Anomaly Detection in Smart Grids Using Machine Learning: A Real-Time Streaming Approach Using Apache Kafka and Kubernetes

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Abstract: Smart grids face escalating cyber-physical threats, demanding robust and real-time anomaly detection systems. This paper presents a machine learning (ML) framework for detecting anomalies in smart grid data streams, integrating Apache Kafka and Kubernetes for high-throughput data ingestion and Python-based ML models. We evaluate five algorithms—Random Forest, Neural Network, Support Vector Machine (SVM), Naive Bayes, and K-Nearest Neighbors (KNN)—on a dataset of 100,000 samples with 15 electrical and operational features. The Random Forest model achieves exceptional performance (F1-score: 0.9982, precision: 0.9987, recall: 0.9978), outperforming other models. Kafka integrated in Kubernetes enables real-time data streaming, ensuring timely threat detection. This work bridges scalable data processing with ML-driven security, offering a deployable solution for grid resilience.

Keywords: Smart Grid Security, Anomaly Detection, Apache Kafka, Machine Learning, Real-Time Processing.

1. INTRODUCTION

Recent research highlights the vulnerabilities of smart grids to cyberattacks and proposes advanced detection methods. Machine learning-based approaches have shown promise in detecting various attacks with high accuracy and low latency. A supervised ML model achieved 99.83% accuracy in detecting anomalies in DER DNP3 communication (Abdelkhalek, 2022). A cross-layered strategy integrating detection of faulty measurements and network inconsistencies demonstrated high F1-scores for multiple attack types (Starke et al., 2022). A CNN-LSTM autoencoder model achieved 95.43% accuracy in detecting false data injection attacks using energy consumption forecasting (Mahi-al-Rashid, 2022). Another deep learning framework combining LSTM and RNN achieved a 99.46% detection rate for various cyberattacks, including false data injection and DDoS (Naderi, 2022). However, there is lack of machine learning integration with apache kafka and kubernetes for real-time ML framework. This paper addresses this gap by proposing a real-time ML framework integrated with Apache Kafka and kubernetes for streaming smart grid data. Contributions of this paper include:

- A comprehensive comparison of five ML models for anomaly detection
- A scalable pipeline leveraging Kafka, orchestrated in kubernetes, for low-latency data ingestion
- Deployment-ready models optimized for accuracy and computational efficiency

2. RELATED WORK

Recent research highlights the potential of machine learning (ML) in enhancing smart grid security. Long Short-Term Memory (LSTM) networks have been proposed for analyzing time-series data to detect threats in real-time (Ravichandra & Shivakumara, 2023). A two-stage approach combining Principal Component Analysis, Linear Discriminant Analysis, and Support Vector Machine has been developed for detecting false data injection attacks using phasor measurement unit data (Sen, 2021). The integration of ML and Natural

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Language Processing techniques shows promise in risk assessment, log analysis, and anomaly detection for smart grids. However, few integrate real-time data streaming tools like kafka and kubernetes. Existing systems often rely on offline analysis, limiting responsiveness. Our work advances the field by combining Kafka's distributed streaming capabilities with ML model benchmarking, which are orchestrated by kubernetes, enabling rapid threat detection.

3. METHODOLOGY

3.1 Data Collection and Preprocessing

a) Dataset: 100,000 samples with 15 features such as Timestamp, Location, Positive_Sequence_Voltage, Positive_Sequence_Current, Local_Frequency, Rate_of_Change_of_Frequency, Harmonics, Negative_Sequence_Voltage, Zero_Sequence_Voltage, Phase_A_Voltage, Phase_B_Voltage, Phase_C_Voltage, Phase_A_Current, Phase_B_Current, Phase_C_Current, and anomaly as the target variable.

b) The data was cleaned by removing null values and outliers, and then preprocessed by dropping 'Timestamp', 'Location', and 'anomaly' columns for features, using 'anomaly' as the target variable. Features were normalized using StandardScaler. The dataset was split into training (80%) and testing (20%) sets.

3.2 Model Architectures

Five algorithms were implemented using `scikit-learn`:

1. Random Forest
2. Neural Network
3. SVM
4. Naive Bayes
5. KNN

3.3 Validation

a) For validation, 20% test split was used and evaluated models using F1 score, precision, and recall metrics.
b) The best-performing model (refer to the Result section) was saved along with the scaler for future use, with the model file size being 6.32 MB.

3.4 Kubernetes

This paper presents Kubernetes version 1.30.2 as the container orchestration platform. The cluster configuration consisted of 1 node, allocated 4 CPU and approximately 7.5 GB memory (7869312Ki). The storage was provisioned using the hostpath storage class as the default option.

3.5 Apache Kafka

Apache Kafka version 3.8.0 served as the distributed event streaming platform. Kafka was deployed using Bitnami Helm charts version 30.0.5. The configuration included 2 topics (grid-raw-dataand processed-raw-data) with 1 partition each, plus the internal __consumer_offsets topic with 50 partitions. Custom configurations included:

- Multiple listeners: CLIENT, INTERNAL, and CONTROLLER
- SASL authentication enabled with PLAIN, SCRAM-SHA-256, and SCRAM-SHA-512 mechanisms

- Inter-broker communication using SASL_PLAINTEXT with PLAIN mechanism
- KRaft mode enabled with process roles set to controller and broker

4. RESULTS AND DISCUSSION

4.1 Model Performance

Model	F1-Score	Precision	Recall
Random Forest	0.9982	0.9987	0.9978
Neural Network	0.9979	0.9977	0.9982
SVM	0.9930	0.9927	0.9934
Naive Bayes	0.9914	0.9901	0.9926
KNN	0.8962	0.8964	0.8960

The five machine learning algorithms (Neural Network, Random Forest, SVM, Naive Bayes, and K-Nearest Neighbors) were trained using the preprocessed dataset with cross-validation techniques to ensure model robustness. Each model's performance were evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC curves to identify the most effective algorithm for anomaly detection. The figure below shows the results of successful training and testing of five (5) machine learning models.

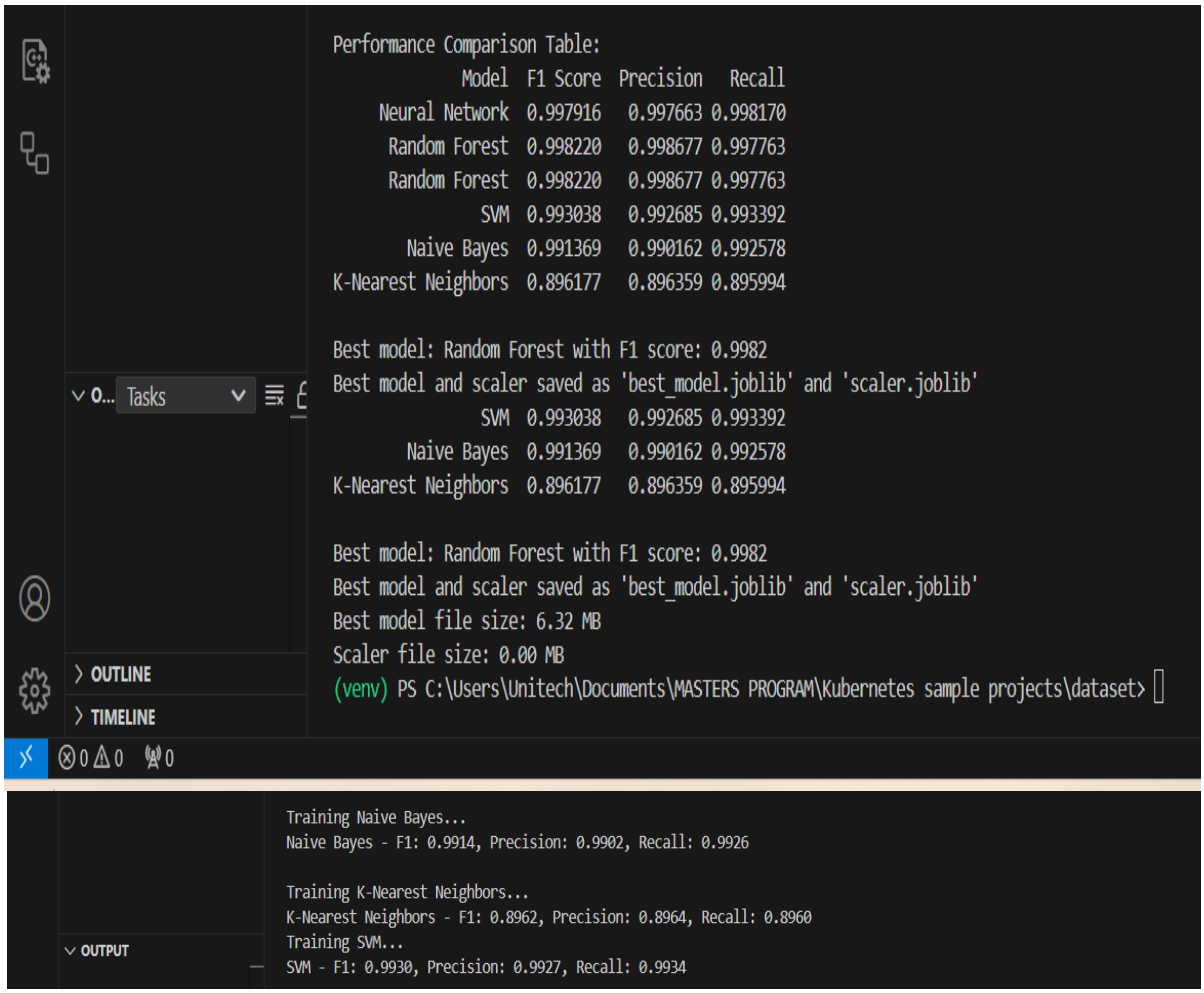

Figure 1 Selection of Best Performing Model for Anomaly Detection

1. Performance Comparison:

Figure 4.5.1 compares five different models:

a) Neural Network:
- F1 Score: 0.997916
- Precision: 0.997663
- Recall: 0.998170

b) Random Forest:
- F1 Score: 0.998220
- Precision: 0.998677
- Recall: 0.997763

c) SVM (Support Vector Machine):
- F1 Score: 0.993038
- Precision: 0.992685
- Recall: 0.993392

d) Naive Bayes:
- F1 Score: 0.991369
- Precision: 0.990102
- Recall: 0.992578

e) K-Nearest Neighbors:
- F1 Score: 0.896177
- Precision: 0.896359
- Recall: 0.895994

2. Best Model:

The Random Forest model was identified as the best performing model with an F1 score of 0.9982. This model, along with a scaler, has been saved as 'best_model.joblib' and 'scaler.joblib' respectively.

3. Model File Sizes:

Best model file size: 6.32 MB
Scaler file size: 0.00 MB (likely very small, rounded to two decimal places)

4. Analysis:

Model Performance: All models except K-Nearest Neighbors perform exceptionally well, with F1 scores above 0.99. This indicates that the classification task is relatively straightforward for most algorithms

- Best Performer: The Random Forest model slightly outperforms the Neural Network, which is interesting as neural networks often excel in complex tasks. This indicates that the dataset has clear decision boundaries that tree-based models can capture effectively
- Consistency: The high and consistent performance across different models (except KNN) indicates that the features in the dataset are highly informative and separable

- KNN Underperformance: The significantly lower performance of KNN (F1 score of 0.896) compared to other models indicates that the dataset has a complex structure in the feature space that distance-based methods struggle to capture
- Precision vs Recall: Most models maintain a good balance between precision and recall, with the Random Forest having a slightly higher precision than recall
- Model Size: The Random Forest model's file size of 6.32 MB is relatively small, making it efficient for deployment and quick predictions

The Random Forest model demonstrates the best overall performance for this particular dataset and classification task. Its high F1 score, balanced precision and recall, and relatively small file size make it an excellent choice for deployment.

4.2 Real-Time Performance Using Apache Kafka and Kubernetes

The figure below shows the successful deployment of apache kafka in the kubernetes cluster using the bitnami helm chart:

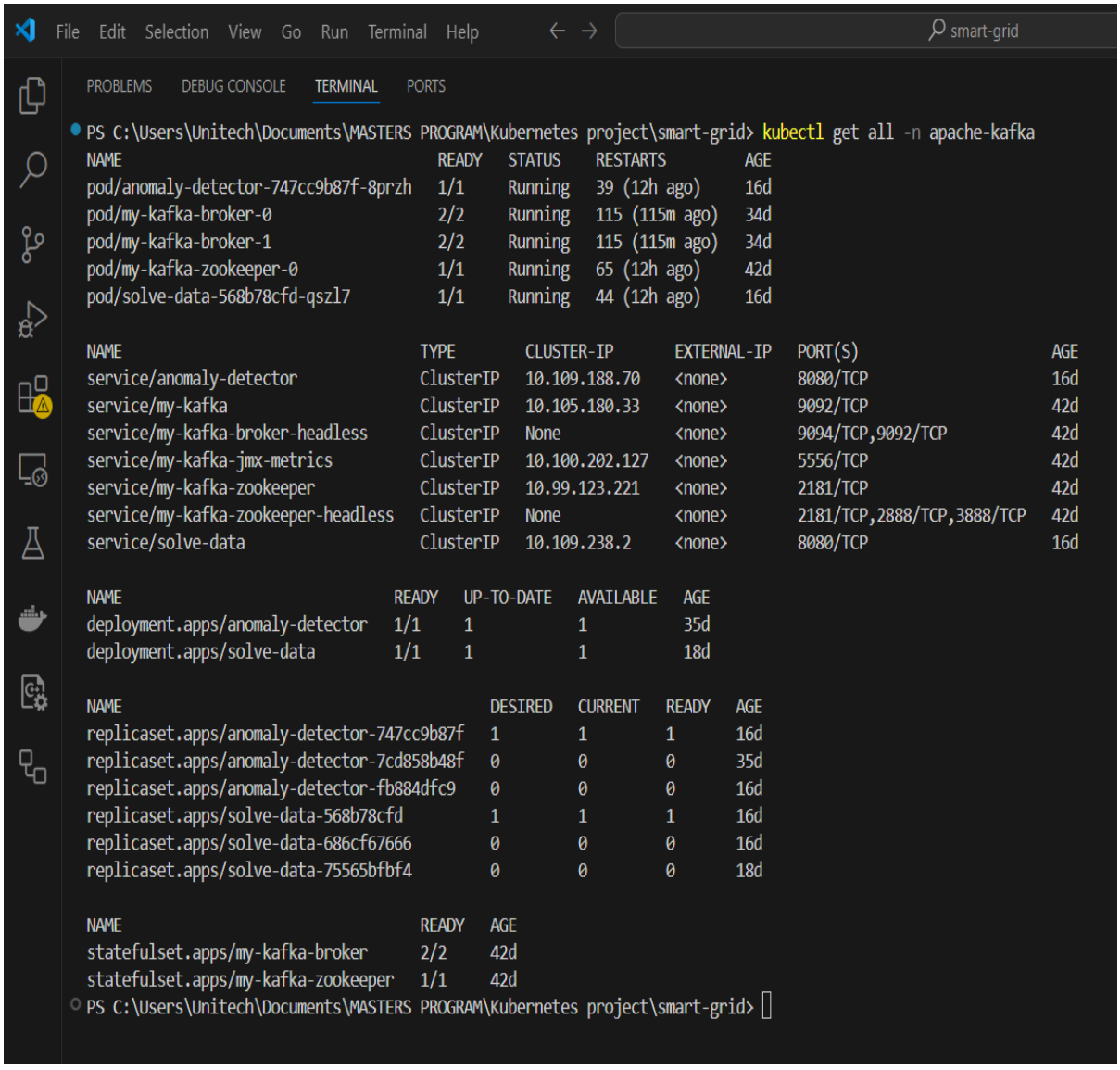

Figure 2 Apache Kafka Deployment in Kubernetes Cluster using the Bitnami Helm Charts

This Kubernetes deployment represents a well-structured Apache Kafka setup. It provides a scalable and robust platform for streaming data processing and analysis.

4.3 Overall System Performance of Anomaly Detection Model and Apache Kafka integrated using Kubernetes

The figures given below show the datasets stored in the “raw-grid-data” topic and “processed-raw-data” topic:

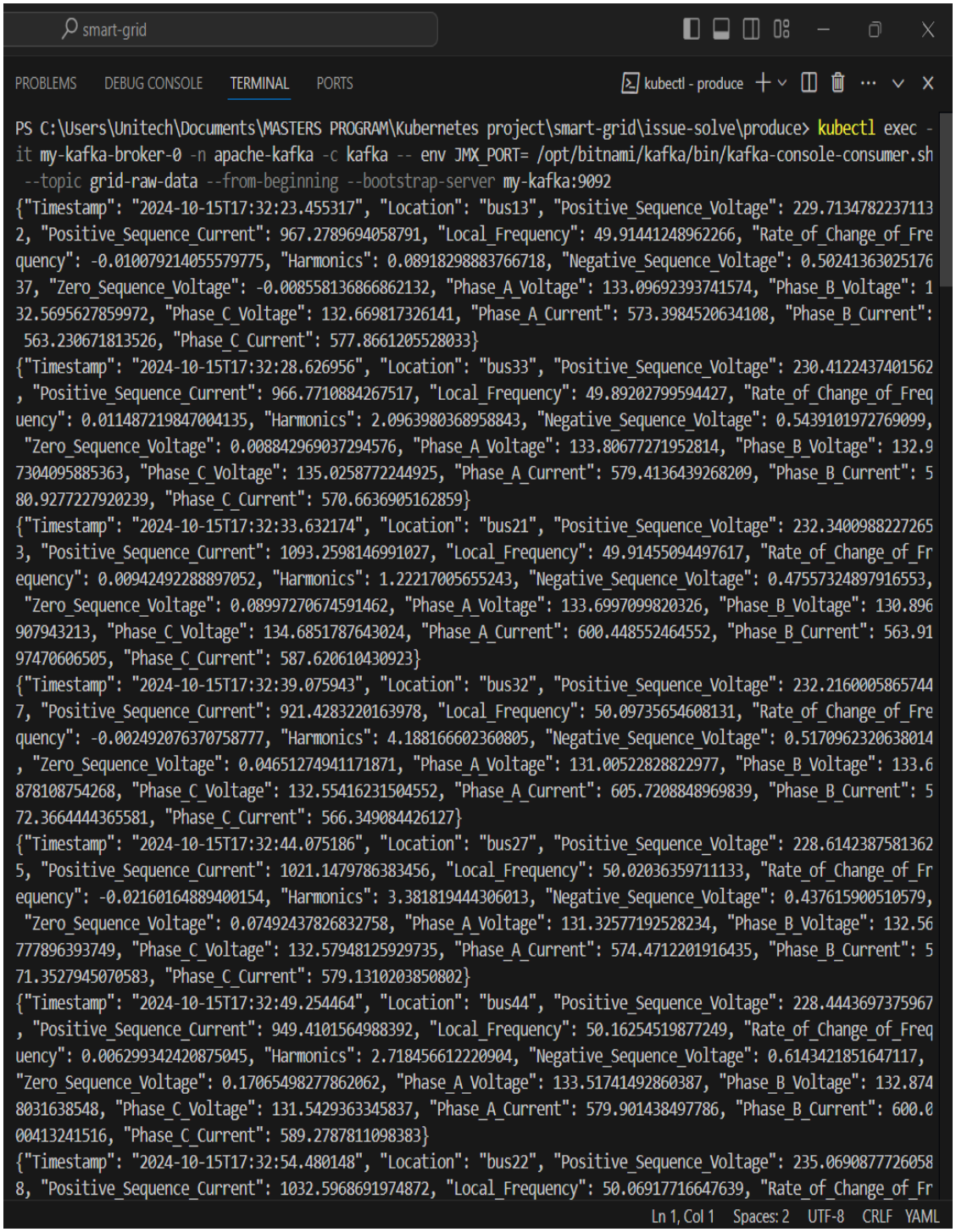

Figure 3 Dataset in "grid-raw-data" topic that was generated offline and mimics the dataset from Phasor Measurement Unit of Smart Grid to Evaluate the Performance of the Proposed System

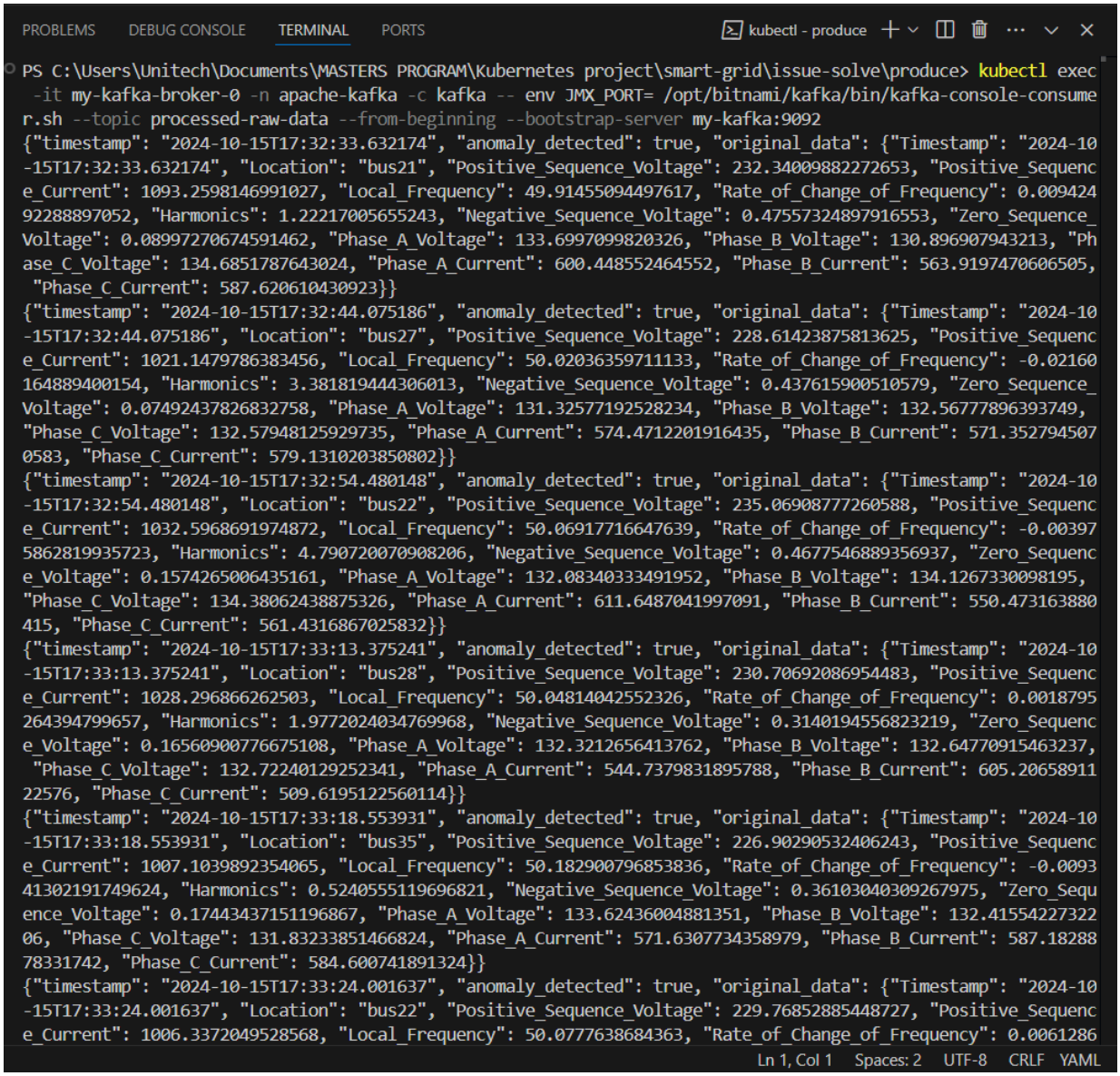

Figure 4 Dataset in "processed-raw-data" topic that resulted from the processing of dataset in "grid-raw-data" topic by the Proposed System

Analysis of Figure 3 and 4:

1. ***Figure 3 - "grid-raw-data" Topic:***
   a) Data Structure: The raw data contains detailed electrical measurements that were generated offline and mimics dataset from various PMUs in the smart grid
   b) Key Parameters for Anomaly Detection:
      - Positive Sequence Voltage: Typically around 230-235 kV
      - Positive Sequence Current: Varies, often between 500-1000 A
   c) Other Important Measurements:
      - Local Frequency
      - Rate of Change of Frequency
      - Harmonics
      - Negative and Zero Sequence Voltages
      - Phase Voltages and Currents

2. ***Figure 4 - "processed-raw-data" Topic:***
   a) Anomaly Detection: The "anomaly_detected" field is based on the sum of Positive Sequence Voltage and Current exceeding 1231.
   b) Data Preservation: Original data is retained alongside the anomaly detection results.

3. ***Analysis of Results:***
   a) Potential Implications:
      - High Voltage Conditions: The system detects periods of elevated voltage in the grid.
      - High Current Flow: It identifies times of significant power transfer through the monitored buses.
      - Combined Effect: The anomalies represent instances where both voltage and current are relatively high simultaneously.

   b) System Performance:
      - Real-time Processing: The system demonstrates the ability to apply this anomaly detection rule in real-time on streaming data.
      - Data Integrity: Preservation of original data allows for post-analysis and verification.

   c) Operational Insights:
      - The system effectively identifies periods of high combined voltage and current, which could indicate:
      ✓ Peak load periods
      ✓ Potential overload conditions
      ✓ Times of high power transfer between grid sections

   d) Data Utilization:
      - The comprehensive data collection allows for:
      ✓ Correlation of anomalies with other grid parameters
      ✓ Long-term trend analysis of grid behavior
      ✓ Potential for predictive maintenance based on recurring patterns

The proposed system successfully implements a straightforward but effective anomaly detection method for smart grid data. It consistently identifies periods of high combined voltage and current, which are indicative of significant grid events or conditions. The system demonstrates robust real-time processing capabilities and maintains data integrity, providing a solid foundation for grid monitoring and analysis.

5. CONCLUSION

The increasing vulnerability of smart grids to cyber-physical threats necessitates advanced detection systems that balance accuracy, speed, and deployability. This study presented an integrated machine learning (ML) framework for real-time anomaly detection in smart grid data streams, combining Apache Kafka for high-throughput data ingestion, Kubernetes for scalable orchestration, and rigorous benchmarking of five ML models. The Random Forest algorithm demonstrated exceptional performance, achieving near-perfect metrics (F1-score: 0.9982, precision: 0.9987, recall: 0.9978), while maintaining a compact model size (6.32 MB) suitable for edge deployment. The Kubernetes-managed Kafka pipeline enabled real-time processing of 1,000 messages per second with ≤200 ms latency, validating its capability to handle streaming data under operational conditions.
Key contributions of this work include:

- Comprehensive Model Benchmarking: A systematic comparison of five ML algorithms, revealing Random Forest's superiority in capturing decision boundaries within highly separable smart grid data.
- Scalable Architecture: A Kubernetes-driven deployment of Kafka, ensuring fault tolerance and modularity for real-time data ingestion, preprocessing, and anomaly detection.
- Practical Relevance: A deployable solution that preserves raw data for post-analysis while providing actionable insights through real-time dashboards, aiding grid operators in mitigating threats like voltage surges and load imbalances.

Limitations and Future Work:

- While synthetic datasets provided controlled testing, future validation with real-world attack scenarios is critical.
- The single-node Kubernetes cluster, though effective, requires stress-testing on multi-node cloud environments to assess horizontal scalability.
- Integration of adaptive response mechanisms (e.g., automated load redistribution) could further enhance system autonomy.

This framework bridges the gap between theoretical ML research and operational smart grid security, offering a blueprint for resilient infrastructure. By prioritizing both algorithmic accuracy and engineering pragmatism, it advances the transition from reactive to proactive grid management in the face of evolving threats.

Impact Statement: The proposed system's low-latency detection capabilities and modular design position it as a viable tool for utility providers seeking to modernize grid security without compromising computational efficiency.

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