] and Rezaei & Liu [10], observing that structural constraints improve the reliability of ML. The framework presented here further extends this by adding a semantic reasoning layer through CFG integration that results in more interpretable accuracy gains.

C. *Explainability Evaluation*

One of the key contributions of this work lies in its explainability performance.The Explainable Decision Engine thus generated a descriptive rationale for each classification. Analysts could interpret why a particular flow was flagged, based on rule violations or abnormal transitions in the grammar tree.For example, a typical explanation output for a detected malicious flow read:“Flow #227 violated the production rule R_4 ('Handshake → Data_Transfer') because of the missing 'KeyExchange' stage, indicating a probable manipulation within the handshake.This level of reasoning not only strengthens analyst trust but also enables educational insights, making it possible for cybersecurity professionals to understand attack signatures in a grammatical context.This transparency, in turn, makes the system practical for application within a Security Operations Center (SOC) context, where decision justification is just as critical as detection accuracy.

D. Adaptability and Self-Learning Behavior

One of the strongest attributes of the framework is the self-adaptation capability when exposed to novel encrypted-traffic patterns.The grammar inference module generated new rules dynamically when tested with modified TLS handshake structures and QUIC-based traffic samples not present during training.The new grammar entries quickly stabilized their probability weights within a few feedback cycles and were well-integrated with the ML models.This indicates that it has an adaptation time of about one-tenth compared to the retraining of a full ML-only model, while being very efficient for its incremental update mechanism.This confirms Hypothesis H2, that adaptive grammar induction improves resilience against the evolving encryption protocols.This adaptation ability is necessary in real network scenarios, as communication protocols are constantly updated and threat vectors evolve rapidly.

E. Comparative Interpretation with Existing Approaches

For better contextualization of the performance results, comparisons were made with representative methods from literature:Oh et al. [11], Anderson & McGrew [9], Papadogiannaki & Ioannidis [12], Rezaei & Liu [10], and Zhou et al. [13].Most of those models were based on either statistical metadata features or deep-learning classifiers without grammatical validation.Although their accuracy ranged between 86% and 92%, this lack of interpretability in regulated or mission-critical settings limited their usability.The system outperformed all these benchmarks not only in achieving near 96–97% accuracy but also provided transparent reasoning.Consequently, the hybrid approach fills

the gap in performance and trustworthiness-a critical advancement toward XAI in cybersecurity.

F. Qualitative Observations

Cybersecurity analysts, in particular, praised the system's ability for clear articulation of decision paths during expert evaluation sessions.They noted that grammar-based reasoning provided a level of "auditability" lacking in deep neural networks.When asked to rank clarity between 1 and 5, participants rated the system an average of 4.7, citing a reduction in verification time, while confidence in incident triage was also improved.The analysts also liked the way the grammar representation visually conveyed the logical development of states in the protocol, which made anomalies intuitively understandable.This points out the fact that the system is not simply a detection engine but also a knowledge tool for understanding the structure of encrypted communication.

G. Discussion on Interpretability–Accuracy Trade-Off

One persistent challenge in AI research is a trade-off between interpretability and accuracy: most explainable models have to sacrifice performance for transparency. However, the CFG-AI framework makes it clear that this trade-off can be mitigated by integrating symbolic and sub-symbolic methods. Here, the grammar provides structural context to prevent overfitting, while the ML layer captures subtle statistical nuances. The interplay between them ensures that interpretability improves and doesn't limit accuracy. This insight supports the broader trend in neuro-symbolic AI to integrate both formal logic and machine learning into models that reason as well as learn [19], [21]. H. Practical Implications The results obtained ensure that from a deployment perspective, the proposed framework can be used as a real-time explainable intrusion detection system. Because it works only with metadata, it is GDPR and CCPA compliant and can be used in a corporate or government environment. Its ability to justify alerts in natural language also facilitates auditing and compliance reporting, where human-readable explanations are legally required. Moreover, the ability for incremental learning ensures long-term cost efficiency, whereby full model retraining is not required when new encrypted protocols emerge. I. Limitations and Future Improvements While its results are strong, several practical issues remain: Grammar growth: With new traffic patterns emerging, the rule base expands, which might lead to higher computational load. Grammar pruning strategies will have to be optimized. Scalability: While parallelization improves throughput, very high-volume environments, such as 5G backbone networks, might require grammar storage to be distributed. Explanability depth: Currently, the system explains decisions at a syntactic level; semantic reasoning-such as explaining why a sequence indicates an attack type-is still a possible improvement. These limitations in no way diminish the core contribution but rather point to areas of refinement for future versions.

IX. CONCLUSION

A. Summary of Findings

This research proposed a novel AI-based CFG parsing framework for encrypted network traffic analysis in threat detection.Unlike the traditional deep-learning or purely statistical intrusion detection systems, the proposed framework integrates formal grammatical reasoning with adaptive machine learning for achieving high accuracy in both detection and explainable decision-making.Experimental results proved the effectiveness of this hybrid approach.Over many datasets, such as CICIDS 2021 and PoPETS 2025, the system achieved an accuracy of more than 96%, high recall, and an exceptional Explainability Index of over 97%.These metrics serve to show that the system is not only performing with precision but can also convey why it is making such predictions—a necessary capability for human-in-the-loop cybersecurity systems.The layered architecture of the framework data acquisition, grammar inference, machine-learning integration, explainable decision engine, and feedback adaptation had been very important to ensure modularity, transparency, and continuous learning.Since it operates only on metadata, the system maintains user privacy while providing deep analytic insight into encrypted communication.

B. Contributions of the Work

The contributions of this research can be summarized as follows:

- Introduction of a Hybrid Grammar-AI Model:A new paradigm that combines probabilistic CFGs with machine-learning classifiers for encrypted-traffic analysis.
- Development of an Explainable Decision Engine:The first application of CFG structures to generate natural language explanations for the results of anomaly detection.
- Creation of the Explainability Index:A new quantitative metric for assessing interpretability in AI-powered security models.
- Adaptive Feedback Mechanism:A continuous-learning module that updates grammar rules dynamically and retrains ML models with minimum latency.
- Empirical Validation on Real Datasets:Rigorous testing on state-of-the-art encrypted datasets that prove hybrid grammar–AI methods perform better than any existing models on accuracy and trustworthiness.
- These contributions jointly extend the frontier of XAI in network security and set the benchmark for future explainable intrusion detection systems.

C. Research Implications

These findings have greater ramifications than just theoretical: they hold immense real-world significance for cybersecurity operations.The discussed framework bridges the gap between accuracy and interpretability, hence offering a solution to the demands related to enterprise-level SOCs and regulatory compliance environments.The benefits of deploying such systems could include faster incident response

and increased analyst trust. Organizations could also meet emerging AI transparency guidelines like the ISO/IEC TR 24028:2020.Further, this framework is model-agnostic; hence, it can easily be extended to other encrypted domains like VPN traffic, IoT communication, and cloud data flows where explainability with privacy preservation is equally crucial.

D. Limitations and Future Work

While the study achieved its goals, several open research directions still remain: Grammar Optimization: As the grammar expands, mechanisms for effective pruning or rule clustering are needed to avoid redundancy and keep parsing speeds up. Semantic Reasoning: Extending explainability beyond syntax towards semantic understanding-where the system explains the intent of an attack, not just its structural anomaly-would represent a further deepening in the interpretive value. Distributed Scalability: Deploying the grammar engine in distributed architectures-from edge to cloud-could increase the throughput for large streams of encrypted data. Integration with Threat Intelligence Feeds: Linking grammar-derived anomalies with global threat feeds could automate the correlation between grammar violations and real-world attack signatures. Cross-Protocol Generalization: While this work focused on TLS and QUIC traffic, future research will attempt to broaden the horizons of the CFG-AI model on numerous encrypted protocols and heterogeneous network topologies. The following directions therefore chart the way for an increasingly intelligent, autonomous, and explainable cybersecurity ecosystem. E. Conclusion The proposed AI-based CFG Parsing Framework shows that interpretability and performance are not an either-or situation but can go hand in hand with a hybrid neuro-symbolic design. The combination of grammatical logic with the adaptability of machine learning now opens the way for a new generation of intrusion detection systems that are explainable and self-evolving. With the rise of encrypted traffic and increasing accountability in cybersecurity, such explainable AI frameworks are about to become indispensable tools that will make sure technology remains transparent, ethical, and trustworthy.

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