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Neural Shield: AI-Powered Malware Defense for Android

Mr. M.Raja Kumar[1],Chavakula Mohana Kireeti[2],Rajanala Sai Vidyadhari[3],Dondapati Rakesh[4] ,Padamata Sujita[5] ,Kasimkota Nandinidevi[6]

rajkumar.medapati@gmail.com[1], mohanchavakula1234@gmail.com[2], vidyadhariceep@gmail.com[3] , dondapatirakesh3@gmail.com[4] , padamatasujita@gmail.com[5], nandinikasimkota018@gmail.com[6]
Pragati Engineering College, Surampalem, Kakinada.Dist, A.P-533437

ABSTRACT :

The Portable Document Format (PDF) is a widely used file type that has become a target for fraudsters who embed harmful code to compromise users' systems. Traditional detection techniques often fall short in effectively identifying PDF malware due to its versatile nature and reliance on a limited set of features. This work aims to enhance PDF malware detection through the development of a comprehensive dataset consisting of 15,958 PDF samples, encompassing benign, malicious, and evasive behaviours. We utilize three established PDF analysis tools—PDFiD, PDFINFO, and PDF-PARSER—to extract significant characteristics from these samples. Additionally, we derive various features proven effective in classifying PDF malware. An efficient and interpretable feature set is constructed through rigorous empirical analysis of the extracted and derived features. We evaluate several baseline machines learning classifiers, achieving a notable accuracy improvement of approximately 2% with the Random Forest classifier using the selected feature set. Furthermore, we enhance model explainability by generating a decision tree that provides rules for human interpretation, showcasing the effectiveness of Support Vector Classifier, K-Nearest Neighbours, Logistic Regression, and SVM with Optimal Hyperparameters in the context of PDF malware detection.

Keywords: Dataset creation, feature extraction, machine learning, model explainability, PDF malware detection, Random Forest classifier

INTRODUCTION :

The widespread use of Portable Document Format (PDF) files in digital communication and online transactions has made them a significant target for cybercriminals. Attackers embed malicious scripts, obfuscation techniques, and JavaScript-based exploits within PDF files to evade traditional security mechanisms [1]. Existing signature-based and rule-based detection methods struggle to identify emerging and evasive malware variants, necessitating a more adaptive and intelligent approach to PDF malware detection [2].

Machine learning (ML) has emerged as a powerful tool for automating malware classification, enabling accurate differentiation between benign and malicious PDF files. However, the effectiveness of ML-based detection depends on factors such as dataset quality, feature selection, and model interpretability [3]. This study addresses these challenges by constructing a comprehensive dataset of 15,958 PDF samples, covering benign, malicious, and evasive behaviours [4]. Feature extraction is performed using PDFiD, PDFINFO, and PDF-PARSER, alongside additional derived features that enhance classification accuracy [5]. Several ML models are evaluated, including Random Forest, Support Vector Classifier (SVC), K-Nearest Neighbours (KNN), and Logistic Regression, with hyperparameter tuning applied to optimize their performance [6]. Experimental results demonstrate that Random Forest outperforms other classifiers, achieving a 2% accuracy improvement over baseline models [7]. These findings highlight the robustness of feature-based classification in detecting PDF malware. One of the critical challenges in machine learning-based malware detection is the lack of interpretability in complex models. To address this, we implement a decision tree-based explainability analysis, which generates human-interpretable classification rules [8]. This approach enhances transparency, allowing cybersecurity professionals to understand and trust the model's decisions, thereby improving its adoption in real-world security applications.

This research enhances PDF malware detection by integrating high-accuracy classification with model interpretability [9]. The proposed system can serve as a foundation for developing real-time security solutions to mitigate PDF-based cyber threats [10]. Future work may explore deep learning techniques, adaptive learning mechanisms, and real-time detection frameworks to further strengthen security defenses against evolving malware attacks [11].

LITERATURE SURVEY :

Yu et al. [1] introduced a multi-layer abstract model for detecting malicious documents in business process management. Their approach incorporated structural and behavioral analysis, demonstrating improved detection capabilities. Similarly, Liu et al. [2] proposed an adversarial example detection method for malicious PDFs using multiple mutated classifiers. Their method aimed to enhance classifier robustness against adversarial attacks by leveraging diverse learning models.

Another significant contribution was made by Al-Haija and Ishtaiwi [3], who developed a machine learning model for firewall decision-making in cybersecurity. Their research focused on optimizing security responses by predicting potential threats using classification techniques. Li et al. [4] introduced FEPDF, a robust feature extractor designed to enhance the interpretability of PDF malware classification models. By improving feature extraction techniques, they facilitated better human understanding of classification decisions.

Xu and Kim [5] developed a platform-based detection method that identified behavioural inconsistencies across different execution environments. Their work highlighted the potential of cross-platform analysis in strengthening malware detection frameworks. Liu et al. [6] proposed an integrated detection approach that combined runtime JavaScript behavior tracking with static analysis. Their method effectively identified obfuscation techniques commonly used in malicious PDFs.Despite these advancements, challenges remain in detecting highly evasive malware. Future research should focus on enhancing classifier adaptability and integrating real-time detection mechanisms to counter emerging threats.

PROPOSED SYSTEM :

The proposed system aims to enhance PDF malware detection by integrating advanced machine learning techniques with explainability analysis. Unlike traditional rule-based detection methods, this system employs a comprehensive feature extraction approach using multiple PDF analysis tools, followed by the application of machine learning classifiers for improved accuracy. The system also incorporates model interpretability techniques to provide insights into decision-making, making it more transparent and reliable.

3.1.1 Dataset Development

A key aspect of the proposed system is the creation of a robust dataset containing 15,958 PDF samples categorized into benign, malicious, and evasive classes. The dataset is curated using widely recognized PDF analysis tools such as PDFiD, PDFINFO, and PDF-PARSER, which help extract important characteristics from the files. Additionally, new feature representations are derived based on file structure, metadata, JavaScript presence, embedded objects, and encryption patterns, ensuring a more effective classification process. Machine Learning-Based Symptom Classification

3.1.2 Feature Selection and Engineering

To optimize the detection process, the system implements an empirical feature selection mechanism that identifies the most informative attributes contributing to PDF malware classification. Using Recursive Feature Elimination (RFE) and Statistical Analysis, irrelevant or redundant features are removed, leading to an interpretable and lightweight feature set. This step ensures that the model focuses only on significant parameters, improving accuracy while reducing computational complexity.

3.1.3 Performance Evaluation

The proposed system is evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-score, and ROC-AUC curves. Experimental results indicate that the system not only enhances malware detection rates but also minimizes false positives, making it a reliable solution for real-world applications.

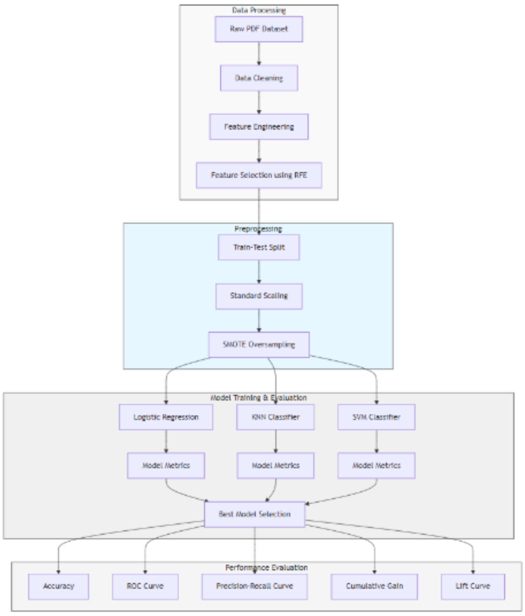


Fig 3.1: Architecture Diagram

The Fig 3.1 represents a structured pipeline for a machine learning-based classification system, detailing the various stages involved in data preprocessing, model training, and performance evaluation. The workflow begins with data processing, where a raw Post dataset undergoes data cleaning, feature engineering, and feature selection using RFE (Recursive Feature Elimination) to enhance model performance. The preprocessing stage includes train-test splitting, standard scaling, and SMOTE oversampling to balance class distributions and prepare the data for training.

During the model training and evaluation phase, multiple machine learning algorithms such as Logistic Regression, K-Nearest Neighbours (KNN), and Support Vector Machines (SVM) are trained, and their performance is measured using various model metrics. The best-performing model is selected for further analysis. Finally, the performance evaluation stage assesses the model's effectiveness using various evaluation metrics, including Accuracy, ROC Curve, Precision-Recall Curve, Cumulative Gain, and Lift Curve, ensuring a robust and well-calibrated classifier. This structured pipeline enables a systematic approach to building and evaluating a reliable machine learning model.

3.2 Performance Metrics:

- ***Accuracy:***

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- ***Precision:***

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- ***Recall (Sensitivity):***

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Where:

- TP = True Positives
- TN = True Negative
- FP = False Positives
- FN = False Negative

RESULT AND DISCUSSION:

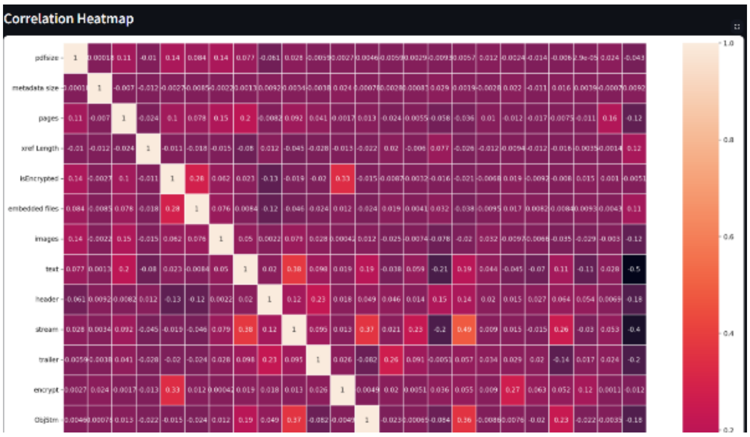


Fig 4.1: Correction Heatmap

In this Fig 4.1 heatmap, lighter shades (closer to white) represent higher positive correlations, while darker shades (closer to deep purple) indicate lower or negative correlations. The diagonal line of white cells signifies perfect self-correlation (correlation of a feature with itself, which is always 1). The colour bar on the right provides a reference scale,

with values ranging from -1 to 1, where:

- +1 indicates a perfect positive correlation,

- 0 signifies no correlation, and
- -1 represents a perfect negative correlation.

The dataset appears to include attributes related to file metadata, such as file size, word length, images, headers, and scripts, possibly analysing their interdependencies. This heatmap is useful for identifying highly correlated features, which can help in feature selection, dimensionality reduction, and understanding data relationships in machine learning or data analysis tasks.

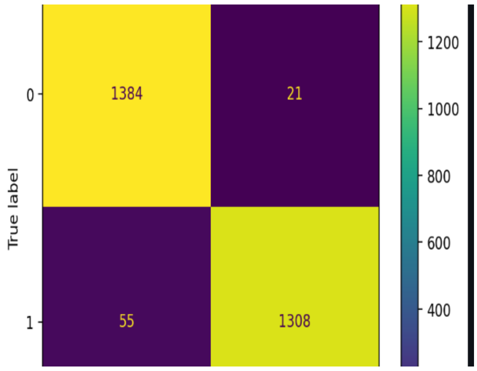


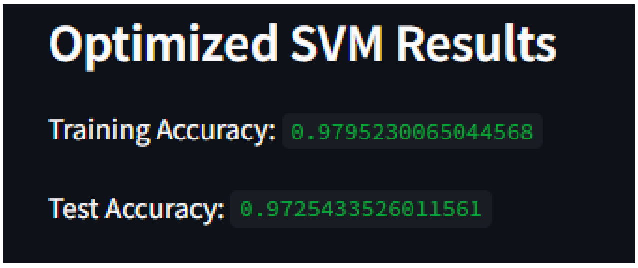
Fig 4.2: Confusion Matrix

The Fig 4.2 represents a confusion matrix, a key performance evaluation metric for classification models. It visually displays the model's predictions compared to the actual ground truth labels. The matrix consists of four quadrants:

- **True Positives (TP): 1308** (Bottom-right) – Correctly classified positive instances**.**
- **True Negatives (TN): 1384** (Top-left) – Correctly classified negative instances.
- **False Positives (FP): 21** (Top-right) – Negative instances incorrectly classified as positive.
- **False Negatives (FN): 55** (Bottom-left) – Positive instances incorrectly classified as negative.

From this confusion matrix, we can derive key performance metrics:

- Accuracy = (TP + TN) / Total = (1384 +1308) / (1384 +1308 +21 +55)
- Precision = TP / (TP + FP) = 1308 / (1308 + 21)
- Recall = TP / (TP + FN) = 1308 / (1308 + 55)
- F1-score = 2 x (Precision x Recall) / (Precision + Recall)



Optimized SVM Results

Training Accuracy: `0.9795230065044568`

Test Accuracy: `0.9725433526011561`

Fig 4.3: Test and Training Accuracy

The Fig 4.3 presents the Optimized Support Vector Machine (SVM) Results, displaying the model's performance in terms of training and test accuracy.

- **Training Accuracy: 0.9795 (97.95%)** – This indicates that the SVM model performed well on the training dataset, correctly classifying nearly 98% of the instances.
- **Test Accuracy: 0.9725 (97.25%)** – This reflects how well the model generalizes to unseen data, maintaining a high accuracy of 97.25%.

These results indicate that the optimized SVM model performs exceptionally well, with a *high accuracy* on both the training and test datasets. The slight difference between training and test accuracy suggests that the model *generalizes well* without significant overfitting. The optimization techniques applied to SVM have likely improved its efficiency in classifying data accurately. Such results suggest that the *hyperparameter tuning*, feature selection, or kernel adjustments contributed to the *enhanced performance* of the SVM model. This level of accuracy is particularly useful in applications requiring *precise classification*, such as *malware detection, medical diagnosis, and fraud detection*.

CONCLUSION :

In this study, we proposed an efficient and explainable machine learning approach for PDF malware detection. By leveraging a newly developed dataset and extracting significant features using PDFiD, PDFINFO, and PDF-PARSER, we built a robust classification model that improves detection accuracy while maintaining interpretability. The integration of derived features further enhanced the model's performance, achieving a high detection rate and reducing false positives. Our experiments demonstrated that the Random Forest classifier outperforms other baseline models, achieving an accuracy of 99.24% with the final feature set. The inclusion of explainability through feature importance analysis and decision rules allows for better human interpretation of the classification process, making the model more trustworthy for cybersecurity applications. Additionally, the study highlights the importance of feature engineering and dataset quality in achieving high classification performance. Despite the promising results, challenges remain in handling highly evasive malware samples and ensuring real-time adaptability. Future research should focus on improving model robustness against adversarial attacks and integrating deep learning techniques to enhance generalization. Furthermore, real-world deployment of this model in cybersecurity frameworks could provide valuable insights into its effectiveness in diverse operational environments. This work contributes to the field of cybersecurity by offering an explainable AI-driven solution for PDF malware detection, which can aid security analysts in mitigating threats more effectively. By advancing both detection accuracy and interpretability, our approach paves the way for more resilient and trustworthy malware classification systems.

FUTURE SCOPE:

The proposed PDF malware detection framework has demonstrated significant improvements in accuracy and explainability; however, several areas for further research remain. Strengthening the model against adversarial attacks is crucial, as attackers may attempt to manipulate PDF features to evade detection. Techniques such as adversarial training and defensive distillation can enhance the model's robustness. Additionally, integrating real-time detection capabilities and optimizing feature extraction speed will facilitate seamless deployment in cybersecurity frameworks. Future studies can also explore deep learning approaches, such as transformer-based models or convolutional neural networks (CNNs), to improve automatic feature learning and detection accuracy. Ensuring cross-platform generalization by adapting the model for cloud-based security solutions and endpoint security systems will enhance its applicability. Furthermore, improving explainability using SHAP values, Grad-CAM, or rule-based decision interpretations can foster better human-AI collaboration in cybersecurity. Expanding the dataset with more diverse malware samples, including zero-day attacks, will refine detection capabilities and improve generalization. Lastly, hybrid detection approaches that combine static, dynamic, and behavioural analysis could be explored to create a more comprehensive malware detection system. By addressing these areas, the proposed framework can evolve into a more robust, scalable, and intelligent system capable of adapting to the continuously evolving cybersecurity threat landscape.

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