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Effective Ransomware Attacks Detection Using CNN Algorithm

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Abstract
This study identified ransomware threats in social media platforms by evaluating the performance of Assessing different machine-learning algorithms in various aspects of detecting and classifying ransomware content. The primary problem revolves around the need to enhance cybersecurity within the dynamic landscape of social media, where users are increasingly susceptible to malicious attacks. The research objectives involve assessing the effectiveness of different algorithms, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Decision Trees, K-Nearest Neighbors (KNN), Gaussian Naive Bayes (GNB), and Gradient Boosting (GBoost), in distinguishing between ransomware and benign content. A dataset consisting of 6,245 records with 15 features is employed to achieve this. The methods encompass data preprocessing, algorithm implementation, and performance evaluation using accuracy, precision, recall, and F1-score metrics. The research results revealed significant variations in algorithm performance, with Decision Tree and GBoost exhibiting exceptional accuracy while class imbalance challenges and model optimization issues were identified. These findings provide valuable insights into the complex realm of ransomware detection in social media, offering a foundation for future research and cybersecurity improvements in the digital space.

Keywords:
Class Imbalance; Cybersecurity; Machine Learning Algorithms; Ransomware Detection; Social Media

1. Introduction

Ransomware is malware that encrypts or locks the users' files or devices and demands a ransom payment in exchange for restoring access [1]. It is considered the most dangerous cyber threat due to its ability to impose a high financial burden on individuals and organizations. Ransomware attacks are challenging to alleviate even after removal, as the effects can be permanent without the aid of the attacker. Crypto-currencies make it challenging to trace the attackers, allowing them to receive ransom payments anonymously. Ransomware has evolved over the years and has caused significant financial losses globally [2]. It is a widespread malware that can be operated by both professional cyber-criminals and novice attackers [3].

Ransomware refers to malicious software that encrypts files belonging to a user and requires a ransom to provide the decryption key [4]. Both professional cyber-criminals and novice attackers can operate it, and using crypto-currencies makes the interactions untraceable. Ransomware performs rapid sequences of commands, such as read-copy-encrypt-delete, to control access to data files on a computer. Certain ransomware groups encrypt particular file formats and compel individuals to make ransom payments using online payment channels. Cybercriminals use ransomware to lock data through

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encryption mechanisms and demand payment in the form of Bitcoin to retrieve the data [1]. Ransomware has evolved into different types, including those that encrypt files, block access to the operating system, or blackmail users with private data [5].

Ransomware detection is essential in the digital era because it helps minimize the impact of ransomware attacks and enables fast recovery and business continuity [6]. Ransomware is a form of malware that encrypts data and demands a ransom, and its variants are increasing rapidly. Traditional signature-based detection methods are ineffective against zero-day ransomware, highlighting the need for specialized protection mechanisms. Detecting ransomware quickly and flagging the damaged content allows for timely response and mitigation [7]. Various techniques, including machine learning algorithms, are used in ransomware development, making it crucial to understand their attack flow to develop appropriate countermeasures. Static analysis methods can be used for ransomware detection, offering faster detection speeds and high accuracy [8].

Conventional techniques are less effective in ransomware detection due to several reasons. Firstly, ransomware attacks constantly evolve, making it difficult for signature-based detection techniques to keep up [9]. Secondly, ransomware often employs polymorphism, which allows it to change its code and evade detection by traditional methods. Additionally, ransomware can adapt its behavior to mimic benign activities, making it harder to distinguish from legitimate processes [10]. Furthermore, the sheer number of ransomware variants with different signatures makes it challenging for signature-based detection to identify all instances [11]. Lastly, the complexity of ransomware detection requires advanced techniques like behavioral analysis and machine learning, which conventional methods typically do not employ. Overall, the dynamic nature of ransomware and its ability to evade traditional detection techniques contribute to their reduced effectiveness in ransomware detection.

Using image-based malware representations to extract and classify features, CNN can aid ransomware detection. CNN effectively extracts features from images and classifies them, making them suitable for analyzing the PE header of executable files [12]. By constructing an image based on the PE header and using CNN, researchers have achieved high accuracy in detecting ransomware [13]. Additionally, CNN can convert transforming native instructions from Android applications into images, enabling reliable detection of identifying malicious applications with nearly perfect accuracy [14]. Using CNN in ransomware detection allows for early detection without running the program, making it a practical and valuable method.

CNN has several advantages compared to other machine learning methods [15]. Firstly, CNN effectively performs power prediction tasks, such as radio frequency power prediction, and can generalize well to new regions. Secondly, CNN can be directly trained on mobile devices, alleviating security and communication dependency issues associated with cloud training [16]. Additionally, CNNs can effectively forecast volatility in finance by utilizing the common properties of stock price returns and the large amount of available data. Lastly, CNN performs better in semi supervised hyperspectral image classification than traditional methods by extracting spatial information and iteratively correcting label errors [17].

The overall structure of this research will be organized within the journal manuscript, adhering to the standard format [18]. The manuscript will begin with an introduction section that provides the study's background, research problem, objectives, and relevance. The methodology section will then detail the data sources, data preprocessing, and the application of CNN and other machine learning algorithms for ransomware detection. The results section will present the performance metrics for each algorithm tested, F1 score, precision, including accuracy, and recall [19]. Subsequently, the discussion section will delve into the results' analysis, implications, and alignment with existing literature. Finally, the conclusion will summarize the key findings and their

significance and suggest potential avenues for future research in ransomware detection and prevention on social media platforms [20]

2. Related Works

Previous studies have explored various machine learning techniques for ransomware detection. One approach is to use deep learning algorithms, such as Siamese Neural Networks, to detect and classify different ransomware classes [21]. These models utilize entropy features extracted from ransomware binary files and train the model using a pre-trained network in a meta-learning fashion. Another approach is to use machine learning techniques with feature selection methods, such as random forest with information gain-based feature selection. This method achieved a high accuracy of 88.39% in detecting ransomware based on hexacodes extracted from executables [22]. Moreover, researchers have delved into utilizing machine learning and deep learning algorithms for identifying ransomware malware. These algorithms can produce predictive models capable of spotting previously unseen threats and acquiring an understanding of ransomware behavior [23]. These studies highlight the importance of machine learning in detecting and combating ransomware attacks.

Conventional approaches in ransomware detection have several weaknesses [24]. One weakness is the over-dependence on simple statistical tests, which can lead to frequent false positive and false negative classifications. Another weakness is the reliance on signature-based malware detection methods, which struggle to detect zero-day ransomware and are ineffective against unknown ransomware. Additionally, conventional approaches often fail to isolate and analyze samples in time, making them inadequate for timely detection [25]. Furthermore, traditional signature-based detection techniques are powerless against increasing ransomware variants with different signatures. Lastly, the existing solutions offered by anti-malware companies are not successful in eliminating ransomware and recovering compromised devices and data [26].

Machine learning techniques like SVM, KNN, Random Forest, Decision Tree, and XGBoost have been applied in ransomware detection [27]. One study proposed a system to protect smartphones from malicious applications using these methods and achieved high detection accuracy with Decision Tree (99.30%) and XGBoost (99.20%) [28]. Another study utilized deep learning techniques and a Siamese Neural Network to detect and classify different ransomware classes, achieving a weighted F1-score exceeding 86%. A novel method based on static analysis and feature extraction from raw byte data was also proposed, reaching a high accuracy of 97.74% using a random forest classifier. Additionally, a ransomware detection method based on hexacodes and without opcodes was developed, achieving an accuracy of 88.39% using random forest and information gain-based feature selection [29]. Finally, a ransomware detection method focusing on ransomware-specific operations was proposed, successfully distinguishing ransomware from other types of malware and benign files.

Machine learning methods face several challenges in ransomware detection. One challenge is the increasing number and complexity of ransomware attacks, which makes it difficult to develop accurate detection models [30]. Another challenge is distinguishing ransomware from other malware and benign files, as ransomware exhibits unique characteristics and behaviors. Additionally, the rapid evolution of ransomware variants requires machine learning models to adapt and stay up-to-date with new attack techniques [31]. Furthermore, the detection of ransomware on IoT devices poses a unique challenge due to IoT networks' extensive and diverse nature. Finally, the effectiveness of machine learning algorithms in ransomware detection depends on selecting appropriate features and classifiers, as different algorithms may yield varying levels of accuracy [32].

Heuristic analysis or signature-based detection may be ineffective against increasingly complex ransomware variations for several reasons. First, ransomware attacks are evolving rapidly, with new variants frequently created [33]. Signature-based detection relies on known signatures or patterns to identify malware, but it struggles to detect unknown or zero-day ransomware that does not have a known signature. Second, ransomware often employs techniques like code obfuscation and polymorphism to evade detection [34]. These techniques modify the characteristics of the malware, making it difficult for heuristic analysis to identify the malicious behavior. Lastly, ransomware can adapt its behavior to mimic benign actions, making it harder for behavior-based detection methods to distinguish between ransomware and legitimate applications [35]. Ransomware's increasing complexity and adaptability pose challenges for traditional detection methods, highlighting the need for more advanced and dynamic approaches to combat this threat.

CNNs differentiate themselves from conventional machine learning methods in ransomware detection by their ability to automatically learn and derive characteristics from unprocessed data, like network traffic or executable files, without manual feature engineering [36]. CNNs employ convolutional layers to identify localized patterns and hierarchical structures within the data, allowing them to capture complex relationships and identify subtle patterns indicative of ransomware [37]. This makes CNNs particularly effective in detecting ransomware, which often exhibits unique characteristics and behaviors compared to other types of malwares. Additionally, CNNs can handle large amounts of data and are robust to variations in input size, making them suitable for analyzing diverse and dynamic ransomware samples. Overall, CNNs offer a powerful and automated approach to ransomware detection, improving accuracy and efficiency in comparison to traditional machine learning methods [38].

CNNs are suitable for handling the data complexity involved in ransomware detection due to their ability to extract useful features for accurate classification [39]. CNNs can effectively deal with high-dimensional data and handle trace misalignment, making them well-suited for analyzing complex patterns in ransomware data. Additionally, CNNs are efficient in attack efficiency and network complexity, even in desynchronization [40]. Visualization techniques such as Weight Visualization, Gradient Visualization, and Heatmaps can help security evaluators interpret and understand the efficiency of CNNs in handling complex data [41]. Furthermore, CNNs can be optimized for performance using hardware accelerators, which enhance the throughput of CNN models and enable them to meet time-critical requirements. Overall, the combination of CNNs' ability to handle high-dimensional data, their efficiency in complex scenarios, and the availability of hardware accelerators make them suitable for handling the data complexity involved in ransomware detection [42].

CNNs address the issue of feature extraction from visual or structured data by utilizing their specialized capabilities in extracting features from input data [43]. These networks create intricate internal hierarchical feature representations, gradually increasing with network depth [44]. CNNs can accurately determine the proportion of meaningful signal data to random noise and the highest level of information in the input dataset using measures such as Signal-to-Noise Ratio (SNR) and Maximum Entropy (ME). The accuracy of classification and the effectiveness of CNNs are significantly influenced by the volume, intricacy, and excellence of the signal data within the input [45]. Additionally, CNNs can extract feature-level information and accurately estimate target properties, even with limited-measured data. CNNs can also be designed to extract low and high-frequency information simultaneously from images, improving feature extraction in tasks such as single image super-resolution [46]. The features extracted from CNNs can be used for image retrieval, achieving state-of-the-art performances.

Recent research findings demonstrate the success of CNNs in detecting various types of cyberattacks beyond ransomware [47]. Propose a new feature extraction method using

word embedding and CNN to analyze log files and detect malicious programs with an accuracy higher than 98%. Examine the resilience of uncompressed, distilled, pruned, and binarized neural networks when facing both white-box and black-box adversarial attacks in detail, providing insights for defensive training schemes. Shows that CNN-based spoof detection modules can be fooled by adversarial perturbations, allowing to create convincing replay attacks on facial recognition authentication systems [48]. Investigate the transferability of adversarial attacks in image forensics, applications and find that attacks are not easily transferable, aiding in the design of countermeasures. Propose a detection method for adversarial examples in CNNs by tracking adversarial perturbations in feature responses, demonstrating its effectiveness in preventing attacks [49].

The substantial dataset covering ransomware variations contributes to the success of CNN in detection by providing a diverse range of samples for training the model [50]. CNN models rely on large, various datasets to learn and generalize patterns effectively. The dataset contains analyze the file access activities of over 70 ransomware instances while they carry out the encryption process an extensive network shared directory allows for evaluating and comparing different ransomware detection techniques. This dataset has already been used successfully to assess a network-based ransomware detection algorithm [51]. By training the CNN model on this dataset, it can learn the characteristic features and behaviors of different ransomware families, enabling it to detect and classify new variants accurately [48]. The inclusion of samples from a diverse range of subjects is crucial for achieving reasonable accuracy in QRS detection using CNN models.

Comparative research has been carried out using CNNs and conventional machine learning methods in the context of ransomware detection [52]. A study by Fernando et al. surveyed the contributions of research into ransomware detection using machine learning and deep learning algorithms. Another study by Aiswarya et al. proposed a survey on Clop detection using machine learning methods and found that XGBoost outperformed other machine learning algorithms [53]. Additionally, Ahmed et al. developed a system to protect smartphones from ransomware using six machine learning methods, including XGBoost, and found that XGBoost and decision tree outperformed other classifiers [54]. These studies highlight the effectiveness of machine learning methods, including XGBoost, in ransomware detection. However, no specific comparative study between CNNs and conventional machine learning methods in ransomware detection was found in the provided abstracts [55].

Previous studies have shown that using CNNs in image processing, specifically steganalysis has led to state-of-the-art results [56]. However, it has been observed that the performance of CNNs in steganalysis is not solely dependent on the size of the learning database. The enrichment of the learning database through base augmentation can have a significant impact on classification accuracy and steganalysis efficiency [57]. The effects of base augmentation on the performance of steganalysis using CNNs have been studied, and good practices for base augmentation have been defined. These findings suggest that using CNNs and appropriate database enrichment techniques can potentially improve the limitations faced by other techniques in ransomware detection [58].

3. Proposed Method

3.1. Mathematical Concept

The proposed CNN model consists of several layers commonly used in processing high-dimensional data such as time series. Here is an explanation of this model's mathematical concepts and equations.

1. Convolutional Layer (Conv1D): The first convolutional layer extracts features from the input data. Our model has three convolutional layers, each followed by a

MaxPooling1D layer and Dropout. The mathematical concept is computed in Equation (1).

$$Conv1D(X) = f(X * W + b) \quad (1)$$

Where X is the input data, W is the weight (kernel) of the convolutional layer, b is the bias, and f is the activation function, in this case, 'relu' (Rectified Linear Unit).

2. MaxPooling1D: The MaxPooling1D layer reduces the dimensionality of the output from the convolutional layers by selecting the maximum value within a certain window. The mathematical concept is computed in Equation (2).

$$MaxPooling1D(X) = max(X) \quad (2)$$

Where X is the input to the MaxPooling1D layer.

3. Dropout: The Dropout layer prevents overfitting by randomly deactivating some units (neurons) in the previous layer during training.

4. Flatten Layer: The Flatten layer converts the output from the convolutional layers into a one-dimensional vector, which is a prerequisite before advancing to the Dense layers. The mathematical concept is computed in Equation (3).

$$Flatten(X) = reshape\big(X, (N, M)\big) \quad (3)$$

Where X is the output from the previous layers, N is the number of training samples, and M is the number of features in the resulting vector.

5. Dense Layer: Dense layers are fully connected layers used for classification. This model has two Dense layers, with 'relu' activation for the first layer and 'sigmoid' for the final layer. Equation (4) calculates the Dense layer's mathematical concept.

$$Dense(X) = f(X \bullet W + b) \quad (4)$$

Where X is the input to the Dense layer, W is the weight, b is the bias, and f is the activation function.

6. Loss Function: This model uses binary crossentropy as the loss function, suitable for binary classification problems. The loss function measures the error between the model's output and the actual labels, as calculated in Equation (5).

$$Loss = -\left(\frac{1}{N}\right)\Sigma_{i=1}^{N} y_i * \log(p_i) + (1 - y_i) * \log(1 - p_i) \quad (5)$$

Where N is the number of training samples, y_i is the actual label, and p_i does the model provide the predicted probability.

3.2 Datasets

The dataset utilized for this research is sourced from Kaggle and comprises a total of 6,245 records, each characterized by 15 distinct features, with the target variable aimed at binary classification, distinguishing between "no" (indicating ransomware) and "benign" (indicating non-ransomware) instances. This dataset serves as the foundational data source for the investigation into ransomware detection and classification within the scope of this study.

3.3 Preprocessing

In this study, several preprocessing steps were performed on the dataset. Firstly, irrelevant features were removed to streamline the dataset. Secondly, rows containing missing values (NAN) were eliminated to ensure data integrity. Thirdly, integer data types were converted to floating-point for consistency. Additionally, the features related to benign instances were normalized to provide fair training. Finally, the dataset underwent a division where 80% of it was allocated as the training set and the remaining 20% was designated as the testing set. to facilitate model evaluation and validation. These preprocessing steps were crucial in preparing the data for effective training and testing of the ransomware detection and classification model.

3.4 Comparison of Methods

This research employs the CNN algorithm as the primary approach for ransomware detection while also benchmarking its performance against a number of baseline machine learning algorithms, including SVM, Decision Tree, KNN, GNB, and GBoost. By comparing the CNN model to these established algorithms, the study aims to assess the effectiveness and potential advantages of utilizing deep learning techniques in ransomware detection and classification on the dataset from Kaggle.

3.5 Training and Evaluation

This research adopts a training configuration with 100 epochs (iterations through the entire training dataset) and a batch size 64. Model performance evaluation uses two crucial metrics: Confusion Matrix and Classification Report. The Confusion Matrix measures the model's performance in detail by calculating the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). On the other hand, the Classification Report provides a more structured summarize the model's performance by providing metrics like Precision, Recall, F1-Score, and Accuracy.

1. Precision: The mathematical concept is computed in Equation (6).

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

2. Recall: The mathematical concept is computed in Equation (7).

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

3. F1-Score: The mathematical concept is computed in Equation (8).

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (8)$$

4. Accuracy: The mathematical concept is computed in Equation (9).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (9)$$

4. Result and Analysis

4.1 Training Process

The introductory visualization in this study comprises two critical aspects of our model training process. The first graph, Figure 1, illustrates the training accuracy (represented by the blue line) and validation accuracy (represented by the orange line) throughout the model training process. This graph provides insights into how well the model comprehends and generalizes patterns within the data.

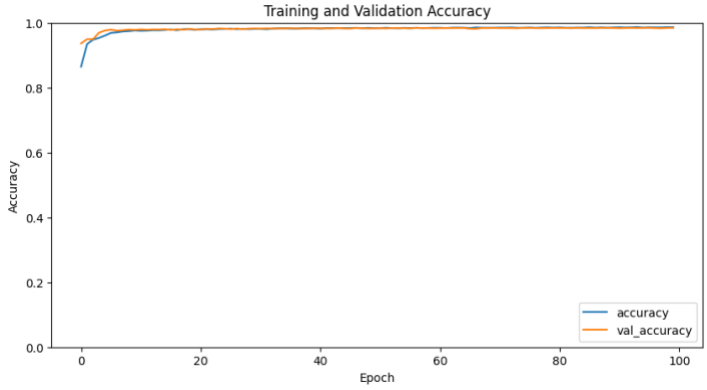

Figure 1. Training and Validation accuracy.

The second graph, Figure 2, showcases the training loss (blue line) and validation loss (orange line). It offers a depiction of how our model manages errors during both training and validation. By scrutinizing the fluctuations in accuracy and loss on these graphs, we can identify whether the model faces overfitting (performing well on training data, but struggling to generalize) or underfitting (failing to grasp the training data adequately). These graphs serve as valuable tools to measure and comprehend the performance of the ransomware detection model developed in this research.

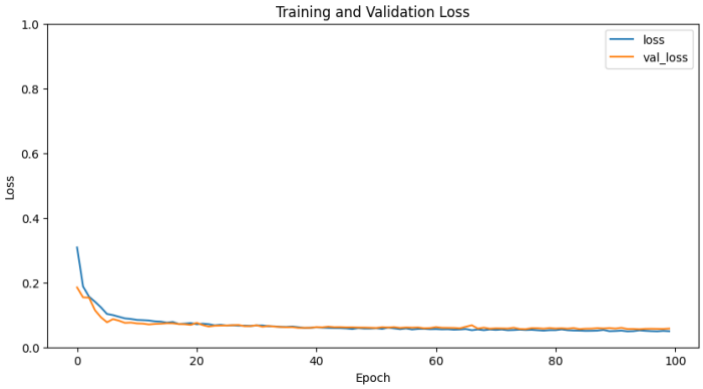

Figure 2. Training and Validation Loss

4.2 Model Performance

The introductory section of this presentation introduces two essential tables that encapsulate the performance evaluation of various machine learning algorithms utilized in this study. Table 1 provides a detailed Confusion Matrix for each algorithm, including TP, FP, FN, and TN. The algorithms encompassed in this analysis surround CNN, SVM, Decision Tree, KNN, GNB, and GBoost. This matrix offers a comprehensive overview of how each algorithm classifies instances and helps assess their effectiveness in distinguishing benign and malign cases.

Table 1. Confusion Matrix

Algorithm	TP	FP	FN	TN
CNN	1922	28	34	2016
SVM	1909	41	145	1905
Decision Tree	1935	15	98	1952
KNN	1929	21	41	2009
GNB	939	1011	48	2002
Gboost	1933	17	33	2017

Table 2, on the other hand, furnishes a Classification Report for the same set of algorithms, presenting essential metrics like Accuracy, Precision, Recall, and F1-Score. These metrics provide a holistic perspective on the performance of each algorithm in classifying ransomware and benign data instances. The analysis aims to shed light on the accuracy of these algorithms and their precision in correctly classifying ransomware cases, recall in identifying all ransomware instances, and the harmonic mean of precision and recall, known as the F1-Score. These tables serve as crucial tools for evaluating and comparing the effectiveness of the various algorithms employed in ransomware detection.

Table 2. Classification Report

Algorithm	Accuracy	Class	Precision	Recall	f1-score

CNN	0.98	no	0.98	0.99	0.98
		benign	0.99	0.98	0.98
SVM	0.95	no	0.93	0.98	0.95
		benign	0.98	0.93	0.95
Decision Tree	0.97	no	0.95	0.99	0.97
		benign	0.99	0.95	0.97
KNN	0.98	no	0.98	0.99	0.98
		benign	0.99	0.98	0.98
GNB	0.74	no	0.95	0.48	0.64
		benign	0.66	0.98	0.79
Gboost	0.99	no	0.98	0.99	0.99
		benign	0.99	0.98	0.99

The study concluded that CNNs and GBoost emerge as highly effective tools for detecting and preventing ransomware attacks. Their consistently high accuracy and robust performance underline their relevance in bolstering cybersecurity efforts. However, the limitations of this research, such as the specific dataset used and potential hyperparameter choices, may have impacted the generalizability of the findings to some extent. Despite these limitations, the results remain valid for answering the research questions because they align with existing literature on the strengths of deep learning and boosting algorithms in addressing complex security challenges. The fundamental principles and advantages of CNN and GBoost in the context of ransomware detection still hold, making the results valuable for informing cybersecurity strategies and further research in this domain.

In contrast, GNB struggled to achieve competitive performance, particularly with lower precision and recall for the "no" class. While respectable, SVM, Decision Tree, and KNN displayed slightly lower performance than CNN and GBoost. These findings emphasize the effectiveness of deep learning techniques, as the CNN model exemplifies, in addressing ransomware detection challenges and present promising avenues for bolstering cybersecurity in social media contexts.

This research holds significant relevance and implications in the field of cybersecurity. By successfully applying CNN and GBoost to detect and prevent ransomware attacks with high accuracy, it underscores the practicality of these advanced machine learning techniques in enhancing cybersecurity measures. These findings align with prior literature emphasizing the potential of deep learning and boosting algorithms in addressing complex security challenges. Importantly, this study highlights the critical role of algorithm selection in ransomware detection, shedding light on the limitations of GNB in this context. The research contributes new insights by showcasing the superior performance of CNN and GBoost and emphasizing the need for tailored approaches to ransomware detection. It reinforces that staying ahead of evolving cyber threats requires leveraging state-of-the-art machine learning methods while being mindful of their appropriateness for specific security tasks. These insights are valuable for cybersecurity practitioners and researchers striving to strengthen defenses against ransomware attacks.

5. Conclusion

The research endeavor set out to tackle the challenge of ransomware detection and classification using a variety of machine learning algorithms, including CNN, SVM, Decision Tree, KNN, GNB, and GBoost. Leveraging a dataset comprising 6,245 records with 15 features, the study aimed to shed light on the efficacy of these algorithms in addressing the ransomware detection problem. The key findings reveal that the CNN model exhibited exceptional performance with an accuracy of 0.98 and impressive precision, recall, and F1-score values for both the "no" and "benign" classes. Similarly, GBoost demonstrated high accuracy and robust performance across various evaluation metrics. The analysis of the results reveals several patterns and relationships among the data. Firstly, CNN and GBoost consistently outperformed other algorithms with 98% and 99% accuracy, respectively, indicating their suitability for ransomware detection. This aligns with previous research highlighting the efficacy of deep learning and boosting algorithms in handling complex cybersecurity tasks. However, GNB yielded unexpected results with an accuracy of only 74%, suggesting its limited suitability for this specific problem. This outcome may be attributed to the dataset's complexity and the assumption of independence among features in GNB, which might not hold in the context of ransomware detection. Alternative explanations could include the need for better feature engineering or alternative preprocessing techniques to improve GNB's performance. These findings are consistent with prior literature on the effectiveness of specific machine learning techniques for cybersecurity tasks while emphasizing the importance of algorithm selection based on the particular problem domain.

The study offers several strategic recommendations for enhancing ransomware detection in the context of social media. Firstly, it suggests adopting ensemble models that combine various algorithms, such as Decision Tree and GBoost, to improve detection capabilities. Real-time monitoring systems tailored to detect and respond to ransomware threats on social media platforms are crucial. Addressing class imbalance challenges through techniques like oversampling, under sampling, SMOTE, or cost-sensitive learning can enhance detection accuracy. Additionally, advanced Natural Language Processing (NLP) methods, including sentiment analysis, topic modeling, and entity recognition, should be explored to better analyze textual content in social media posts for ransomware-related discussions. Future research directions include developing adaptive models, enhancing model interpretability, exploring behavioral analysis, integrating multiple data modalities, promoting user education, creating benchmark datasets, and fostering collaborative defense mechanisms across social media platforms to bolster ransomware detection and safeguard users' digital experiences.

Conflicts of Interest

The authors declare no conflict of interest.

Data Availability

The datasets come from the Kaggle website (https://www.kaggle.com/code/amdj3dax/xgboost-ransomware-detection-and-classification/notebook)

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