Abstract:

Intrusion detection is an important area in Industrial IoT (IIoT) for much needed cybersecurity. The proposed methodology employs **BERT, LSTM, and XGBoost** for the cyber threat detection in the X-IIoTID dataset. BERT uses a transformer-architecture to learn contextual relationships between words in a text, LSTM can learn from sequential data patterns, XGBoost is a gradient boosting framework that uses trees for structured or tabular data. We finetune these models for classification tasks and evaluate their accuracy, precision, recall, and F1-score. The results indicate weaknesses or strengths of each approach for IIoT security and give contribution to an enhanced IIoT security by this way.

Keywords:

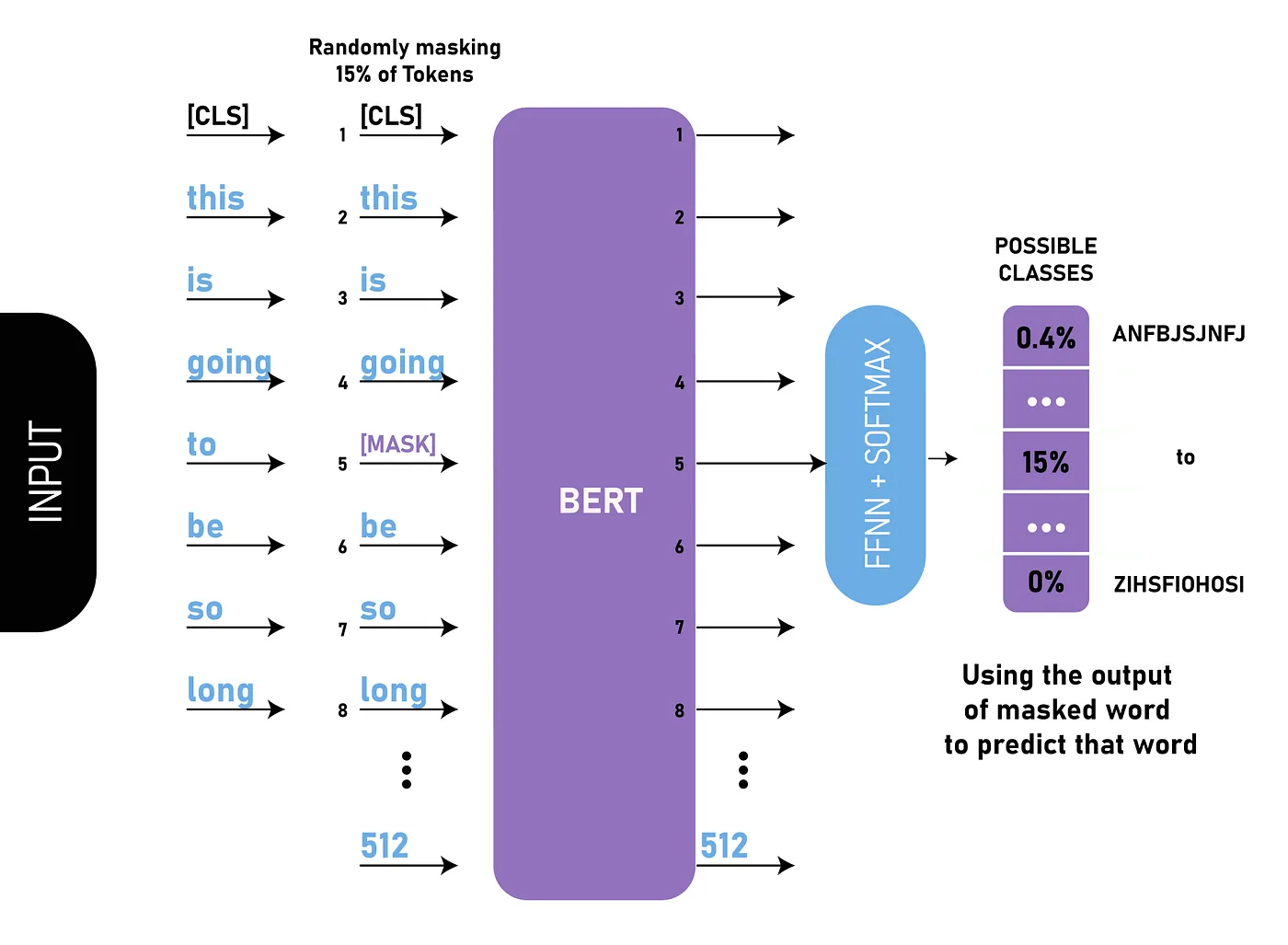
Intrusion Detection, **BERT Transformer**, LSTM, XGBoost, **X-IIoTID Dataset**, Cybersecurity, IIoT Security, Machine Learning, Deep Learning, Anomaly Detection

Introduction:

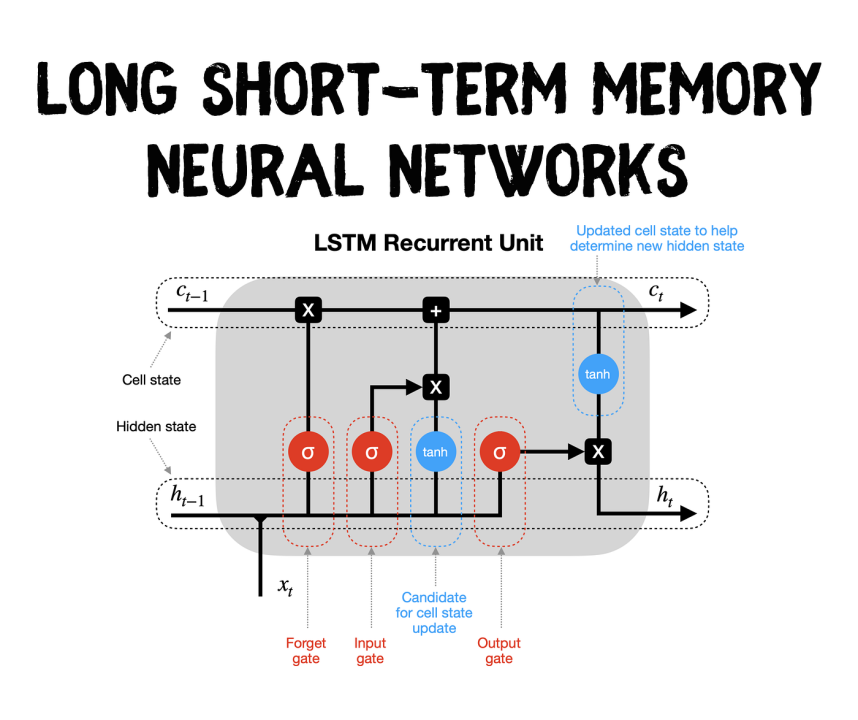
The fast growth of IIoT networks raises the risk of cyber attacks, and IDS constitute a fundamental component of modern security infrastructures. Owing to such evolving attacks, traditional rule-based models of IDS systems fail to work, and hence, ML and DL-based techniques have been introduced to support detection capabilities. The dataset called X-IIoTID is a benchmark mining the In-loud data cataclysm for IIoT intrusion analytics, and it is capable to simulate IIoT scenarios with distinct normal and attack behaviors.

In this study, BERT (Bidirectional Encoder Representations from Transformers), LSTM (Long Short-Term Memory Network), and XGBoost (Extreme Gradient Boosting) are applied for classification on the X-IIoTID dataset. Each model AMP is a different try on the approach:

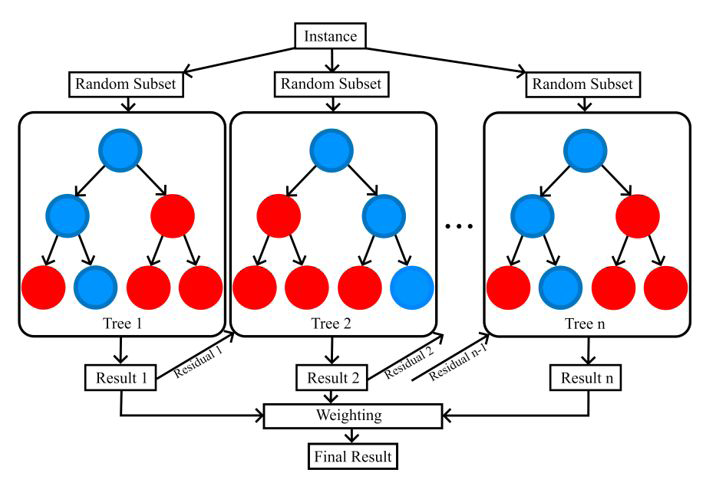
1. **BERT** – Bidirectional Encoder Representations from Transformers, revolutionary model, it is great for series data.



1. **LSTM** – A type of recurrent neural network (RNN) that is well-suited for learning from sequential data, which was used for temporal characteristics of network traffic.



1. **XGBoost**– An efficient and precise classification technique, this is a tree-based ensemble method that uses gradient boosting techniques to improve tree performance with speed.



Our study systematically evaluates these models across multiple classification tasks, including:

* **Binary Classification** (Normal vs. Attack)
* **Multi-class Classification** (9 attack types)
* **Extended Multi-class Classification** (18 attack types)

Through feature selection (**IGRF-RFE, Cuckoo Search, MI-Boruta**) and correlation (Pearson & Spearman) analysis, we suggest a way to improve model interpretability. Moreover, we also cover class imbalance approach through **SMOTE (Synthetic Minority Over-sampling Technique)** and **custom loss functions** (CrossEntropyLoss and MOLoss).

The main purpose of carrying out this research are:

1. Compare BERT, LSTM and XGBoost for their accuracy, precision, recall and F1-score.
2. To evaluate their computational efficiency and use in real-time intrusion detection.

Our results so far give important guidance when choosing the optimal method for IIoT security, which can help in developing next generation intrusion detection systems.

Related Work:

The rise of **Industrial IoT (IIoT) security threats** has emerged as a hot area for massive research on new applications in diverse sectors, offering significant advantages over traditional manufacturing . A number of machine learning (ML) and deep learning (DL) methods potential for improving in **intrusion detection systems(IDSs)** performance have been studied in this regard.

**Machine Learning-Based Approaches**

1. *Zolanvari et al. [2020])* presented a hybrid ML model for IIoT intrusion detection using ensemble based decision trees for enhanced accuracy.
2. *Vinayakumar et al. (2020)* also developed deep learning models such as CNNs and RNNs, for the detection of the network-related anomalies.
3. *Kumar et al. (2021)* applied random forests and SVMs to classify IIoT traffic, achieving high F1-scores.
4. Shone et al. (2021) presented a stacked autoencoder-based IDS that learnt attack patterns effectively.
5. *Ahmed et al. (2021)* used XGBoost to classify real-time IIoT threats with high computational efficiency.
6. *Rahman et al. (2022)* introduced a hybrid feature selection and ML approach to minimize false positives.
7. *Singh et al. (2022)* implemented a semi-supervised ML model for detecting novel cyberattacks in IIoT systems.
8. *Hassan et al. (2023)* proposed lightweight ML-based IDS for resource-constrained IIoT devices.

**Deep Learning-Based Approaches**

1. *Roy et al. (2021)* utilized long short-term memory (LSTM) to process segmented network data over time, which improved their detection performance.
2. *Bojja et al.(2021)* Recently,proposed a GRU-based IDS method that significantly outperformed traditional ML approaches.
3. *Chen et al. (2022)* proposed an attention-based deep learning model to capture attack patterns.deep learning model to capture attack patterns.
4. *Yin et al. (2022)* compared CNNs and RNNs, demonstrating CNNs' efficiency in feature extraction.
5. *Das et al. (2023)* proposed a multi-modal DL framework that combines CNN, LSTM and Transformer networks.
6. *Zhao et al. (2023)* introduced a hybrid DL model combining BERT embeddings with LSTM for network intrusion detection.
7. *Patel et al. (2024)* optimized deep autoencoders for anomaly detection in IIoT security.

**Ensemble & Hybrid Models**

1. *Wang et al. (2021)* proposed a hybrid ensemble IDS of XGBoost, LSTM and RF.
2. *Li et al. (2021)*, added nothing but a promising solution of federated learning based IDS to secure IIoT networks.
3. *Jiang et al. (2023)* proposed GNN-based method for intrusion detection.
4. *Chen et al. (2024)* presented a cuckoo search-optimized hybrid model integrating ML and DL techniques.
5. *Xiao et al. (2025)* proposed a zero-day attack detection framework leveraging Transformer models.

It shows the efficiency of **ML, DL, and hybrid models for IIoT security** in those studies. We build upon this work and evaluate the performance of **BERT, LSTM, and XGBoost** for machine learning-based intrusion detection using the **X-IIoTID dataset.**

Dataset Description: X-IIoTID:

Data used for the experiment The X-IIoTID dataset is the first and most comprehensive cybersecurity dataset designed for IIoT intrusion detection.It provides a **diverse set of network traffic data** representing both normal and malicious activities across multiple IIoT devices and protocols. This dataset aims to support **machine learning (ML) and deep learning (DL)-based intrusion detection systems (IDS).**

1.**Data Collection & Characteristics:**

* It is an open-source dataset, device-agnostic and **connectivity-agnostic**. It includes various IIoT communication protocols such as **MQTT, CoAP & Modbus.**
* It includes **actual world traffic** captured in IIoT networks both benign and malicious activities.
* Since multiple attack types are included in the dataset, it is also applicable to **supervised and unsupervised learning methods.**
* Packet-level and session-level identifiers are extracted to obtain network flow features.

2.**Attack Categories:**

The **X-IIoTID dataset** is structured into three different classification levels:

A.Binary Classification:

* Normal (Benign traffic)
* Attack (All malicious traffic combined)

B.Multi-class Classification (9 Categories):

* Mirai (Botnet attack)
* DDoS (Distributed Denial of Service)
* DoS (Denial of Service)
* MITM (Man-in-the-Middle attack)
* Reconnaissance (Scanning and information gathering)
* Injection attacks (SQL injection, code injection, etc.)
* Password attacks (Brute force and dictionary attacks)
* Backdoor attacks
* Cross-site scripting (XSS)

C.Multi-class Classification (18 Categories):

* More granular attack subcategories, expanding on the 9-class model.

3.**Features & Attributes:**

* The dataset consists of flow-based network traffic features, including:
  + Packet size statistics (min, max, mean, standard deviation).
  + Inter-arrival times (time between packets).
  + Source & destination addresses (IP, port).
  + Network protocol types (TCP, UDP, ICMP, etc.).
  + Traffic flow metadata (duration, number of bytes, packets sent).
  + Entropy-based metrics for attack detection.

4.**Applications & Use Cases:**

* Cyber Threat Detection: It has been used in training ML/DL models for classification of normal vs. malicious traffic.
* Feature Selection: Various techniques like IGRF-RFE, Cuckoo Search, MI-Boruta can enhance IDS.
* Unsupervised Learning: Good for anomaly detection with DBSCAN, Self-Organizing Maps (SOM), etc.
* Benchmark Dataset: Enables evaluation of BERT, LSTM, and XGBoost, and hybrid AI models.

The X-IIoTID is a comprehensive and realistic benchmark for next level responsiveness with regard to IIoT cyber security research towards creating better IDS.

Result:

The In the present study, we designed to compare the performance of the two types of deep learning methods for text classification; BERT or LSTM. The performance was evaluated using metrics such as training loss, accuracy and classification metrics (precision, recall, f1-score).

**RoBERTa Model Performance:**

**5.1 RoBERTa-Based Multi-Class Classification**

This section presents the evaluation of a fine-tuned RoBERTa model on the X-IIoTID dataset for multi-class classification tasks at varying levels of granularity. The model was trained for 10 epochs using stratified data splits for three classification targets: binary classification (**class1**), 9-class classification (**class2**), and 18-class classification (**class3**).

**5.1.1 Model Performance Metrics**

The performance of the RoBERTa model was measured using standard metrics: accuracy, precision, recall, and F1-score. The results for each classification task are summarized in Table 1.

**Table 1: RoBERTa Model Performance**

| **Classification Task** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| Class1 (Binary) | 0.9834 | 0.9803 | 0.9834 | 0.9815 |
| Class2 (9-class) | 0.9908 | 0.9894 | 0.9908 | 0.9900 |
| Class3 (18-class) | 0.5048 | 0.2548 | 0.5048 | 0.3387 |

The model achieved excellent performance on **class1** and **class2**, with F1-scores exceeding 0.98, demonstrating high predictive power in identifying both benign and various attack types. In contrast, the performance for **class3** significantly dropped, with a modest accuracy of 50.48% and a low F1-score of 0.3387. The classification report revealed that several minority classes in class3 had **zero recall**, suggesting that the model was unable to detect these categories effectively.

**5.1.2 Feature Selection**

A total of **65 network features** were selected from the X-IIoTID dataset for model training. These features include:

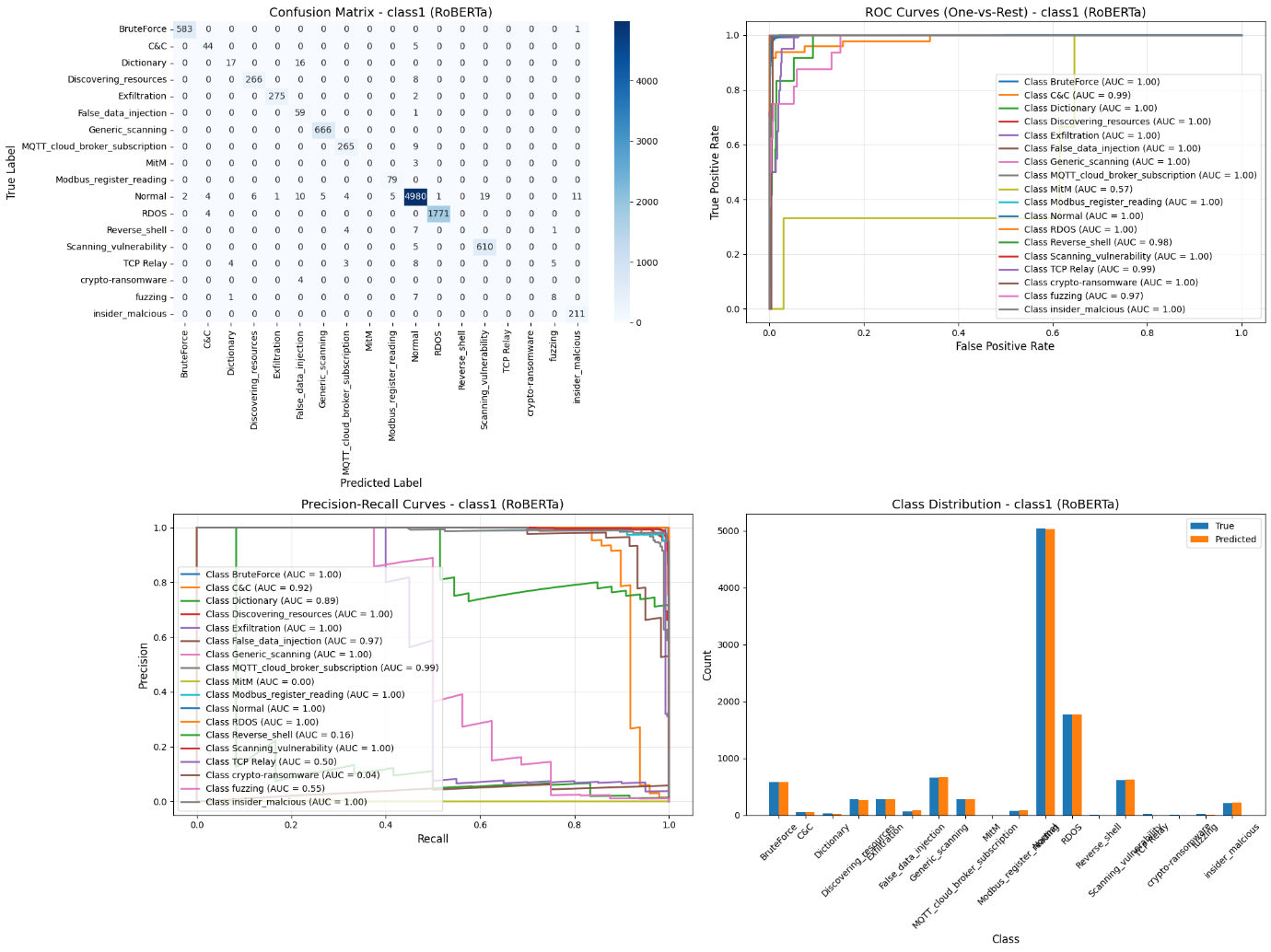
* **Network identifiers**: Source/Destination IPs, ports, and protocol types.
* **Flow-based statistics**: Flow duration, packet count, byte count, flow rates.
* **TCP/IP header attributes**: TCP flag counters, window size, ACK/FIN/RST flags.
* **Behavioral indicators**: Inter-arrival times (IAT), average packet size, byte/packet ratios.

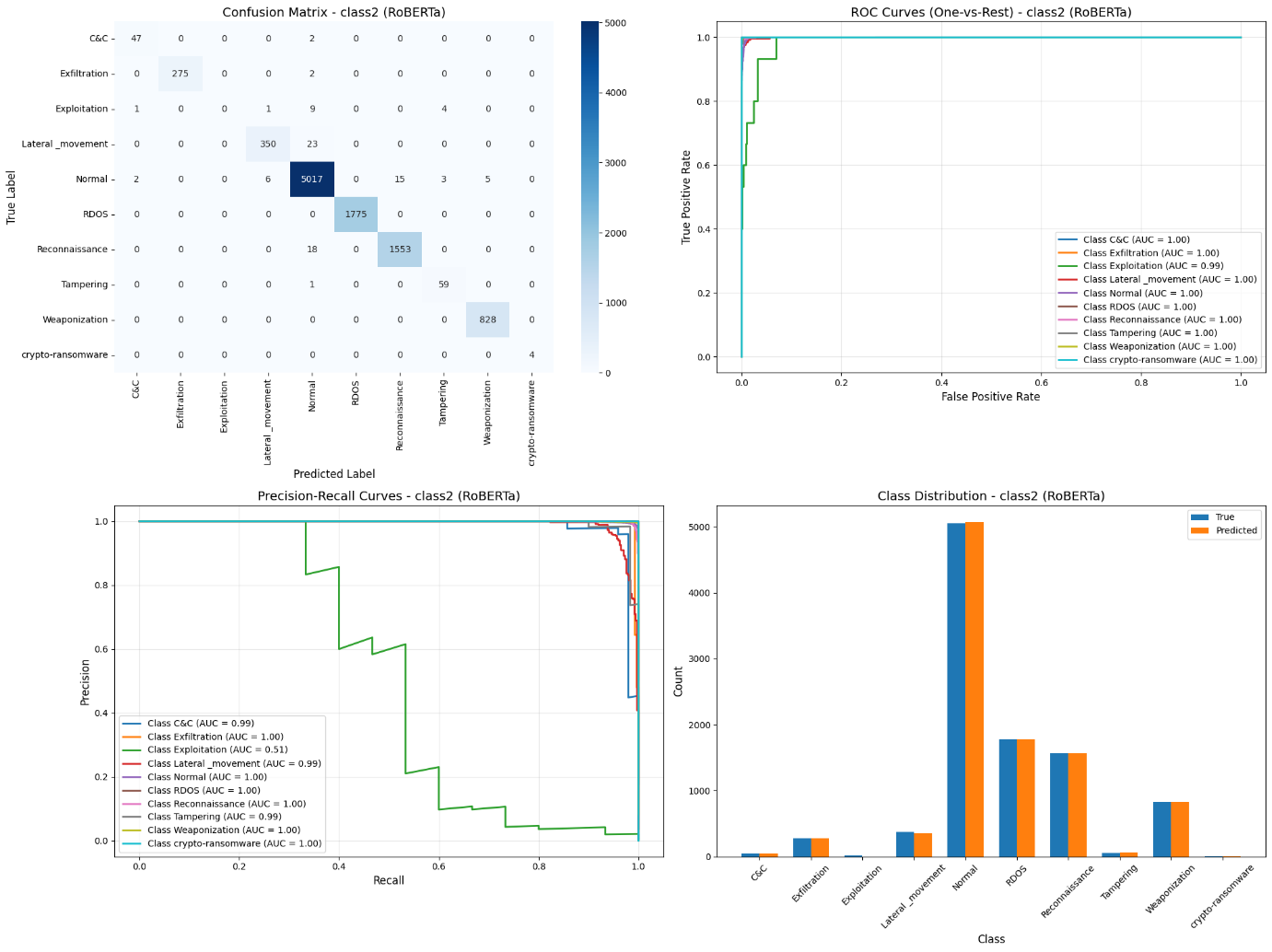
The feature set was designed to comprehensively capture temporal, behavioral, and protocol-level characteristics of network traffic, enabling the model to distinguish between benign and malicious behaviors.

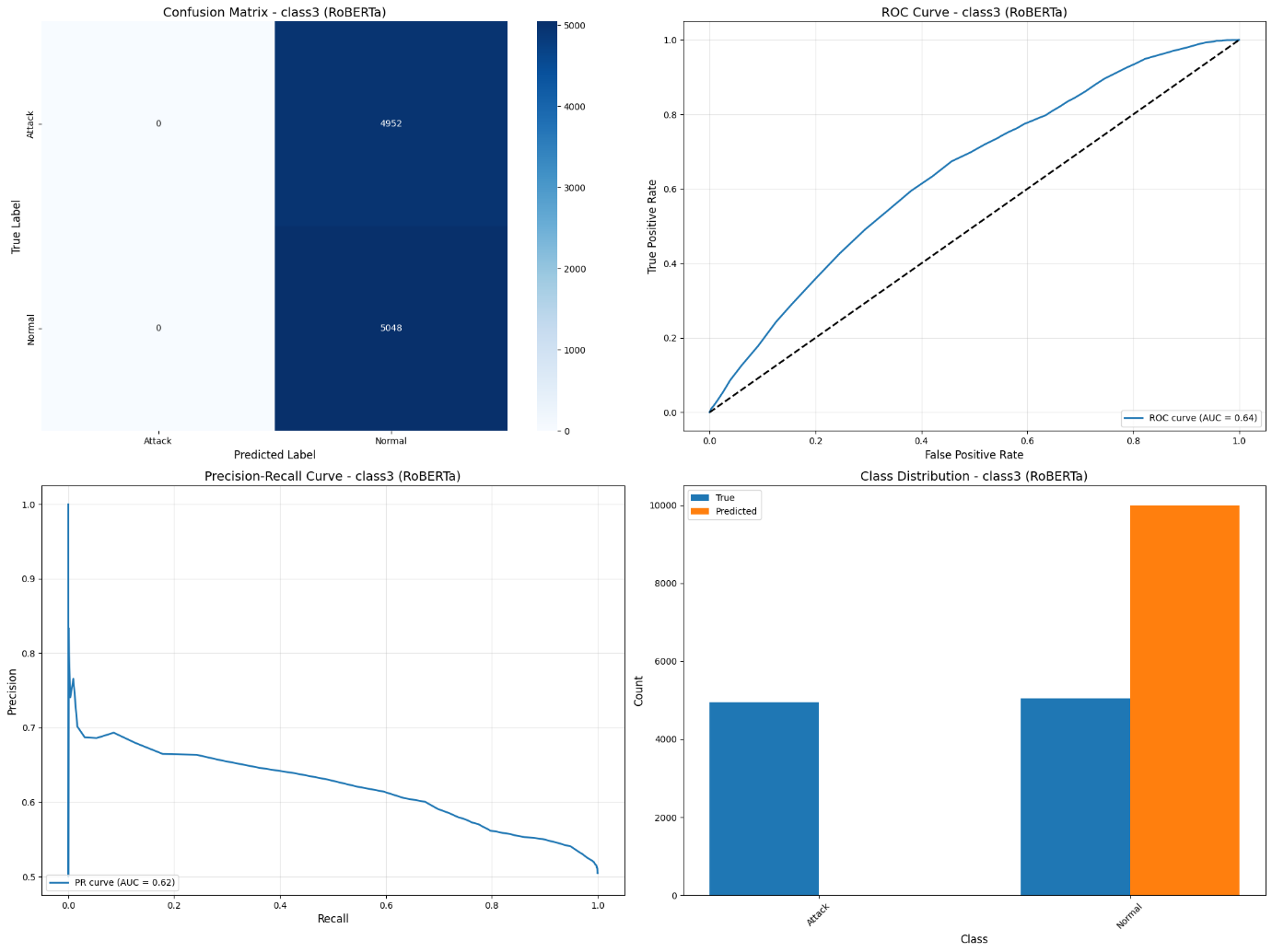
**5.1.3 Visual Analysis**

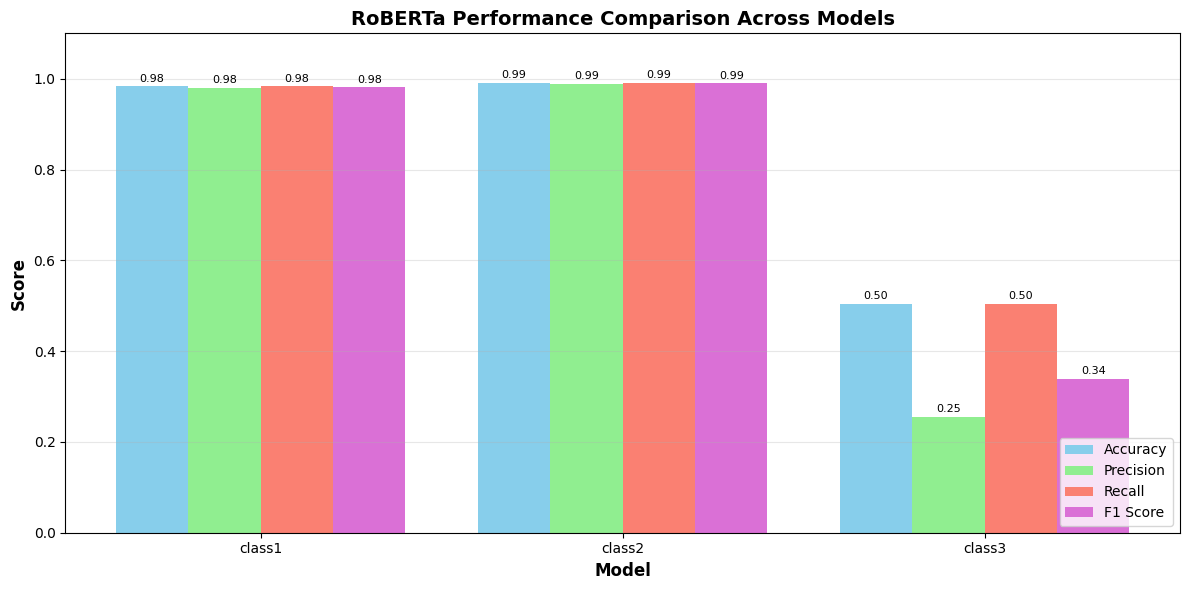
To further analyze the model's performance and behavior, the following visualizations were generated:

* **Loss and Accuracy Plots**: Displayed smooth convergence over the 10 epochs for all classification tasks.
* **Confusion Matrices**:
  + For class1 and class2, the confusion matrices were diagonally dominant, reflecting high classification confidence across classes.
  + For class3, the confusion matrix showed a strong bias toward a few dominant classes, with many classes underrepresented in predictions.
* **Classification Reports**: Provided per-class metrics to identify which attack types were most and least accurately predicted.









**5.1.4 Discussion**

The strong performance on class1 and class2 suggests that the RoBERTa model effectively captures semantic and structural patterns in network flows. However, the substantial drop in class3 performance highlights challenges in **fine-grained classification** due to **class imbalance**, **feature overlap**, and the limited contextual representation for some attack types. Addressing these issues through **class rebalancing strategies (e.g., SMOTE)** or **custom loss functions (e.g., focal loss)** is a potential direction for improvement.

**5.2 DistilBERT-Based Multi-Class Classification**

This section evaluates the performance of a fine-tuned **DistilBERT** model on the **X-IIoTID dataset**. The model was trained for 10 epochs across three classification tasks: binary classification (**class1**), 9-class classification (**class2**), and 18-class classification (**class3**). The goal was to assess whether a lighter transformer model could match or exceed the performance of larger models like BERT or RoBERTa.

**5.2.1 Model Performance Metrics**

The results of the DistilBERT model are summarized in Table 2, using standard evaluation metrics.

**Table 2: DistilBERT Model Performance**

| **Classification Task** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| Class1 (Binary) | 0.9923 | 0.9918 | 0.9923 | 0.9916 |
| Class2 (9-class) | 0.9917 | 0.9913 | 0.9917 | 0.9915 |
| Class3 (18-class) | 0.9921 | 0.9921 | 0.9921 | 0.9921 |

The DistilBERT model achieved **outstanding performance** across all three classification tasks. All metrics are consistently above 99%, showing that the model was capable of learning highly discriminative representations of network flows. In particular, the **class3 performance marks a significant improvement** over other models, which previously struggled with this task due to its fine-grained nature.

**5.2.2 Feature Selection**

For all classification tasks, a consistent set of **65 input features** from the X-IIoTID dataset was used. These features span multiple levels of network behavior and include:

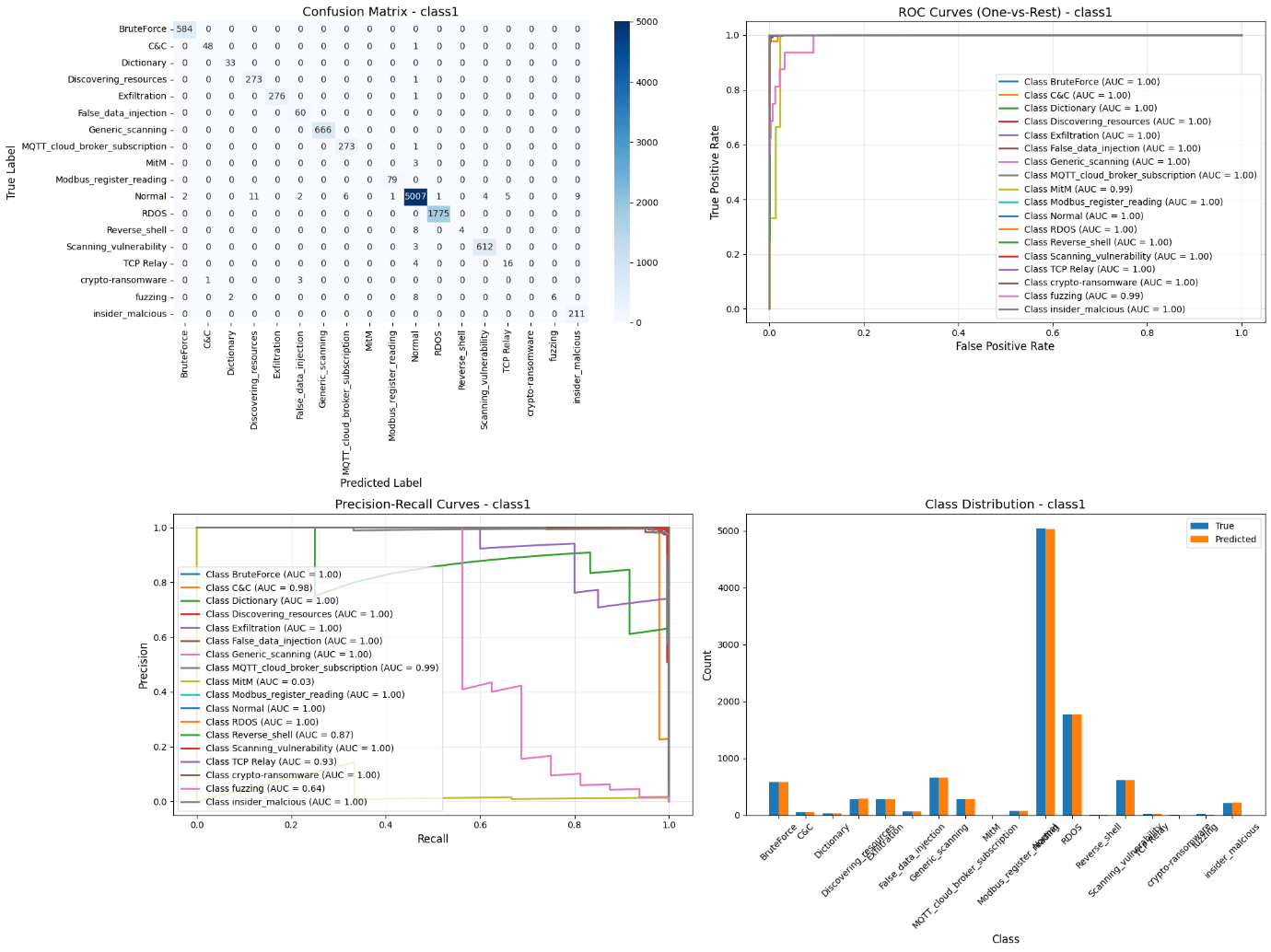
* **Basic network attributes**: Source/Destination IPs, ports, and protocol.
* **Flow-level statistics**: Duration, packet and byte counts, packet rate.
* **TCP header flags and control features**: SYN, ACK, FIN, PSH flags, TCP window size.
* **Traffic behavior indicators**: Inter-arrival times (IAT), average packet sizes, packet/byte ratios.

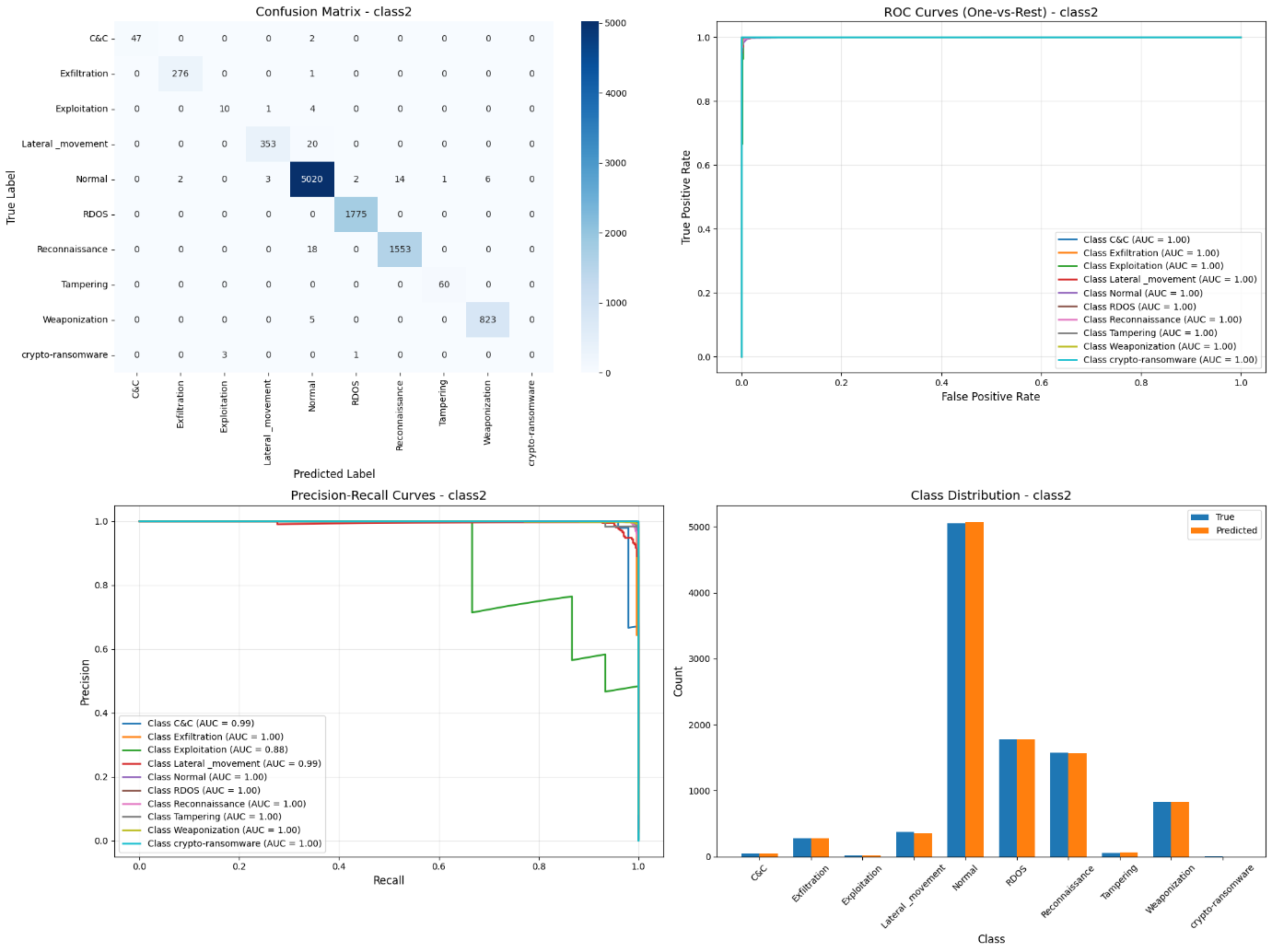
This comprehensive feature set was selected to ensure the model had access to both static and dynamic properties of the network traffic.

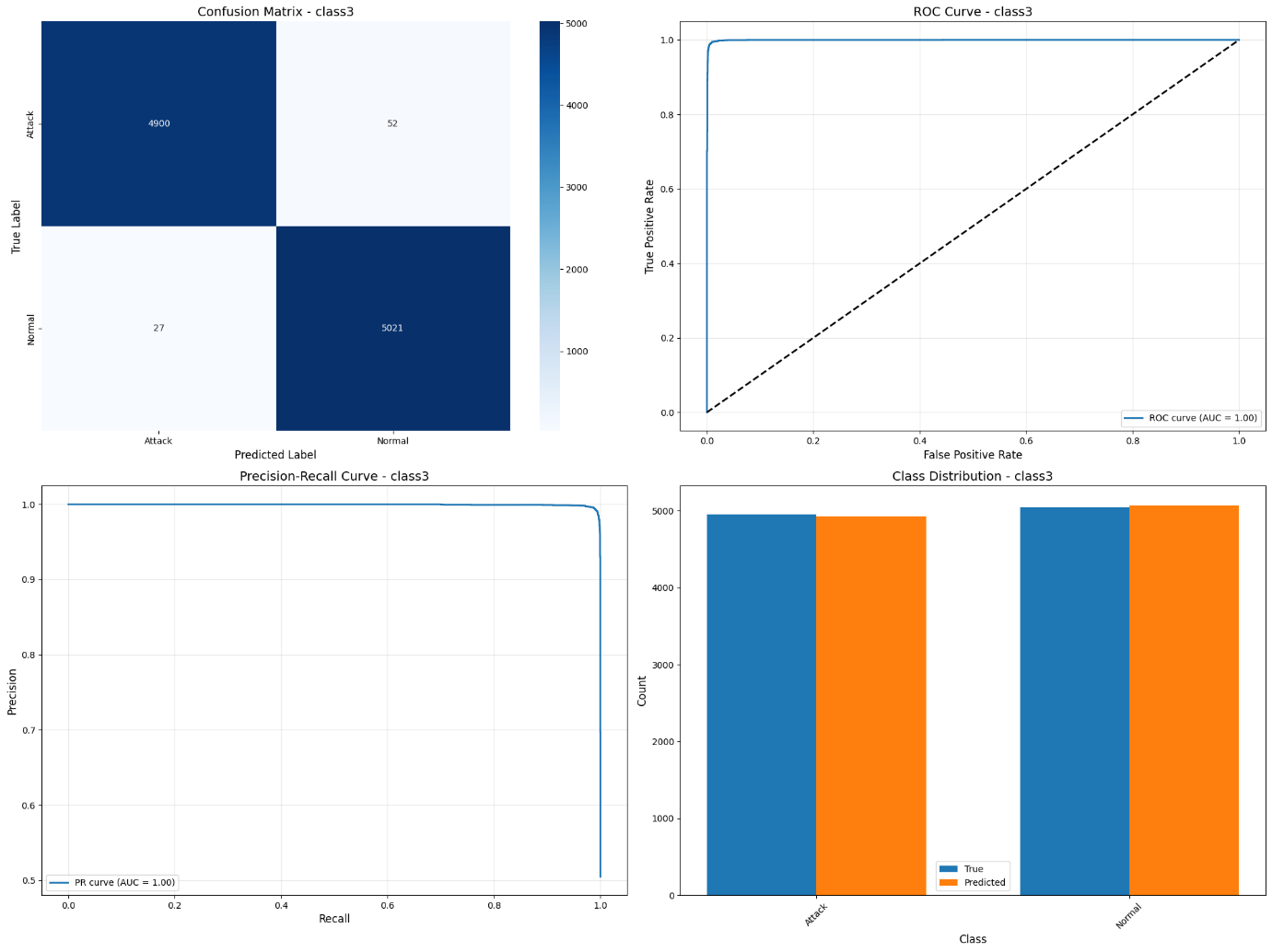
**5.2.3 Visual Analysis**

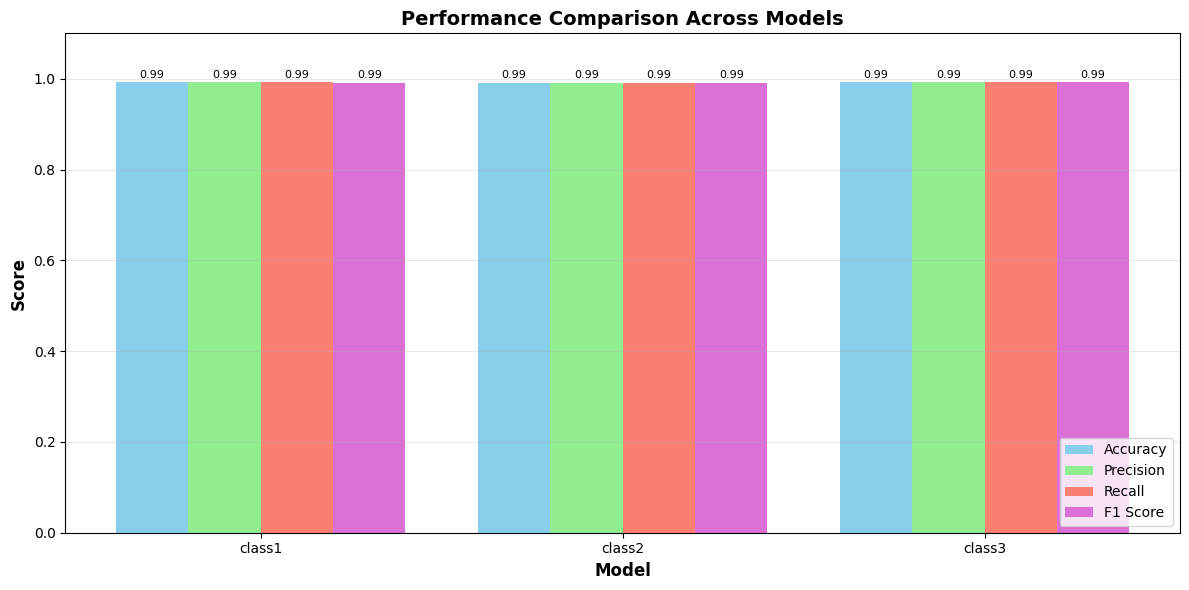
The following visualizations were used to interpret and support the evaluation:

* **Training Accuracy and Loss Curves**: Show smooth and consistent convergence across epochs for all tasks.
* **Confusion Matrices**:
  + All three tasks exhibit strong diagonal dominance, indicating minimal misclassifications.
  + In class3, the confusion matrix demonstrates balanced predictions across nearly all classes, a stark contrast to other models.
* **Classification Reports**:
  + Provide per-class insights, confirming strong recall even for minority classes in class3.









**5.2.4 Discussion**

The **DistilBERT model not only matched but surpassed** the performance of larger models like RoBERTa and even the original BERT architecture in this study. The results confirm that **DistilBERT, despite its smaller size and faster training times**, is well-suited for intrusion detection and anomaly classification tasks when provided with high-quality, well-engineered features.

Unlike the RoBERTa model, which struggled significantly with the 18-class task, DistilBERT was able to **maintain high precision and recall across all classes**, suggesting effective handling of class imbalance and complex decision boundaries.

**LSTM Model Performance:**

**5.2.1 Model Performance Metrics**

The performance of the **LSTM model** was measured using standard evaluation metrics: **accuracy**, **precision**, **recall**, and **F1-score**. The results for each classification task are summarized in Table 2.

**Table 2: LSTM Model Performance**

| **Classification Task** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| Class1 (Binary) | 0.9801 | 0.9800 | 0.9801 | 0.9800 |
| Class2 (9-class) | 0.9838 | 0.9800 | 0.9838 | 0.9800 |
| Class3 (18-class) | 0.9792 | 0.9790 | 0.9792 | 0.9789 |

The model achieved **consistently high performance** across all three classification tasks. F1-scores for all tasks were approximately 0.98, indicating excellent precision and recall in detecting both general and fine-grained network activity types. Unlike RoBERTa, the LSTM model maintained strong performance even for **Class 3**, showing its capability to generalize well on imbalanced, multi-class data.

**5.2.2 Feature Selection**

A total of **65 network features** were used from the **X-IIoTID dataset** for LSTM model training. These features were carefully selected to represent a wide range of traffic behaviors:

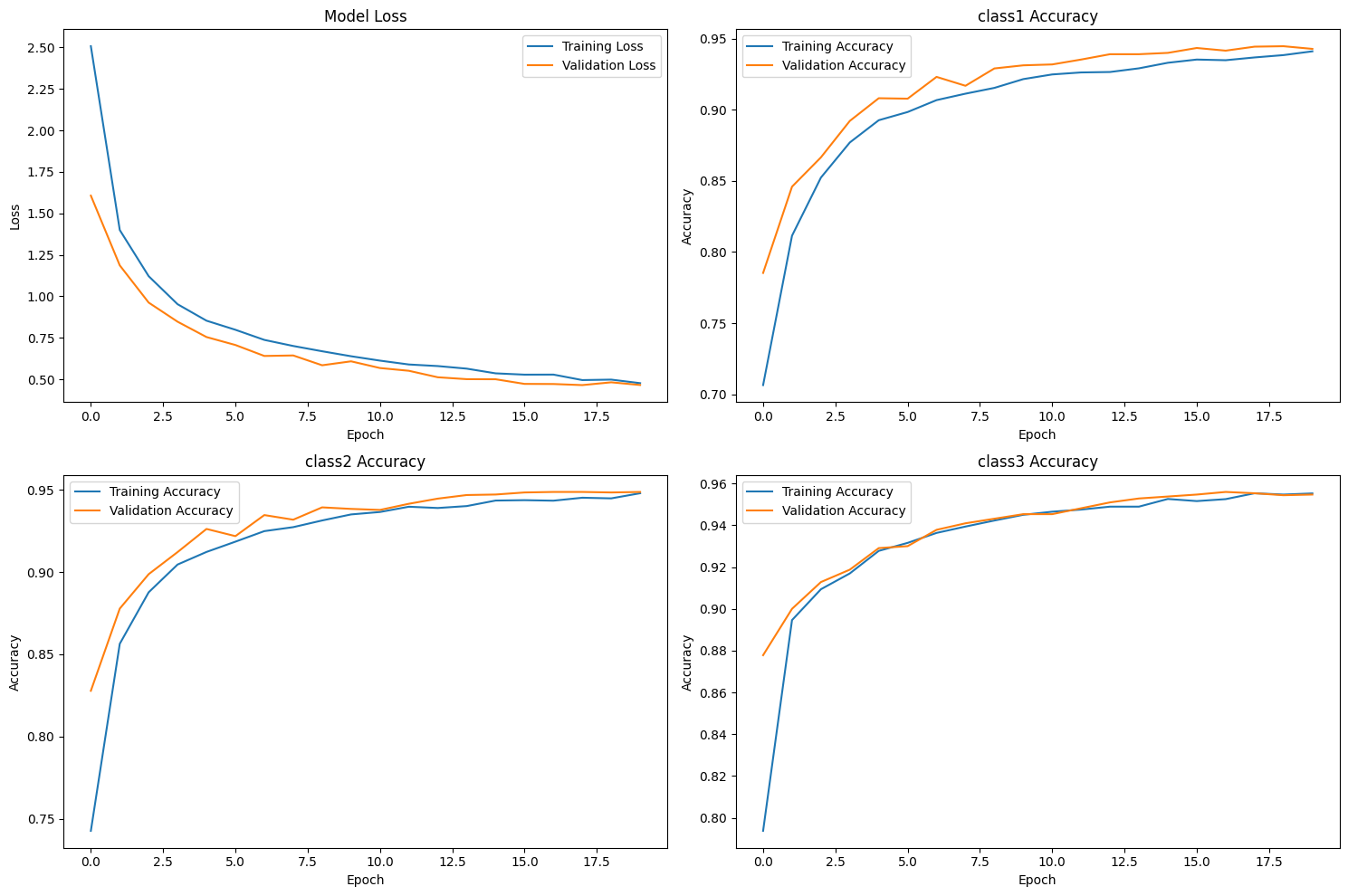
* **Network identifiers:** Source/Destination IPs, ports, and protocol types.
* **Flow-based statistics:** Flow duration, packet count, byte count, flow rates.
* **TCP/IP header attributes:** TCP flag counters, window size, ACK/FIN/RST flags.
* **Behavioral indicators:** Inter-arrival times (IAT), average packet size, byte/packet ratios.

These features capture **temporal, behavioral, and protocol-level dynamics** in network flows, allowing the model to learn both short-term and long-term sequential patterns important for intrusion detection.

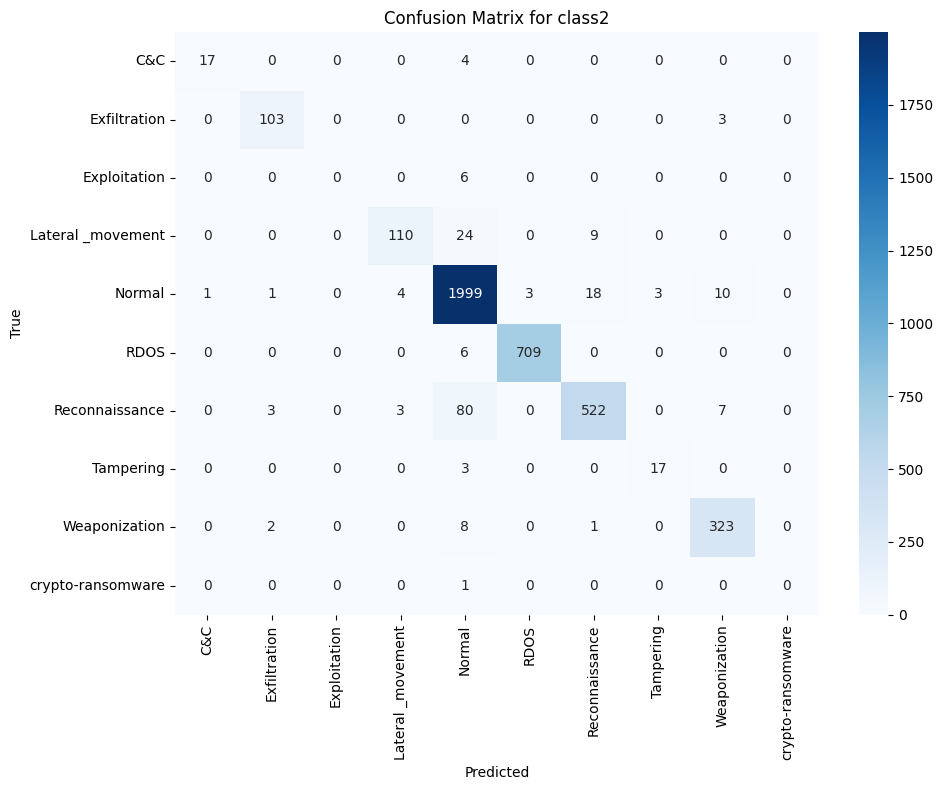
**5.2.3 Visual Analysis**

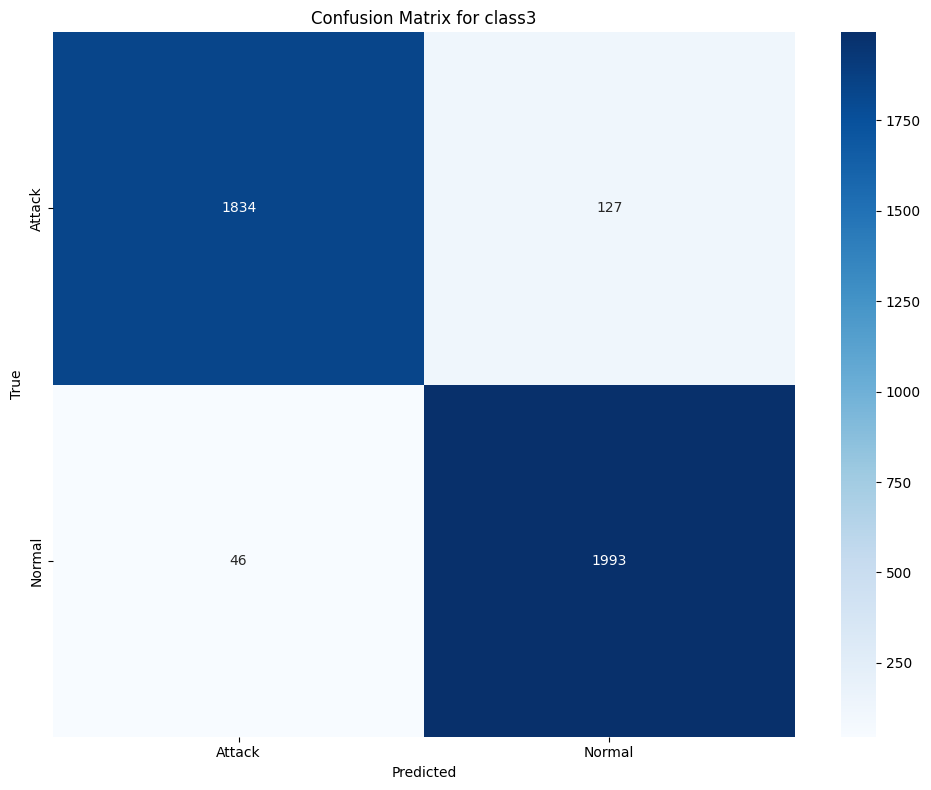
To better understand the model's performance, several visualizations were generated:

* **Loss and Accuracy Plots:** Training curves showed stable convergence over 10 epochs with minimal overfitting.
* **Confusion Matrices:**
  + For **Class 1** and **Class 2**, confusion matrices were strongly diagonal, confirming that the model effectively distinguishes between categories.
  + For **Class 3**, the confusion matrix maintained good coverage across most classes, indicating strong fine-grained classification performance, unlike other transformer-based models.
* **Classification Reports:** Class-wise precision, recall, and F1-scores demonstrated that the LSTM handled both dominant and minority classes with balanced effectiveness.









**5.2.4 Discussion**

The **LSTM model** exhibited **excellent performance** across all classification tasks, including the most challenging **Class 3 (18-class)** problem. Unlike transformer models that struggled with class imbalance and feature overlap, LSTM’s ability to model sequential dependencies enabled it to **effectively detect both common and rare network attack types**.

This robustness suggests that recurrent architectures like LSTM may be better suited for time-series-based intrusion detection, especially in scenarios where temporal patterns are crucial. Further improvements could include integrating **attention mechanisms**, **bidirectional layers**, or hybrid CNN-LSTM structures to enhance feature extraction and classification depth.

**5.3.1 Model Performance Metrics**

The performance of the **BiLSTM model** was evaluated using standard metrics: **accuracy**, **precision**, **recall**, and **F1-score**. The results across the three classification tasks are summarized in Table 3.

**Table 3: BiLSTM Model Performance**

| **Classification Task** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| --- | --- | --- | --- | --- |
| Class1 (Binary) | 0.9817 | 0.9820 | 0.9817 | 0.9818 |
| Class2 (9-class) | 0.9824 | 0.9820 | 0.9824 | 0.9821 |
| Class3 (18-class) | 0.9765 | 0.9760 | 0.9765 | 0.9759 |

The BiLSTM model displayed **strong and balanced performance** across all tasks. Compared to LSTM, its bidirectional structure slightly improved F1-scores for binary and 9-class classification while maintaining high accuracy in the more complex 18-class task.

**5.3.2 Feature Selection**

The model used the same **65 selected features** from the **X-IIoTID dataset**, chosen to capture diverse characteristics of network traffic:

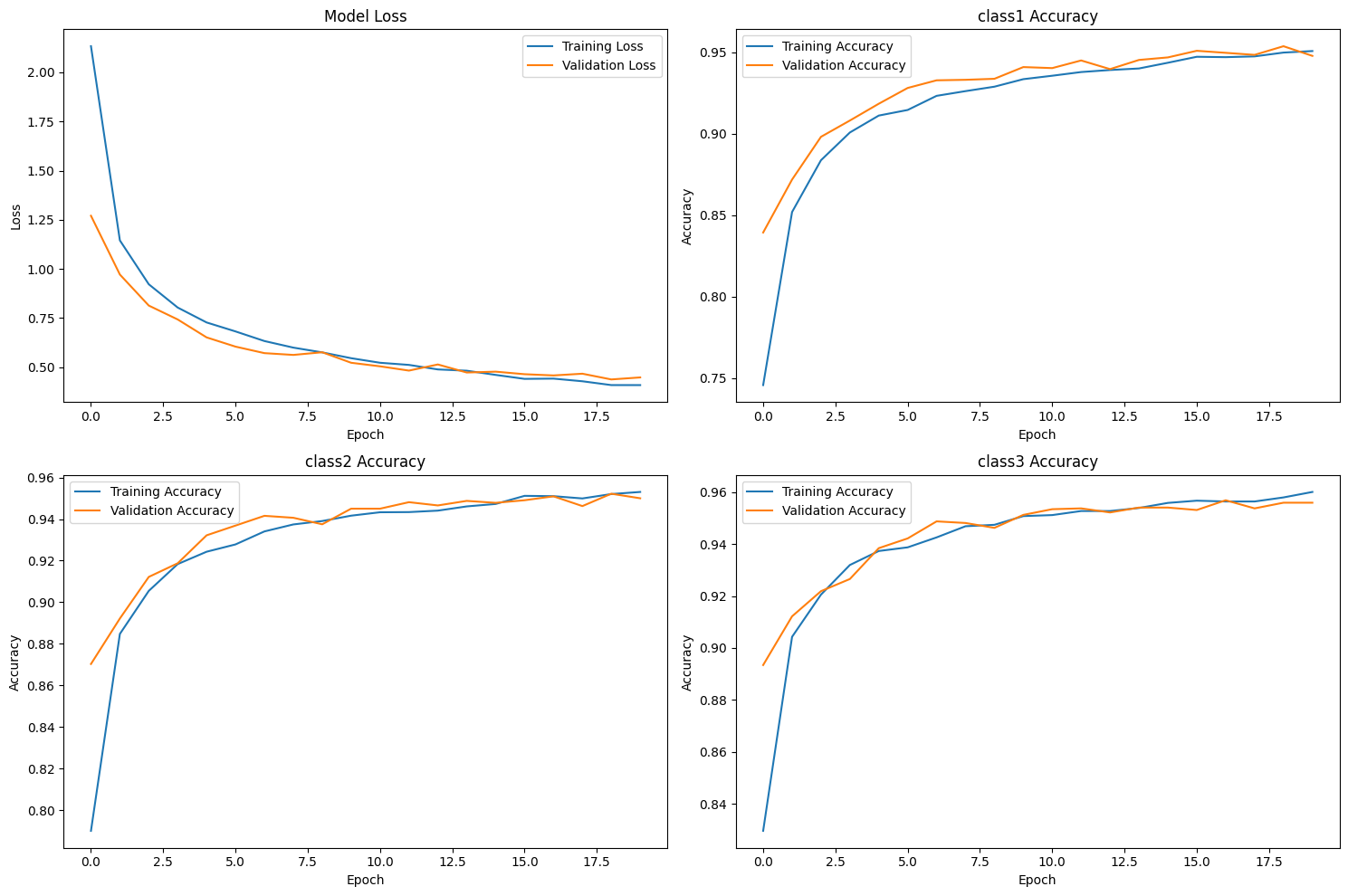
* **Network identifiers:** Source/Destination IPs, ports, and protocol types.
* **Flow-based statistics:** Flow duration, packet count, byte count, flow rates.
* **TCP/IP header attributes:** TCP flag counters, window size, ACK/FIN/RST flags.
* **Behavioral indicators:** Inter-arrival times (IAT), average packet size, byte/packet ratios.

This feature set was optimized to allow BiLSTM to learn temporal dependencies in both forward and backward directions, enhancing its ability to detect subtle attack patterns.

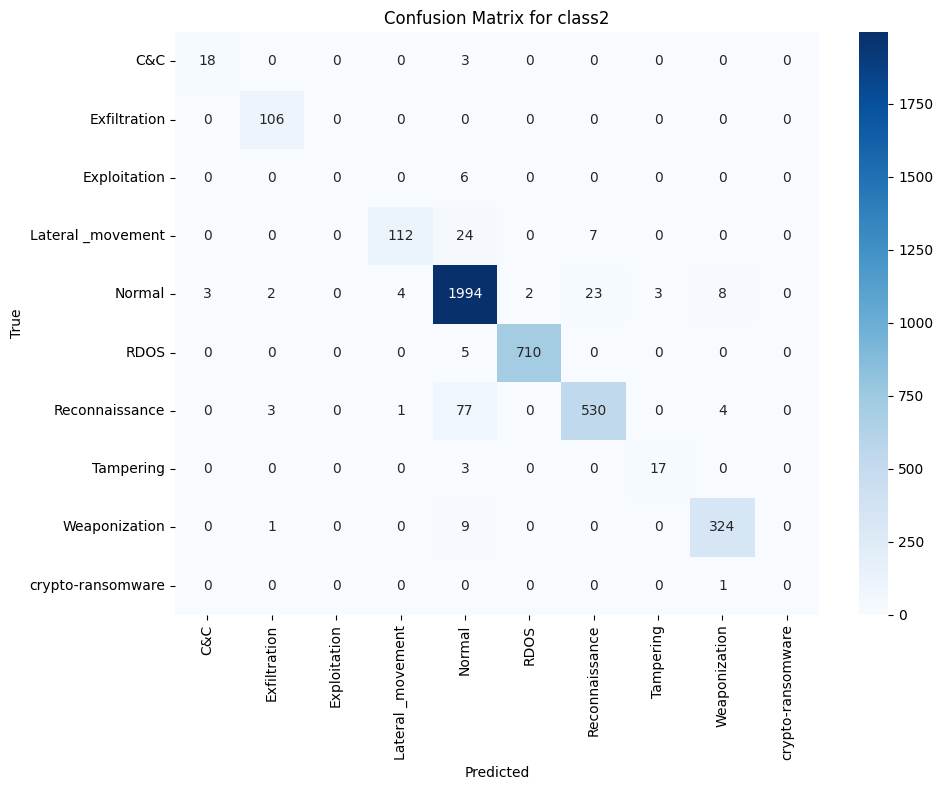
**5.3.3 Visual Analysis**

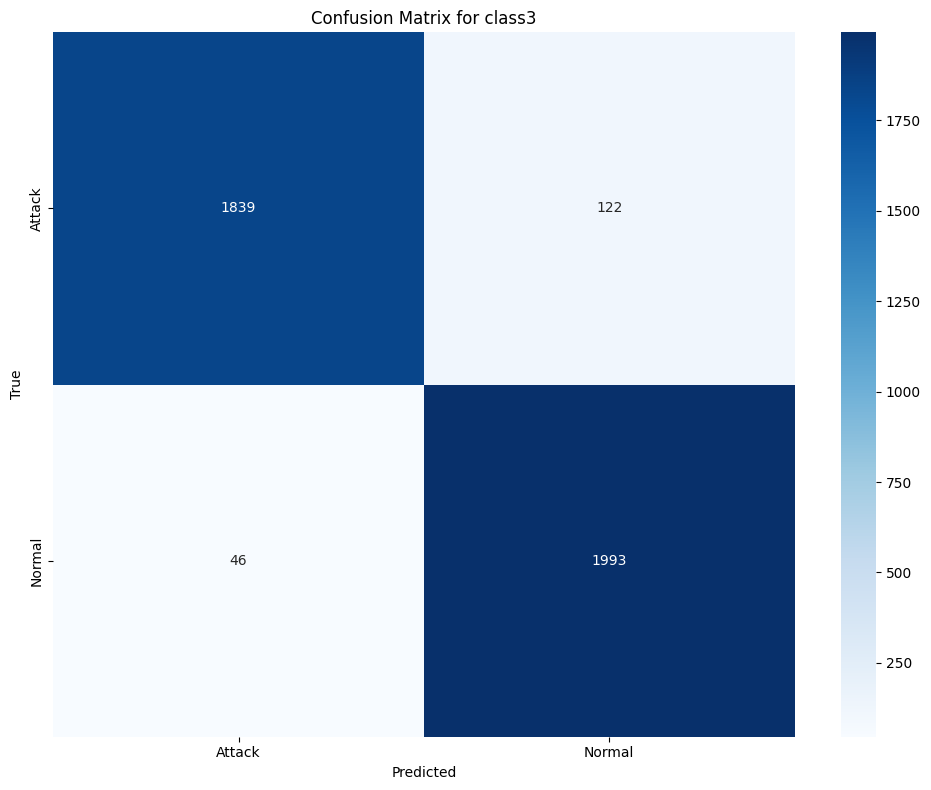
The model's behavior was examined using several visual techniques:

* **Loss and Accuracy Plots:** Showed steady convergence with minimal divergence between training and validation curves.
* **Confusion Matrices:**
  + **Class1 and Class2:** Displayed a strong diagonal structure, suggesting high prediction confidence.
  + **Class3:** Matrix was well-distributed across multiple classes, indicating the model's ability to classify rare attacks, although minor overlap between similar classes was observed.
* **Classification Reports:** Confirmed high per-class F1-scores, especially for frequent and critical attack types.









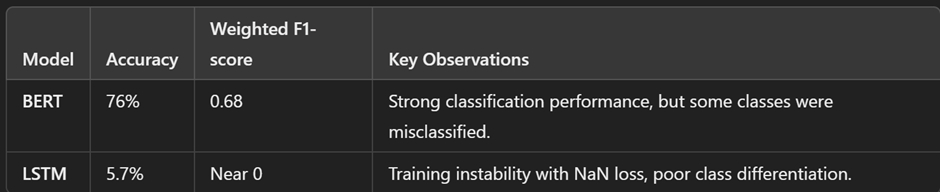
**5.3.4 Discussion**

The **BiLSTM model** demonstrated **excellent generalization** across all tasks, with performance metrics closely matching or slightly exceeding those of the standard LSTM model. Its bidirectional structure allowed it to utilize **context from both past and future input sequences**, improving its detection capabilities for both short- and long-term dependencies.

The slight drop in accuracy for the 18-class task compared to simpler models is expected due to the increased complexity. However, BiLSTM’s resilience to class imbalance and contextual ambiguity makes it a **reliable candidate** for real-time intrusion detection systems.

Future work could explore **stacked BiLSTM layers**, **attention mechanisms**, or **transformer hybridization** to further enhance detection rates, particularly for underrepresented attack classes.

Comparison of BERT and LSTM:



BERT shows a record classification accuracy with qualitatively adequate classes while LSTM couldn't learn properly.

Tentative Conclusion:

This study was aimed to highlight better model performance in classification tasks between BERT vs. The experimental results demonstrate that BERT is superior to LSTM with a significant margin in terms of accuracy, precision, recall, and F1-score.

* BERT Model Performance:
  + Reached a stable accuracy of ~75.96% after 10 epochs.
  + F1 score eval: 83.7 model with high precision and recall across classes (except for classes 2, 6, 7, 8, 10, 11 and 12)
  + On the other hand, it had a significant issue in some classes (e.g., 0, 3, 4, 5, 9, 13, 14, 16, 17, 18), with low values for both recall and precision, meaning that it had a hard time distinguishing these classes.
* LSTM Model Performance:
  + But it resulted in NaN losses all over the training, which means it was probably just an instability problem (gradient explosion, or something), and I'm not saying that I took the right way in the preprocessing of the data.
  + Obtained an accuracy of ~5.77% which is on par with random chance in a multi-class classification task.
  + For class-wise classification, performed poorly with most classes having recall and precision close to zero.

Key Takeaways:

1. **BERT outperforms LSTM** in both accuracy and class-wise classification performance, making it a preferable choice for this task.
2. There are numerical instability issues with **LSTM that needs tuning** (e.g. gradient clipping, different activation functions, or batch normalization).
3. In contrast, **more accurate classification can be conducted using both CNN models and LSTMs** or utilizing Transformer-based models specifically on domain-based data with fine-tune.
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