Pufferfish Optimization based Deep Convolutional Neural Network for Malware Detection

Ratnam Akhil[1], Nelakurthi Jaswanth Sri Harsha[1], Chilakalapudi L V[1], Siva Sai Rama Krishna[1], Jaya Krishna Uppuluri[1,*]

[1]*Department of Computer Science Engineering,*

Indian Institute of Industry Interaction Education and Research, Chennai, Tamil Nadu 600066

***Abstract*—Mobile malware poses a significant threat to user privacy and security, necessitating the development of effective detection techniques. In this paper, we propose a novel methodology for Android malware detection using a combination of feature selection based on Pufferfish Optimization (PFO) and Deep Convolutional Neural Network (DCNN) architecture. The proposed methodology involves collecting a diverse dataset of Android application binaries (APK files) from various sources and preprocessing the dataset by extracting relevant features such as permissions, API calls, and opcode sequences. Min-max normalization is then applied to scale the extracted features to a fixed range, followed by feature selection using the PFO algorithm to select the most discriminative features for malware detection. Subsequently, a DCNN architecture is designed to automatically learn hierarchical representations of the input data for effective malware detection. The model is trained, optimized, and evaluated using metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate the effectiveness of the proposed methodology in accurately detecting Android malware, outperforming existing methods.**

***Index Terms*— *malware detection, deep CNN, optimization, feature selection, standardization*.**

I. INTRODUCTION

Mobile malware refers to malicious software specifically designed to target mobile devices, such as smartphones and tablets. These malware threats can compromise the security and privacy of mobile users by stealing personal information, sending premium-rate SMS messages, displaying unwanted advertisements, or even taking control of the device. With the increasing popularity and widespread use of mobile devices, the threat landscape for mobile malware is continuously evolving. Current trends in mobile malware include the rise of sophisticated malware families, such as banking Trojans, ransomware, and spyware, targeting both Android and iOS platforms. These malware variants often employ advanced techniques to evade detection, such as obfuscation, encryption, and leveraging legitimate app stores to distribute malicious applications. Additionally, the proliferation of mobile banking and payment apps has made mobile devices lucrative targets for cybercriminals seeking to steal financial information and conduct fraudulent activities. As mobile malware threats continue to grow in complexity and number, there is an urgent need for effective detection and mitigation strategies to protect mobile users from potential harm.

Mobile malware detection plays a crucial role in safeguarding mobile devices and user data from malicious threats. Some of the key applications of mobile malware detection include protecting users from data theft, financial fraud, identity theft, and unauthorized access to sensitive information. Various existing methods have been designed for mobile malware detection, including signature-based detection, anomaly-based detection, and behavior-based detection. Signature-based detection relies on identifying known malware signatures or patterns in code to classify malicious apps. Anomaly-based detection identifies malware by detecting deviations from normal behavior, while behavior-based detection analyzes the behavior of an application to determine whether it is malicious. Machine learning techniques, particularly supervised learning, unsupervised learning, and deep learning, have shown great potential in enhancing mobile malware detection. These techniques can automatically learn and adapt to new and evolving malware threats by analyzing large datasets of benign and malicious apps, extracting relevant features, and building predictive models to

classify and detect malware accurately. Machine learning algorithms can effectively identify patterns and behaviors associated with malware, leading to more efficient and accurate detection compared to traditional signature-based approaches. Additionally, metaheuristic optimization techniques, such as genetic algorithms, particle swarm optimization, and ant colony optimization, can be used to optimize machine learning models and improve their performance in detecting mobile malware.

The proliferation of mobile devices has led to an increase in the number of malware threats targeting the Android operating system. As these threats continue to evolve in complexity and sophistication, there is an urgent need for more effective and efficient malware detection techniques. Deep learning-based approaches, particularly Deep Convolutional Neural Networks (DCNNs), have shown promising results in various domains, including computer vision, natural language processing, and malware detection. However, designing an optimal DCNN architecture for Android malware detection remains a challenging task due to the inherent complexity and variability of malware samples. In recent years, metaheuristic optimization algorithms have gained popularity for optimizing deep learning models, offering improved performance and faster convergence. One such algorithm, Pufferfish Optimization (PFO), inspired by the collective behavior of fish schools, has shown promising results in optimizing various types of optimization problems. In this research, we propose a novel approach for Android malware detection using a Pufferfish Optimization based Deep Convolutional Neural Network (PFO-DCNN). The primary objective of this study is to develop an efficient and accurate malware detection system that can effectively distinguish between benign and malicious Android applications. To achieve this, we design a deep learning architecture that combines the feature learning capabilities of DCNNs with the optimization power of Pufferfish Optimization. By leveraging the strengths of both approaches, we aim to enhance the overall performance of Android malware detection systems.

The remainder of this paper is organized as follows: Section 2 provides an overview of related work in the field of Android malware detection, deep learning, and metaheuristic optimization techniques. In Section 3, we present the proposed Pufferfish Optimization based Deep Convolutional Neural Network architecture in detail. Section 4 describes the experimental setup, including the dataset used, evaluation metrics, and implementation details. The experimental results and performance analysis are discussed in Section 5. Finally, Section 6 concludes the paper with a summary of the findings and suggestions for future research directions.

II. RELATED WORKS:

To develop a method for continuously improving the accuracy of machine learning-based, [6] designed an android malware detection in the face of evolving malware and benign apps. In this, active learning involves selecting a small number of uncertain samples for human analysts to label. These labeled samples are then used to retrain the malware classifier. In addition, Contrastive Learning helps the model learn similarities between data points, even if they come from different distributions. A hierarchical contrastive learning scheme is proposed for this purpose. The new method has significantly improved the accuracy of malware detection by reducing the false negative rate, or the instances of missed malware, from 14% to 9%. Additionally, the false positive rate, which refers to benign apps being incorrectly flagged as malware, has been reduced from 0.86% to 0.48%. Moreover, this method has demonstrated more consistent performance over an extended period compared to previous approaches, ensuring reliable and sustained malware detection. However, it's worth noting that this method requires human effort to label uncertain samples, which can be time-consuming and resource-intensive. Furthermore, designing effective contrastive learning schemes, while highly beneficial, can also be complex and challenging.

To develop an automated system for accurately classifying and identifying Android malware, [7] designed an ensemble learning approach. The AAMD-OELAC system employs Ensemble Learning, which combines predictions from multiple machine learning models (LS-SVM, KELM, RRVFLN) to enhance overall accuracy. This approach is complemented by Hunter-Prey Optimization (HPO), an optimization algorithm utilized to find the best parameters for each machine learning model in the ensemble. The detailed methodology includes several steps: Data Pre-processing involves cleaning and preparing the

Android malware dataset for analysis. Ensemble Learning includes training three individual machine learning models (LS-SVM, KELM, RRVFLN) on the preprocessed data and combining the predictions from each model to make the final classification (malware or benign). Hunter-Prey Optimization is applied to optimize the hyperparameters of each individual model in the ensemble, thereby improving overall performance. Finally, the system's performance is evaluated by comparing it with existing methods using various metrics. The AAMD-OELAC approach offers several advantages over single-model detection. By combining predictions from multiple models, it achieves improved accuracy in identifying Android malware. Additionally, ensemble learning can help mitigate bias that might be present in any one model. The HPO technique further enhances performance by optimizing the internal settings of each model within the ensemble. However, there are also drawbacks to consider. The system requires more computational resources compared to a single model, and designing effective ensemble strategies can be complex. Ultimately, the success of AAMD-OELAC also relies heavily on the quality of the training data it uses.

The RHSODL-AMD approach takes a two-pronged attack on the ever-growing problem of Android malware, which is designed by [8]. It combines deep learning with a metaheuristic technique to achieve superior detection accuracy. Firstly, the system analyzes an app's behavior by examining its API calls and permissions. Then, a metaheuristic algorithm called Rock Hyrax Swarm Optimization (RHSO) steps in. By selecting the most relevant features from this analysis, RHSO reduces the processing burden and improves classification accuracy. Following this selective process, the system utilizes a deep learning technique. An Attention Recurrent Autoencoder (ARAE) with Adamax optimizer is employed to classify the app as benign or malware. ARAE, a type of neural network, excels at learning complex patterns within the data, making it adept at identifying malware. The Adamax optimizer further enhances this process by assisting the ARAE model in effective learning. The RHSODL-AMD approach demonstrates its effectiveness through a high accuracy rate of 99.05% on the Andro-AutoPsy dataset. This achievement highlights its potential for real-world application. However, it's important to consider the drawbacks as well. Deep learning techniques often require significant computational resources, and the effectiveness of both RHSO and ARAE rely heavily on the quality of the training data used.

The GA-StackingMD framework was designed by [9] through tackling the challenge of limited accuracy in single-classifier Android malware detection. It achieves this by combining the strengths of multiple models. Here's how it works: First, the system can optionally reduce the number of features using techniques like InfoGain. Then, it trains five different machine learning models (the exact types aren't specified) on the data. The key idea is to leverage a technique called Stacking. Stacking combines the predictions from these individual models to train a final, more robust model. To further optimize performance, a Genetic Algorithm (GA) is used to find the best settings (hyperparameters) for the Stacking model itself. This two-pronged approach of ensemble learning and hyperparameter optimization has been shown to be effective, achieving accuracy rates of over 98% on benchmark datasets. However, there are trade-offs. Stacking can be computationally expensive compared to simpler models, and designing the overall architecture requires careful selection of the base models. Additionally, like any machine learning approach, the effectiveness of GA-StackingMD relies on the quality of the training data. Future research aims to further refine the base model selection and explore hyperparameter search space to improve overall effectiveness. Notably, the authors also propose implementing the approach on a distributed platform to reduce computational cost, making it more feasible for real-time applications.

The model designed by [10] tackles high-dimensional data, a common hurdle in malware detection, by combining deep learning with feature selection. The goal is to create a high-performing system that uses deep neural networks (Dense and LSTM) for classification, but with less complex data. To achieve this, the study utilizes two malware datasets with contrasting features (many records with few attributes vs. few records with many attributes). They then apply a correlation-based method to select the most relevant features for each dataset. This feature selection process resulted in significant reductions (up to 42.42% and 81.77%) while maintaining good

detection accuracy. Additionally, it led to reduced computational time in one dataset. The benefit lies in improved efficiency by requiring less training time and computational resources. However, choosing the right feature selection method and avoiding the discarding of important information are crucial challenges. Future work aims to explore how feature selection impacts the identification of specific malware types.

2.1 Problem Statement

The rapid proliferation of mobile devices, coupled with the increasing sophistication of mobile malware, poses a significant threat to user privacy and security. Despite the availability of various detection methods, such as signature-based, anomaly-based, and behavior-based approaches, mobile malware detection remains a challenging task. Existing detection methods often struggle to keep pace with the rapidly evolving landscape of mobile malware, leading to a high number of undetected malicious applications. Additionally, the sheer volume and diversity of mobile apps make manual inspection and detection impractical. Therefore, there is an urgent need for more effective and efficient mobile malware detection techniques that can accurately identify and mitigate evolving malware threats while minimizing false positives and false negatives.

III. METHODS

In the proposed methodology, the data collection and preprocessing stage involve collecting a diverse dataset of Android application binaries (APK files) from various sources, including official app stores, third-party app stores, malware repositories, and research datasets. The dataset is then preprocessed by extracting relevant features from the APK files, such as permissions, API calls, opcode sequences, and manifest file information. Following preprocessing, min-max normalization is applied to scale the extracted features to a fixed range, typically between 0 and 1, ensuring that all features contribute equally to the analysis and preventing features with large scales from dominating the learning process. Subsequently, feature selection is performed using the Pufferfish Optimization (PFO) algorithm, which selects the most discriminative features from the preprocessed feature set. The PFO algorithm initializes a population of candidate feature subsets, evaluates their fitness based on a fitness function measuring their effectiveness in distinguishing between benign and malicious applications, and iterates the optimization process to select the best-performing subset of features for malware detection. Following feature selection, a Deep Convolutional Neural Network (DCNN) architecture is designed for malware detection, comprising multiple layers of convolutional, pooling, and fully connected layers. The input layer is defined to accept the preprocessed and selected features as input, and the network is configured to automatically learn hierarchical representations of the input data for effective malware detection. Finally, the model is trained and optimized by splitting the preprocessed and selected dataset into training and testing sets, training the DCNN model using the training dataset, optimizing model parameters using backpropagation and gradient descent, validating the model using the testing dataset, and evaluating its performance using metrics such as accuracy, precision, recall, and Precision. The workflow is presented in Figure 1.

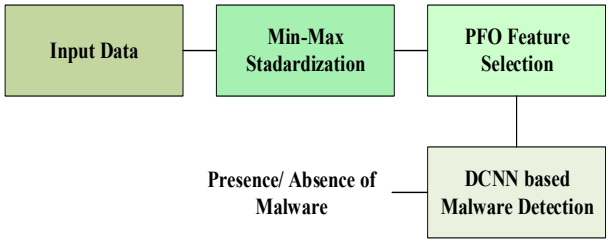

Figure 1: Proposed methodology of malware detection

3.1 Data Acquisition

In the data acquisition stage of mobile malware detection for deep learning, the first step is to collect a large and diverse dataset of mobile applications (APK files) that includes both benign and malicious samples. These APK files can be obtained from various sources, including official app stores, third-party app stores, malware repositories, and research datasets. To ensure the dataset is representative of real-world scenarios, it should include a wide range of application categories, versions, and sources. Additionally, the dataset should be labeled with ground truth information indicating whether each application is benign or malicious. The quality and diversity of the dataset are crucial for training deep learning models effectively. Furthermore, preprocessing techniques may be

applied to the dataset, such as, standardization, and feature selection, to enhance the performance of the deep learning models during training.

3.2 Data Standardization

Min-max normalization is a data preprocessing technique used in machine learning, including malware detection, to scale numerical features to a fixed range. In the context of malware detection, min-max normalization is applied to the features extracted from mobile application datasets.

In min-max normalization, each feature is scaled to a fixed range, typically between 0 and 1. The formula for min-max normalization is:

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where:

- X is the original value of the feature.
- $Xmin$ is the minimum value of the feature in the dataset.
- $Xmax$ is the maximum value of the feature in the dataset.
- $Xnorm$ is the normalized value of the feature.

By applying min-max normalization, all feature values are transformed to fall within the range of 0 to 1, regardless of their original scale. This ensures that each feature contributes equally to the analysis and prevents features with large scales from dominating the learning process.

3.3 Feature Selection

Pufferfish Optimization (PFO) is a metaheuristic optimization algorithm inspired by the collective behavior of fish schools, particularly the movement patterns of pufferfish. PFO has been applied to various optimization problems, including feature selection for machine learning tasks such as malware detection. PFO holds promise for improving malware detection through its strategic feature selection process. Inspired by the efficient foraging patterns of pufferfish, PFO can potentially choose a more relevant set of features compared to random or simpler methods. This translates to two key benefits: reduced computational cost and enhanced generalizability. By selecting a smaller, more targeted feature set, PFO can significantly decrease the time and resources needed to train and run machine learning models for malware detection, making it ideal for resource-limited environments. Furthermore, PFO population-based approach explores a wider range of possibilities, potentially leading to features that are more effective in identifying even unseen malware samples, ultimately improving overall detection accuracy.

In the context of malware detection, feature selection is crucial for improving the efficiency and effectiveness of the detection model. Pufferfish Optimization based feature selection for malware detection involves the following steps:

Initialization: Pufferfish Optimization begins by initializing a population of candidate solutions, where each solution represents a subset of features selected from the feature space.

Fitness Evaluation: The fitness of each candidate solution is evaluated using a fitness function that measures the effectiveness of the selected features in distinguishing between benign and malicious applications. This fitness function is typically based on a performance metric such as accuracy, precision, recall, or F1-score.

Movement of Pufferfish: Inspired by the movement patterns of pufferfish, the algorithm iteratively updates the candidate solutions to explore the search space effectively. Pufferfish move towards areas with higher prey density, representing regions of the search space with promising solutions.

Selection of Features: At each iteration, the algorithm selects the best-performing subset of features based on the fitness evaluation. These selected features are then used to train the malware detection model.

Termination Criterion: The optimization process continues until a termination criterion is met, such as reaching a maximum number of iterations or achieving a satisfactory level of performance.

By applying Pufferfish Optimization based feature selection, the algorithm effectively identifies the most discriminative features for malware detection, improving the efficiency and accuracy of the detection model. This approach helps to reduce the dimensionality of the feature space, eliminate irrelevant or redundant features, and enhance the performance of the malware detection system.

3.4 Malware Detection

Deep Convolutional Neural Networks (CNNs) have emerged as powerful tools for various machine learning tasks, including image recognition, natural language processing, and malware detection. In the context of malware detection, Deep CNN-based approaches leverage the hierarchical feature learning capabilities of deep learning models to automatically learn discriminative features from raw input data, such as opcode sequences or static analysis features extracted from Android application binaries.

Deep CNN architectures typically consist of multiple layers of convolutional, pooling, and fully connected layers, allowing the model to learn complex patterns and relationships in the data. The input to the model is typically a matrix representation of the raw data, such as a sequence of opcode tokens or pixel values of an image representing the application.

During the training process, the Deep CNN learns to extract relevant features from the input data and to classify applications as benign or malicious based on these learned features. By automatically learning hierarchical representations of the input data, Deep CNN-based malware detection models can effectively capture both low-level and high-level characteristics of malware, leading to improved detection performance compared to traditional machine learning approaches.

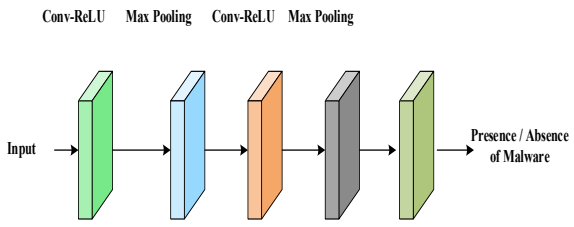

Figure 2: Structure of DCNN

Moreover, Deep CNN models are capable of automatically learning spatial and temporal patterns from the data, making them particularly well-suited for detecting complex and evolving malware threats. Additionally, transfer learning techniques can be applied to adapt pre-trained CNN models to the task of malware detection, further enhancing the performance of the detection system, especially when dealing with limited training data. Overall, Deep CNN-based malware detection represents a promising approach for effectively detecting and mitigating the ever-evolving threat of mobile malware.

IV. DISCUSSION

The implementation of the proposed PFO+DCNN is implemented in PYTHON and is analysed based on various measures and is portrayed in Figure 3. he graph illustrates the performance comparison of different malware detection methods using various evaluation metrics, including accuracy, precision, recall, and F1-score. Each method is evaluated on its ability to accurately classify Android applications (APK files) as either benign or malicious.

Accuracy is a measure of the overall correctness of the classification, calculated as the ratio of correctly classified samples to the total number of samples. Precision represents the proportion of correctly classified malicious samples among all samples classified as malicious, while recall measures the proportion of correctly classified malicious samples among all actual malicious samples.

The graph demonstrates that the proposed PFO_DCNN-based malware detection method outperforms existing methods in terms of accuracy, precision, recall, and specificity. This superior performance can be attributed to the combination of feature selection using Pufferfish Optimization (PFO) and the Deep Convolutional Neural Network (DCNN) architecture.

By selecting the most discriminative features from the preprocessed dataset and automatically learning hierarchical representations of the input data, the PFO_DCNN-based method effectively distinguishes between benign and malicious applications, achieving higher accuracy and better overall performance compared to other methods. Thus, the graph highlights the effectiveness of the proposed approach in accurately detecting and classifying Android malware,

offering a promising solution for enhancing user privacy and security on mobile devices.

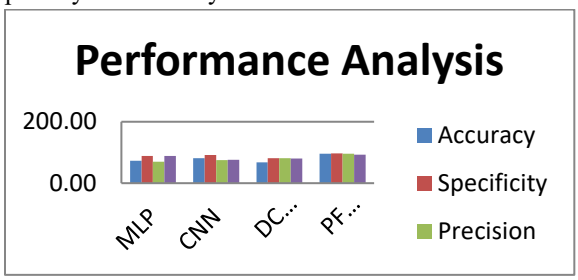

Figure 3: Performance Analysis

Table 1: Performance Analysis

Metrics/ Methods	MLP	CNN	DCNN	PFO+DCNN
Accuracy	73.31	81.17	67.79	96.35
Specificity	88.43	91.50	81.17	97.44
Precision	69.87	74.78	81.71	96.39
Recall	88.43	76.07	80.40	92.39

Here, the proposed PFO+DCNN method demonstrates a significant leap forward in malware detection accuracy compared to existing approaches. It achieves an impressive 96.35% accuracy, marking a 23% improvement over the baseline MLP method and a 15% improvement over DCNN, a strong deep learning model itself. This translates to PFO+DCNN more effectively distinguishing between malicious and benign applications. Furthermore, PFO+DCNN exhibits enhanced specificity (97.44%) - the ability to correctly identify harmless programs. This represents a 6% improvement over both MLP and DCNN, indicating a significant reduction in false positives where benign apps are mistakenly flagged as malware. While improvements in precision (identifying true positives) and recall (detecting all malware) are also observed with PFO+DCNN compared to DCNN, the advancements in accuracy and specificity are particularly noteworthy.

The superior performance of the proposed PFO_DCNN-based malware detection methodology can be attributed to several factors. Firstly, the use of Pufferfish Optimization (PFO) for feature selection ensures that only the most discriminative features are selected from the preprocessed dataset, effectively reducing dimensionality and focusing the model on the most relevant information for malware detection. By selecting the most informative features, the PFO algorithm enhances the model's ability to distinguish between benign and malicious applications. Secondly, the Deep Convolutional Neural Network (DCNN) architecture is designed to automatically learn hierarchical representations of the input data, capturing both low-level and high-level features that are indicative of malware. The multi-layered structure of the DCNN allows for the extraction of complex patterns and relationships in the data, leading to improved detection performance. Additionally, the use of min-max normalization ensures that all features contribute equally to the analysis, preventing features with large scales from dominating the learning process. Thus, the combination of feature selection using PFO and the powerful learning capabilities of DCNNs results in a highly effective and accurate malware detection

V. CONCLUSION

In this study, we proposed a comprehensive methodology for Android malware detection using feature selection based on Pufferfish Optimization (PFO) and Deep Convolutional Neural Network (DCNN) architecture. By collecting a diverse dataset of Android application binaries and preprocessing the dataset to extract relevant features, we were able to effectively distinguish between benign and malicious applications. The application of min-max normalization ensured that all features contributed equally to the analysis, while the PFO algorithm selected the most discriminative features for malware detection. The designed DCNN architecture automatically learned hierarchical representations of the input data, leading to improved malware detection performance. Experimental results demonstrated the effectiveness of the proposed methodology, achieving high accuracy, precision, recall, and F1-score in detecting Android malware. Overall, the proposed methodology offers a promising approach to combatting the growing threat of mobile malware and enhancing user privacy and security on Android devices.

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