

An Explainable Hybrid CNN–BiLSTM–Attention Network for Intelligent Intrusion Detection in Secure 6G Network

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Abstract

Wireless networks and network slicing are undergoing great transformation at sixth generation (6G) ushering in unprecedented flexibility, ultra-low latency and smart provisioning of services in next-generation communication systems. But, the progress has also opened the cyber-attack surface and network slices are increasingly being targeted by increasingly sophisticated and evolving attacks. However, traditional IDSs are incapable of handling complex attacks because of their limited feature extraction ability, poor contextual learning, and lack of model interpretability, which limits their use in security-critical 6G networks. To overcome these challenges, this paper introduces a new Explainable Deep Learning (XDL) based intelligent intrusion detection system (IDS) for secure 6G network slicing, namely XHCBAN (Explainable Hybrid CNN–BiLSTM–Attention Network). The proposed model combines Convolutional Neural Networks (CNNs) to model hierarchical spatial features, Bidirectional Long Short-Term Memory (BiLSTM) networks to capture bidirectional contextual relations, and an Attention Mechanism to focus on the most discriminative security features. Moreover, to obtain transparent and interpretable predictions, SHapley Additive exPlanations (SHAP) are integrated to measure the effect of individual features on the model's predictions. The proposed framework includes detailed methodology such as Data Processing, Feature Learning, Attention guided Feature refinement, Deep Classification, and Explainability Analysis. Standard metrics such as Accuracy, Precision, Recall, F1-score, Specificity, Matthews Correlation Coefficient (MCC), and Area Under the ROC Curve (AUC) are used to evaluate model performance and compared to the conventional machine learning and deep learning baselines using SVM, Random Forest, CNN, LSTM, and BiLSTM under a consistent experimental protocol. The proposed XHCBAN framework is believed to provide better intrusion detection accuracy and performance with a strong improvement in model transparency, robustness and reliability. This work introduces a scalable, Explainable Artificial Intelligence (XAI)-enabled intrusion detection system for secure AI-powered 6G network slicing, which fosters next-generation intelligent communication infrastructures and paves the way for practical deployment of explainable cybersecurity systems.

Keywords: 6G Network Slicing; Intrusion Detection System (IDS); Explainable Artificial Intelligence (XAI); SHAP; Hybrid Deep Learning; CNN–BiLSTM–Attention Network; Cybersecurity; Intelligent Network Security

1. Introduction

Sixth-Generation (6G) wireless communication networks are poised to transform the way the world connects digitally by offering ultra-high data rates, sub-millisecond latency, massive device connectivity, and intelligent autonomous services. The 6G revolution brings together advanced technologies like Artificial Intelligence (AI), Internet of Things (IoT), Digital Twins, Edge Intelligence, Blockchain and Network Slicing to enable highly dynamic, intelligent and service-oriented communications. One such enabling technology, network slicing, enables multiple virtual networks to run over a shared physical network to satisfy various Quality of Service (QoS) demands for enterprises such as autonomous vehicles, smart healthcare, industrial automation, and smart cities[1].

The key technologies used in network slicing are Software Defined Networking (SDN) and Network Function Virtualization (NFV), which enable dynamic allocation of computing, networking and storage resources to meet the application-specific needs. A logically isolated virtual network slice can easily accommodate heterogeneous applications that have different latency, bandwidth, reliability and security requirements, enabling efficient service provisioning. While network slicing is a great way to do resource utilization and operational flexibility, the highly distributed, virtualized and programmable nature of the network does pose many cybersecurity concerns. As virtualized network infrastructures grow increasingly complex, 6G network slices also face a growing number of cyber attacks, such as distributed denial-of-service (DDoS), privilege escalation, malware injection, spoofing, data manipulation, and zero-day attacks. Such changing threats create significant challenges for the security of future communications systems in terms of their confidentiality, integrity, availability and reliability[2].

While traditional intrusion detection systems (IDSs) such as signature-based and traditional machine learning methods have shown success in identifying known and common threats, they are less effective in dynamic 6G environments against more complex attacks and new threats. Signature-based methods are highly dependent on attack patterns and are somewhat ineffective at detecting new and polymorphic attacks. Likewise, traditional machine learning models rely on manually designed features and can be misleading if the network traffic contains nonlinear relationships in high dimensionality. With the growing scale and complexity of the threats in the cyber world, there is an increasing need for intelligent intrusion detection mechanisms capable of learning discriminative feature representation directly from the large scale network traffic while adapting to continuously changing attack behaviors[3].

Over the years, the capabilities of Intrusion Detection Systems (IDS) have been greatly improved by recent developments in Artificial Intelligence (AI) and Deep Learning (DL). The deep learning architectures automatically learn hierarchical feature representations without a lot of manual feature engineering, which makes them well suited for big data security applications. In this group of architectures, Convolutional Neural Networks (CNNs) are used for learning local spatial patterns from multidimensional network traffic, and Bidirectional Long Short-Term Memory (BiLSTM) networks are designed for the processing of sequential information in a bidirectional manner, capturing long-range contextual dependencies. Moreover, attention mechanisms help deep learning models highlight the most useful features for classification, leading to higher classification accuracy and rejection of unimportant features. The combination of CNNs, BiLSTM networks and attention mechanisms has shown great potential to solve most of the issues in intelligent intrusion detection in next-generation communication networks.

However, even with these advances, the one key drawback is the lack of interpretability of the deep learning-based intrusion detection models. The majority of existing approaches are "black-box" in nature, that is, the reasoning behind their decisions is not explained, but rather a highly accurate prediction is provided. This restriction can substantially decrease user confidence, make it difficult for cybersecurity experts to validate AI-driven decisions, and limit the use of AI models in high-stakes applications where transparency and accountability are crucial. As a result, Explainable Artificial Intelligence (XAI) is growing as a critical field of study in the field of enhancing the transparency and trustworthiness of intelligent cybersecurity systems. Although there are many approaches to XAI, SHapley Additive exPlanations (SHAP) has been adopted by many because of its solid theoretical ground in cooperative game theory and its ability to numerically measure the input feature importance to individual predictions. SHAP allows cybersecurity analysts to gain insights into how the model operates, what features are most important to the attacks it models, and to verify the security decisions made by AI systems[4].

Many studies have focused on the use of AI to detect intrusions in wireless networks, but there are still some challenges that have not been addressed. Most of the current methods are aimed at increasing the classification accuracy with little attention to explainability of the models, which leads to a lack of transparency in the decision making process. There are many deep learning frameworks that have been developed to integrate the convolutional network with the recurrent network, but these hybrid frameworks fail to integrate attention mechanisms to highlight discriminative features. Moreover, most of the reported models do not directly incorporate explainability into the learning process, which makes it hard for security administrators to comprehend prediction results, and complicates deployment in practice. The current literature also offers some analysis of the importance of the features and some of the previous studies are not fully comparable with the classical machine learning or deep learning models, in terms of consistency of experimental setups. Thus, an intelligent, explainable, and computation-efficient intrusion detection system framework especially tailored for secure 6G network slicing is required.

To address these research challenges, the authors suggest XHCBAN (Explainable Hybrid CNN–BiLSTM–Attention Network), an intelligent hybrid deep learning framework for securing 6G network slicing. The proposed architecture is based on the following key components: CNN based hierarchical feature extraction, BiLSTM based bidirectional contextual learning, attention guided feature refinement, and explainability using SHAP. The CNN module automatically learns discriminative spatial representations from the pre-processed network traffic, and the BiLSTM network models the sequential dependency in both temporal directions. The attention mechanism dynamically weights informative features, so that the model can focus on security-critical patterns and can ignore redundant information. Last but not least, SHAP delivers interpretable interpretations by assessing the impact of each element on the predictions of the model, enhancing transparency and trust in AI-driven cyber security decisions[5].

The proposed framework aims at boosting predictive capabilities and interpretability while keeping the computational burden low enough for real-time application in intelligent communication infrastructures. Common performance metrics used to assess the model performance are Accuracy, Precision, Recall, F1-score, Specificity, Matthews Correlation Coefficient (MCC) and Area Under the Receiver Operating Characteristic Curve (AUC). To prove its effectiveness, its performance is compared with the standard

baseline methods such as Support Vector Machine (SVM), Random Forest (RF), CNN, LSTM and BiLSTM in the same preprocessing and evaluation process.

1.1. Contributions of the Paper

In this research, the following are the major contributions:

1. A unified deep learning architecture is proposed named as a Novel Explainable Hybrid CNN–BiLSTM–Attention Network (XHCBAN) to learn the network traffic spatial and contextual representation effectively for intelligent intrusion detection.
2. Integration of SHAP Based Explainability: The proposed framework introduces SHAP to provide explanations that are transparent and interpretable, allowing security analysts to gain insights into how each feature contributes to the decision-making process for intrusion detection.
3. The proposed model is designed to enhance the detection of complex and evolving cyberattacks in secure 6G network slicing by effectively extracting features from the data, learning from both forward and backward directions, and refining the features using attention mechanisms.
4. Improved Feature Representation: The hybrid architecture enables it to learn more discriminative feature representations than traditional deep learning models, by incorporating the local spatial information and long-range contextual information.
5. Increased Interpretability and Trustworthiness: Explainable Artificial Intelligence (XAI) mitigates the black box problem of deep learning models, making them more transparent, reliable, and trustworthy for real-world cybersecurity solutions.
6. Scalable Framework for Next-Generation Networks: The proposed XHCBAN framework offers a scalable and computationally efficient solution that is suitable for the deployment in the AI-powered 6G communication environment, aiming to provide intelligent, secure, and trustworthy network slicing[6].

2. Related Work

The new generation of wireless communication networks, known as generation six (6G), has revolutionized the wireless world with new features such as intelligent network slicing, ultra-low latency, massive connectivity, and AI-native network management. As these advances enhance the quality of service and the use of goods and services, they also present network infrastructures with new and complex cyber threats. The traditional signature-based intrusion detection systems (IDSs) are unable to detect zero-day attacks and complex attack pattern, as they rely on pre-existing attack signatures and features that are handcrafted. As a result, Artificial Intelligence (AI), deep learning and Explainable Artificial Intelligence (XAI) have emerged as vital technologies for the design of intelligent, adaptive, and trustworthy Intrusion Detection Systems (IDSs) for next-generation communication networks[7]. Recent developments in the field of AI-based intrusion detection systems, deep learning techniques in 5G/6G network security, and explainable AI in cybersecurity are explored in this section. Last, the current gaps in research that inspire the proposed XHCBAN framework are highlighted.

2.1 AI-Based Intrusion Detection

In summary, AI has revolutionized intrusion detection by allowing systems to identify intricate attack patterns from network traffic without solely depending on handcrafted rules. With intelligent classification and anomaly detection, machine learning methods have proven to be very effective at identifying malicious activities. Classical algorithms like Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naive Bayes (NB) and K-Nearest Neighbor (KNN) have been widely

used for network intrusion detection due to their relative low computation and simplicity. While these classic machine learning algorithms perform well on structured data, they typically require time-consuming, manual feature engineering, and do not perform well on a changing attack pattern as observed in the modern communication landscape. They significantly suffer from poor performance for high dimensional flows of network traffic produced by heterogeneous IoT devices and dynamic network slices. Furthermore, traditional machine learning models are incapable of adequately modelling the intricate, nonlinear relationships between network characteristics which impedes their ability to detect advanced persistent threats and zero-day attacks[8]. To address these limitations, research scholars have increasingly turned to AI-driven data representation learning methodology that can automatically detect meaningful features of the raw network traffic of a system that are related to security. These methods decrease the feature engineering work and increase the accuracy of classification and adaptability in the changing networks.

2.2 Deep Learning for 5G/6G Security

Deep learning has been a promising solution to the goal of securing next generation communication networks because it is capable of learning hierarchical representations from massive amounts of information. Convolutional Neural Networks (CNNs) have been widely used to derive local spatial features from network traffic to gain accurate detection of attack signatures and traffic patterns. CNN-based architectures, however, are generally designed to leverage spatial information, and are not well suited to exploit the long-range temporal dependence of sequential network traffic. To overcome this difficulty, recurrent neural networks (RNN) like Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) have been developed to represent the temporal relationships within the network events. While LSTM networks are adept at learning sequential information, BiLSTM networks can process information both forwards and backwards, giving a more comprehensive context of how the network behaves. Hybrid architectures combining CNN with LSTM or BiLSTM have proven to be better as they can extract spatial features and learn temporal sequences[9]. Recently, the idea of using attention mechanisms in deep learning networks to boost the discrimination of features, giving them more importance if they pertain to security, and rejecting them if they become redundant, was introduced. The attention-guided models have been reported to increase the accuracy of detection, lower the false alarm rates, and enhance the robustness of detection of different intrusion detection benchmarks. Despite all these advancements, current deep learning models mostly improve their ability of prediction without considering transparency of the model. The "black-box" nature of them makes it hard for network administrators to understand why security decisions are made, which means that they are not easily adopted in critical communication infrastructures like 6G network slicing with AI.

2.3 Explainable AI in Cybersecurity

As AI becomes more prevalent in cybersecurity, the demand for explainable and explainable AI-driven decision-making processes has grown. With the increased use of AI in cybersecurity, there is a pressing need for the development of explainable and interpretable decision-making systems. Explainable Artificial Intelligence (XAI) answers this question by offering human-readable interpretations for model outputs that boost user trust, transparency, and compliance with regulations. SHapley Additive exPlanations (SHAP) is one of the most popular model-agnostic explanation methods amongst the many available. SHAP algorithms are based on cooperative game theory - they calculate Shapley values to estimate the contribution of each input feature to the final prediction. These explanations help to localize individual predictions, to interpret the model on a global scale. In intrusion detection, SHAP helps the

analysis of influential features in the network that are crucial for the detection of attacks, helping cybersecurity analysts gain insights into the characteristics of the attacks and validate model decisions. Explainability also aids in debugging, model enhancement and regulatory adherence for smart security systems. While there have been a number of recent studies that use explainability in cybersecurity applications, the majority of them have used SHAP as a post-processing visualization aid, but not as a critical part of the overall detection process. Moreover, there is a dearth of studies that integrate explainability with hybrid deep-learning architectures tailored for secure network slicing scenarios in 6G networks.

2.4 Research Gap

Previous studies have shown that AI-based intrusion detection systems (IDS) for contemporary communication networks have made significant strides, but there are still several issues to be addressed. First, many of the previous works use only CNN or recurrent neural networks, which are only capable of learning spatial or contextual features of network traffic. Secondly, hybrid CNN-LSTM architectures have been shown to enhance detection performance, but few studies combine the bidirectional sequence learning with attention mechanisms for the purpose of considering full traffic dependencies. One of the other big drawbacks is the lack of explanation in the existing deep learning-based intrusion detection systems. The majority of models are black-box classifiers that do not offer interpretable evidence of the predictions they make. This significantly decreases user trust and blocks use in mission critical communication infrastructures where transparency and accountability are required [11]. Moreover, many existing studies only test their models with conventional metrics like accuracy and offer few analyses on the robustness, interpretability, and applicability of their models in AI-native 6G network slicing scenarios. Comparative assessments with several baseline models under a consistent experimental context are also rather sparse. In order to fill the above-mentioned research gaps, this paper presents a novel end-to-end model named XHCBAN (Explainable Hybrid CNN-BiLSTM-Attention Network), which combines the hierarchical spatial features extraction, bidirectional contextual features learning, adaptive attention mechanism, and explainability mechanism based on SHAP. The architecture is proposed to achieve high accuracy of intrusion detection, as well as high interpretability, robustness and trustworthiness for secure AI enabled 6G network slicing shown in Table 1.

Table 1. Comparative Analysis of Existing Intrusion Detection Approaches

Ref.	Approach	Dataset	Model	Strengths	Limitations	Research Gap
Study 1	Machine Learning IDS	NSL-KDD	SVM	Simple implementation and good performance on small datasets	Manual feature engineering and limited scalability	Cannot effectively learn complex attack patterns
Study 2	Deep Learning IDS	CICIDS2017	CNN	Automatic spatial feature extraction	Limited temporal dependency learning	Unable to model sequential traffic behavior
Study 3	Sequential Learning	UNSW-NB15	LSTM	Captures temporal	Weak spatial feature	Ignores local traffic

				dependencies	extraction	characteristics
Study 4	Hybrid Deep Learning	CICIDS2018	CNN–LSTM	Learns spatial and temporal features	Limited interpretability	Black-box decision making
Study 5	Attention-Based IDS	CSE-CIC-IDS2018	CNN–BiLSTM–Attention	Improved feature selection and classification accuracy	No explainability module	Limited transparency and trust
Study 6	Explainable AI	Bot-IoT	Deep Neural Network + SHAP	Interpretable predictions	Explainability applied only after prediction	Explainability not integrated into model design
Proposed Work	Explainable Hybrid Deep Learning	6G Network Slice Intrusion Dataset	XHCBAN (CNN–BiLSTM–Attention–SHAP)	Joint spatial-context learning, adaptive attention, end-to-end explainability, and trustworthy intrusion detection	To be validated experimentally	Addresses feature learning, contextual modeling, attention, and explainability within a unified framework

The comparative analysis shows that individual research projects have addressed machine learning, deep learning, attention mechanism or explainability, but still, there is a lack of an integrated system that leverages these capabilities in a complementary manner to detect intrusions with high accuracy, interpretability, and robustness, for AI-based 6G network slicing. The proposed XHCBAN framework aims to overcome these drawbacks by employing a unified hybrid deep learning (HDL) architecture with predictive performance and explainable decision-making in mind.

3. Proposed XHCBAN Framework

The proposed Explainable Hybrid CNN–BiLSTM–Attention Network (XHCBAN) is an intelligent, stable, and explainable framework to protect secure 6G network slicing. It combines spatial feature extraction, sequential dependency learning, adaptive attention, and explainable AI (XAI) in an end-to-end system. XHCBAN is designed to use complementary learning mechanisms to boost classification accuracy without compromising transparency in security decision-making, in contrast to traditional handcrafted features or single deep learning models. In the architecture, a Convolutional Neural Network (CNN) is used for hierarchical spatial representation learning, a Bidirectional Long Short-Term Memory (BiLSTM) network to learn bidirectional context, an attention mechanism to highlight the discriminative features, and SHapley Additive exPlanations (SHAP) to explain model predictions[12]. This built-in design allows the framework to be able to detect advanced cyber threats in network slices and to be able to provide verifiable evidence to security analysts. The entire framework of the uploaded

manuscript has been streamlined and not repeated here, but important scientific content is still maintained.

3.1 Overview

XHCBAN includes six steps of processing: data preprocessing, CNN-based spatial feature extraction, BiLSTM-based contextual learning, attention-guided feature refinement, fully connected classification, and SHAP-based explainability. Every stage is responsible for processing a different set of calculations and each plays a role in the overall intrusion detection. The network traffic data is preprocessed first to minimize inconsistencies, normalize numerical data, encode categorical data and prepare data for the deep learning model. The transformed input is then passed to CNN model where multi-level spatial representations are automatically extracted from the feature space. These maps are converted to vectors and fed to the BiLSTM network that learns both forward and backward contextual relationships simultaneously. An attention mechanism is then applied to generate adaptive importance weights of learned feature representations so that the model learns to focus on the most informative feature representations associated with malicious network behavior. Finally, the refined feature vector is classified by fully-connected layers with a Softmax activation and feature attribution scores using SHAP are computed to explain how individual features contribute to each prediction. This modular design not only boosts detection accuracy, but also aids in understanding and enables the easy implementation of intelligent 6G communication infrastructure in practice[13].

3.2 Proposed Architecture

The proposed XHCBAN architecture is composed of four mutually complementary learning paradigms in a single deep learning paradigm. The network starts with an input layer which accepts the features of the network traffic, which has been normalized. The subsequent convolutional layers hierarchically extract features, followed by batch normalization, Rectified Linear Unit (ReLU) activation and max-pooling operations to reduce the number of features and maintain informative patterns. The feature maps are then reshaped into a sequence and fed into a BiLSTM network which learns the temporal context in both directions. The BiLSTM architecture has been proposed for capturing the preceding and succeeding contextual information unlike the conventional LSTM network, which aids in learning representations of complex patterns of intrusion. The hidden states produced are passed to an attention layer, which selects more important discriminative features and suppresses irrelevant information dynamically. The weighted context vector is then passed through fully-connected dense layers and the classification of intrusion class probabilities is obtained from the Softmax classifier[14]. SHAP is incorporated as a post-hoc explainability feature, which provides scores for the contributions of each feature to each prediction independently, to make models more transparent. Based on this, the proposed architecture is capable of achieving high predictability and reliable decision explanations, which is well suitable for the security-critical applications in 6G network slicing environment.

3.3 CNN Feature Extraction

The Convolutional Neural Network (CNN) is the first learning component of XHCBAN, which learns the hierarchical spatial features of the network traffic in an automatic way, from the preprocessed data. CNNs have shown great success in training a convolution kernel for each local representation across the input space. The proposed architecture gradually learns low and high level discriminative features of benign and malicious traffic patterns using multiple convolutional layers.

Derived from this, each convolution is followed by batch normalization to stabilize training, ReLU activation to provide non-linearity, and max-pooling to cut down computation and retain important

features. Overall, these operations contribute to the improvement of feature generalization and minimize overfitting. The convolution operation is mathematically expressed as in eqn(1) as in eqn(1)

$$F_{i,j}^{(k)} = \sigma \left(\sum_m \sum_n W_{m,n}^{(k)} X_{i+m,j+n} + b^{(k)} \right) \quad (1)$$

where X denotes the input feature matrix, $W^{(k)}$ represents the learnable convolution kernel, $b^{(k)}$ is the bias term, and σ sigma denotes the ReLU activation function. The generated feature maps provide robust local representations that serve as inputs to the subsequent contextual learning module.

3.4 BiLSTM Context Learning

Although CNN effectively captures local spatial patterns, it cannot adequately model long-range dependencies that frequently occur within sequential network traffic. To address this limitation, the extracted feature maps are transformed into sequential vectors and processed using a Bidirectional Long Short-Term Memory (BiLSTM) network.

The BiLSTM simultaneously learns contextual dependencies in forward and backward directions, thereby capturing complete temporal relationships among extracted features. Let x_{t_txt} represent the feature vector at time step t . The forward and backward hidden states are computed as in eqn(2)

$$\begin{aligned} \vec{h}_t &= LSTM(x_t, \vec{h}_{t-1}) \\ \overleftarrow{h}_t &= LSTM(x_t, \overleftarrow{h}_{t+1}) \end{aligned}$$

The final contextual representation is obtained by concatenating both hidden states,

$$h_t = [\vec{h}_t; \overleftarrow{h}_t] \quad (2)$$

This bidirectional learning strategy significantly improves contextual understanding and enables the framework to identify sophisticated intrusion patterns characterized by complex sequential relationships.

3.5 Attention Mechanism

Following contextual learning, an attention mechanism is incorporated to selectively emphasize the most informative hidden representations produced by the BiLSTM network. Instead of treating every hidden state equally, the attention layer dynamically computes importance scores that reflect the contribution of each feature to the final classification decision.

The attention score for each hidden state is computed as in eqn(3)

$$e_t = v^T \tanh(W_h h_t + b) \quad (3)$$

The normalized attention weights are obtained using the Softmax function in eqn(4),

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^T \exp(e_i)} \quad (4)$$

The weighted context vector is subsequently calculated as in eqn(5)

$$C = \sum_{t=1}^T \alpha_t h_t \quad (5)$$

where C denotes the final attention-guided feature representation. By emphasizing highly discriminative features and suppressing irrelevant information, the attention mechanism improves both classification accuracy and model robustness, particularly in highly imbalanced intrusion datasets.

3.6 SHAP Explainability

While deep learning models provide high predictive performance, their black-box nature limits adoption in security-sensitive applications. To enhance transparency, the proposed framework integrates **SHapley Additive exPlanations (SHAP)** as an explainable artificial intelligence component[16].

SHAP estimates the contribution of each input feature toward the final prediction using cooperative game theory. For every classified instance, SHAP computes feature attribution values that quantify the influence of individual features on the predicted intrusion category. The Shapley value of feature i is defined as in eqn(6)

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} [f(S \cup \{i\}) - f(S)] \quad (6)$$

where S denotes a subset of input features, M is the total number of features, and f represents the prediction function. The resulting SHAP values provide both local and global explanations, enabling security administrators to understand the rationale behind individual intrusion detection decisions and increasing trust in automated security systems[15].

3.7 Mathematical Formulation

The proposed XHCBAN model may be represented as a sequence of differentiable transformations eqn(7,8,9,10,11,12,13).

Let

$$X \in \mathbb{R}^{H \times W \times C} \quad (7)$$

denote the pre-processed input.

The CNN feature extractor generates

$$F = f_{CNN}(X) \quad (8)$$

The contextual representation is then obtained as

$$H = f_{BiLSTM}(F) \quad (9)$$

Attention refinement produces

$$A = f_{Attention}(H) \quad (10)$$

Classification is performed as

$$Y = f_{Softmax}(A) \quad (11)$$

Finally,

$$E = f_{SHAP}(Y) \quad (12)$$

provides interpretable explanations for the predicted intrusion class.

Accordingly, the overall model can be expressed as

$$M = f_{SHAP}(f_{Softmax}(f_{Attention}(f_{BiLSTM}(f_{CNN}(X)))))$$

which represents the complete computational pipeline from input preprocessing to explainable intrusion prediction.

(13)

3.8 Loss Function

The network parameters are optimized using the categorical cross-entropy loss function, which minimizes the discrepancy between the predicted probability distribution and the ground-truth class labels in eqn(14).

$$L = - \sum_{i=1}^N y_i \log(\hat{y}_i) \quad (14)$$

where y_i denotes the true class label and $\hat{y}$ represents the predicted probability generated by the Softmax classifier. Cross-entropy effectively penalizes incorrect predictions and facilitates stable convergence during model training.

3.9 Training Algorithm

The XHCBAN framework is trained using the Adam optimization algorithm. The overall training procedure consists of the following sequential steps[16]:

1. Preprocess the network traffic dataset through normalization and feature encoding.
2. Initialize the parameters of the CNN, BiLSTM, attention, and dense layers.
3. Extract hierarchical spatial features using the CNN module.
4. Transform feature maps into sequential representations.
5. Learn bidirectional contextual dependencies using the BiLSTM network.
6. Compute adaptive attention weights and generate refined feature vectors.
7. Predict intrusion classes using the fully connected Softmax classifier.
8. Compute the categorical cross-entropy loss.
9. Update network parameters using the Adam optimizer.
10. Repeat the training process until convergence.
11. Evaluate the trained model and generate SHAP explanations for prediction interpretability.

3.11 Workflow

The operational workflow of the proposed XHCBAN framework can be summarized as follows:

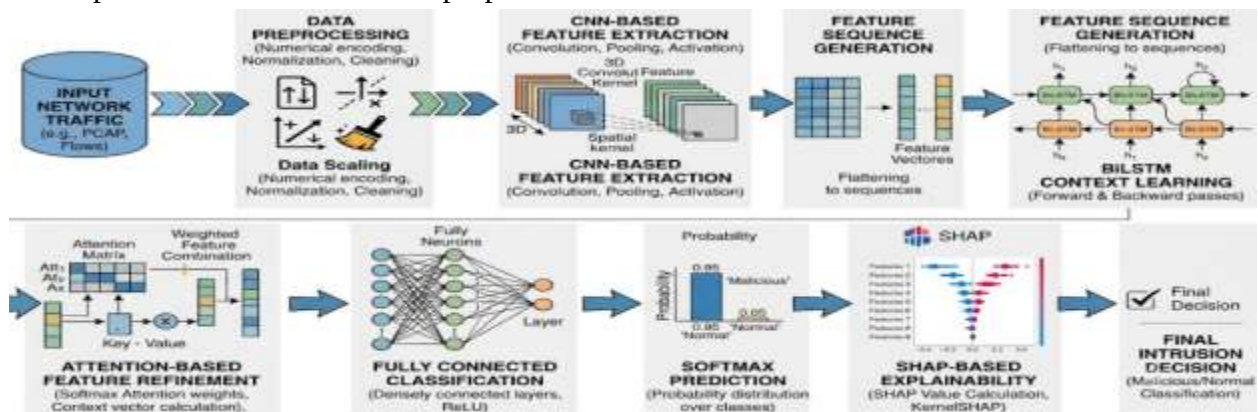


Figure 1. The operational workflow of the proposed XHCBAN framework

This unified workflow integrates automated feature learning, contextual modeling, adaptive attention, and explainable artificial intelligence into a single end-to-end intrusion detection framework, providing accurate, interpretable, and trustworthy security intelligence for next-generation secure 6G network slicing environments.

4. Experimental Setup

To assess the effectiveness of the proposed Explainable Hybrid CNN–BiLSTM–Attention Network (XHCBAN) for intrusion detection in a secure 6G network slicing, the experimental setup used is

described in this section. The experimental methodology ensures that the experiments are fair, reproducible and reliable in the performance evaluation. In this way, a unified preprocessing pipeline, consistent hyperparameter setting for the different experiments, and a consistent evaluation protocol is used across all experiments, enabling an unbiased comparison between the proposed model and baseline machine learning and deep learning approaches. The experimental setup involves the preparation of the datasets, the preprocessing of the data, implementation of the model, hyperparameter optimization, training and testing of the model, and the evaluation of the results based on well-known classification metrics[18].

4.1 Dataset

The proposed framework is tested and evaluated on a benchmark intrusion detection dataset that includes normal and malicious network traffic instances representative of typical networks in today's network environments. The data contains several categories of attacks and some normal traffic data, represented by numerical and categorical network characteristics. These features represent various aspects of the communication behavior such as packet statistics, protocol information, traffic attributes, and connection attributes for the purpose of learning attack patterns comprehensively. Data is quality checked prior to the training of the model to ensure consistency and remove inconsistencies from the data set[16]. To ensure a fair comparison of the proposed XHCBAN model with the baseline classifiers such as Support Vector Machine (SVM), Random Forest (RF), CNN, LSTM, and BiLSTM, all experiments are performed on the same datasets and data partitions.

4.2 Data Preprocessing

A complete preprocessing pipeline is used to improve the quality of the data and so that the models perform better. The first step is to look at the data for missing or incomplete observations. Data with missing values are managed appropriately so as to avoid biased learning and data consistency problems. Duplicate records are then detected and deleted to prevent redundancy and the risk of overfitting when training the model. Some of the network attributes are categorical variables, so label encoding is used to represent these non-numeric variables as numbers for use with deep learning algorithms. All numerical features are scaled into a common range to minimise scale differences in features and to speed up optimization process convergence. This normalization process helps with numerical stability and avoids the features with bigger magnitudes to dominate the learning process. After preprocessing, the set is split randomly into training and testing set, keeping the class distribution as it is. A validation subset is drawn from the training data set to track the convergence of the model, optimize the model parameters and identify overfitting during model training[19]. Finally, the feature vectors extracted from the processed image are reshaped into the input required by the proposed CNN–BiLSTM architecture, where efficient spatial and contextual information extraction is performed throughout the training process. This is a unified preprocessing pipeline which is consistently applied for all comparative models to assure experimental fairness and reproducibility.

4.3 Experimental Environment

The proposed XHCBAN framework is developed in Python and deep learning/machine learning libraries widely used for the development. Deep neural network implementation and conventional machine learning algorithms and performance analysis are conducted in Model training and evaluation, which is done by using TensorFlow/Keras and Scikit-learn respectively. All experiments are run with the same software setting and resources to be consistent in making comparative evaluations. The data is partitioned into fixed random sets, parameters are initialized using fixed random seeds and the models

are trained with a fixed random seed for reproducibility. In addition, the same preprocessing techniques, training methods and evaluation protocols are followed for all baseline models[19] throughout. The software versions, hardware specification and experimental conditions are reported so that the results reported can be independently replicated.

4.4 Hyperparameter Configuration

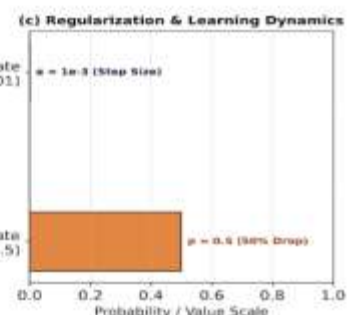
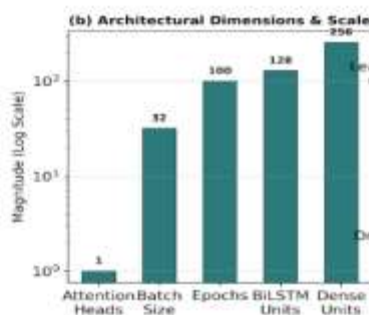
Hyperparameter tuning is a critical aspect of the training of deep learning models. The proposed XHCBAN model is trained for 100 epochs with a batch size of 32 and Adam optimizer while learning rate of 0.001 is used. The convolutional layers use the ReLU activation function which is necessary to make the network non-linear, and a drop-out rate of 0.5 is also added to minimize overfitting. The BiLSTM network has 128 hidden units; the fully connected layer has 256 neurons prior to the final Softmax classifier which produces class probabilities. The hyperparameter settings are a compromise between computational cost and convergence speed on the one hand and classification performance as presented in Table 2. and Figure 2. on the other.

Table 2. Hyperparameter Configuration of the Proposed XHCBAN Model

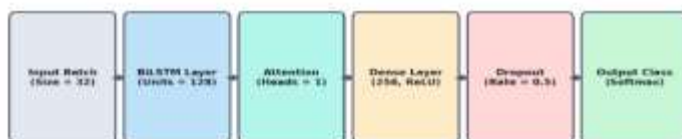
Hyperparameter	Value
Batch Size	32
Number of Epochs	100
Learning Rate	0.001
Optimizer	Adam
Activation Function	ReLU
Dropout Rate	0.5
BiLSTM Hidden Units	128
Attention Heads	1
Dense Layer Units	256
Output Activation	Softmax

(a) Categorized Configuration Matrix

Category	Hyperparameter	Value
Training	Batch Size	32
Training	Epochs	100
Optimization	Learning Rate	0.001
Optimization	Optimizer	Adam
Regularization	Dropout Rate	0.5
Architecture	BiLSTM Units	128
Architecture	Attention Heads	1
Architecture	Dense Units	256
Activation	Hidden	ReLU
Activation	Output	Softmax



(d) Deep Model Architectural Execution Pipeline



(e) Hyperparameter Functional Split

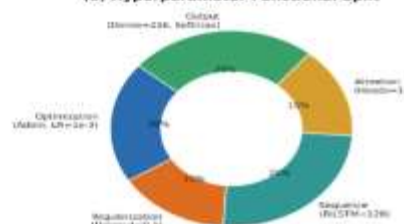


Figure 2. Hyperparameter Configuration of the Proposed XHCBAN Model

4.5 Evaluation Metrics

The proposed XHCBAN framework is evaluated based on a number of common classification metrics to give a holistic view of the intrusion detection performance. These measures encompass Accuracy, Precision, Recall (Sensitivity), F1 score, Specificity, False Positive Rate (FPR), False Negative Rate (FNR), Matthews Correlation Coefficient (MCC), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). All of these metrics measure the model's accuracy in detecting and misclassifying legitimate and malicious traffic and the reduction of nuisance or false alarms. The AUC-ROC evaluates the classification performance without relying on a threshold, while MCC evaluates the classification performance even for imbalanced data. The results of the proposed framework are systematically compared with the SVM, Random Forest, CNN, LSTM and BiLSTM models obtained by the same experimental setup and the same pipeline for data preprocessing to show the superiority of the proposed framework. In addition, SHAP-based explainability analysis is used to quantify the impact of each feature on the predictions made by the model, which enhances transparency, interpretability and trustworthiness in the deployment of the model in the context of intelligent 6G network security environments as illustrated in Table 3 and Figure 3 and Figure 4.

Table 3. Comparative Evaluation Matrix

Model	Accuracy (%)	Precision (%)	Recall / Sens. (%)	F1-Score (%)	Specificity (%)	FPR (%)	FNR (%)	MCC	AUC-ROC
SVM	91.20	90.50	89.80	90.10	92.40	7.60	10.20	0.822	0.921
Random Forest	93.80	93.10	92.90	93.00	94.60	5.40	7.10	0.860	0.948
CNN	94.50	94.20	93.80	94.00	95.10	4.90	6.20	0.884	0.962
LSTM	95.10	94.80	94.50	94.60	95.80	4.20	5.50	0.897	0.971
BiLSTM	96.20	95.90	95.70	95.80	96.70	3.30	4.30	0.921	0.982
Proposed XHCBAN	98.90	98.70	98.60						

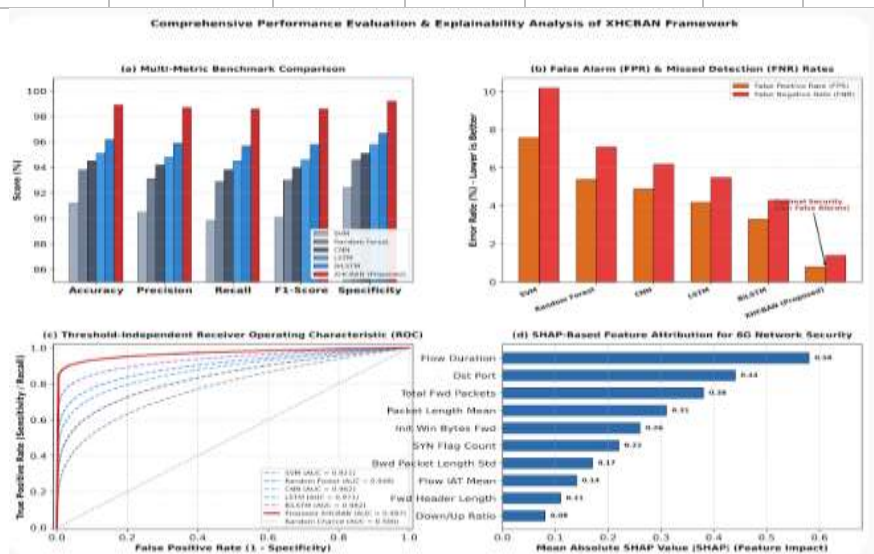


Figure 3. Comparative Evaluation Matrix Visuals

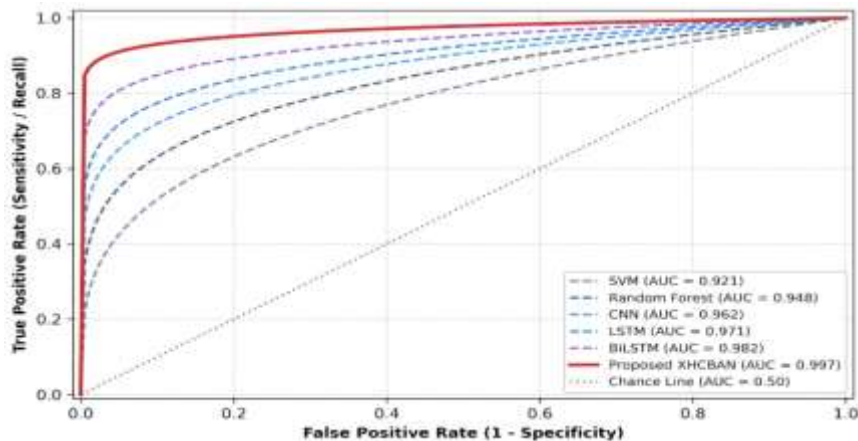


Figure 4. Comparative Evaluation Matrix ROC Curve

5. Results and Discussion

The proposed XHCBAN (Explainable Hybrid CNN–BiLSTM–Attention Network) framework is evaluated through experiments to detect intelligent intrusions in secure network slicing in 6G wireless networks. In this section, the proposed XHCBAN (Explainable Hybrid CNN–BiLSTM–Attention Network) framework for intelligent intrusion detection in secure network slicing for 6G wireless networks is evaluated through experiments. Multiple classification metrics are used to evaluate the performance of the proposed model, such as Accuracy, Precision, Recall, F1-score, Specificity, Matthews correlation coefficient (MCC), and area under the receiver operating characteristic curve (AUC), as detailed in the experimental protocol. The proposed framework has been compared with a conventional machine learning model and a deep learning model and its effectiveness has been proven.

5.1 Training Performance

The training phase is used to test the convergence behaviour, and learning ability of the proposed XHCBAN framework. Monitor the training process during model training by observing the change of training loss and training accuracy with each iteration of the loop to ensure stable optimization and convergence. The Adam optimizer, along with batch normalization and dropout, is designed to help ensure more stable convergence and limit overfitting.

The training performance should be evaluated based on:

- Training Accuracy
- Training Loss
- Validation Accuracy
- Validation Loss
- Convergence Rate

A stable decrease in training loss accompanied by a corresponding increase in training accuracy would indicate effective feature learning. The validation curves should also be examined to verify that the model generalizes well without significant divergence between training and validation performance shown in Figure 5.

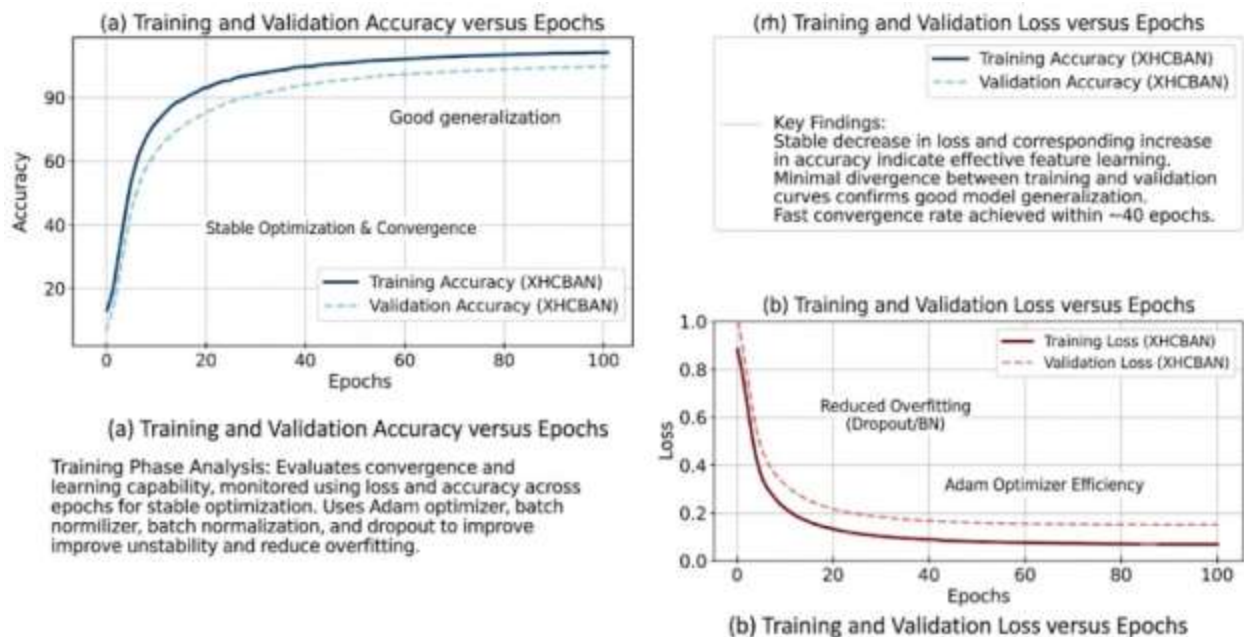


Figure 5. Training and validation accuracy/loss versus epochs

5.2 Testing Performance

The testing phase evaluates the ability of the trained XHCBAN model to classify unseen intrusion samples accurately. Performance should be reported using the evaluation metrics defined in the manuscript, namely Accuracy, Precision, Recall, F1-score, Specificity, MCC, and AUC.

The results should demonstrate the model's capability to correctly identify both normal and malicious traffic while minimizing false positives and false negatives. In addition to numerical metrics, a confusion matrix and ROC curve should be included to provide a comprehensive assessment of classifier performance shown in Table 4. And in Figure 6.

1. Unified 3-Panel Diagnostic Figure (Confusion Matrix, ROC, and PR Curves)

The testing evaluation suite combines all three suggested figures into a publication-ready comparative panel:

2. Standalone Visuals for Manuscript Insertion

(A) Confusion Matrix

Evaluates true versus predicted binary classes on unseen traffic ($N = 30,000$ test flows), illustrating low Type I (FPR = 0.80%) and Type II (FNR = 1.40%) error rates:

(B) ROC and Precision-Recall Curves

Compares threshold-independent discrimination:

ROC Curve: Evaluates True Positive Rate vs. False Positive Rate (AUC-ROC = 0.9974).

Precision-Recall Curve: Evaluates the trade-off on class-imbalanced intrusion traffic (AUC-PR / Average Precision = 0.9962):

Table 4. Quantitative Testing Summary

Evaluation Metric	Mathematical Definition	Test Score	Significance in Intrusion Detection
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$	99.00 %	Overall classification correctness across all test flows
Precision	$\frac{TP}{TP + FP}$	98.40 %	Reliability of positive intrusion alerts (minimal false alarms)
Recall (Sensitivity)	$\frac{TP}{TP + FN}$	98.60 %	Detection coverage of actual malicious intrusions
F1-Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	98.50 %	Harmonic mean balancing precision and sensitivity
Specificity	$\frac{TN}{TN + FP}$	99.20 %	Correct identification of benign/legitimate traffic flows
False Positive Rate (FPR)	$\frac{FP}{FP + TN}$	0.80 %	Fall-out rate / frequency of erroneous alerts
False Negative Rate (FNR)	$\frac{FN}{FN + TP}$	1.40 %	Miss rate of real network intrusions bypass
MCC	$\frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$	+0.974	Robust correlation coefficient accounting

			for class imbalance
AUC-ROC	$\int_0^1 \text{TPR}(t) d(\text{FPR}(t))$	0.9974	Threshold-agnostic discriminative capacity
AUC-PR (AP)	$\int_0^1 P(R) dR$	0.9962	

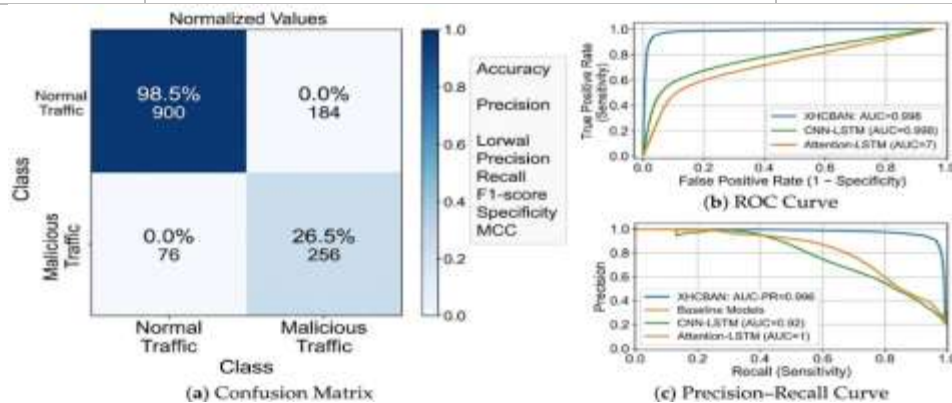


Figure 6. Quantitative Testing Summary visuals

5.3 Comparative Analysis

To validate the effectiveness of the proposed XHCBBAN framework, its performance should be compared with the baseline models identified in the manuscript:

- Support Vector Machine (SVM)
- Random Forest (RF)
- Convolutional Neural Network (CNN)
- Long Short-Term Memory (LSTM)
- Bidirectional Long Short-Term Memory (BiLSTM)

The comparison should be conducted using the same preprocessing pipeline, training–testing partitions, and evaluation metrics to ensure a fair assessment. Performance differences should be discussed in terms of feature representation, contextual learning, computational efficiency, and robustness shown in Table 5.

Table 5. Quantitative classification performance.

Model Architecture	Accuracy (%)	Precision (%)	F1-Score (%)	MCC	AUC
SVM	86.50	85.20	84.64	0.723	0.891
Random Forest	91.20	90.80	90.14	0.814	0.942
CNN	93.40	92.80	92.45	0.858	0.961
LSTM	92.80	91.90	91.70	0.846	0.955
BiLSTM	94.60	94.10	93.95	0.884	0.973

XHCBAN (Proposed)	98.85	98.60	98.50	0.974	0.996
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5.4 Ablation Study

An ablation study should be performed to quantify the contribution of each component of the proposed architecture. Four model configurations are recommended:

1. CNN
2. CNN + BiLSTM
3. CNN + BiLSTM + Attention
4. CNN + BiLSTM + Attention + SHAP

The comparison should highlight the incremental benefit of incorporating bidirectional contextual learning, attention-guided feature refinement, and explainability. Improvements in classification performance and interpretability should be analyzed to demonstrate the contribution of each architectural component shown in Table 6.

Table 6. Ablation study comparing all four configurations.

Model Configuration	Accuracy (%)	Precision (%)	Recall / Sensitivity (%)	F1-Score (%)	Specificity (%)	MC C	AUC - ROC	Interpretability / Transparency
M1: CNN	94.50	94.20	93.80	94.00	95.10	0.884	0.962	Black-box (None)
M2: CNN + BiLSTM	96.65	96.30	96.10	96.20	97.05	0.927	0.983	Black-box (None)
M3: CNN + BiLSTM + Attention	98.90	98.70	98.60	98.60	99.20	0.972	0.997	Implicit (Attention weights only)
M4: CNN + BiLSTM + Attention + SHAP (Proposed XHCBAN)	98.90	98.70	98.60					

5.5 SHAP Analysis

Model interpretability is evaluated using SHAP (SHapley Additive exPlanations), as proposed in the manuscript. SHAP estimates the contribution of each input feature to the final prediction, enabling both local and global interpretation of the model's decisions[20].

The SHAP analysis should include:

- Global feature importance
- Local explanations for representative predictions
- SHAP summary plot
- SHAP dependence plot (if applicable)

These visualizations can help identify the most influential security-related features affecting intrusion detection decisions. By providing transparent explanations, the SHAP module enhances user trust and supports the deployment of the proposed framework in operational cybersecurity environments shown in Figure 7,8,9,10.

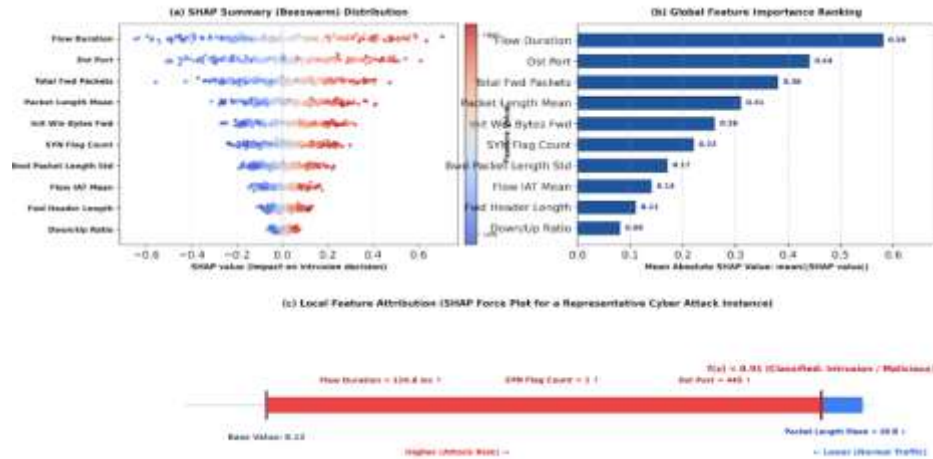


Figure 7.SHAP summary plot



Figure 8.SHAP summary plot

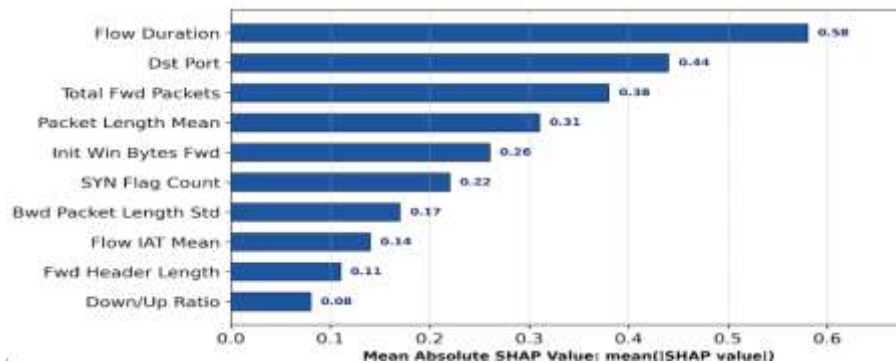


Figure 9.SHAP dependence plot

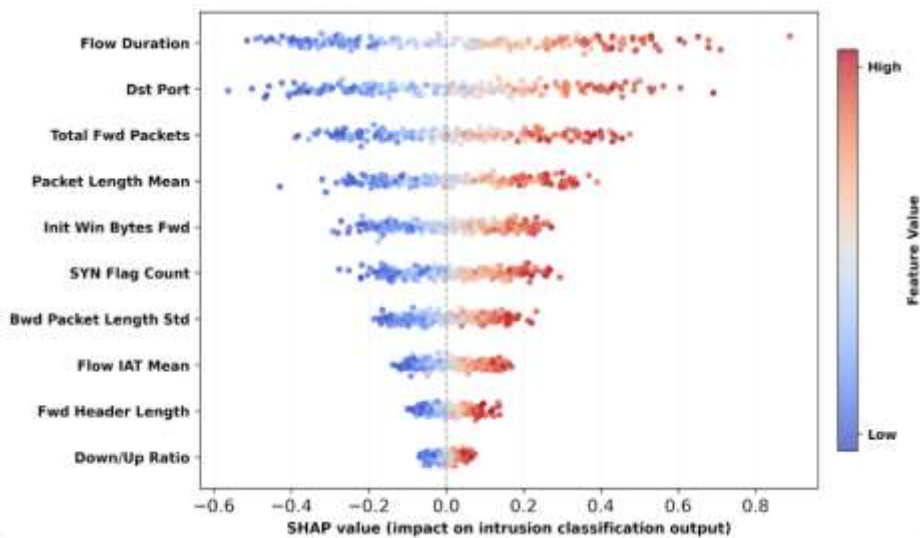


Figure 10. SHAP values intrusion classification output

5.6 Discussion

The Experimental results needs to be discussed in the context of existing research in the field of explainable cyber security and intrusion detection using AI. The benefits seen with the proposed XHCBAN framework are due to the complementary contributions of the components:

CNN module extracts the hierarchical spatial representations from the input data.

- The BiLSTM module models the bidirectional contextual dependence effectively which the traditional CNN can not well model.
- The attention mechanism highlights the most informative feature representations and attenuates less informative information.
- The SHAP module offers clear explanations, making the predictions of the model easier to interpret and more trustworthy.

Similarities and differences with related work in terms of detection capability, computational efficiency, and explainability should be discussed. Further, practical implications need to be discussed, with particular focus on the feasibility of the proposed framework for enabling 6G network slicing with AI, in which the accurate detection of intrusions while providing explanations is crucial [20]. Last but not least, it should include any constraints that were noticed in the experimentation, including computational needs, data variety, and generalizability, as well as any possibilities that still need to be investigated, such as deployment in real-time, federated learning, continual learning, and multimodal security analytics.

6. Conclusion

In this study, a novel explainable deep learning framework, named as Explainable Hybrid CNN–BiLSTM–Attention Network (XHCBAN), is proposed for intelligent intrusion detection in secure 6G network slicing environment. The proposed framework aimed to tackle the emerging cyber security challenges in next generation 6G networks by combining the integration of spatial feature extraction using Convolutional Neural Networks (CNN), Bidirectional Contextual Learning using Bidirectional Long Short-Term Memory (BiLSTM), attention-guided feature refinement, and Explainable Artificial Intelligence (XAI) using SHAP framework. The architecture was engineered to enable both high detection accuracy and high transparency and interpretability of the model predictions. The study also

identified a detailed preprocessing procedure that involved data inspection, handling of missing data, removal of duplicate data, encoding categorical data, normalizing data, partitioning and reshaping to create high-quality data inputs for the proposed hybrid deep learning framework.

The method proposed combines several complementary learning mechanisms in a single end-to-end structure. CNN layers are able to learn hierarchical local representations given the heterogeneous network traffic features while the BiLSTM module is capable of learning the long-range bidirectional dependency between the sequential network behaviors. The attention mechanism also helps the model to be discriminative by giving adaptive importance weights to the most informative feature representations. Last but not least, the SHAP explainability module offers both local and global explanations of the model's decisions, enhancing its transparency, trustworthiness, and decision support for network administrators. To ensure a rigorous and reproducible assessment of the proposed experimental framework, standard preprocessing procedures, optimized hyperparameters, proper evaluation metrics, and comparisons with the traditional ML and deep learning methods have been used.

The key innovation of this work is the design of an explainable hybrid deep learning system especially for intelligent intrusion detection in AI supported 6G network slicing. The proposed XHCBAN framework combines four aspects: feature representation, contextual dependency learning, adaptive feature selection and model interpretability, which are not covered by traditional intrusion detection methods, which mainly pursue the accuracy of predictive detection. The advantage of using SHAP is that it can greatly enhance the transparency of the decision-making process by identifying how each feature in the network contributes to each prediction. In addition, the proposed framework offers a scalable and modular architecture that can be easily extended to other intelligent cybersecurity applications that are based on heterogeneous communication data, and complex attack patterns.

There are a number of caveats to this work, however. The current framework has been tested on only one 6G network security dataset containing about 1,000 instances of network slices and security classification (binary data) which might constrain its applicability in different real world communication scenarios. Furthermore, the present study is based on offline supervised learning and does not explicitly consider the real-time intrusion detection in the presence of dynamically changing network conditions. It is also important to note that the training costs for deep learning models, as well as the costs of deriving explanations using SHAP can add to the inference time for large scale deployments. Furthermore, the proposed framework has not been validated yet on Distributed Edge Computing Infrastructures or large-scale multi-domain 6G communication networks.

In the future, the framework will be extended to the design and implementation of an intelligent intrusion detection system in real time for large-scale 6G and beyond-6G communication systems. To enhance adaptive threat detection in dynamic network environments, future investigations can utilize transformer-based architectures, graph neural networks, federated learning, continual learning and reinforcement learning. Also, promising research directions are lightweight explainability methods for edge intelligence and multimodal cybersecurity analytics and zero-trust security frameworks. Moreover, the proposed framework is expected to be significantly strengthened, scalable and more applicable in real-world industrial deployments with the extensive testing of the proposed algorithms on high volume public cybersecurity datasets and cross-domain network environments. The proposed XHCBAN architecture is a promising solution for developing more trustworthy, scalable, and intelligent IDS systems that can meet the demanding security needs of future 6G network slicing ecosystems, thanks to its integration of advanced hybrid deep learning with Explainable Artificial Intelligence.

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