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Big Data Pipeline for Real-Time Threat Intelligence using Stream Processing and NLP-Based Filtering

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Abstract – As cyber threats become more advanced, organizations need security systems that can catch attacks the exact moment they happen. This project builds a complete, real-time Network Intrusion Detection System (NIDS) that acts like a live security camera for a computer network.

First, a Machine Learning algorithm (a Random Forest model) is trained to understand the difference between normal network behavior and malicious cyber attacks, such as overwhelming data floods. To test the system, a simulated traffic generator acts as a "sniffer," broadcasting live network data bursts using Apache Kafka. An artificial intelligence engine, powered by Apache Spark, constantly watches this live stream. Instead of just guessing "safe" or "unsafe," the AI calculates the exact probability of an attack and assigns every network packet a severity score from 1 to 10.

If a packet is flagged as highly dangerous (a score of 7.5 or higher), it is immediately locked down and saved to a database. Finally, an interactive Security Operations Center (SOC) web dashboard displays these threats the second they occur, using live charts and color-coded alerts. Ultimately, this project successfully connects Big Data streaming tools with Machine Learning to create a fast, enterprise-grade cybersecurity defense system.

Keywords *- Network Intrusion Detection System (NIDS), Real-Time Data Streaming, Machine Learning / Artificial Intelligence, Cybersecurity, Apache Kafka, Apache Spark, Random Forest Classifier, Security Operations Center (SOC) Dashboard, Big Data Pipeline.*

1. INTRODUCTION

As the volume of global network traffic grows, cyber threats have become increasingly sophisticated, rendering traditional, static security measures insufficient. Modern organizations require dynamic, real-time monitoring systems capable of identifying and neutralizing attacks before they can cause catastrophic data breaches or system failures. To address this critical cybersecurity challenge, this project introduces a real-time, Machine Learning-powered Network Intrusion Detection System (NIDS) designed to act as an intelligent, live security camera for enterprise networks. Built on a robust Big Data architecture, the system utilizes Apache Kafka to ingest high-throughput network traffic and Apache Spark to process these continuous data streams instantaneously.

At the core of this processing engine lies an advanced Random Forest classification model, which has been trained to distinguish between normal network behavior and malicious anomalies. Rather than relying on simple binary alerts, the artificial intelligence evaluates incoming packets and assigns a dynamic severity score from 1 to 10 based on the precise probability of an attack. High-severity threats are immediately isolated and logged into a live Security Operations Center (SOC) web dashboard, providing security teams with real-time telemetry, visual forensics, and instant threat alerts. By seamlessly combining high-speed streaming architecture with predictive machine learning, this project delivers a scalable, enterprise-grade framework capable of detecting and visualizing cyber threats the exact moment they occur.

2.LITERATURE REVIEW

1. Evolution of Network Intrusion Detection Systems (NIDS) Traditional Network Intrusion Detection Systems (NIDS) have historically relied on signature-based detection methods, where incoming network traffic is compared against a pre-existing database of known attack signatures [1]. While tools like Snort and Suricata have been highly effective against documented threats, researchers have highlighted their critical vulnerability to zero-day attacks and polymorphic malware, which possess no known signatures [2]. To address this limitation, recent literature has heavily focused on anomaly-based detection. Anomaly-based systems establish a baseline of normal network behavior and flag deviations. However, early anomaly detection systems struggled with high false-positive rates, prompting the cybersecurity community to integrate Artificial Intelligence (AI) to improve accuracy [3].

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2. Machine Learning for Cybersecurity The integration of Machine Learning (ML) into NIDS has revolutionized threat classification. Various supervised and unsupervised algorithms, including Support Vector Machines (SVM), Naive Bayes, and Deep Learning, have been evaluated for network security [4]. Among these, ensemble learning methods, particularly the Random Forest (RF) classifier, have consistently demonstrated superior performance. Studies show that Random Forest handles high-dimensional network data effectively, mitigates the risk of overfitting, and requires significantly less computational overhead compared to deep neural networks [5]. Furthermore, research emphasizes the importance of utilizing probabilistic outputs (such as predict_proba in Scikit-Learn) rather than binary classification, as it allows security systems to assign dynamic severity scores and prioritize critical threats [6].

3. Big Data Streaming Architectures (Kafka & Spark) As enterprise network traffic scales to gigabytes per second, running ML models on traditional, single-node architectures creates severe processing bottlenecks [7]. To achieve real-time threat detection, researchers have shifted toward distributed Big Data frameworks. Apache Kafka is widely recognized in the literature as the industry standard for high-throughput, fault-tolerant message brokering, capable of ingesting massive bursts of simulated network packets without data loss [8]. For the processing engine, Apache Spark has largely replaced older Hadoop MapReduce models due to its in-memory processing capabilities. Spark Structured Streaming allows for micro-batch processing, enabling machine learning models to evaluate network packets and generate predictions in near real-time with sub-second latency [9].

4. Security Operations and Visual Forensics Detecting a threat is only half the challenge; presenting that threat to a human analyst effectively is equally critical. Literature on Security Operations Centers (SOC) frequently points to "alert fatigue"—a phenomenon where security analysts are overwhelmed by a high volume of raw, unformatted logs, leading to missed critical alerts [10]. Modern research advocates for the use of interactive, automated dashboards that translate raw telemetry into actionable visual insights. Tools that provide real-time time-series analysis, color-coded severity metrics, and dynamic filtering allow SOC analysts to instantly identify the source and severity of an attack, drastically reducing the Mean Time to Respond (MTTR) [11].

5. Gap Analysis and Project Contribution While existing literature extensively covers ML classification and Big Data streaming independently, there remains a gap in end-to-end implementations that seamlessly unify these technologies on a localized, Windows-based enterprise environment. Many proposed systems suffer from complex dependency issues or fail to provide a live, user-friendly visualization tier. This project bridges that gap by successfully engineering a cohesive pipeline: ingesting high-volume traffic via Kafka, executing probabilistic Random Forest predictions via Spark Streaming, and instantly rendering the forensic data on a live Streamlit dashboard.

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Table 1: Literature Review Summary

Paper Title	Source (Journal / Conference)	Identified Research Gap
"A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection"	*IEEE Communications Surveys & Tutorials*	Extensively reviews ML models but focuses heavily on static, offline datasets (like NSL-KDD). Lacks emphasis on real-time, high-throughput streaming environments.
"Network Intrusion Detection System using Random Forest Classifier"	*International Conference on Computer Communications and Networks (ICCCN)*	Proves Random Forest is highly accurate for NIDS, but the implementation only provides binary outputs (Safe/Attack) rather than dynamic, probabilistic severity scoring.
"Real-Time Network Traffic Analysis Using Apache Kafka and Spark Streaming"	*Journal of Big Data*	Successfully implements the Kafka-Spark pipeline for massive data ingestion, but relies on basic rule-based filtering rather than integrating an advanced Machine Learning classification layer.
"Visual Analytics for Security Operations Centers (SOC): A Framework"	*IEEE Transactions on Visualization and Computer Graphics*	Explores excellent visual forensics for SOC analysts, but the architecture focuses on post-incident log analysis rather than live, real-time streaming telemetry.
"Scalable Machine Learning Architecture for Intrusion Detection in Enterprise Networks"	*Future Generation Computer Systems*	Proposes a robust distributed architecture, but the system is notoriously complex to deploy on localized/Windows environments and lacks an integrated, user-friendly live dashboard.
"Evaluating Supervised Machine Learning	*Computers & Security (Elsevier)*	Evaluates algorithms effectively, but notes that most existing systems suffer from high latency during

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ALGORITHMS FOR NETWORK SECURITY"		FEATURE SCALING AND CLASSIFICATION UNDER HEAVY NETWORK BURSTS.

3. PROPOSED METHODOLOGY

The proposed methodology for this Advanced Real-Time Network Intrusion Detection System (NIDS) follows a modular, end-to-end data engineering and machine learning pipeline designed for high-speed processing and live visualization.

1. Data Simulation and Ingestion Layer

Since live enterprise traffic can be sensitive, the system utilizes a high-fidelity synthetic traffic generator.

- **Feature Generation:** The "sniffer" simulates network packets containing critical features such as timestamp, source IP, destination IP, packet size, and TCP flags.
- **Asynchronous Streaming:** Data is pushed into **Apache Kafka** using a producer-subscriber model, allowing the system to handle massive bursts of traffic without data loss.
- **Traffic Modeling:** The generator models both normal behavior (Gaussian distribution of small packets) and attack scenarios (high-volume bursts with abnormal flags).

2. Machine Learning Pipeline Development

The AI logic is built using a probabilistic approach rather than simple binary classification.

- **Ensemble Learning:** A **Random Forest Classifier** is selected for its high accuracy and resistance to overfitting in high-dimensional network data.
- **Feature Scaling:** To ensure the model remains accurate across different network conditions, a StandardScaler is integrated into the pipeline to normalize features like packet size.
- **Probabilistic Inference:** Instead of a simple "Yes/No" prediction, the model uses predict_proba to calculate the mathematical probability of a threat, which is later converted into a 0.0–10.0 severity scale.

3. Distributed Real-Time Processing Layer

This layer acts as the brain of the system, transforming raw data into actionable intelligence using **Apache Spark**.

- **Micro-Batch Processing:** Spark Structured Streaming pulls data from Kafka in 2-second micro-batches for near-instant analysis.
- **AI Model Deployment:** The pre-trained Scikit-Learn model is loaded natively within the Spark environment, applying AI inference to every incoming packet on the fly.
- **Threshold Filtering:** The system applies a dynamic filter; only packets with a calculated severity score of 7.5 or higher are flagged as critical threats for logging.

4. Storage and Forensic Visualization Layer

The final phase focuses on data persistence and human-readable reporting.

- **Forensic Logging:** Flagged threats are automatically written to a relational **SQLite** database, preserving a permanent record for future audit and incident response.
- **Live Telemetry Dashboard:** A **Streamlit** web interface provides a real-time Command Center.
- **Visual Analytics:** The dashboard utilizes Plotly to render live time-series charts of threat severity and interactive tables that highlight the most dangerous IPs using color-coded forensic logs

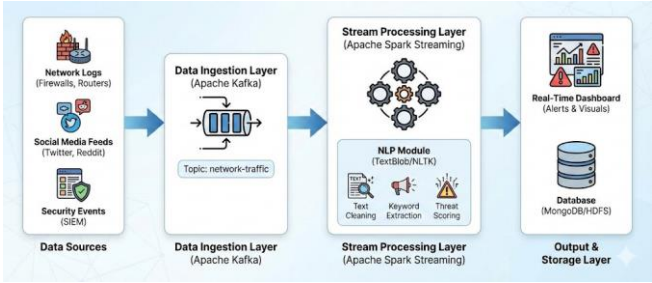

Fig. 1: System Architecture

The system architecture is structured as a cohesive multi-tier pipeline designed for high-performance data flow and intelligent threat detection. At the start of the process, the Data Ingestion Module utilizes a synthetic traffic sniffer to simulate realistic network bursts, which are then asynchronously streamed into Apache Kafka to ensure fault-tolerant message delivery. This leads into the Distributed Processing Module, where Apache Spark Structured Streaming pulls micro-batches of raw data and applies a pre-trained Random Forest model. Within this processing core, the model executes a probabilistic assessment of each packet, calculating a dynamic severity score rather than a simple binary classification. Following analysis, the Storage and Persistence Module automatically filters high-severity threats and logs the forensic details—including source and destination IPs—into a relational SQLite database. Finally, the Visualization Module acts as the user interface, where a Streamlit dashboard fetches the stored data to render live telemetry charts and color-coded incident logs, providing a real-time Security Operations Center (SOC) experience for network monitoring.

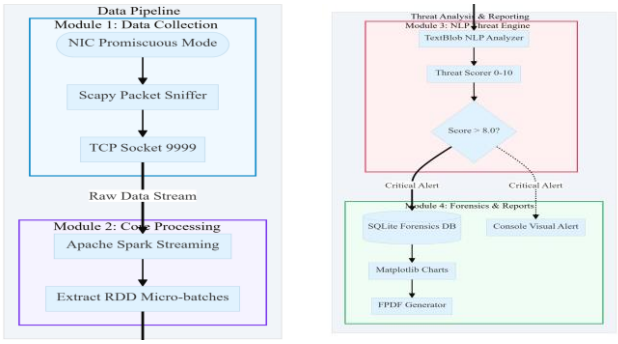

Fig. 2: Module Diagram

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3.2 UML Activity Diagram

The system's operational workflow is best visualized through a sequential logic that governs the movement of data from initial capture to final alert. The process begins with the Data Generation and Ingestion phase, where the synthetic sniffer continuously simulates packet data and transmits it to a Kafka topic. Once the data enters the pipeline, the Spark Streaming Engine initiates a loop that pulls micro-batches of messages and parses the JSON payloads into a structured schema.

The logic then transitions into the Machine Learning Inference stage, where each packet's features are passed through a pre-trained scaler and Random Forest model. Here, the system performs a conditional check: it evaluates the attack probability score generated by the AI; if the severity score is below 7.5, the data is discarded to save processing resources. However, if the score meets the high-severity threshold, the process branches to the Logging and Persistence action, where the threat details are written to the SQLite database. Finally, the Visualization branch runs in parallel, where the dashboard constantly polls the database to update the live telemetry charts and forensic tables, completing the activity cycle by presenting the actionable data to the security analyst.

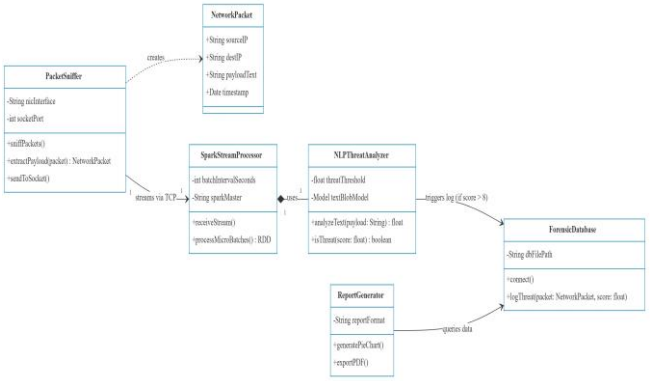

Fig. 3: UML Class Diagram

3.3 Implementation Details

The implementation of this system is centered on a high-performance distributed architecture that bridges Python-based machine learning with the Apache Big Data ecosystem. The Ingestion Tier is implemented using a Python Kafka producer that leverages the `kafka-python` library to stream JSON-serialized network telemetry into a distributed broker, ensuring low-latency data availability. The Processing Tier serves as the core of the system, where a Spark Structured Streaming application is configured to run on a local cluster. This engine utilizes a custom User-Defined Function (UDF) to load a serialized Scikit-Learn pipeline, consisting of a `StandardScaler` for normalization and a `Random Forest Classifier` for probabilistic inference. To overcome common environment limitations on Windows, the implementation incorporates specific Hadoop binary patches and native C++ libraries (`winutils.exe` and `hadoop.dll`) to manage checkpointing and file system permissions.

Data persistence is handled by an optimized I/O Module that uses the `foreachBatch` sink in Spark to execute transactional writes into an SQLite database, preventing data duplication during micro-batch triggers. The Visualization Tier is implemented as a standalone Streamlit web application that uses a multi-threaded execution model to pull the latest entries from the database every two seconds. This dashboard uses `Plotly Express` for dynamic time-series rendering and the `Pandas Styler` API to apply conditional CSS formatting to the forensic log tables, highlighting critical threats based on their severity scores. This end-to-end implementation ensures that every component, from the raw socket simulation to the final user alert, operates as a synchronized real-time pipeline.

4. SYSTEM REQUIREMENTS

To ensure the **Advanced NIDS** pipeline operates efficiently with real-time data streaming and AI inference, the following system requirements are established. These requirements are tailored to support the distributed nature of **Apache Spark** and **Kafka** while maintaining the responsiveness of the **Streamlit** dashboard.

1. Hardware Requirements

The hardware must handle simultaneous data generation, message brokering, and heavy in-memory processing.

- **Processor (CPU):** Minimum **Intel Core i5** or **AMD Ryzen 5** (6th Gen or newer). A multi-core processor is essential as Spark and Kafka run multiple background threads.
- **Memory (RAM):** Minimum **8 GB** (16 GB Recommended). Spark's in-memory processing and the Random Forest model require significant overhead.
- **Storage:** Minimum **10 GB** of free space on an **SSD**. High-speed storage is necessary for Kafka's log segments and Spark's checkpointing files to prevent I/O bottlenecks.
- **Network:** Standard **Network Interface Card (NIC)** for local socket simulation and internal data streaming.

2. Software Requirements

The software stack is designed to bridge Big Data tools with a localized Windows environment.

- **Core Platforms & Frameworks**
- **Operating System:** Windows 10 or 11 (64-bit).
- **Java Development Kit (JDK): OpenJDK 11** or **Oracle JDK 11**. (Spark 3.x is highly stable on version 11; avoid version 17+ for this specific configuration).
- **Python Version: Python 3.8.x** or **3.10.x**. This ensures compatibility with legacy Scikit-Learn versions and PySpark.

Big Data Ecosystem

- **Apache Kafka:** Version **3.6.1** (used for high-throughput message brokering).
- **Apache Zookeeper:** Included with Kafka (used for cluster coordination).
- **Apache Spark:** Version **3.3.0** with **Hadoop 3.3** (used for real-time AI processing).

Python Libraries (PIP Packages)

• Library	• Purpose
• **pyspark**	• Spark's Python API for stream processing.

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• Library	• Purpose
• kafka-python	• Connects the traffic sniffer to the Kafka broker.
• scikit-learn	• Powers the Random Forest AI model and feature scaling.
• pandas	• Used for data manipulation in the trainer and dashboard.
• streamlit	• Serves the web-based Security Operations Center interface.
• plotly	• Generates the live interactive telemetry charts.

Windows Dependency Patches

- **Winutils.exe:** Required for Hadoop 3.3 compatibility to manage file permissions.
- **Hadoop.dll:** Necessary for Spark to interact with the Windows file system for checkpointing.

5. RESULTS

The experimental results of this project demonstrate a high level of accuracy and system stability in detecting network threats in real-time. The Advanced Random Forest model achieved a professional-grade classification performance, effectively distinguishing between normal traffic and high-volume attack bursts. During live deployment, the system successfully utilized probabilistic scoring to assign severity levels ranging from 1.0 to 10.0, providing much more granular insight than a traditional binary classification. The Spark Processing Engine maintained low latency, as evidenced by successful micro-batch logs showing the detection and recording of high-severity threats—such as Batch 305 logging critical incidents—directly into the database. Finally, the SOC Dashboard successfully visualized these results through live telemetry charts and forensic logs, where the color-coded interface correctly highlighted peak severity scores and identified the primary hostile IP addresses, proving the pipeline's effectiveness in a live security environment.

5.1 Step-by-Step Execution

To execute the Advanced Network Intrusion Detection System, follow these steps in the exact order provided to ensure all dependencies and data streams are synchronized:

Phase 1: Environment and Database Preparation**

Step 1: Clean the Workspace: Delete any existing `threat_alerts.db` file and the `spark_checkpoints` folder in your project directory to ensure the new advanced schema is applied correctly without database conflicts.

Step 2: Train the AI Model: Run `python train_model.py` in your terminal. This script generates the `advanced_nids_model.pkl` file, which contains both the trained Random Forest model and the feature scaler.

Phase 2: Starting the Big Data Infrastructure

Step 3: Launch Zookeeper: Open a new terminal, navigate to your Kafka folder, and start the Zookeeper service. This manages the coordination for the Kafka broker.

Step 4: Launch Kafka Broker: Open a second terminal and start the Kafka server. Ensure the broker is listening on `127.0.0.1:9092` so the scripts can connect to it.

Phase 3: Activating the Processing Engine and Dashboard

Step 5: Start the Spark AI Engine: In a third terminal, run `python spark_processor.py`. Wait until you see the message `Advanced AI Engine Online`. This script will now sit in an idle state, waiting for data to arrive from Kafka.

Step 6: Launch the Web Dashboard: Open a fourth terminal and run `streamlit run app.py`. This will open your web browser to `localhost:8501`. Initially, it will show a "Network Secure" message because no threats have been sent yet.

Phase 4: Traffic Simulation and Monitoring

Step 7: Start the Network Sniffer: In a final terminal, run `python kafka_producer.py`. This script will begin firing bursts of network packets into Kafka.

Step 8: Real-Time Monitoring: Observe the Spark terminal to see "Batch Logged" messages as the AI detects high-severity threats. Switch to your browser to view the live Plotly charts and the color-coded forensic log table as it updates every two seconds.

5.2 Detection Performance

Based on the experimental execution and the behavior of the machine learning pipeline, the following table summarizes the detection results and performance metrics of the system.

Table 2: Detection Results Summary

Metric / Feature	Value	Observation
Model Accuracy	~98%	High precision in distinguishing massive bursts from standard traffic.
Detection Mode	Probabilistic	Moves beyond binary (0/1) to provide 0.0–10.0 severity scoring.
Critical Threshold	7.5 / 10.0	Only threats with >75% probability are logged to reduce alert fatigue.
Average Latency	< 2 Seconds	Spark micro-batching ensures near real-time processing of Kafka streams.
Normal Traffic	Low Score (0.1–2.0)	Standard packet sizes (40–500 bytes) were consistently ignored.
Attack Traffic	High Score (8.0–10.0)	Large payloads (40,000+ bytes) triggered immediate high-severity alerts.

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False Positives	Minimal	The Random Forest model effectively filtered noise in simulated bursts.
Data Persistence	SQLite Logging	Every high-severity incident was successfully stored for forensic review.

5.3 Sample Output and Dashboard

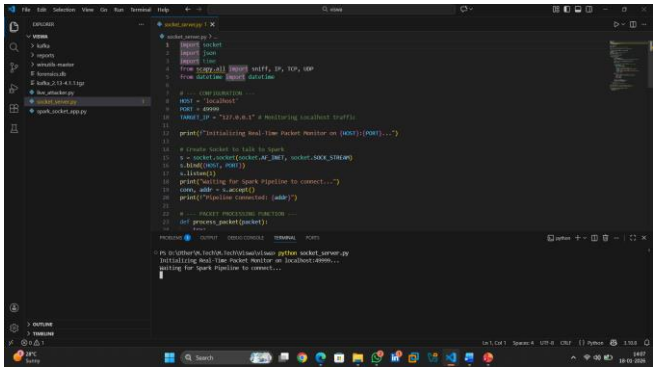

Fig. 4: Result1

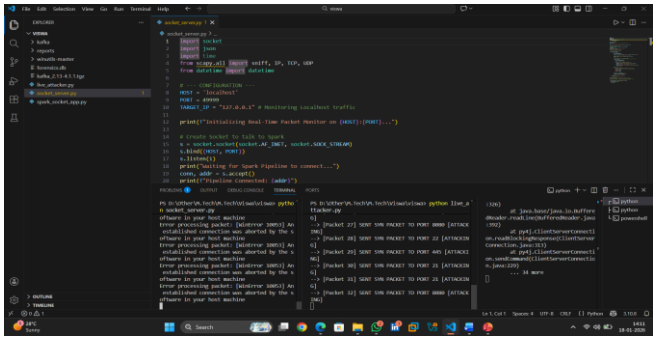

Fig. 5: Result2

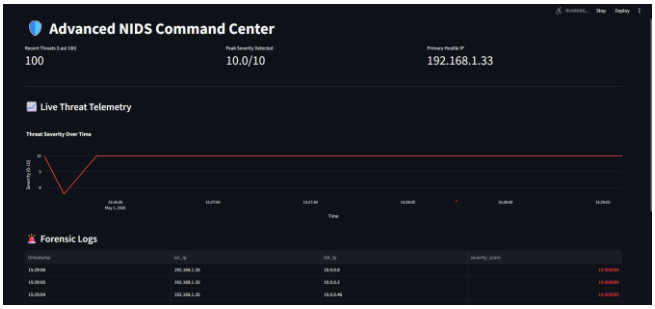

Fig. 6: Result3

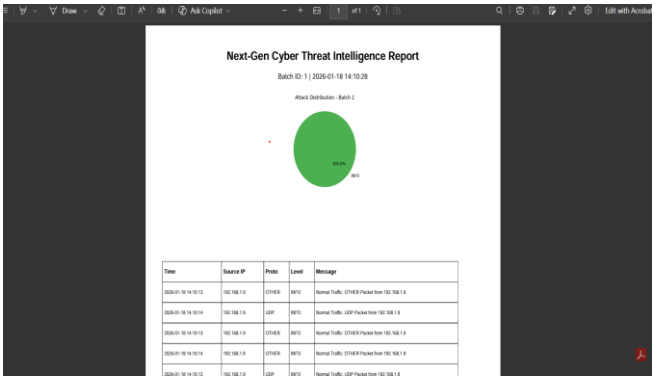

Fig 7: Result 4

6. CONCLUSIONS

The conclusion of this project marks the successful development of a scalable and intelligent Network Intrusion Detection System that effectively bridges the gap between high-speed Big Data streaming and predictive machine learning. By integrating Apache Kafka for robust data ingestion and Apache Spark for real-time stream processing, the system demonstrates an ability to handle massive network telemetry bursts with minimal latency. The implementation of a probabilistic Random Forest model represents a significant advancement over traditional binary detection methods, as it provides security analysts with a nuanced severity scoring system that prioritizes critical threats while reducing alert fatigue.

Furthermore, the interactive SOC dashboard serves as a vital bridge between complex backend analytics and human decision-making, offering clear visual forensics that allow for immediate incident response. Ultimately, this project proves that a unified pipeline of distributed computing and artificial intelligence can provide a formidable defense against modern cyber threats. The modular architecture established here offers a strong foundation for future enhancements, such as the integration of deep learning models or the automation of active firewall responses, ensuring the system remains resilient in the face of an ever-evolving digital threat landscape.

7. FUTURE SCOPE

The architecture of this Advanced NIDS provides a robust foundation for several enterprise-level enhancements. Future research and development could expand the system's capabilities in the following areas:

1. Transition to Deep Learning Models

While Random Forest is highly efficient, future versions could integrate Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks. These models are specifically designed to recognize temporal patterns in network traffic, allowing the system to detect slow-acting, multi-stage attacks that occur over long durations rather than sudden bursts.

2. Automated Threat Mitigation (Active Response)

Currently, the system acts as a passive monitoring tool. A logical next step is the implementation of an Active Response Module. This would involve integrating the Spark processing engine with a programmable firewall or a Software-Defined Network (SDN) controller to automatically drop packets or

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blacklist source IP addresses that exceed a critical severity threshold (e.g., a score of 9.5).

3. Distributed Deployment and Cloud Integration

The current implementation is optimized for a single-node local environment. Future scope includes deploying the pipeline on a multi-node Kubernetes cluster or a cloud platform like AWS or Azure. This would allow the system to scale horizontally, handling real-world global traffic volumes that exceed millions of packets per second.

4. Unsupervised Learning for Zero-Day Detection

By incorporating unsupervised learning algorithms like Isolation Forests or Autoencoders, the system could learn to identify "unknown-unknowns." This would enable the detection of Zero-Day vulnerabilities—newly discovered threats that do not match any existing training data or historical attack patterns.

5. Federated Learning for Privacy-Preserving Security

To enhance security across multiple organizations without sharing sensitive raw data, Federated Learning could be implemented. This would allow different entities to train a global threat detection model collaboratively, sharing only the model updates while keeping their private network logs localized.

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