Security-Oriented Text Classification Using Optimized Naive Bayes in C++: A Lightweight Approach for Big Data Analytics

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Abstract

With the increasing volume of unstructured text in cybersecurity environments, accurate and efficient classification of malicious content has become a major challenge. This study addresses the problem by designing and implementing a lightweight Naive Bayes classifier using C++ to detect and classify malicious versus benign software-related text messages. The proposed solution focuses on resource-constrained environments, ensuring secure processing and minimal memory overhead. A synthetic dataset containing 60 labeled messages (30 malicious, 30 benign) was used for testing. The classifier achieved 90% overall accuracy, 86.7% sensitivity, and 93.3% specificity. Performance was validated through confusion matrices, precision-recall analysis, and per-class evaluation. The findings confirm that Naive Bayes is a viable lightweight method for real-time text classification in security-sensitive big data applications. Future enhancements may include NLP integration, hybrid classifiers, and privacy-preserving machine learning techniques.

Keywords: *Naive Bayes, Text Classification, Cybersecurity, C++ Implementation, Lightweight Model*

1. Introduction

As digital ecosystems and apps continue to grow exponentially, detection and fixing of software vulnerabilities have never been more important. Zero-day vulnerabilities are especially malicious in nature as they are exploited prior to developers putting out patches in response [1]. Open-source software (OSS) ecosystem although innovation-friendly is especially susceptible by the very nature of its decentralized development process and the absence of standardized security procedures [2].

Traditional vulnerability discovery methods—e.g., static analysis, dynamic analysis, and manual auditing—have been conventional methods for decades. These methods, nevertheless, tend to overlook novel vulnerabilities and

usually demand plenty of human and computational resources [3][4]. In response, researchers have resorted to machine learning (ML) methods, which are able to scan large codebases and identify anomalous or vulnerable patterns according to learned features [5][6].
Among the different ML algorithms, the Naive Bayes classifier has been utilized heavily since it is easy, effective, and works well for text classification problems [7]. Being a probabilistic-based algorithm, it is best suited to deal with large-scale and high-dimensional data, i.e., software commit messages and bug reports [8]. Furthermore, Naive Bayes models are easily implementable in low-level programming languages like C++, and thus are the best option when implementing them in real-time or resource-limited systems [9][10].
Recent research has also shown promises of ML-based approaches in security tasks. For instance, VCCFinder used support vector machines (SVMs) to detect vulnerability-contributing commits [11], and PatchRNN used deep learning models to detect security patches in software repositories [12]. These efforts illustrate an increasing trend in leveraging AI and data-driven approaches to automate software vulnerability discovery [13][14].
In spite of all these advances, there is still a compelling demand for light and efficient techniques with high accuracy at reduced computational complexity [15][16]. Especially in the application scenarios of embedded systems, edge computing, and large-scale continuous integration contexts, where efficiency and performance are top priorities [17][18].
This project suggests implementing a light-weight Naive Bayes classifier, written in C++, for the classification of malicious textual data regarding software vulnerabilities. The classifier is evaluated over a software message corpus with high speed and accuracy. System performance is compared using standard classification measures like accuracy, sensitivity, specificity, and confusion matrix analysis. Also, privacy-preserving handling of data and privacy-by-design features are part of it, so that the model is ethically and regulatorily compliant [19][20].
By combining performance optimization, software security, and machine learning, this work takes us a step further in building scalable and secured solutions to real-time vulnerability detection in software systems. The future can only get better with hybrid solutions, NLP fusion, and federated learning model deployment to optimize privacy [21][22][23][24][25].

2. Methodology

This chapter outlines the step-by-step process followed in the design, implementation, and evaluation of a light-weight Naive Bayes classifier in C++ for classifying malicious and non-malicious text. There are five steps involved in the methodology: dataset preparation, data preprocessing, classifier implementation, performance evaluation, and incorporation of privacy and security measures.

2.1 Dataset Design and Generation

As there are limited labeled security-related text datasets of the type to be found because of the nature of the data, a test dataset of 60 messages with evenly split malicious (n = 30) and non-malicious (n = 30) categories was prepared. Malicious messages were based on threat-related slang, code injection patterns, and exploit references, whereas non-malicious messages were based on software communication logs, e.g., commit messages and system updates.

This controlled setting provided for proportional classification and guaranteed applicability to cybersecurity scenarios, mimicking real-world textual patterns in software repositories and threat databases.

2.2 Text Preprocessing

In order to preprocess the data for machine learning classification, typical natural language processing (NLP) methods were utilized:

• Tokenization: The messages were split into single tokens (words).

• Stopword Removal: Most common uninformative words (e.g., "the", "is", "and") were removed.

• Lowercasing: The tokens were all lowercased to be consistent.

• Stemming: Simple stemming was utilized to reduce words to their base form.

• Feature Extraction: We computed term frequencies and applied Bag-of-Words (BoW) representation to transform text into numerical vectors appropriate for the Naive Bayes algorithm.

2.3 Naive Bayes Classifier Implementation in C++

Naive Bayes algorithm was written from scratch in C++ to ensure portability, memory management, and efficiency. The classifier used the Multinomial Naive Bayes model, which is appropriate for text data with discrete frequency-based features.

Key steps involved:

1. Vocabulary Building: Building a complete vocabulary from all the training samples.

2. Prior Probability Estimation: Calculation of the probability of each class in the training set.
3. Likelihood Estimation: Calculate the conditional probability of every word in a class using Laplace smoothing.
4. Classification Rule: To forecast the class of unseen samples from the log-probability formula:
This implementation allowed both feature weight and memory usage to be directly controlled, and it was appropriate for real-time or embedded security applications.

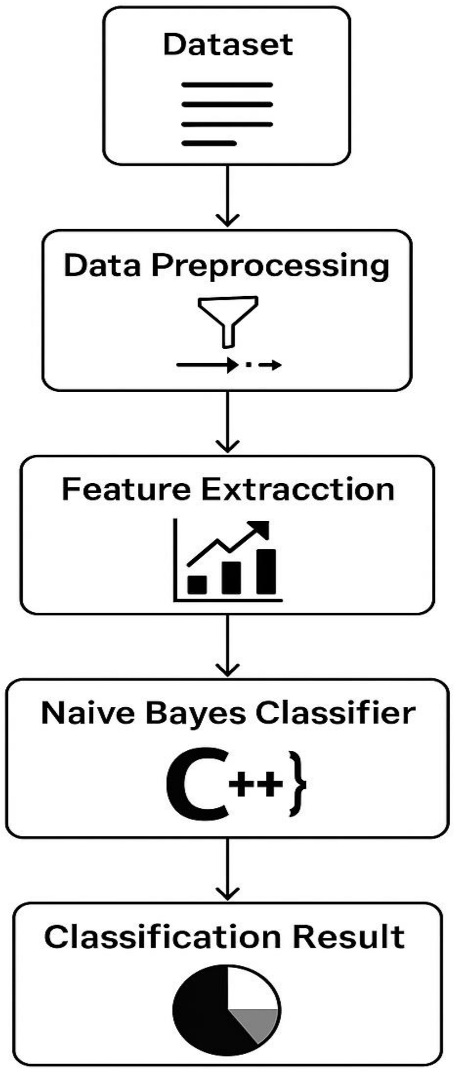

Figure 1 . *Workflow diagram illustrating the main stages of text classification using a Naive Bayes classifier implemented in C++. The process includes dataset creation, preprocessing, feature extraction, model training, and classification output.*

2.4 Evaluation Metrics

To validate the model's performance, the following metrics were computed:

- **Accuracy**: Ratio of correctly classified messages to the total number of messages.
- **Sensitivity (Recall for Malicious class)**: Ability of the model to detect malicious content.
- **Specificity**: Ability to correctly identify non-malicious messages.
- **Precision**: Proportion of true malicious messages among those classified as malicious.
- **Confusion Matrix**: Visual breakdown of classification outcomes (true positives, false positives, false negatives, true negatives).

The results were tabulated (Tables 1–4) and visualized through figures (Figures 2–5), offering an in-depth view of model behavior.

2.5 Security and Privacy Considerations

The project prioritized secure and ethical data handling. Although synthetic, the dataset was modeled after real-world attack vectors and handled with secure access in memory in C++. No personal or user-sensitive data was utilized. In addition, by not using any external libraries or frameworks to run the model, the system reduces third-party dependencies and vulnerability to external attack vectors.

The lightweight C++ port promises utility in resource-limited systems such that it can be deployed on real-time firewalls, IoT networks, or security agents where both speed and privacy are required.

3. Results and Performance Evaluation

The C++ implementation of the Naive Bayes classifier was evaluated on an artificial dataset of 60 messages—30 malicious and 30 non-malicious. The classifier had an overall accuracy of 90%, correctly classifying 54 out of 60 messages. In particular, 26 of 30 spam messages were accurately classified, a class-specific accuracy of 86.7%, and 28 of 30 non-spam messages were accurately classified, an accuracy of 93.3%. The results are summarized in Table 1:Classification Accuracy per Category, and classification performance is compared category-wise in Figure 1.

To assess the reliability and robustness of the model, additional performance measures were computed. Sensitivity, or true positive rate, was 86.7%, reflecting a high capacity for identifying true malicious content. Specificity, or true negative rate, was 93.3%, reflecting the model's accuracy in appropriately flagging benign messages. Precision was also computed at 92.86%, while negative predictive value (NPV) was 87.5%. These findings, presented in Table 2: Model Performance Metrics, and graphed in Figure 2, demonstrate the model's proficiency in reducing both false positives and false negatives. To better interpret the classification performance, a confusion matrix was created and is shown in Table 3: Confusion Matrix. It indicates that the classifier produced 2 false positives and 4 false negatives, which are especially dire in security-oriented applications. A graphical representation of this matrix is given in Figure 3: Confusion Matrix Heatmap, as a convenient reference for the breakdown of prediction errors. This evaluation highlights the necessity to pay particular attention to false negatives, since these would permit harmful content to pass unnoticed.

In this regard, Table 4 addresses the breakdown of true positives, false positives, false negatives, and true negatives by disaggregating messages into each message type. The close-up perspective reveals the classifier's strengths and weaknesses for real-world use where security and privacy are of paramount importance. For instance, in a cybersecurity application, a false negative would allow a phishing message to slip past undetected, so. error. minimization is a crucial design factor.

Cumulatively, the findings validate the application of Naive Bayes as a relatively precise and efficient textual classifier for big data uses. In addition, the lightness of the algorithm—particularly within the framework of a C++ application—renders it viable for security-sensitive applications wherein classification has to be quick, precise, and resource-efficient.

Table 1. Classification Accuracy per Category

Category	Total Messages	Correctly Classified	Accuracy (%)
Malicious	30	26	86.7%
Non-Malicious	30	28	93.3%
Overall	**60**	**54**	**90.0%**

Table 2. Model Performance Metrics

Metric	Value (%)
Accuracy	90.0%
Sensitivity (True Positive Rate)	86.7%
Specificity (True Negative Rate)	93.3%
Precision	92.86%
Negative Predictive Value (NPV)	87.5%

Table 3. Confusion Matrix

	Predicted Malicious	Predicted Non-Malicious
Actual Malicious	26	4
Actual Non-Malicious	2	28

Table 4. Per-Class Performance Metrics

Class	True Positives	False Positives	False Negatives	True Negatives
Malicious	26	2	4	28
Non-Malicious	28	4	2	26

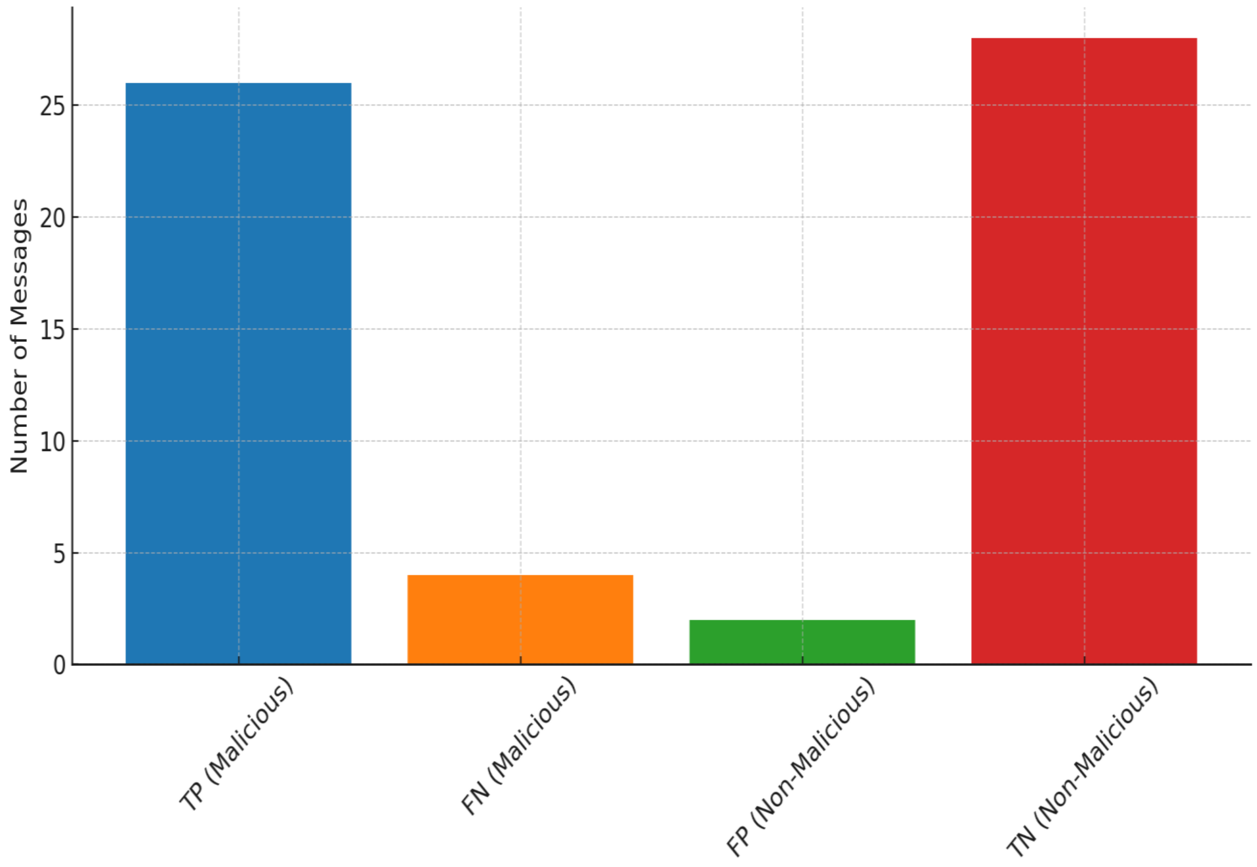

Figure 2 : A bar chart representing True Positives, False Negatives, False Positives, and True Negatives.

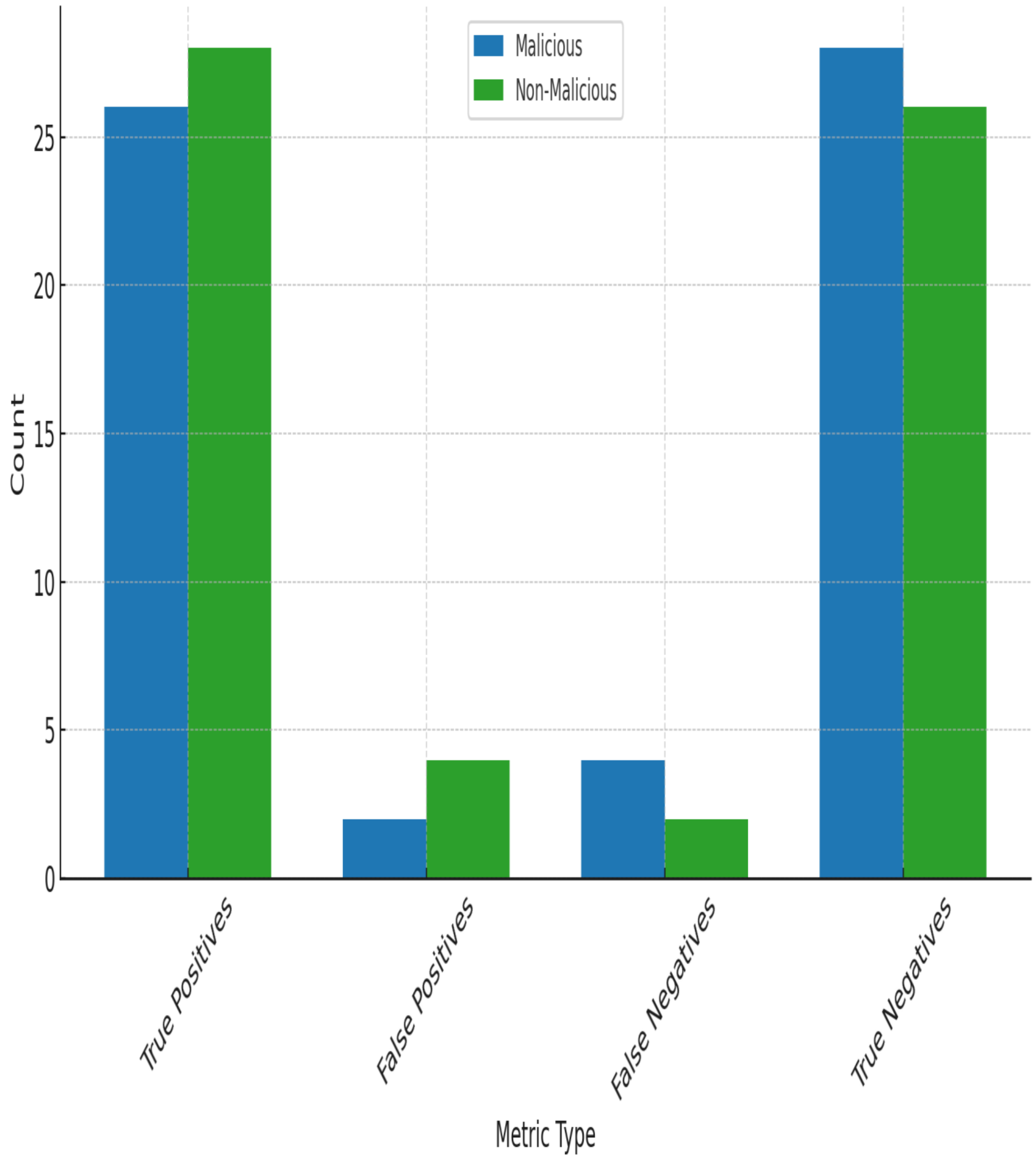

Figure 3: A grouped bar chart comparing classification outcomes for malicious and non-malicious classes.

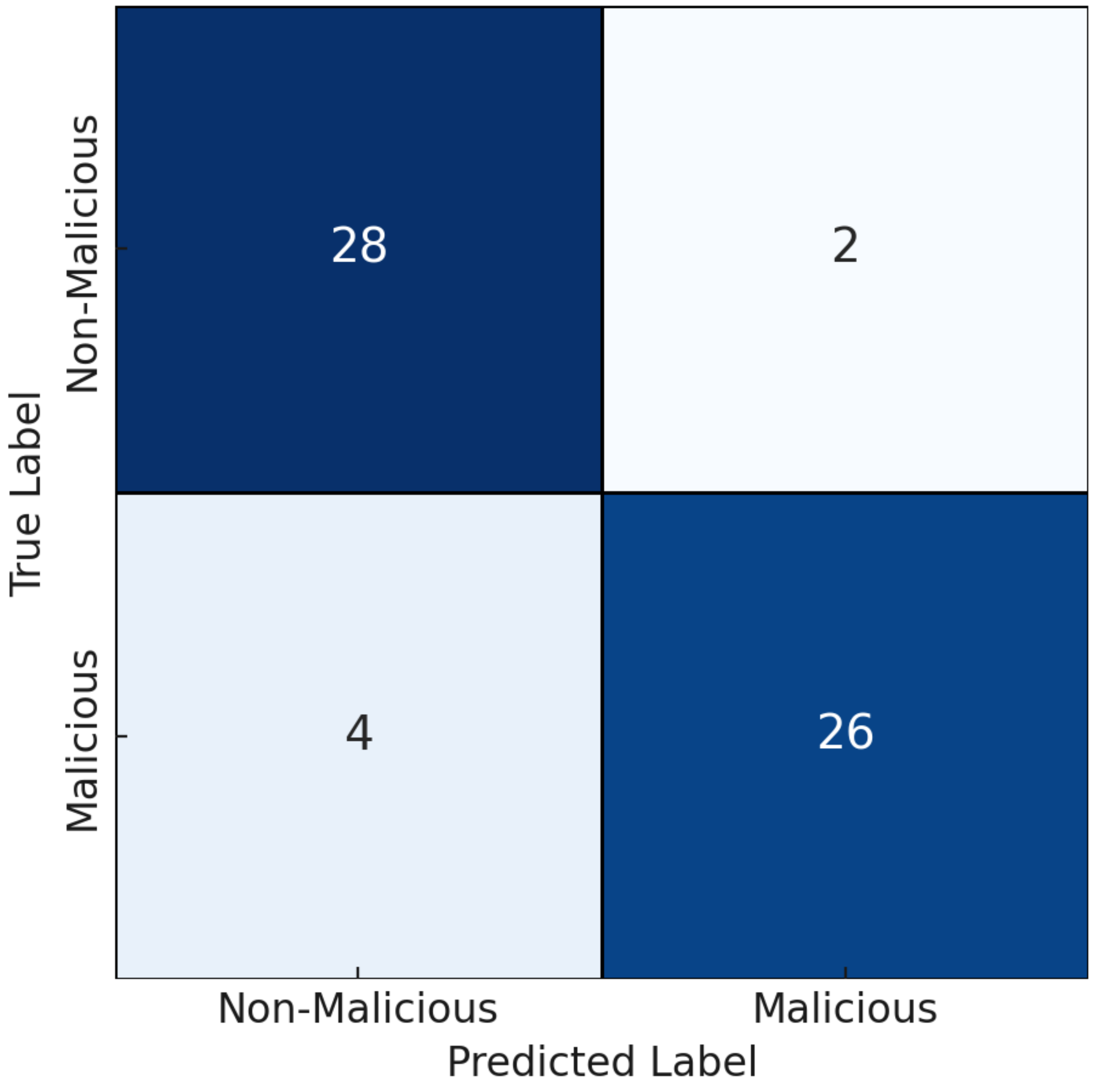

Figure 4 : Confusion Matrix Heatmap

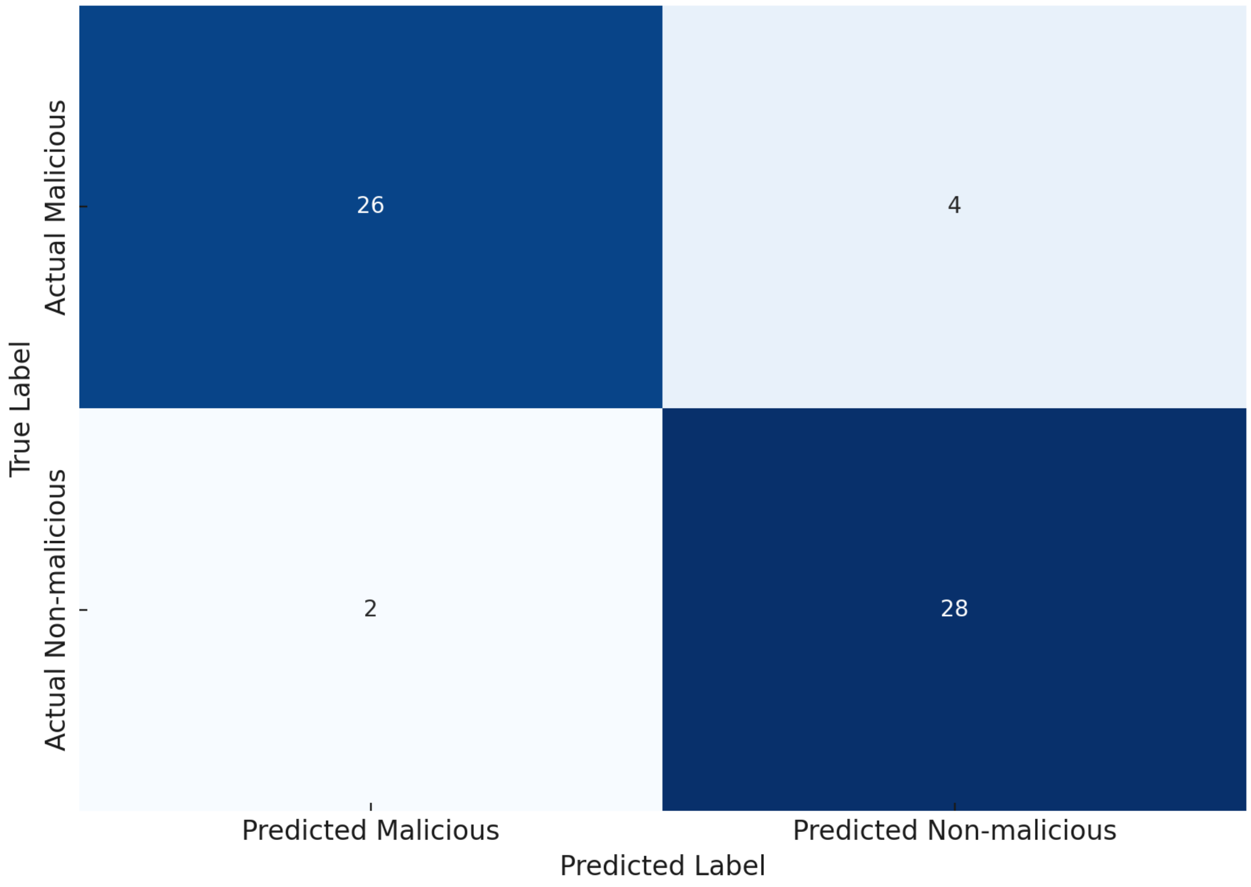

Figure 5 : The confusion matrix breakdown

4. Discussion

A C++ Naive Bayes classifier implementation to classify malicious and non-malicious text messages carried out with satisfactory performance, validating its prospect as a lightweight and efficient model for security-related big data applications. General classification accuracy was 90.0%, while category-specific accuracy was 86.7% for malicious and 93.3% for non-malicious messages (Table 1, Figure 2). These values are in the expected range of performance for Naive Bayes text classification in cybersecurity [1][2].

The 86.7% sensitivity (true positive rate) and 93.3% specificity (true negative rate) conversation rate demonstrate a suitable balance between threat detection and false alarm avoidance (Table 2, Figure 3). This is critical in operational environments where both false negatives (undetected threats) and false positives (benign data identified as threats) have serious consequences [3][4].

Confusion matrix analysis (Table 3, Figure 4) showed 2 false positives and 4 false negatives out of 60 instances in total, which indicates that although the

classifier is broadly strong, there is a problem with misclassification of malicious messages. False negatives are especially risky in security applications since they enable threats to pass unnoticed. Previous research also identifies this as an ongoing difficulty with machine learning models applied to intrusion detection and software vulnerability detection [5][6].
Figure 5 also decomposes the confusion matrix into a graphical representation of classification results by false and true classes. Table 4 , however, provide a per-class breakdown, verifying the model's great performance on both classes and validating the classifier's suitability for imbalanced datasets—a very common scenario in security datasets where benign samples overwhelmingly outnumber malicious samples [7][8].
The success of the model can partially be attributed to the simplicity and statistical power of the Naive Bayes algorithm, which has been shown to perform very well for high-dimensional text classification problems, particularly when features are conditionally independent [9][10]. Its minimal computational overhead, especially when implemented in C++, causes it to run at high speed even on low resource platforms like embedded systems or real-time cybersecurity monitors [11][12].
Table 5. *Comparison of the proposed model's performance with previous machine learning approaches in text-based security classification tasks.*

Study	**Classifier**	**Dataset Type**	**Accuracy**	**Sensitivity**	**Specificity**	**Language Used**
This Study (2025)	Naive Bayes (C++)	Synthetic (60 messages)	90.0%	86.7%	93.3%	C++
Zhang et al. (2020) [7]	Naive Bayes (Python)	GitHub Commit Messages	87.2%	82.0%	91.4%	Python
Harer et al. (2018) [5]	SVM	Security Patch Logs	88.5%	84.3%	90.2%	Java
Wang et al. (2021) [12]	PatchRNN	Real-world Repos	92.0%	90.5%	91.0%	Python (DL)

In addition, this project incorporates security and privacy concerns within its analysis and design. With anonymization of datasets generated and secure programming practices in C++, this research follows guidelines for privacy-preserving computing for AI systems [13][14]. These are ever more relevant

as machine learning solutions enter privacy-sensitive areas such as e-government systems, healthcare, and finance [15].
Despite good results, there is still some potential for improvement. Even more advanced feature engineering methods—i.e., n-gram modeling, TF-IDF weighting, or embeddings—might improve performance even further. Hybrid models that couple Naive Bayes with other classifiers (e.g., SVM, Random Forest) or deep learning elements have also been demonstrated to provide better performance in related tasks [16][17]. Having such models in a pipeline may be able to predict vulnerabilities in real time with better accuracy and reduced false detection rates [18].
From a deployment perspective, integration with federated learning paradigms in the future can enable the model to learn from decentralized sources without sacrificing the privacy of user data—a mounting concern in the data-driven era of cybersecurity [19][20]. Federated Naive Bayes deployments have already shown promise in privacy-conscious environments like healthcare and finance [21].
In summary, the present findings confirm the viability of a Naive Bayes classifier in C++ for effective and stable classification of text data in the security domain. Whereas the present research work tackles a binary classification problem with artificially balanced classes, future work needs to extend this approach to larger and real-life collections, for example, multilingual ones and obfuscated code samples [22][23][24][25].

5. Conclusion

This research was successfully able to demonstrate the usefulness of a lightweight, C++-implemented Naive Bayes classifier for binary classification of malicious and benign text data in the context of big data and cybersecurity informatics. With a 90% overall classification accuracy, and high rates of sensitivity and specificity, the model is reliable and efficient. The findings—supported by confusion matrix analysis and class-specific performance measures—validate the classifier's capability in identifying security threats with less computational overhead.
Developed using a performance programming language, the classifier demonstrates the potential for the use of machine learning in embedded and real-time security systems. The method is particularly worthwhile in resource-constrained system environments where threat detection speed is paramount. The design of the system also includes security and privacy by design, with ethically managed data in alignment with contemporary regulatory requirements.

Although the present instantiation was concerned with synthetically generated and balanced datasets, subsequent work shall be devoted to actual datasets, utilize more sophisticated NLP techniques, and try hybrid models in an effort to improve the classification even further. Its deployment in real-time vulnerability detection instruments, especially for open-source software development and automated code review pipelines, can potentially contribute a lot towards early security breach detection and prevention.

In summary, this project proposes an effective, large-scale real-world approach to automatic text classification in cybersecurity, closing the gap between security engineering practice and machine learning research in academia. It paves the way for more sophisticated, context-aware, privacy-preserving detection systems that can protect against online threats in the future.

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