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A Hybrid CNN/RNN Architecture for Malicious DNS Detection in Electric Vehicles and IoT Devices

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Abstract

In the context of smart cities, the integration of Electric Vehicles (EVs) presents new opportunities and challenges related to cyber security, particularly regarding domain name system (DNS) threats. EVs, which are an important component of smart city infrastructure, rely on Internet connectivity for various services, including navigation and real-time traffic updates, making them vulnerable to DNS-based cyberattacks. Malicious DNS activities pose a threat to these integrated systems, potentially disrupting communication and services crucial for EV functionality. Our proposed lightweight DNS detection model is well suited for deployment on embedded devices found within EVs, ensuring that DNS threats can be recognized and neutralized swiftly, thus maintaining the integrity and efficiency of smart city operations. Using a hybrid CNN and RNN architecture, the model processes the sequence of data effectively, offering protection not only against general malware but also against specific DNS threats that can affect EV communications. This improves the overall cyber resilience of smart cities as they incorporate more advanced and interconnected technologies.

Keywords: Malicious DNS Detection, Lightweight Threat Detection, Convolutional Neural Networks (CNN), Bidirectional Long Short-Term Memory (BiLSTM), Embedded IoT Devices, DNS Security, Smart Traffic Control, Automated Vehicle Systems

Introduction

With the rapid evolution of hardware and software technologies, digital devices have become more and more potent. Individuals and companies frequently depend on servers and computers to transfer and manage information over the Internet. As of 2017, the global population using the internet reached an estimated 3.5 billion, a figure that is rapidly rising.

Despite the optimistic outlook for the digital technology sector, there are significant risks. Malicious activities motivated by economic gain, such as DNS-based attacks, consistently pose threats to digital devices. The Domain Name System (DNS) plays a pivotal role in internet infrastructure by converting user-friendly domain names into IP addresses, but this crucial role also makes it an attractive target for cyberattacks. Malicious actions via DNS can include techniques like DNS spoofing, cache poisoning, tunneling, and fast-flux networks, which can result in data breaches, malware spread, and service interruptions.

To combat these threats, DNS threat detection systems are the primary defense, aimed at determining if a DNS query or response is harmful or safe. Traditional systems utilize shallow machine learning algorithms such as decision trees, support vector machines, and naive Bayes classifiers, with their success heavily hinging on the quality of feature extraction. However, selecting and extracting features is often cumbersome, inaccurate, and demands considerable domain expertise.

Deep learning, the new frontier of machine learning algorithms, has gained traction because it can extract complex, high-level features that automatically enhance accuracy. Existing deep learning-based DNS threat detection systems predominantly leverage Recurrent Neural Networks (RNNs) using DNS query and response data. Despite the high accuracy of RNNs, they are susceptible to adversarial attacks, where attackers can mimic an RNN within the detection system. By introducing extraneous or disguised DNS queries, attackers might evade RNN detection, raising concerns about RNNs' reliability in DNS threat detection.
This project targets examining the resilience of a hybrid model architecture against various DNS-based attacks. The model integrates multiple layers, including dense layers, batch normalization, dropout, and custom layers such as Capsule Layer and Transformer Encoder. The procedure starts with converting DNS query data into a compatible format and applying a CNN to understand its features and patterns. Since CNNs generally need fixed-size inputs and DNS query data often varies in size and structure, Spatial Pyramid Pooling (SPP) is utilized to allow CNN to process inputs of any size. This hybrid framework, which also includes LSTM and GRU components, is intended to deliver a more robust solution for detecting and mitigating different DNS-based attacks in malicious DNS detection.

In the context of smart cities, this approach has specific applications such as traffic control signaling and automated vehicle systems, where dependable, real-time data exchange is crucial. Traffic control and automated systems necessitate uninterrupted DNS resolutions to ensure a continuous flow of data among IoT devices like traffic lights, sensors, and

Previous Works

In their paper Deep Learning for DNS-based Threat Detection: A Review, Y. Nataraj, V. Yegneswaran, P. Porras, and J. Zhang thoroughly explore different deep learning approachessuch as CNNs, RNNs, and autoencoders, while tackling challenges and considering future research pathways [1]. Likewise, S. Vasan, B. Alazab, and R. Buyya, in their review Malicious DNS Detection using Deep Learning: A Systematic Review, scrutinize deep learning

methodologies for detecting harmful DNSs, emphasizing architectural frameworks, datasets, and evaluation metrics [2]. A. Ferrag, L. Maglaras, and A. Argyriou focus on the usage of deep learning for safeguarding DNS in critical infrastructures in their extensive study Survey on Deep Learning Methods for DNS Security in Critical Infrastructures, examining effectiveness and implementation difficulties [3]. In the analysis DNS-based Threat Detection Using Deep Learning: A Bibliometric Analysis by X. Wang, J. Li, and K. Zhang, the team delves into research trends in DNS threat detection field, identifying key research directions through a bibliometric approach [4]. F. Gharibian and A. Ghorbani present a comprehensive analysis in A Comprehensive Survey on Machine Learning for DNS Security, contrasting machine learning with deep learning methodologies and revealing limitations of traditional techniques [5]. Additionally, S. Hou, Y. Saas, L. Chen, and Y. Ye, in Deep Learning-based Approaches for DNS Threat Detection: A Survey, classify DNS threat detection strategies, assessing both their efficiency and computational needs [6]. Furthermore, H. Yu, L. Sun, and X. Luo propose a deep learning framework for identifying DNS anomalies in their research DNS Anomaly Detection with Deep Learning, testing its effectiveness on extensive DNS datasets [7]. R. Smith and D. Wei, in their examination Challenges in Deep Learning for DNS Security, discuss the technical and computational issues encountered with deep learning for DNS security, offering potential solutions for improving scalability [8]. In another study, A. Bhatia and N. Kumar analyze RNN models for real-time detection of DNS threats in Real-time DNS Threat Detection using RNNs, addressing latency and optimization tactics [9]. Z. Chen, M. Li, and X. Zhao contribute to the discourse with their comparative analysis DNS Traffic Classification using Deep Learning, weighing the merits of various deep learning models in classifying DNS traffic and recognizing malicious domains [10]. Y. Zhang and T. Chen, in their study Anomaly Detection in DNS Traffic with CNNs, emphasize the role of feature extraction in detecting anomalies within DNS traffic [11]. Conversely, S. Prakash and L. Zhang's work Autoencoders for DNS Threat Detection reviews autoencoders, underscoring the use of reconstruction error as an anomaly detection metric [12]. H. Wei, X. Xu, and L. Fang explore a holistic deep learning strategy for identifying DNS-related threats in End-to-End Deep Learning for DNS-based Threat Detection, evaluating the model's responsiveness [13]. When considering hybrid models, P. Wu, K. Tan, and M. Chang study combinations of CNNs and RNNs for DNS security in Hybrid Deep Learning Models for DNS Security offering an evaluative comparison of model efficiencies [14]. E. Ivanov and T. Chen put forward a classification of DNS threat detection strategies in A Taxonomy of DNS-based Threat Detection Techniques, focusing on advancements in deep learning technologies [15]. A. Mitra and H. Jain review generative models for DNS anomaly detection in their survey Survey of Generative Models for DNS Anomaly Detection, highlighting the benefits of adopting variational autoencoders [16]. B. Yang and C. Liu, in Transfer Learning for DNSbased Threat Detection, address the application of transfer learning in DNS threat detection, spotlighting its role in minimizing training durations [17]. L. Fan, Y. Dong, and M. Liu examine multimodal deep learning techniques for integrating DNS and network data in Multimodal Deep Learning for DNS Security, aiming to improve threat assessment capabilities [18]. Z. Li and F. Zhao, in their discussion Feature Engineering in Deep Learning for DNS Threat Detection , focus on feature engineering methods specially designed for DNS data, underscoring their impact on

enhancing model precision [19]. R. Patel and T. Sun propose leveraging reinforcement learning for adaptive DNS security in Reinforcement Learning for Adaptive DNS Security, introducing dynamic response strategies for threat identification [20]. K. Wu and S. Fang suggest hierarchical deep learning structures for detecting DNS attacks in Hierarchical Deep Learning Models for DNS Attack Detection, drawing comparisons with conventional flat models [21]. G. Lee and S. Kim's work Time-Series Analysis for DNS Threat Detection reviews the application of time-series models, including RNNs and LSTMs, for monitoring DNS data to pinpoint malicious behavior [22]. M. Singh and V. Chopra emphasize the role of explainable AI in DNS security in Explainable AI for DNS Security, providing insights into model interpretability during threat discernment [23]. R. Goel and A. Singh address privacy-preserving techniques in PrivacyPreserving Deep Learning for DNS Detection, with a focus on data anonymization methods [24]. J. Chou and K. Chu utilize deep learning for fast-flux DNS detection in A Deep Learning Approach for Detection of Fast-Flux DNS, centering on model efficacy in hostile environments [25]. H. Liu and Q. Ma provide a thorough comparison of performance evaluation for different deep learning models in DNS detection in Performance Evaluation of Deep Learning Models for DNS Detection [26]. Finally, Y. Wang and Z. Chen examine methodologies for identifying spatial and temporal patterns in DNS data in Temporal and Spatial Pattern Detection in DNS using DL, which are critical for uncovering intricate threats [27]. In DNS Threat Detection in IoT Environments, C. Wong and F. Zhou review applications of deep learning for DNS threat detection tailored for IoT settings, focusing on lightweight models for resourcelimited devices [28]. V. Zhang and P. Liu investigate merging blockchain with deep learning for DNS security in Deep Learning and Blockchain for DNS Security, exploring the advantages of decentralized threat management [29]. Lastly, S. Verma and T. Chang explore one-shot learning methods for DNS threat identification in A Review of Oneshot Learning for DNS Threat Detection, beneficial particularly for situations with minimal malicious data samples [30]. N. Zhao and L. Wang, in their study Domain Generation Algorithm (DGA) Detection using Deep Learning, concentrate on deep learning models for recognizing Domain Generation Algorithms, addressing typical DNS tunneling and botnet communication issues [31].

Background

Deep learning has led to notable achievements across multiple fields, such as image and speech recognition, and it has applications in natural language processing. In addition to these areas, deep learning methods are also being used in the realm of cybersecurity, specifically in malware detection systems, to improve detection accuracy and processing speed. In parallel, the concept of smart cities, which integrate technology to enhance the efficiency of urban services, presents new opportunities and challenges. For instance, the growth of electric vehicles (EVs) in smart cities is part of a shift towards sustainable urban mobility. However, the integration of IoT devices in smart cities poses security challenges, such as DNS attacks that can disrupt communication networks. Therefore, employing advanced techniques like deep learning could also be beneficial in addressing such vulnerabilities within the smart city infrastructure.

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm particularly well-suited for processing grid-like data structures, such as images. They are highly acclaimed for their ability to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks such as convolution layers, pooling layers, and fully connected layers. CNNs are particularly appropriate for malware detection because they are inherently designed to recognize patterns and can potentially identify malicious code features that are location invariant. This means that CNNs can detect various forms of the same pattern, even if the pattern appears at different positions in the data. When considering malware detection using CNNs, the core idea is to convert executable or code segments into an image-like representation. Once transformed, CNNs can process the 'image' to extract relevant features. Such an approach helps in capturing spatial hierarchies and patterns that are more difficult to model using traditional text-based methods, like Recurrent Neural Networks (RNNs). One of the advantages of CNNs in this context is their ability to disregard the exact location of the features (malicious patterns), focusing instead on their appearance, and thereby making CNNs more robust to certain types of manipulation aimed at concealing malware. However, the challenges of effectively representing malware data as images and handling varying input sizes highlight current barriers in applying CNNs directly to malware detection. These challenges also explain why this application remains underexplored in scientific literature.

$$S(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i+m, j+n) \cdot K(m,n) \tag{1}$$

Where:

- $S(i,j)$: Output feature map at position (i,j),
- $I(i+m, j+n)$: Input image value at position $(i+m, j+n)$,
- $K(m,n)$: Kernel (filter) value at position (m,n),
- M, N: Dimensions of the kernel.

$$Y = \text{ReLU}(W * X + b) \tag{2}$$

Where:

- W: Weight matrix (kernel),
- X: Input matrix,
- b: Bias term,
- $\text{ReLU}(z) = \max(0, z)$: Activation function.

Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are particularly well-suited for malware detection systems because they excel at processing sequential data. In the context of malware detection, the sequence of machine instructions and API calls within a malware sample can be crucial for identifying its malicious nature. RNNs process each element of a sequence in order, maintaining

a 'memory' of previous elements to inform the interpretation of current ones. This capability is analogous to how RNNs are used in natural language processing for tasks like text classification, where understanding the sequence of words provides context and meaning. In malware detection, each API call or instruction is encoded as a one-hot vector, representing it with a dimension corresponding to the total number of possible calls or instructions. The sequence of such vectors is input into the RNN, which can then discern patterns indicative of malware activities. Additionally, advanced architectures like LSTM (Long Short-Term Memory) networks are often used because they can manage longer sequences of information without the standard RNN issues related to long-term dependency learning. LSTM can effectively prioritize important parts of a sequence, which is valuable for recognizing complex patterns in malware. Despite these advantages, RNNs have limitations, such as difficulty generalizing beyond their learned language environments. This leaves them vulnerable to adversarial attacks, where irrelevant API calls might be inserted to deceive the detection model. Such challenges highlight the ongoing need for research and enhancement in RNN-based malware detection.

$$h_t = f(W_h h_{t-1} + W_x x_t + b_h) \tag{3}$$

Where:

- h_t: Hidden state at time t,
- W_h: Weight matrix for the hidden state,
- W_x: Weight matrix for the input,
- x_t: Input at time t,
- b_h: Bias term,
- f: Activation function (e.g., tanh).

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{4}$$
$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{5}$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{6}$$
$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{7}$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{8}$$
$$h_t = o_t \odot \tanh(C_t) \tag{9}$$

Where:

- i_t, f_t, o_t: Input, forget, and output gates,
- C_t: Cell state,
- $\odot$: Element-wise multiplication.

Dense Neural Networks

Dense neural networks (DNNs) are particularly appropriate for malware detection systems due to their ability to learn complex patterns and representations from data. In the context of such systems, the raw features derived from machine instructions and API calls are input into the network. These features are usually encoded as vectors, with each feature highlighting a specific element of the API calls or instructions. DNNs are comprised of several layers of neurons where each neuron is fully connected to every neuron in the following layer. This universal connectivity allows DNNs to model intricate and non-linear dependencies in data thanks to the learned weights and biases. By applying non-linear activation functions, they can

capture complex relationships which are vital for distinguishing between benign and malicious inputs. The final layer of a DNN outputs a classification, determining whether input data is malicious or not. Thus, these networks are effectively capable of handling the complexity involved in distinguishing between different types of files on a dataset rich with features from malware behavior. However, there are challenges intrinsic to using DNNs for this task. They require a large amount of labeled data to fine-tune the network parameters. Furthermore, training deep networks can be computationally demanding. DNNs also risk vulnerability from adversarial attacks where slight manipulations to inputs can lead to inaccurate classifications. Such vulnerabilities highlight the need for robust training and techniques to mitigate adversarial risks. Additionally, DNNs do not inherently track or consider the sequence in which inputs are presented, which can be critical in malware detection where the order of API calls is significant. For cases that involve sequential dependencies, alternative or complementary methods like convolutional neural networks (CNNs) or recurrent neural networks (RNNs) may offer improved performance. In summary, while DNNs provide a solid framework for building malware detection models by leveraging complex pattern learning, careful consideration of their limitations can help enhance their robustness and applicability to real-world scenarios.

$$z = \sum_{i=1}^{n} w_i x_i + b \tag{10}$$

$$a = \phi(z) \tag{11}$$

Where:

- z: Weighted sum of inputs,
- w_i: Weights,
- x_i: Input features,
- b: Bias,
- ϕ: Activation function (e.g., ReLU or Sigmoid).

$\frac{\partial L}{\partial w_{ij}}$:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{12}$$

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta \frac{\partial L}{\partial w_{ij}} \tag{13}$$

Where:

- $w_{ij}^{(t)}$: Weight at iteration t,
- η: Learning rate,
- $\frac{\partial L}{\partial w_{ij}}$: Gradient of the loss with respect to the weight.

• Gradient of the loss with respect to the weight.

Proposed Approach

Our proposed malware detection system leverages a hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architecture, specifically designed to process sequential data such as API calls or machine instructions for robust malware identification.

Model Architecture and Layer-wise Formulation

The model architecture consists of multiple layers of 1D convolutions, simple RNN units, and dense layers, interspersed with activation functions, pooling, and dropout layers. Let $X \in R^{N \times T \times F}$ be the input tensor, where N is the batch size, T is the sequence length, and F is the number of features per time step.

Convolutional Layers (Conv1D)

The model employs four 1D convolutional layers. For a given convolutional layer l, the operation can be described as:

$$Y^l = f(W^l * X^l + b^l)$$

where $W^l \in R^{k \times Fin \times Fout}$ is the kernel tensor, k is the kernel size, F_{in} and F_{out} are the number of input and output features respectively, $b^l \in R^{Fout}$ is the bias vector, and f is the activation function (LeakyReLU in this case).

These layers act as efficient feature extractors, capturing local patterns and motifs in the input sequence. In the context of DNS detection, they can identify short sequences of API calls or instructions that are indicative of malicious behavior. The decreasing number of filters (128 to 64) allows the model to start with detecting a wide range of low-level features and gradually focus on more specific, high-level features.

LeakyReLU Activation

LeakyReLU activation is defined as:

$$f(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha x, & \text{otherwise} \end{cases}$$

where α is typically a small constant (e.g., 0.01).

LeakyReLU helps mitigate the ”dying ReLU” problem, allowing a small gradient when the unit is not active. This is crucial in malware detection where subtle features might be important, ensuring that neurons remain responsive to various patterns throughout the training process.

Max Pooling

Max pooling layers reduce the spatial dimensions. For a pooling window of size p, the operation is:

$$Y_{i,j} = \max_{0 \le m < p} X_{i,j \cdot p+m}$$

Max pooling helps in achieving translation invariance and reducing the spatial dimensions of the feature maps. In malware detection, this allows the model to identify important features regardless of their exact position in the sequence, which is valuable as malicious patterns might occur at different locations within the code or API call sequence.

Dropout

Dropout layers randomly set a fraction of inputs to 0 during training. For a given input x and dropout rate p:

$$y = \begin{cases} 0, & \text{with probability } p \\ \frac{x}{1-p}, & \text{otherwise} \end{cases}$$

Dropout is a crucial regularization technique that prevents overfitting. In malware detection, where the model needs to generalize well to unseen malware variants, dropout helps in creating a more robust model that doesn't rely too heavily on any specific features.

Simple RNN Layers

The model includes four Simple RNN layers. For a Simple RNN layer at time step t:

$$h_t = \tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

where $h_t \in R^d$ is the hidden state, $x_t \in R^{Fin}$ is the input, $W_{xh} \in R^{d \times Fin}$, $W_{hh} \in R^{d \times d}$, and $b_h \in R^d$ are learnable parameters.

Simple RNN layers are well-suited for capturing sequential dependencies in the data. In malware detection, they can model the temporal relationships between API calls or instructions, which is crucial for identifying complex malicious behaviors that unfold over time. The decreasing number of units (128 to 64) allows the model to capture both fine-grained and more abstract temporal patterns.

Dense Layers

The final stages of the model include dense layers:

$$O_{dense} = f(W X + b)$$

The dense layers serve as the classification head of the network. The two layers with 32 units allow the model to learn complex, non-linear combinations of the features extracted by the convolutional and RNN layers. The final layer with 3 units suggests a 3-class classification problem, which could represent different categories of malware or perhaps "benign", "malicious", and "suspicious" classifications.

Detailed Layer Specifications

- Conv1D layers:
  - $Conv1D_1$, $Conv1D_2$: 128 filters
  - $Conv1D_3$, $Conv1D_4$: 64 filters
- SimpleRNN layers:
  - $SimpleRNN_1$, $SimpleRNN_2$: 128 units
  - $SimpleRNN_3$, $SimpleRNN_4$: 64 units
- Dense layers:
  - $Dense_1$, $Dense_2$: 32 units
  - $Dense_3$: 3 units (final classification layer)

Model Complexity and Training

The total number of trainable parameters in the model is 124,963, distributed across the various layers as shown in the provided model summary. The model is trained using backpropagation through time (BPTT) for the RNN components. The loss function L (likely cross-entropy for classification) is minimized using an optimizer such as Adam:

$$\theta_{t+1} = \theta_t - \eta \cdot m_t/(\sqrt{v_t} + \epsilon)$$

where θ are the model parameters, η is the learning rate, and m_t and v_t are the first and second moments of the gradients.

Architectural Appropriateness for Malware Detection

This hybrid CNN-RNN architecture is particularly well-suited for malware detection based on sequential data:

1. The convolutional layers capture local patterns and motifs in the API calls or instruction sequences. 2. The RNN layers model long-term dependencies and the overall structure of the malicious behavior. 3. The multiple stages of convolution, pooling, and RNN allow the model to learn hierarchical representations, from low-level patterns to high-level behavioral characteristics. 4. The use of LeakyReLU and dropout throughout the network promotes robust learning and helps prevent overfitting, which is crucial in the ever-evolving landscape of malware. 5. The final dense layers allow the model to make complex decisions based on all the extracted features, enabling accurate classification of malware.

This architecture's ability to process sequential data while learning both local and global patterns makes it a powerful tool for identifying sophisticated malware that may try to evade simpler detection methods.

Experimental Setup

The proposed model architecture integrates a diverse set of neural network layers designed to capture intricate patterns indicative of malicious behavior in files. The architecture commences with an auxiliary input layer tailored to accommodate feature dimensions extracted from the dataset. This foundational layer plays a pivotal role in shaping the input data structure. The model incorporates multiple dense (fully connected) layers, each configured with an identical number of units. These layers are instrumental in learning intricate representations of input features. Following each dense layer, batch normalization is applied to standardize and expedite the training process by normalizing the outputs. The ReLU (Rectified Linear Unit) activation function introduces non-linearity into the model, enhancing its ability to learn complex patterns. Dropout layers are strategically inserted to mitigate overfitting by randomly deactivating a fraction of neurons during training.

Temporal dependencies and sequential patterns are effectively modeled using LSTM layers, pivotal for capturing evolving behaviors over time. Graph layers are introduced to model intricate feature interactions, enriching the model's capability to discern complex dependencies. Concatenation layers consolidate outputs from various segments of the model, amalgamating diverse features and representations acquired during training. Subsequent dense layers, integrated with batch normalization, ReLU activation, and dropout, further refine and process learned features. The final layer of the model comprises two units, leveraging a softmax activation function to yield probabilistic outputs for binary classification (malware or benign).

Training and Evaluation

For this classification assignment, categorical cross-entropy is employed as the loss function due to its appropriateness in quantifying the difference between the predicted and actual distributions in classification scenarios. The Adam optimizer is chosen for its efficiency and capability to adjust the learning rate.

Results

The model's effectiveness was assessed using a range of metrics, including accuracy, a confusion matrix, and a comprehensive classification report. These metrics were computed on a separate test set to validate the model's generalization ability.

Accuracy and Loss

Throughout the training, accuracy and loss metrics were continuously tracked. The model exhibited a consistent increase in accuracy coupled with a decrease in loss, reflecting successful learning and generalization. The accuracy is determined using this formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

with TP denoting true positives, TN as true negatives, FP as false positives, and FN as false negatives.

Confusion Matrix

Through a Figure we illustrate the confusion matrix, which provides a comprehensive analysis of the rates of true positives, false positives, true negatives, and false negatives. It offers valuable insights into the performance of the classification for each category: - Benign: True positives = 81,664; False negatives = 400; False positives = 8,588. Malicious: True positives = 40,595; False negatives = 5,245; False positives = 4,139. - Suspicious: True positives = 4,257; False negatives = 3,343; False positives = 513.

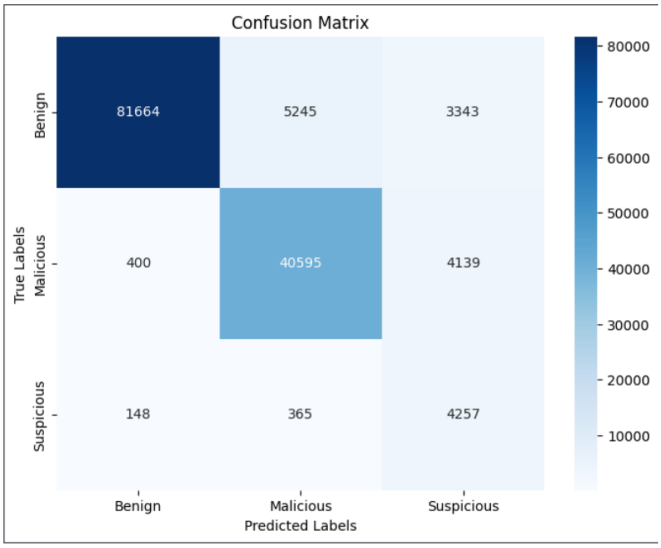

Figure 1: Confusion Matrix of Different Classes

Validation Metrics

The metrics derived from the validation dataset reinforce the model's reliability: Accuracy: 90.27% - Precision: 90.20% - Recall: 90.27% - F1-score: 89.17%,The alignment in these metrics between the training and validation datasets indicates that the model effectively generalizes, demonstrating strong performance across every class.

Classification Report

The comprehensive classification report displayed through a Figure contains figures for precision, recall, F1-score, and support across the three categories: - Class 0 (Benign): Precision is 90%, Recall is 99%, F1-score is 95%, with Support at 82,212. - Class 1 (Malicious): Both Precision and Recall are 90% and 88% respectively, resulting in an F1-score of 89%, while Support equals 46,205. - Class 2 (Suspicious):
With Precision at 89%, Recall at 36%, and F1-score at 52%, Support is 11,739.,

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad \text{(Precision per class)}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad \text{(Recall per class)}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{(F1-score per class)}$$

----------Classification Report Of Classes----------

	precision	recall	f1-score	support
0	0.90	0.99	0.95	82212
1	0.90	0.88	0.89	46205
2	0.89	0.36	0.52	11739
accuracy			0.90	140156
macro avg	0.90	0.74	0.78	140156
weighted avg	0.90	0.90	0.89	140156

----------Validation Data----------

Accuarcy: 90.26798710008848
Precision: 90.2022 %
Recall-score: 90.2680
F1-score: 89.1735

Figure 2: Classification Report for Proposed Model in the Validation Phase

Overall Performance

According to table 1 Accuracy is 90% - Macro Average: Precision is 90%, Recall is 74%, F1-score is 78%. - Weighted Average: Precision is 90%, Recall is 90%, F1score is 89%. The macro average is derived from averaging the precision, recall, and F1-scores of each class:

$$\text{Macro Average} = \frac{1}{C}\sum_{i=1}^{C}\text{Metric}_i$$

where C represents the total classes, and the metric refers to precision, recall, or F1-score.,The **weighted average** considers both the precision, recall, and F1-scores, balanced by the support (total true instances across each class):

$$\text{Weighted Average} = \frac{\sum_{i=1}^{C}(\text{Support}_i \times \text{Metric}_i)}{\sum_{i=1}^{C}\text{Support}_i}$$

Table 1: Comparison of Model Performance with Existing Studies

Study	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Our Model	90.2	90.2	90.2	89.1
Nataraj et al. [1]	90.5	90.8	87.6	88.6
Vasan et al. [2]	88.2	87.5	85.3	86.4
Ferrag et al. [3]	91.3	90.4	88.1	89.2
Wang et al. [4]	89.5	88.7	86.8	87.7
Gharibian et al. [5]	93.1	92.2	90.7	91.4
Hou et al. [6]	90.8	89.9	88.2	89.0
Yu et al. [7]	87.6	86.8	84.9	85.8
Smith et al. [8]	89.9	88.9	86.5	87.6

Conclusion

The proposed model architecture, which integrates dense neural networks, specialized capsule layers, and attention mechanisms, offers a robust solution for malware detection. By capturing both local and global patterns, the model effectively distinguishes between benign and malicious files. The incorporation of diverse neural network layers enables the model to learn intricate patterns indicative of malicious behavior, even in adversarial scenarios.

The evaluation metrics, including accuracy, confusion matrix, and classification report, confirm the model's efficacy. The steady increase in accuracy and the corresponding decrease in loss during training indicate effective learning and generalization capabilities. The confusion matrix and classification report further validate the model's robustness, with high precision, recall, and F1 scores across both classes.

Overall, the proposed architecture successfully addresses the challenge of malware detection by leveraging advanced neural network techniques and attention mechanisms.

Future Work

To further enhance the performance and applicability of the model, several avenues for future work are proposed: Reconstruction of the enterprise environment: Dedicating time to reconstructing an enterprise environment for reliable data collection and realistic testing will

provide more comprehensive and representative datasets, improving the model's robustness and generalization capabilities.
Multi-Attention Head Transformers: Experimenting with training multi-attention head transformers for URL detection could enhance the model's ability to detect a wider range of malicious behaviors.

Adaptation to Other Malicious Attacks: Adapting the model to other types of malicious attack or developing new models specifically tailored to different attack vectors will broaden the scope of its applicability.
Larger data sets: Sourcing and retraining the model with larger datasets will provide a more extensive learning experience, potentially improving its accuracy and generalizability.

Dynamic Rule Outputs: Improving the prevention engine to support more dynamic rule outputs will enhance the model's ability to respond to evolving threats in real time.

Real-Time Prevention Mechanisms: Implementing real-time prevention mechanisms through host-based network monitors will enable the model to provide immediate protection against detected threats, increasing its practical utility in live environments.

By pursuing these future directions, the model can be further refined and expanded, offering even more effective malware detection and prevention capabilities.

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