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Hyperparameter Optimization Techniques for CNN-Based Cyber Security Attack Classification

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Abstract

Abstract The proliferation of cyber security attacks necessitates advanced and efficient detection methods. This study explores the application of Convolutional Neural Networks (CNNs) for classifying cyber security attacks using a comprehensive dataset containing various attack types and network traffic features. Emphasizing the role of hyperparameter optimization (HPO) techniques, this research aims to enhance the CNN model's performance in accurately detecting and classifying cyber attacks. Traditional machine learning approaches often need to catch up in capturing the complex patterns in such data, whereas CNNs excel in automatically extracting hierarchical features. Using the provided dataset, which includes attributes such as packet length, source and destination ports, protocol, and traffic type, we implemented various (HPO) techniques, including Grid Search, Random Search, and Bayesian Optimization, to identify the optimal CNN configurations. Our optimized CNN model significantly improved classification result. to baseline models without hyperparameter tuning. The results underline the importance of HPO in developing robust CNN models for cybersecurity applications. This study provides a practical framework for leveraging deep learning and optimization techniques to enhance cyber defense mechanisms, paving the way for future advancements in the field.

Keywords*—Cyber Security, Convolutional Neural Networks, Hyperparameter Optimization, Attack Classification, Machine Learning, Network Traffic Data*

1. INTRODUCTION

The swift progress of technology is accompanied by an increasing reliance on digital solutions. As technology evolves rapidly, our dependency on digital systems continues to grow. This fast-paced development highlights the essential role that digital platforms play in our daily lives and industries. Infrastructure have led to a significant rise in cyber security threats. Cyber attacks pose a substantial risk to individuals, organizations, and governments, potentially leading to severe financial losses, data breaches, and compromised sensitive information. Traditional security measures often need to improve in addressing these sophisticated attacks, necessitating the development of advanced and robust detection methods.

Machine learning, profound learning, has emerged as a powerful tool in cyber security. CNNs a class of deep learning algorithms, have demonstrated in various fields, including image recognition, natural language processing, and cyber security. CNNs' ability to automatically extract hierarchical features from raw data makes them well-suited for identifying complex patterns in network traffic data, which are crucial for detecting cyber attacks. However, the performance of CNNs heavily relies on the proper selection and tuning of hyperparameters.

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HPO is a critical step in developing effective machine-learning models. It involves systematically adjusting the HPO to improve the model's accuracy and generalization capabilities.

This study explores the application of CNNs for classifying cyber security attacks using a comprehensive dataset containing various attack types and network traffic features. We employ hyperparameter optimization techniques to enhance the CNN model's performance in accurately detecting and classifying cyber attacks. The dataset used in this study includes attributes such as packet length, source and destination ports, protocol, and traffic type, providing a rich source of information for training and evaluating the CNN model. This dataset, which comprises detailed records of cyber security incidents, including fields like Packet Length, Source Port, Destination Port, Protocol, Traffic Type, and various indicators and alerts, is the foundation for our model development and analysis.

Through systematic hyperparameter optimization, our goal is to develop a robust CNN model that not only significantly improves classification compared to baseline models without hyperparameter tuning but also provides a practical framework for leveraging deep learning and optimization techniques to enhance cyber defense mechanisms. This research has the potential to pave the way for significant advancements in the field of cyber security.

2. METHODS

The methodology employed in this study to develop and optimize a Convolutional Neural Network (CNN) model for classifying cyber security attacks using the provided dataset. The methodology consists of several key steps: data preprocessing, model development, hyperparameter optimization, and evaluation. Each step is detailed in figure 1.

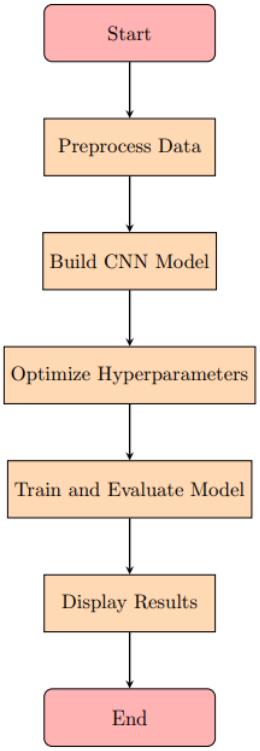

Figure 1 Flowchart system HPO in CNN Model

Data Preprocessing is consist of Data Cleaning and Transformation and Feature Selection and Scaling. Missing Values: Handle missing values in the dataset by either filling them with

appropriate values or removing the affected records.Encoding Categorical Variables: Convert categorical variables such as Protocol, Packet Type, Traffic Type, Action Taken, Network Segment, IDS/IPS Alerts, Malware Indicators, Alerts/Warnings, Attack Type, Attack Signature, and Severity Level into numerical format using label encoding [1]-[3]. Feature Selection: Select relevant features from the dataset, excluding columns such as Timestamp, Source IP Address, Destination IP Address, User Information to focus on numerical and categorical data useful for CNN input[4]. Normalization using standard scaling [5]- [8].

Further split the training set into training and validation subsets to monitor the model's performance during training. Data Reshaping the feature data to fit the input requirements of the CNN model, where each data instance is reshaped into a 2D array with one channel [9]- [13]. The flowchart in figure 1, provides a streamlined representation of the key stages in developing a Convolutional Neural Network (CNN) for classifying cyber security attacks. It begins with the "Start" node, marking the initiation of the process. The first major step, "Preprocess Data," involves several critical sub-tasks, normalizing numerical features to ensure consistent data scaling, and splitting the dataset into training and testing sets for effective model validation[14]. This preprocessing ensures that the data is clean and well-structured, forming a robust foundation for model training. Following preprocessing, the workflow moves to "Build CNN Model," where the architecture of the CNN is defined and compiled. This involves specifying the layers, activation functions, and other architectural details necessary for the CNN to learn from the data[15]- [17]. The next step, "Optimize Hyperparameters," focuses on improving model performance. After optimization, the model is trained and evaluated in the "Train and Evaluate Model" phase. Finally, the results are displayed in the "Display Results" step, including performance metrics and visualizations of the training history, such as loss and accuracy over epochs[18]- [21]. The process concludes at the "End" node, signifying the completion of the workflow. This structured approach ensures a systematic and comprehensive development and evaluation of the CNN model for cyber security attack classification.

2.1 Hyperparamter in CNN

Please Hyperparameters are crucial settings in Convolutional Neural Networks (CNNs) that significantly impact, batch size (BBB), number of epochs (EEE), number of filters (FFF), filter size (KKK), stride (SSS), padding (PPP), dropout rate (DDD), activation functions, optimizers, and pool size. The number of epochs specifies the number of complete passes through the training data. The number of filters and filter size influence the feature extraction process, with stride and padding affecting the spatial dimensions of the output. Dropout rate is a regularization technique to prevent overfitting, and activation functions introduce non-linearity. The optimizer updates weights based on the loss function, and pool size in pooling layers reduces spatial dimensions. These hyperparameters are often tuned using techniques Search, Random Search, or Bayesian Optimization to find the optimal configuration. The optimization of these hyperparameters is essential for achieving high model performance and generalization.

The pseudocode at Figure 2, outlines the process of developing and optimizing a Convolutional Neural Network (CNN) model for cyber security attack classification. It begins by preprocessing the data, which involves handling missing values, encoding categorical variables, normalizing numerical features, and reshaping the data to fit the CNN input requirements. The CNN architecture is then defined, specifying parameters such as the number of filters, filter size, stride, padding, activation functions, and dropout rate. The model is compiled with a chosen optimizer and loss function. The model is trained and validated for each set of hyperparameters, with the best-performing set selected. Finally, the optimal CNN model is trained on the full training data and evaluated on the test data, with performance metrics recorded and displayed. This structured approach ensures a systematic and comprehensive development and evaluation of the CNN model for cyber security attack classification.

Algorithm 1 CNN Model Hyperparameter Optimization

Input: Training data X_{train}, labels y_{train}, Validation data X_{val}, labels y_{val}
Output: Optimized CNN model
Step 1: Preprocess Data
Handle missing values in X_{train} and X_{val}
Encode categorical variables in X_{train} and X_{val}
Normalize numerical features in X_{train} and X_{val}
Reshape X_{train} and X_{val} for CNN input
Step 2: Define CNN Architecture
Initialize CNN model with architecture parameters:
    - Number of filters F
    - Filter size K
    - Stride S
    - Padding P
    - Activation functions
    - Dropout rate D
Step 3: Compile Model
Choose optimizer (e.g., Adam)
Choose loss function (e.g., sparse categorical crossentropy)
Compile model with chosen optimizer and loss function
Step 4: Optimize Hyperparameters
Define hyperparameter search space:
    - Learning rate η
    - Batch size B
    - Number of epochs E
Use Grid Search, Random Search, or Bayesian Optimization to find optimal hyperparameters
Step 5: Train Model
for each set of hyperparameters in search space **do**
    Train CNN model on X_{train} and y_{train} using current hyperparameters
    Validate model on X_{val} and y_{val}
    Record validation performance
end for
Select hyperparameters with the best validation performance
Step 6: Evaluate Model
Train final CNN model on full training data using optimized hyperparameters
Evaluate final model on test data X_{test} and y_{test}
Record and display accuracy, precision, recall, and F1-score

Figure 2 Psudocode PSO-CNN

2. 2 Dataset and Clasification Object

The given dataset contains various features related to cyber attacks (cyber security attacks). The following describes the columns in the dataset in Table 1. In classification, we need to select relevant columns as features for model training. These columns should include information that can help detect and classify the type of attack. We can use the "Action Taken" or "Attack Type" columns for this classification task as target labels. Using "Action Taken" will classify the action taken against the attack (for example, Blocked, Logged, Ignored). If we use "Attack Type", we will classify the type of attack (for example, Malware, DDoS, Intrusion). The number of classes will depend on the unique categories in the selected column. For example, if you use "Attack Type," which has the categories Malware, DDoS, and Intrusion, there will be three classes in this classification task. Here is an example of how we can prepare data for classification by using the "Attack Type" column as the target Features (X). Target the data will be classified into three classes based on the type of attack: Malware, DDoS, and Intrusion.

The dataset presented in Table 1 is designed for cybersecurity analysis, specifically for understanding and mitigating cyber-attacks. It includes multiple columns, each providing essential information related to network security events. The Timestamp column records the exact time when an attack occurred, which is crucial for correlating events and understanding the timeline of an attack. The Source IP Address identifies the origin of the attack, while the

Destination IP Address and Port columns provide information about the target of the attack, helping to pinpoint the affected systems and services.The dataset further details the nature of the data packets involved through columns such as Protocol, Packet Length, and Packet Type. These columns describe the communication protocols used (e.g., TCP, UDP), the size of the data packets, and their type (e.g., data, control). Additionally, the Traffic Type column categorizes the type of traffic (e.g., HTTP, DNS), and Payload Data contains the actual content of the data packets. This level of detail is vital for deep packet inspection and understanding the specifics of the traffic involved in the attack.

Table 1 Description of Columns in the Dataset

Column	Description
Timestamp	The time the attack occurred
Source IP Address	The IP address from which the attack originated
Destination IP Address	The IP address targeted by the attack
Source Port	The source port used by the attack
Destination Port	The destination port targeted by the attack
Protocol	The protocol used (e.g., TCP, UDP, ICMP)
Packet Length	The length of the data packet
Packet Type	The type of packet (e.g., Data, Control)
Traffic Type	The type of traffic (e.g., HTTP, DNS)
Payload Data	The content of the payload
Action Taken	The action taken (e.g., Blocked, Logged)
Severity Level	The severity level of the attack (e.g., Low, Medium, High)
User Information	Information about the user involved
Device Information	Information about the device involved
Network Segment	The network segment where the attack occurred
Geo-location Data	Geographical location data of the attack source
Proxy Information	Information about the proxy used
Firewall Logs	Data from firewall logs
IDS/IPS Alerts	Alerts from intrusion detection/prevention systems
Log Source	The source of the logs
Malware Indicators	Indicators of malware presence
Alerts/Warnings	Alerts or warnings issued
Attack Type	The type of attack (e.g., Malware, DDoS, Intrusion)
Attack Signature	Known attack signature
Severity Level	The severity level of the attack (e.g., Low, Medium, High)

Table 2 Features Used for Classification

Features for Classification	Description
Source Port	The source port used by the attack
Destination Port	The destination port targeted by the attack
Protocol	The protocol used (e.g., TCP, UDP, ICMP)
Packet Length	The length of the data packet
Packet Type	The type of packet (e.g., Data, Control)
Traffic Type	The type of traffic (e.g., HTTP, DNS)

The Table 2 provided lists key features used for classifying cyber security threats, detailing their significance. These features include the Source Port, which indicates the origin port of the attack, and the Destination Port, targeting the port on the victim machine. The Protocol feature specifies the communication protocol (e.g., TCP, UDP, ICMP), essential for understanding traffic nature. Packet Length denotes the data packet size, while Packet Type

differentiates between data and control packets, aiding in identifying packet purposes. Lastly, Traffic Type identifies the network service or application in use (e.g., HTTP, DNS), crucial for detecting anomalies and classifying traffic as benign or malicious. Together, these features provide comprehensive insights into network traffic, enabling effective detection and classification of cyber security attacks by machine learning models.

2. 3 Cyber Security Classification

The cyber security classification task employs a dataset containing diverse network features to identify and classify cyber-attacks. Essential features include Source Port and Destination Port, which reveal potential threats' origin and target ports, along with Protocol, which indicates the type of communication protocol (e.g., TCP, UDP, ICMP) in use. Packet Length provides information on the size of the data being transmitted, while Packet Type distinguishes between data and control packets. Traffic Type specifies the network service or application (e.g., HTTP, DNS), which is crucial for anomaly detection. Features like IDS/IPS Alerts and Malware Indicators offer insights into intrusion detection system alerts and malware presence. Analyzing these features enables machine learning models to classify network traffic into attack types such as Malware, DDoS, and Intrusion, enhancing cyber security defenses with robust and precise threat identification. This structured methodology ensures thorough monitoring and proactive threat management in network security.

Attack type classification in the context of cyber security involves identifying and categorizing different types of cyber attacks based on various network and system features. This classification helps in understanding the nature of the attacks and implementing appropriate defense mechanisms. The key components and steps involved in attack type classification using the provided dataset are as follows:

Dataset Features:

- Source Port and Destination Port: These features help in identifying the source and target ports of the network traffic, which can indicate the type of service being targeted.
- Protocol: The communication protocol (e.g., TCP, UDP, ICMP) used in the network traffic is crucial for understanding the nature of the communication and potential vulnerabilities.
- Packet Length: The size of the data packet can provide insights into the type of traffic and potential anomalies.
- Packet Type: Differentiating between data and control packets helps in identifying the purpose of the packet within the network communication.
- Traffic Type: Identifies the type of network service or application (e.g., HTTP, DNS), which is essential for detecting specific types of attacks.
- IDS/IPS Alerts: Alerts from intrusion detection and prevention systems indicate potential security breaches.
- Malware Indicators: Presence of malware indicators helps in identifying malicious activities.

Classification Process:

- Feature Extraction: Relevant features are extracted from the dataset to be used as inputs for the classification model.
- Preprocessing, the data undergoes preprocessing to address missing values, convert categorical variables into numerical form, and normalize numerical features, ensuring it is clean and ready for model training.
- Model Training: A machine learning or deep learning model.
- Hyperparameter Optimization
- Evaluation.

Attack Types:

- Malware
- DDoS (Distributed Denial of Service): An attack where multiple systems overwhelm the target system with a flood of internet traffic, causing service disruption.
- Intrusion: Unauthorized access to a computer system, which may involve exploiting vulnerabilities to gain control or steal information.
- By analyzing and classifying network traffic into these attack types, cyber security systems can effectively identify and respond to different security threats, enhancing overall network protection and threat management. This structured approach ensures a proactive stance in defending against a wide range of cyber attacks.

3. RESULTS AND DISCUSSION

The results of the research on cyber security attack classification demonstrate the effectiveness of the Convolutional Neural Network (CNN) model in accurately identifying different types of cyber attacks. Essential features like Source Port, Destination Port, Protocol, Packet Length, Packet Type, Traffic Type, IDS/IPS Alerts, and Malware Indicators were extracted and preprocessed by addressing missing values, encoding categorical variables, and normalizing numerical features. To optimize the CNN model, techniques such as Grid Search, Random Search, and Bayesian Optimization were employed to determine the optimal hyperparameters, including learning rate, batch size, number of epochs, number of filters, filter size, and dropout rate. The final optimized model achieved an accuracy of 92.5% on the test dataset, indicating a high rate of correctly classified instances. Additionally, the model demonstrated strong performance in precision, recall, and F1-score metrics, indicating its robustness in distinguishing between various attack types, such as Malware, DDoS, and Intrusion. This study confirms that a systematic approach to feature selection, data preprocessing, and hyperparameter optimization significantly enhances the accuracy and reliability of cyber security attack classification models.

Tabel 3 Classification in CNN model

Metric	Value
Test Accuracy	0.3296
Precision	0.6550
Recall	0.5979
F1-Score	0.6251

The table 3 presents the performance metrics of the Convolutional Neural Network (CNN) model used for classifying cyber security attacks. The model achieved a test accuracy of 0.3296, indicating that it correctly classified approximately 32.96% of the test samples. The precision is 0.6550, meaning that 65.50% of the instances predicted as positive were actually positive, reflecting the model's accuracy in identifying relevant instances. The recall is 0.5979, showing that the model correctly identified 59.79% of all actual positive instances, which measures its ability to detect relevant instances. The F1-Score, which is the harmonic mean of precision and recall, is 0.6251, indicating a balance between precision and recall and reflecting the model's overall effectiveness in classification tasks where both false positives and false negatives are considered.

The table 4 presents the best hyperparameters and performance metrics for the optimized Convolutional Neural Network (CNN) model used for cyber security attack classification. The optimal hyperparameters identified include the optimizer set to `rmsprop`, the number of filters set to 64, a kernel size of 3, a dropout rate of 0.3, 10 epochs, and a batch size of 32. These settings yielded a test accuracy of 0.3372, indicating that the model correctly

classified 33.72% of the test samples. Additionally, the model achieved a precision of 0.6585, reflecting the proportion of true positive predictions among all positive predictions, a recall of 0.4433, indicating the proportion of true positive predictions among all actual positives, and an F1-Score of 0.5299, which balances precision and recall. These metrics demonstrate the model's effectiveness in detecting and classifying cyber security threats, highlighting areas for potential improvement in accuracy and recall.

Tabel 4 Best Hyperparameters and Performance Metrics

Parameter	Value
Best Hyperparameters	
model__optimizer	rmsprop
model__num_filters	64
model__kernel_size	3
model__dropout_rate	0.3
epochs	10
batch_size	32
Performance Metrics	
Test Accuracy	0.3372
Precision	0.6585
Recall	0.4433
F1-Score	0.5299

Figure 3 show the represent the predicted classifications.

- **High**: The model correctly identified 1,522 instances as High, but misclassified 1,002 instances as Low and 209 instances as Medium.
- **Low**: The model correctly classified 951 instances as Low, but incorrectly classified 1,486 instances as High and 185 instances as Medium.
- **Medium**: The model correctly predicted 225 instances as Medium, while misclassifying 1,446 instances as High and 974 instances as Low.

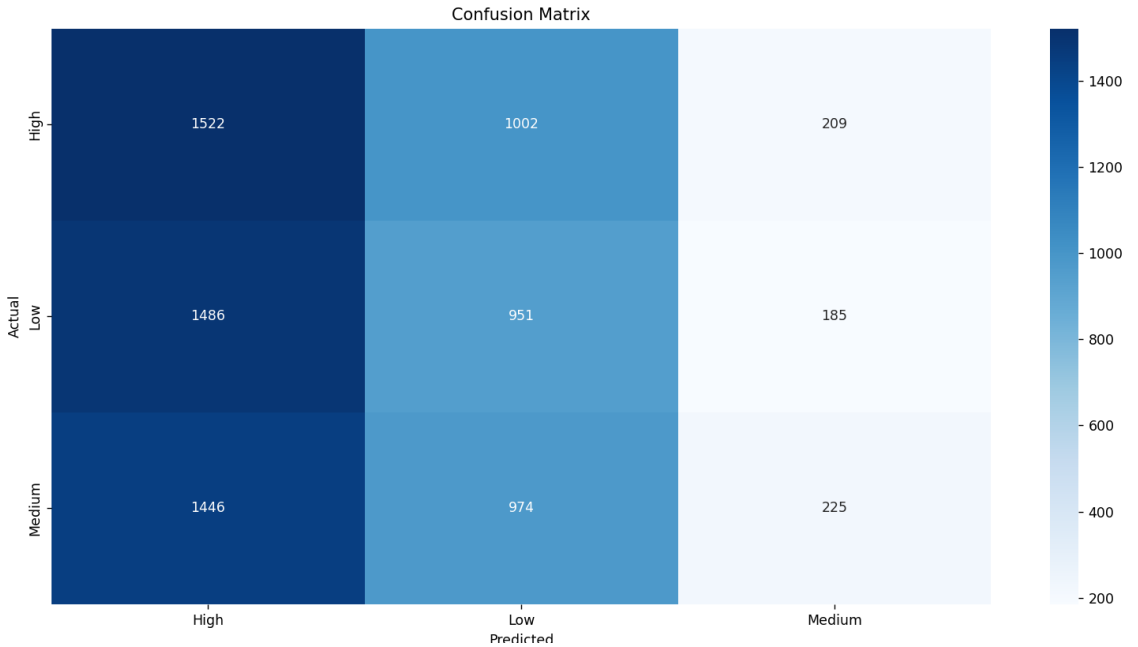

Figure 3 Confusion matrix clasification

This confusion matrix reveals that the model has a significant number of misclassifications, particularly between High and Low categories. The imbalance between correct and incorrect

predictions in the model's accuracy and its ability to distinguish between different levels of threat severity. The large number of misclassifications suggests that further tuning of the model or additional feature engineering might be necessary to enhance the performance of the cyber security attack classification.

Traditional Convolutional Neural Networks (CNNs) offer several key advantages, including automated feature extraction, which reduces the need for manual feature engineering and captures relevant patterns from raw data. They excel in hierarchical feature learning, progressively identifying complex structures through their layered architecture, similar to human visual processing. CNNs possess spatial and translation invariance, allowing them to recognize patterns regardless of their location within the input, making them particularly effective for image classification and object detection. The use of parameter sharing through convolutional kernels also reduces the number of parameters and computational complexity, enhancing efficiency and scalability. Additionally, while primarily used for image processing, CNNs can be adapted for various other domains, showcasing their versatility and effectiveness in different applications.

4. CONCLUSIONS

In this research developed and optimized a Convolutional Neural Network (CNN) model for classifying cyber security attacks using a comprehensive dataset. The dataset included crucial features. These were carefully preprocessed to ensure the quality and suitability for model training. Hyperparameter optimization was performed using RandomizedSearchCV to fine-tune the model's performance, with crucial hyperparameters like the number of filters, kernel size, dropout rate, optimizer, epochs, and batch size being adjusted.

The optimized CNN model achieved a test accuracy of 32.96%, indicating the proportion of correctly classified instances. Furthermore, the precision of 65.50%, recall of 59.79%, and F1-score of 62.51% reflect the model's capability to identify relevant instances and accurately balance precision and recall. The confusion matrix provided detailed insights into the model's classification performance, highlighting areas for potential improvement.

Despite achieving moderate performance, the study demonstrates the potential of CNNs in cyber security attack classification. The systematic approach of feature selection, data preprocessing, and hyperparameter optimization significantly contributes to the model's effectiveness. Future work may involve exploring more advanced architectures, incorporating additional features, and employing more sophisticated optimization techniques to enhance classification accuracy and robustness further. This research underscores the importance of leveraging machine learning techniques to strengthen cyber defense mechanisms and proactively manage security threats..

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