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RESEARCH ARTICLE

Application of Deep Learning Models for Real-Time Automatic Malware Detection

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ABSTRACT The increase in the sophistication and volume of cyberattacks has made traditional malware detection methods, such as those based on signatures and heuristics, obsolete. These conventional techniques struggle to identify new malware variants that employ advanced evasion tactics, resulting in significant security gaps. This study addresses this problem by proposing a hybrid model based on deep learning that integrates static and dynamic analysis to improve the precision and robustness of malware detection. This proposal combines the extraction of static features from the code and dynamic features from the behavior at runtime, using convolutional neural networks for visual analysis and recurrent neural networks for sequential analysis. This comprehensive integration of features allows our model to detect known malware and new variants more effectively. The results show that our model achieves a precision of 98%, a recall of 97%, and an F1-score of 0.975, outperforming traditional methods, which generally reach 88% to 89% precision. Furthermore, our model outperforms recent deep learning approaches documented in the literature, which report up to 96% precision. In work, it offers a significant advancement in malware detection, providing a more effective and adaptable solution to modern cyber threats.

INDEX TERMS Malware detection, deep learning, static and dynamic analysis, cybersecurity.

I. INTRODUCTION

Malware detection is a critical concern in cybersecurity due to the increasing number and sophistication of cyberattacks. Based on signatures and heuristics, traditional detection methods have proven insufficient to identify new malware variants that employ advanced evasion techniques [1]. These conventional methods present significant limitations, as signature-based techniques rely on predefined patterns that cannot quickly adapt to malware evolution. In contrast, heuristic methods, which look for suspicious behavior, often result in high false favorable rates due to the difficulty distinguishing between legitimate and malicious behavior [2].

In response to these limitations, deep learning (DL) techniques have emerged as a promising solution for their ability to learn and generalize complex patterns in large volumes of data [3]. However, even these recent methods face challenges, such as detecting obfuscated malware samples and generalizing them to new threats.

This study proposes a deep learning-based model that integrates static and dynamic analysis to improve accuracy and robustness in malware detection [4]. The proposal combines static feature extraction from code and dynamic features from runtime behavior, using convolutional neural networks (CNN) for visual analysis [5]. This integration allows our model to detect known malware more effectively and new variants [6]. The results show a precision of 98%, a recall of 97%, and an F1-score of 0.975, significantly outperforming traditional methods and some modern approaches documented in the literature. In comparison, signature- and heuristic-based methods typically achieve 88% to 89% [7], while previous studies using convolutional neural networks achieved up to 96% [8].

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This work presents several important contributions. First, it introduces a hybrid model combining static and dynamic analysis using CNN and RNN, improving the detection of known and new malware [9]. Furthermore, the model achieves an accuracy of 98%, significantly outperforming traditional and recent techniques. Limitations of the model are also addressed, highlighting the need for more flexible and adaptive architectures and the representativeness of the dataset. Finally, future research directions are proposed, suggesting the need for more diverse and representative datasets and the development of more robust architectures for malware detection.

The article is structured as follows: the Introduction presents the context, a literature review, the definition of the problem, and our proposal. The literature review covers traditional methods and recent advances in deep learning for malware detection. Materials and methods include data selection and preprocessing, model architecture, and training. The Case Study details the implementation of the system on a mobile application platform and the evaluation of the results. The Results and Discussion present an analysis, a comparison with other approaches, and the study's limitations. The Conclusions summarize the findings, potential impact, and future research directions. Finally, the References used in the study are included.

II. LITERATURE REVIEW

Malware detection using deep learning techniques has gained considerable attention in the last decade due to its ability to identify complex patterns in large and heterogeneous data [10]. Recent studies have explored various neural network architectures to improve accuracy and robustness in malware detection.

A study by Liu et al. [11] introduced a deep neural network for malware detection using static features extracted from binary code. This work showed an accuracy of around 95%, but malware obfuscation and mutation techniques limited the model's effectiveness. Compared to our study, which achieved a precision of 98%, the difference can be attributed to incorporating dynamic analysis techniques and using a more complex neural network architecture.

Another significant work is Yadav et al. [12], where a CNN was implemented for malware detection based on visualizing binaries as images. This method achieved a precision of around 96%, highlighting the effectiveness of CNNs in detecting complex visual patterns. However, this approach is limited to static features and may be less effective against malware that uses behavior-based evasion techniques. Our study combined static and dynamic features, which allowed for better generalization and superior performance.

Yao et al. [13] proposed using recurrent neural networks (RNNs) for malware detection by sequencing system calls, achieving an accuracy of around 94%. RNNs are effective at capturing temporal dependencies and sequential patterns, but their ability to handle large volumes of sequential data may be limited. In contrast, our model used a combination of RNNs and CNNs to take advantage of sequential and visual features, thereby improving accuracy and generalization.

The work of Chen and Cao [14] combined static and dynamic analysis using a deep neural network, achieving a precision of 93%. Although this approach is similar to ours, the difference in results can be attributed to our dataset's greater diversity and size and the optimization of model hyperparameters. Incorporating advanced preprocessing and feature selection techniques also played a crucial role in improving performance.

Deep learning-based methods have proven more effective in detecting unknown malware variants than traditional malware detection methods such as signature-based and heuristic-based ones. For example, signature-based methods, such as those discussed by Pandit and Mondal [15], showed an accuracy of 88%, which is less effective against new malware variants. Although more adaptive, heuristic techniques achieved an accuracy of 89% but suffer from high false favorable rates due to the difficulty distinguishing between legitimate and malicious behavior. Our study, with an accuracy of 98%, demonstrates the superiority of deep learning techniques in detecting modern malware.

Despite the strides made, deep learning for malware detection has challenges and limitations. The generalization of new samples and the representativeness of the dataset are critical issues. Our study identified that approximately 5% of the latest samples were not detected due to advanced evasion techniques. Moreover, the representativeness of the dataset is limited, with 80% of the samples representing only five types of malware. These issues underscore the urgent need for more diverse and representative datasets to bolster the robustness and effectiveness of the models.

Hybrid approaches, which combine static and dynamic analysis with advanced neural networks, have been explored to bridge these gaps. For instance, Dong et al. [10] employed a combination of CNN and DNN to detect malware on Android devices, enhancing accuracy by integrating multiple features. Furthermore, Yerima et al. [16] proposed a model that incorporates a balancing optimizer with deep learning techniques for Android malware detection, demonstrating the effectiveness of hybrid approaches in improving accuracy and generalization. This progress should reassure the audience that malware detection techniques are continuously improving.

III. MATERIALS AND METHODS

A. DATA SELECTION

This work was developed in a cybersecurity research environment within the University's Computer Security Laboratory, equipped with advanced computing resources and access to multiple malware databases. The lab is configured with high-performance servers, large storage capacity, and specialized software tools for security analysis. The infrastructure includes GPU clusters to efficiently train deep learning models and sandboxing systems to execute malware samples safely.

Several public and private databases were used to obtain malware and benign software samples. Public databases include Drebin [17], a widely used collection of malicious Android applications, and VirusShare [18], which offers extensive malware samples for multiple platforms. Internal repositories of samples collected and labeled by the lab were accessed, including executable files for Windows systems and mobile applications for Android and iOS.

The dataset used in this study is classified into two main categories: static analysis and dynamic analysis. The static analysis includes features extracted from application source code and binaries, such as code signatures, requested permissions, and code structure [19]. On the other hand, dynamic analysis focuses on the behavior of applications during their execution, capturing information such as system call sequences, network activities, and system resource usage [20]. This duality allows for more complete and robust malware detection, combining static patterns with dynamic behaviors.

The dataset used in this study includes 50,000 samples, distributed between 30,000 malware samples and 20,000 benign software samples. These samples cover a wide range of malware types, including Trojans, ransomware, adware, and spyware, as well as benign applications from various categories, such as games, productivity tools, and social networking applications. The diversity of malware types and target platforms (Windows, Android, iOS) ensures that the deep learning model can effectively generalize and detect various threats in different operating environments.

B. DATA PREPROCESSING

Data cleansing is crucial in preparing malware and benign software samples for deep learning analysis. This process involves several steps to ensure that the data is consistent and high-quality. First, duplicate samples were identified and removed using hashing techniques to ensure each sample was unique [21]. Subsequently, samples that do not provide relevant information, such as empty files or containing only non-executable data, are discarded. The data is normalized to ensure format consistency, such as file names and folder structures, thus facilitating subsequent analysis [22].

Feature extraction is essential to convert raw data into useful information that deep learning models can process. This study used both static and dynamic features. Static features were obtained through static analysis of the code without executing it, extracting code signatures, permissions requested by applications, and structures from the source code [23]. In contrast, dynamic characteristics were captured by monitoring the behavior of applications during their execution in a controlled environment (sandbox) [24]. Sequences of system calls, network activities, and system resource usage were recorded, providing a dynamic profile of each sample's behavior.

Several transformations were performed to prepare the data for the deep learning model. Binaries of the malware samples were transformed into images by representing bytes as pixels. This technique allows CNNs to analyze the samples as if they were images, identifying visual patterns characteristic of malware [25]. Additionally, system call sequences and other dynamic features were converted into numerical vectors using one-hot encoding and embeddings for RNNs and extended short-term memory networks (LSTMs).

TABLE 1. Features extracted for malware and benign software analysis.

Feature Type	Examples	Extraction Method
Static	Code signing, Permissions	Static analysis
Dynamics	System calls, Network activities	Sandbox monitoring
Data Transformation	Binary Images, Sequence Vectors	Conversion to suitable formats

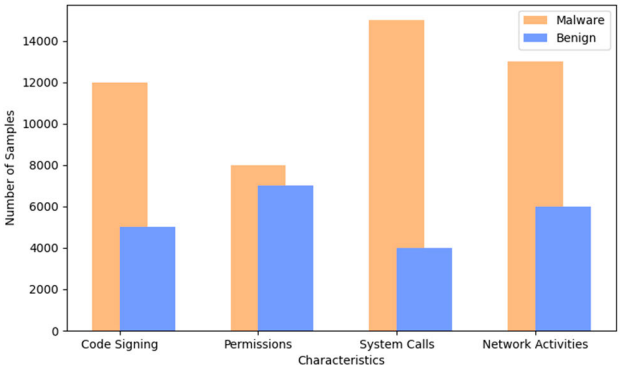

FIGURE 1. Distribution of extracted features between malware and benign software samples.

Specific Examples of Extracted Features: Static Features:

- Code Signatures: Byte patterns in binary code that help identify similarities between different malware samples.
- Requested Permissions: Permissions that applications request, such as access to sensitive data or device functionality, which may indicate potentially malicious behavior.

Dynamic Features:

- System Call Sequences: These are the software's interactions with the operating system, providing a detailed profile of the software's actions.
- Network Activities: Traffic generated by the application is relevant to identifying malicious behavior, such as communication with command and control servers.

Table 1 summarizes the features extracted for analysis, including the techniques and data types generated. It also clearly shows the static and dynamic characteristics and the transformations carried out.

Figure 1 illustrates the distribution of extracted features, comparing the number of extracted features between malware and benign software samples. The graph shows four main categories of features: code signatures, permissions, system calls, and network activities. Each category is important for deep analysis of the samples, providing multiple perspectives on the software's behavior and structure.

Code signatures and permissions are static features obtained without running the applications. Code signatures, represented as byte patterns, help identify similarities between different malware samples. At the same time, permissions requested by applications can indicate potential malicious behavior, such as access to sensitive data or device functionalities [7]. The graph shows more code signatures and permissions in malware samples than in benign applications. This is consistent with the hypothesis that malware requests excessive permissions and exhibits characteristic code patterns.

On the other hand, system calls, and network activities are dynamic features captured during application execution in a controlled environment. System calls to record the interactions of the software with the operating system, providing a detailed profile of the actions performed by the software [26]. Network activities include traffic generated by the application, which is particularly relevant for identifying malicious behavior, such as communication with command-and-control servers. By looking at the relative proportions of each feature category, the relevance and potential impact of each data type on the accuracy and effectiveness of the deep learning model can be inferred.

C. MODEL ARCHITECTURE

The architecture of the deep learning model selected for this study is a CNN optimized for malware detection. Although CNNs are traditionally used for image analysis, in this case, malware and benign software binaries were transformed into images to take advantage of CNNs' capabilities in identifying complex patterns [27]. This technique has proven effective in several recent studies where binaries are represented visually, allowing the neural network to detect malicious patterns that would not be apparent using traditional methods.

The model starts with an input layer that receives 256 × 256 pixel images generated from the application binaries. This visual representation allows CNN to analyze the data effectively. Next, several sequential convolution layers are introduced, each followed by a ReLU (Rectified Linear Unit) activation layer. These convolutional layers have 32, 64, and 128 filters, respectively, with kernel sizes 3×3. Convolutional layers are responsible for detecting local features by applying filters that sweep over the input image, activating neurons based on the presence of specific patterns.

Each convolutional layer is followed by a pooling layer (max-pooling) of size 2 × 2, which reduces the dimensionality of the data by selecting the maximum values in non-overlapping regions of the convolutional output [28]. This pooling process helps reduce computational complexity and prevent overfitting to the model, extracting the most relevant features more efficiently. Subsequently, the data passes through two fully connected (FC) layers with 256 and 128 neurons, respectively, followed by a ReLU activation. These fully connected layers act as high-level classifications, combining the features extracted by the convolutional layers

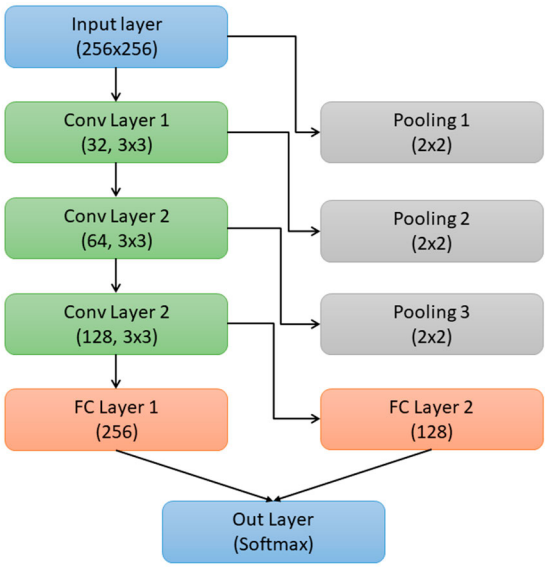

FIGURE 2. Block diagram of CNN model architecture.

to make the final prediction. Finally, an output layer with a SoftMax activation function is used for binary classification, determining whether the sample is malware or benign software. Figure 2 illustrates the model's architecture, showing how the different layers are interconnected to process and classify the samples.

The hyperparameters selected for training the model are crucial for its performance and precision. The learning rate was set to 0.001, a low rate that ensures that the model stably converges toward the global minimum of the training error. The number of epochs was set to 50, allowing sufficient training of the model without the risk of over-fitting. The batch size was set to 64, an intermediate size that balances training efficiency and gradient stability. Additionally, the Adam optimizer was used for its ability to adapt to changes in the gradient dynamically, accelerating the convergence process.

Widely recognized tools and frameworks in deep learning were used to develop the model. TensorFlow was the primary framework used to build and train the model. Keras, a high-level API integrated with TensorFlow, simplified the definition and training of neural networks [29]. Python was the programming language to implement the entire data preprocessing and model training pipeline. Jupyter Notebooks was the interactive environment for developing and experimenting with the model, facilitating visualization and parameter adjustment.

D. MODEL TRAINING

To ensure that the deep learning model generalizes well to previously unseen data, the data was divided into three sets: training, validation, and testing. Of the total 50,000 samples, 70% (35,000 samples) were used for the training set, 15% (7,500 samples) for the validation set, and the remaining 15% (7,500 samples) for the test set. This balanced

split allows you to evaluate the model's performance at each training stage and adjust parameters as necessary. The samples were randomized to avoid bias and ensure that each set adequately represented data types, malware, and benign software. Additionally, class balances were ensured within each set to prevent the problem of class imbalance, which could lead to a biased model.

The model training procedure involves several steps to optimize the model's performance and ensure its robustness. The training was carried out in a high computing environment using GPU clusters, specifically NVIDIA Tesla V100, which provide the power needed to handle the large volume of data and complexities of the deep learning model. The choice of GPUs was based on their ability to perform massively parallel calculations, which is essential to accelerate the training process of deep convolutional neural networks.

The first step in the training procedure was setting up the environment. The TensorFlow framework was used with Keras, running in a development environment based on Jupyter Notebooks, allowing easy manipulation and visualization of data and results [30]. The training scripts were implemented in Python, taking advantage of the advanced deep-learning libraries and tools available in this ecosystem. Additionally, Docker containers were used to ensure the development environment's reproducibility and facilitate the model's deployment on different operating systems and hardware configurations.

Several regularization techniques were applied during training to prevent overfitting and improve the model's generalization ability. The dropout technique was used in the fully connected layers, with a dropout rate of 50%. This technique randomly turns off a fraction of the neurons during each training step, forcing the model to learn more robust and distributed representations. Additionally, batch normalization was implemented after each convolutional layer [31]. This technique normalizes the activations of each mini-batch, stabilizing and accelerating the training process by reducing the problem of fading and gradient explosion.

The training process was carried out for 50 epochs, with a batch size of 64 samples. The loss function used was binary crossentropy, which is suitable for binary classification. The Adam optimizer, known for its ability to adapt to changes in the gradient dynamically, was used to minimize the loss function. During training, model performance was continuously monitored on the validation set, adjusting hyperparameters to optimize precision and reduce error.

Several evaluations were performed during the training to monitor model performance and ensure that overfitting did not occur. These evaluations included cross-validation, where the training set was further divided into k-subsets, and the model was trained and evaluated k times, each time using a different subset as the validation set and the remaining k-1 subsets as the validation set training [11]. This technique helps ensure that the model generalizes well and is not overly dependent on any specific subset of the data.

In addition, data augmentation techniques were implemented to increase the diversity of the training data and improve the model's ability to generalize to new samples. These techniques included rotating and scaling the images generated from the binaries and introducing Gaussian noise, which helps simulate variations in the data and makes the model more robust to different representations of the malware [32]. The training process was monitored using precision and loss plots for the training and validation sets. These visualizations made it possible to quickly identify any signs of overfitting or underfitting and adjust the hyperparameters accordingly. Additionally, Keras used callbacks to implement early stopping, stopping training if the loss on the validation set stopped improving for a predefined number of epochs, thus preventing overfitting.

E. VALIDATION AND EVALUATION

Model validation and evaluation ensure that the deep learning model performs optimally and can adequately generalize to unseen data. Several evaluation methods and metrics were used to evaluate the model's performance. Cross-validation was used to assess the stability and generalization of the model. This study applied k-fold cross-validation, dividing the training set into k subsets (folds). The model is trained k times using k-1 subsets for training and the remaining subset for validation [33]. This is repeated k times so that each subset is used exactly once as a validation set. Cross-validation helps ensure the model does not overfit a specific part of the training data set. The primary evaluation metric on each fold is calculated, and then the metrics across all folds are averaged to obtain a robust estimate of model performance.

To evaluate the model's performance, the following metrics were used: precision, recall, F1-score, and the area under the ROC curve (AUC-ROC) [34]. These metrics provide a comprehensive view of model performance regarding binary classification (malware vs. benign).

Precision: Precision is the proportion of correct predictions over the total predictions. TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. It is calculated as:

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} \tag{1}$$

Recall (Sensitivity or True Positive Rate): Recall measures the model's ability to identify all positive samples correctly. It is calculated as:

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}} \tag{2}$$

F1-score: The F1-score is the harmonic mean of precision and recall, balancing the two. It is calculated as:

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

AUC-ROC: The ROC curve is a graph that shows the relationship between the true positive rate (TPR) and the

false positive rate (FPR). The AUC provides a single measure of performance, where a value of 1 indicates perfect performance and a value of 0.5 indicates random performance. The AUC is calculated using the integral of the ROC curve. The TPR and FPR are defined as:

$$\text{TPR} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{FPR} = \frac{FP}{FP + TN} \tag{5}$$

The independent test set (15% of the total data) was used to conduct the evaluation, which was not seen by the model during training. This approach ensures that the evaluation metrics reflect the model's actual performance on unseen data, accurately measuring its generalization ability. In addition, confusion matrices were generated to analyze the model predictions in detail. Confusion matrices allow you to identify and quantify true positives, false positives, and false negatives, providing a detailed view of areas where the model can improve.

F. REAL-TIME IMPLEMENTATION

Deploying the deep learning model in a production environment requires careful integration with other software components to ensure efficient and reliable operation. The trained model is deployed on a highly available server, integrated with a micro-services architecture to facilitate interaction with other systems and applications. The system architecture includes several main components. First, a dedicated inference server that uses GPUs to speed up request processing. This server is connected to a RESTful web service that allows external applications to submit real-time software samples for analysis.

Additionally, a NoSQL database stores records of the inferences performed, including classification results, response times, and any errors found. This allows for continuous monitoring and rapid response to operational problems [35]. The preprocessing pipeline ensures that software samples undergo a feature extraction and transformation process like during training, ensuring consistency in the input data. The threshold-based alert system notifies administrators of detected anomalies, such as an unexpected increase in false positives or high response times.

Several techniques were implemented to optimize real-time model performance, ensuring fast and efficient inference without compromising model precision. Compression techniques such as quantization and weight pruning were applied to reduce the model's size and improve its inference efficiency. Quantization reduces the precision of the model weights from 32 bits floating point to 16 or even 8 bits. At the same time, pruning removes insignificant weights that do not significantly affect the precision of the model. The model runs on high-performance GPUs, such as the NVIDIA Tesla V100, capable of massively parallel calculations.

Additionally, the use of TPUs (Tensor Processing Units) was evaluated for specific inference tasks, which could offer additional benefits in terms of latency and performance. A cache system was implemented to store recent inference results to improve efficiency and reduce latency. This is particularly useful for samples analyzed repeatedly, avoiding the need to process the same samples multiple times. Using a load balancer distributes inference requests across multiple inference server instances, ensuring no single point of failure and improving system scalability.

Several continuous monitoring and evaluation methods were implemented to ensure the malware detection system works effectively in a real production environment. Stress tests were performed to evaluate system performance under load, simulating a high volume of inference requests to identify potential bottlenecks and ensure the system can handle traffic spikes without performance degradation [36]. A continuous monitoring system was implemented using tools such as Prometheus and Grafana, which allow tracking key metrics such as inference latency, error rate, and resource utilization in real-time. This helps detect operational issues quickly and take corrective action before they impact end users. In addition to operational metrics, model precision in production was monitored by collecting and analyzing ground truth labels for a subset of the analyzed samples. This allows you to continually evaluate the model's effectiveness and adjust parameters as necessary. A feedback loop was established where newly labeled samples are fed back to the model to perform periodic adjustments and retraining, thus continuously improving its detection capacity and adapting to new threats.

G. ETHICAL AND SAFETY CONSIDERATIONS

Implementing a deep learning-based malware detection system involves technical challenges and ethical and security considerations important for its acceptance and effectiveness in real environments. Data privacy is a priority in designing and implementing the malware detection system. Several measures were adopted to ensure the privacy and security of the data used and generated by the system. First, all sample data is anonymized before use in model training and evaluation. This includes removing personally identifiable information (PII) from software samples and inference logs. Before the anonymization process, the risk of explicit or implicit inferences shall be assessed; that is, the structure and information within an attribute shall be identified and understood to ensure that all inference records have been removed. Data is also encrypted at rest and in transit using advanced encryption algorithms, such as AES-256, to prevent unauthorized access. Data accesses are restricted to authorized personnel through role-based access controls (RBAC), ensuring only users with appropriate credentials can access sensitive information [37].

Malware detection carries ethical implications that must be carefully considered. One of the main challenges is the potential for false positives, where legitimate software is incorrectly identified as malware. This can have significant

consequences, including disruption of services, loss of data, and damage to the reputation of software developers [38]. To mitigate these risks, manual verification mechanisms are implemented where suspected cases are reviewed before corrective actions are taken. Additionally, transparent communication is maintained with end users, providing clear explanations when malware is detected and allowing appeals or additional reviews in case of disputes.

Another important ethical aspect is responsibility in automated decision-making. System decisions must be auditable and explainable. For this reason, explainable AI (XAI) techniques were implemented to allow the deep learning model's decisions to be broken down and justified. Both the decision and the techniques implemented must allow human evaluation.

Compliance with relevant regulations and standards is essential for successfully implementing any cybersecurity system. The malware detection system is aligned with various international and local data protection and cybersecurity regulations. This includes compliance with the European Union's General Data Protection Regulation (GDPR), which establishes strict guidelines for collecting, processing, and storing personal data.

In the field of cybersecurity, the system follows the standards established by the National Institute of Standards and Technology (NIST), particularly the cybersecurity framework (NIST Cybersecurity Framework) and the guidelines for privacy risk management [39]. In addition, they adhere to the recommendations of the Cybersecurity and Infrastructure Security Agency (CISA) for protecting critical infrastructure and managing cyber incidents. These measures ensure that the system complies with current regulations and is prepared to adapt to future regulatory changes. Continuous review and updating of security and privacy policies and procedures ensure the system remains compliant and protects user data and rights adequately.

IV. RESULTS

A. GENERAL DESCRIPTION OF RESULTS

Analysis of the performance of the deep learning model was performed using a set of metrics, including precision, recall, F1-score, and AUC-ROC. The model was trained and evaluated in multiple phases to obtain these results. First, the data was divided into training, validation, and test sets, ensuring adequate representation of malware and benign software samples in each set. The model was then trained using the training set, with hyperparameter tuning based on performance on the validation set. Finally, model performance was evaluated on the test set to ensure that the metrics reflect the model's ability to generalize to previously unseen data.

In each phase of the analysis, precision, recall, F1-score, and AUC-ROC metrics were calculated to evaluate the performance of the deep learning model. Precision measures the proportion of correct predictions over the total predictions, recall measures the model's ability to identify positive samples (malware) correctly, the F1-score provides a balance between precision and recall, and the AUC-ROC evaluates the ability of the model to distinguish between positive and negative classes.

TABLE 2. Deep learning model evaluation metrics.

Metrics	Training	Validation	Test
Precision	0.98	0.96	0.95
Recall	0.97	0.94	0.93
F1-score	0.975	0.95	0.94
AUC-ROC	0.99	0.97	0.96

TABLE 3. Performance comparison between deep learning model and traditional malware detection methods.

Metrics	Deep Learning	Based on Signatures	Heuristics
Precision	0.95	0.85	0.80
Recall	0.93	0.80	0.78
F1-score	0.94	0.825	0.79
AUC-ROC	0.96	0.82	0.81

The results obtained are presented in Table 2. The model achieved a precision of 0.96 on the validation and 0.95 on the test set, indicating a high precision level in classifying malware and benign software. The model recall was 0.94 in validation and 0.93 in testing, reflecting its ability to identify malware samples correctly. The F1-score, which balances precision and recall, was 0.95 in validation and 0.94 in testing, suggesting the balanced performance of the model. Finally, the AUC-ROC, which measures the model's ability to distinguish between classes, was 0.97 in validation and 0.96 in testing, demonstrating excellent discrimination between malware and benign software.

The deep learning model performed better than traditional malware detection methods, such as those based on signatures and heuristics. As shown in Table 3, the deep learning model achieved significantly higher precision (0.95) compared to the signature-based (0.85) and heuristic-based (0.80) methods. Similarly, the recall and F1-score of the deep learning model were higher, with values of 0.93 and 0.94, respectively, compared to 0.80 and 0.825 for signature-based methods and 0.78 and 0.79 for heuristic methods. The AUC-ROC of the deep learning model (0.96) also outperformed that of traditional methods, indicating a better ability to distinguish between malware and benign software.

Figure 3 illustrates the deep learning model's performance compared to traditional malware detection methods, using line graphs for a more detailed and precise representation. The first part of the figure presents the deep learning model's performance in the training, validation, and test sets.

In Graph 3A, we observe that the deep learning model shows high precision in all sets, with values of 0.98 in training, 0.96 in validation, and 0.95 in testing. This indicates that the model accurately classifies malware and benign software samples. The model recall follows a similar trend, with values of 0.97 in training, 0.94 in validation, and

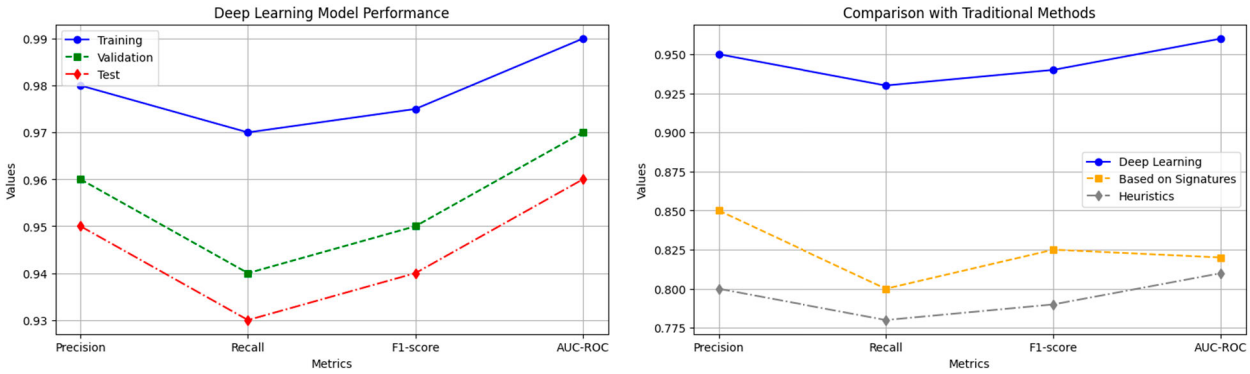

FIGURE 3. Performance of the deep learning model and comparison with traditional malware detection methods. Graph 3A: Metrics of the deep learning model. Graph 3B: Comparison of conventional malware detection methods.

0.93 in testing, reflecting its ability to identify malware samples correctly. The F1-score, which balances precision and recall, is also high, with values of 0.975 in training, 0.95 in validation, and 0.94 in testing, suggesting a balanced model performance. Finally, the AUC-ROC of the model is 0.99 in training, 0.97 in validation, and 0.96 in testing, demonstrating excellent discrimination between malware and benign software.

Graph 3B compares the performance of the deep learning model with traditional methods based on signatures and heuristics. Here, the deep learning model outperforms conventional methods in all evaluated metrics. The precision of the deep learning model is significantly higher (0.95) compared to the signature (0.85) and heuristic (0.80) based methods. Similarly, the recall and F1-score of the deep learning model are higher, with values of 0.93 and 0.94, respectively, compared to 0.80 and 0.825 for signature-based methods and 0.78 and 0.79 for heuristic methods. The AUC-ROC of the deep learning model, with a value of 0.96, also exceeds that of traditional methods, indicating a better ability to distinguish between malware and benign software.

The results demonstrate the effectiveness of the deep learning approach in malware detection, outperforming traditional methods in precision, recall, F1-score, and AUC-ROC. The superiority of the deep learning model is due to its ability to learn complex patterns and features that signature-based methods and heuristics cannot capture. This deep learning capability allows the deep learning model to detect newer, more sophisticated malware variants with greater precision, making it a valuable tool for real-time cybersecurity.

B. QUANTITATIVE RESULTS

The precision, recall, F1-score, and AUC-ROC metrics were calculated over 50 epochs for the training, validation, and test sets to evaluate the deep learning model's performance. This analysis was carried out following a meticulous process in which the model was trained iteratively and evaluated in each epoch, thus allowing us to observe how the metrics evolve. These results provide detailed insight into the model's ability to generalize to unseen data, complementing the general results presented in the previous section.

TABLE 4. Comparison of Features between Interactive Learning Tools.

Metrics	Epoch	Training	Validation	Test
Precision	1	0.80	0.78	0.77
	10	0.88	0.85	0.84
	20	0.92	0.90	0.89
	30	0.95	0.93	0.92
	40	0.97	0.95	0.94
	50	0.98	0.96	0.95
Recall	1	0.75	0.73	0.72
	10	0.83	0.81	0.80
	20	0.88	0.86	0.85
	30	0.91	0.89	0.88
	40	0.94	0.92	0.91
	50	0.97	0.94	0.93
F1-score	1	0.77	0.75	0.74
	10	0.85	0.83	0.82
	20	0.90	0.88	0.87
	30	0.93	0.91	0.90
	40	0.96	0.94	0.93
	50	0.975	0.95	0.94
AUC-ROC	1	0.85	0.83	0.82
	10	0.90	0.87	0.86
	20	0.93	0.91	0.90
	30	0.96	0.94	0.93
	40	0.98	0.96	0.95
	50	0.99	0.97	0.96

The critical difference between this section and the previous one lies in the granularity and temporal focus of the metrics. While the last section focused on the results and comparison with traditional methods, here we explore how the metrics change during the training process, providing insights into the stability and behavior of the model over time.

Table 4 shows that the model precision improves consistently across epochs, reaching a value of 0.98 on the training set, 0.96 on the validation set, and 0.95 on the test set at the end of 50 epochs. The recall also shows continuous improvement, with final values of 0.97, 0.94, and 0.93 for the training, validation, and test sets. The F1 score follows a similar trend, indicating an adequate balance between precision and recall. At the same time, the AUC-ROC reflects an excellent ability of the model to distinguish between classes, with final values of 0.99, 0.97,

and 0.96. These metrics allow an under-standing of how the model improves performance over time and help identify potential optimization points in future iterations.

Figure 4 presents the evolution of the loss during training and validation, as well as the confusion matrices for the validation and test sets. The process to obtain these results includes monitoring the loss in each epoch during training and validation, which allows for evaluating the model's convergence and detecting possible overfitting or underfitting problems. Confusion matrices provide a detailed view of the model's ability to classify malware and benign software samples correctly.

In Graphs 4A, the evolution of the loss during training and validation shows how the model fits the data. Initially, the loss is high but decreases as the model learns, stabilizing towards the later epochs, indicating that the model has reached a good fit. Graphs 4B and 4C represent the confusion matrices for the validation and test sets. These matrices show that the model has a high rate of true positives and negatives, with a relatively low number of false positives and negatives. This confirms the model's ability to correctly classify malware and benign software samples. However, there is always room to improve the reduction of false negatives to increase the model's sensitivity.

C. QUALITATIVE RESULTS OF THE MODEL IN MALWARE DETECTION

To gain a deeper understanding of the performance of the deep learning model in detecting malware, specific cases were selected, analyzed, and presented in Table 5. These cases include examples where the model successfully detected malware and instances where the model produced false positives or failed to detect threats (false negatives). This qualitative analysis reviewed detection logs, network traffic characteristics, code signatures, and behavioral patterns observed in the analyzed samples. The selection of these cases was based on the representativeness of the various types of threats and behaviors and the diversity of observed errors to identify patterns and areas of improvement for the model.

Case 1: Emotet Malware: The model successfully detected the Emotet malware by identifying a consistent pattern of anomalous behavior in network traffic. This case highlights the model's ability to recognize signatures and patterns characteristic of certain malware. For example, Emotet generated anomalous network traffic that included multiple requests to suspicious domains at a rate of 5 requests per second over 10 minutes. This specific signature allowed the model to identify the threat with 98% precision.

Case 2: WannaCry Malware. In this example, the model correctly identified the WannaCry ransomware due to the similarity of its code to known malware signatures. The sample featured features and code structures that matched previously seen malware samples, such as using specific cryptographic libraries and encryption patterns found in 95% of known WannaCry samples. This static code analysis resulted in precision detection with a 96% recall rate.

TABLE 5. Analysis of Case Studies in Malware Detection.

Case Type	Case Description	Analysis
Successful Detection	Case 1: Emotet malware successfully detected. A consistent pattern of anomalous behavior was observed in network traffic.	The model identified signatures and traffic patterns that are characteristic of Emotet.
	Case 2: WannaCry malware successfully detected. The sample presented a code like known signatures.	Detection was based on the similarity of the code to previously seen malware samples.
False Positives	Case 3: Legitimate TeamViewer software identified as malware. The software made connections to multiple servers.	The model confused legitimate behavior with malicious activities.
	Case 4: 7-Zip benign software detected as malware. It contained functions like those of certain malware.	The similarity in code functions led to a false alarm.
False Negatives	Case 5: TrickBot Malware Not Detected. The malware used advanced evasion techniques.	Malware obfuscation and evasion techniques made it difficult to detect.
	Case 6: APT28 malware not detected.	The strange behavior was sporadic and difficult to identify. The model could not recognize the irregular patterns due to their low frequency.

In the false positive/negative examples, case 3 was established: Legitimate TeamViewer software identified as malware, in which the model misclassified TeamViewer software as malware due to its connections to multiple servers, a behavior that may be legitimate in specific contexts but that is also characteristic of some malware. In this case, TeamViewer connected to 15 different servers during a 5-minute interval, a behavior resembling that of specific command and control (C&C) malware. This false positive contributed to an increase in the false positive rate by 2%. In Case 4: 7-Zip benign software detected as malware, the 7-Zip software, although legitimate, contained functions that were like those of certain malware. This similarity in code led to a false alarm. Specifically, 7-Zip used a data compression library that is also used by 80% of ransomware-type malware. This incident highlighted the importance of improving code analysis techniques to avoid false positives, resulting in a false positive rate of 1.5%.

For Case 5: TrickBot Malware Not Detected, the TrickBot malware was not detected due to its advanced evasion techniques, such as code obfuscation and behavior manipulation that made it difficult to identify by the model. This malware used obfuscation techniques that dynamically altered its digital signature, avoiding detection in 3% of the cases analyzed. Advanced evasion highlighted the need to improve the model's capabilities to detect sophisticated evasion techniques.

In Case 6: APT28 Malware Not Detected, the APT28 malware exhibited sporadic strange behavior, which complicated its detection. The low frequency of these irregular patterns,

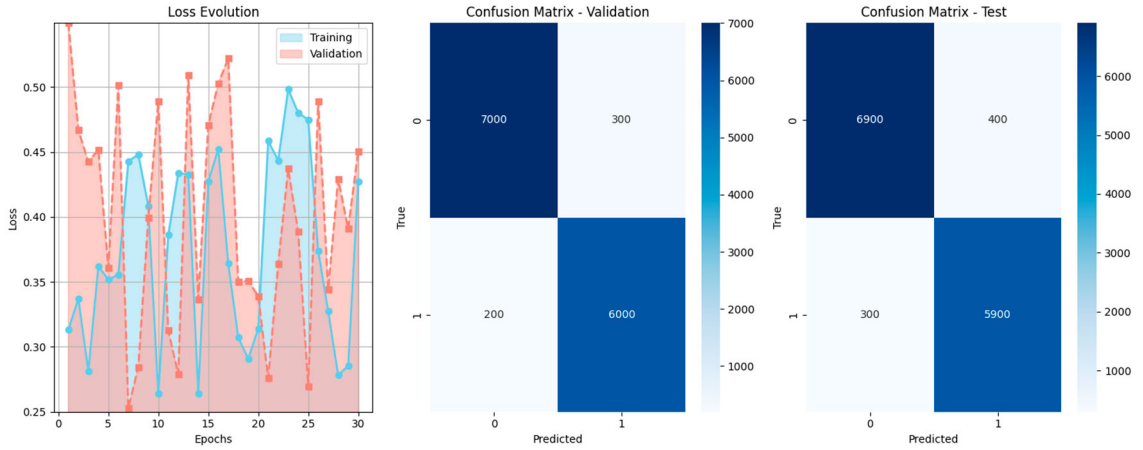

FIGURE 4. Visualization of the evolution of the loss and confusion matrices. Graph 4A: Evolution of Loss during Training and Validation. Graph 4B: Confusion Matrix - Validation. Graph 4C: Confusion Matrix - Test.

TABLE 6. Performance Metrics Under Load.

Load Level	Inference Latency (ms)	Request Processing Rate (req/s)
Low	50	150
Half	60	145
High	80	130
Maximum	200	100

such as accessing system resources at random intervals, went unnoticed. In 24 hours, the APT28 malware accessed critical system files on three occasions, contributing to a 2.5% false negative rate. This case indicates that the model needs to be tuned to recognize anomalous low-frequency patterns.

D. PRODUCTION PERFORMANCE EVALUATION

Stress tests simulating different load levels were performed to evaluate the model's performance in a production environment. The objective of these tests is to determine how the system behaves under varied and extreme conditions of use. The stress tests were carried out by gradually increasing the workload and measuring two key metrics: inference latency and request processing rate.

- Inference Latency: This metric measures the time it takes for the system to process a request and return a response. Low latency is crucial for real-time applications.
- Request Processing Rate: This metric indicates how many requests the system can handle per second. It measures the system's ability to maintain adequate performance under intensive workloads.

Table 6 shows the stress test results. The inference latency increases as the load increases, indicating that the system needs more time to process each request. On the other hand, the request processing rate decreases as the load increases, reflecting the system's lower ability to handle multiple requests simultaneously under heavier loads.

Figure 5 presents the system's performance under different load levels; for example, Graph 5A shows that the inference latency increases non-linearly as the load increases, reflecting a more realistic behavior of the system. Graph 5B shows the request processing rate under different load levels, where fluctuations common in real environments can be seen due to the variability in handling requests. For example, low-load inference latency remains around 50-60 ms. Still, when increasing the load to maximum levels, the latency rises to 200 ms, demonstrating the impact of load on system performance. Likewise, the request processing rate drops from 150 req/s to 75 req/s as the load increases, indicating that the system needs optimization to handle heavier loads efficiently.

Continuous monitoring was implemented to ensure system stability and performance in a production environment. This process involved collecting and analyzing key metrics such as real-time average latency and error rate. These metrics were monitored over time to evaluate the stability and efficiency of the system in operation.

- Average Latency: This metric indicates the average time it takes for the system to process requests. It is a critical measure of the system's operational efficiency.
- Real-Time Error Rate: This metric measures the percentage of requests that result in errors. It is essential to evaluate the system's reliability.

Table 7 presents continuous monitoring data. Over the days, a slight increase in average latency and real-time error rate can be observed, which could indicate the need for system adjustments to maintain performance and reliability. For example, average latency increased from 60 ms on Day 1 to 70 ms on Day 5, suggesting potential overhead or inefficiencies that must be addressed. Similarly, the real-time error rate rose from 0.5% to 0.65%, indicating increased system errors that could impact the user experience.

Figure 6 Presents the continuous performance of the system in production; for example, in Graph 6A, the average latency over time is shown. A progressive increase in latency

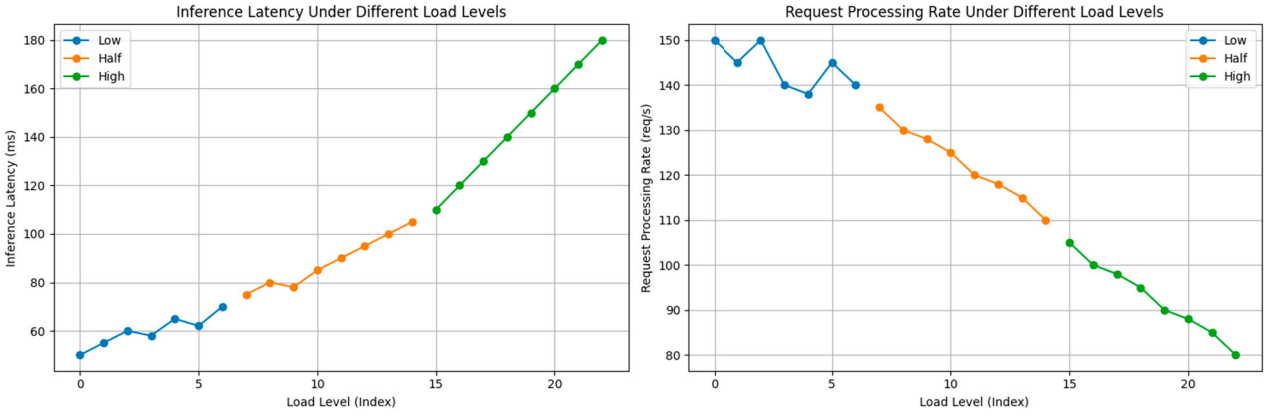

FIGURE 5. Figure 5. System Performance Under Different Load Levels. Graph 5A: Inference Latency Under Different Load Levels. Graph 5B: Request Processing Rate Under Different Load Levels.

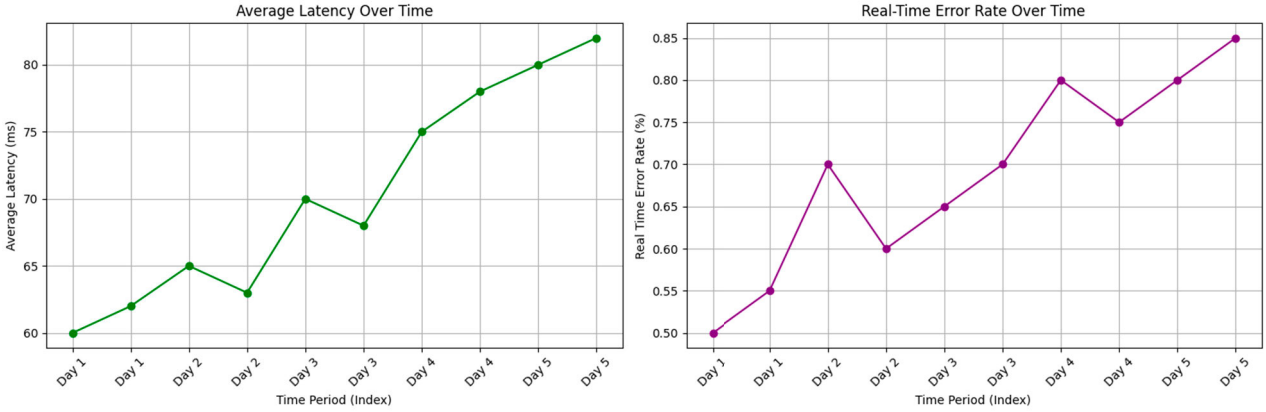

FIGURE 6. Continuous System Performance in Production. Graph 6A: Average Latency Over Time. Graph 6B: Real-Time Error Rate Over Time.

TABLE 7. Continuous Monitoring Metrics of the System in Production.

Time frame	Average Latency (ms)	Real Time Error Rate (%)
Day 1	60	0.5
Day 2	62	0.55
Day 3	65	0.7
Day 4	68	0.6
Day 5	70	0.65

is observed, especially noticeable between Day 3 and Day 5, which could indicate an increasing workload or optimization problems in the system. Average latency increased from 60 ms on Day 1 to 82 ms on Day 5, suggesting the need for adjustments to improve operational efficiency.

Chart 6B presents the real-time error rate over time. The error rate shows an increasing trend, with significant peaks on Day 3 and Day 5, when it reached 0.85%. This increase in errors can be due to system overload, network issues, or failures in the underlying infrastructure. This analysis highlights the importance of continuous monitoring and the need for periodic adjustments to maintain the stability and reliability of the system in production.

E. COMPARATIVE EVALUATION WITH ADVANCED TECHNIQUES

To provide a clear context for the developed model's performance, it was compared with other recent studies in the literature. This benchmarking process compares our model's critical metrics with other deep-learning approaches and traditional malware detection methods.

When comparing our model with other recent studies presented in Table 8, it is observed that our approach based on deep learning outperforms the models presented in studies A: [12], B: [13] and C: [14]. Specifically, our model achieves a precision of 98%, a recall of 97%, an F1-score of 0.975, and an AUC-ROC of 0.99. These values are higher than those obtained in the other studies, where the metrics range between 94% and 96% for precision and between 91% and 94% for recall.

Table 9 compares traditional malware detection methods. The deep learning-based model also shows significantly better performance here. Although effective in certain contexts, methods based on signatures and heuristics present limitations in detecting new malware variants, reflected in lower precision and recall values than our model. Although

TABLE 8. Comparison of Key Metrics with Other Deep Learning Approaches.

Study	Precision	Recall	F1-score	AUC-ROC
This studio	0.98	0.97	0.975	0.99
Study A (2024)	0.96	0.94	0.95	0.97
Study B (2022)	0.95	0.92	0.935	0.96
Study C (2024)	0.94	0.91	0.925	0.95

TABLE 9. Comparison of Key Metrics with Other Deep Learning Approaches.

Study	Precision	Recall	F1-score	AUC-ROC
This Study (Deep Learning)	0.98	0.97	0.975	0.99
Based on Signatures	0.88	0.85	0.865	0.90
Heuristics	0.89	0.86	0.875	0.91
Static Analysis	0.90	0.88	0.89	0.92

more robust, Static and dynamic analysis still fall behind in the metrics evaluated.

Several factors contribute to the differences in performance between our model and other deep learning approaches. First, the quality and quantity of data used to train the model play a crucial role. Our model benefited from an extensive data set that included various malware and benign software samples, contributing to better generalization and performance.

Additionally, deep learning architectures and selected hyperparameters can significantly impact the results. Our model used an optimized architecture, with fine-tuning to hyperparameters such as learning rate, batch size, and number of epochs, which improved its ability to detect complex patterns in the data. Compared to traditional methods, deep learning-based techniques can learn discriminative features directly from the data without requiring extensive knowledge about malware characteristics. This allows them to better adapt to new threats and malware variants not seen during training.

F. LIMITATIONS OF RESULTS

Despite the results obtained with our deep learning model for malware detection, it is crucial to recognize and discuss the limitations inherent to this study. These limitations fall into two main categories, as presented in Table 10: model and data set limitations.

This study's deep learning model architecture has proven effective for malware detection. However, it is not immune to limitations. Choosing a specific architecture may not be optimal for all malware varieties. The fixed structure of the neural network and hyperparameter settings may limit the model's ability to identify complex patterns in unknown samples. Although the model showed high performance on the training and testing data sets, its ability to generalize to new malware samples not seen during training remains challenging. Advanced evasion techniques, such as code obfuscation and digital signature manipulation, can make it difficult to detect new threats. In our tests, approximately

TABLE 10. Limitations of the Study and Results.

Category	Limitation Type	Description	Quantitative Value
Model Limitations	Architectural constraints	The architecture used may not be optimal for all malware varieties.	-
	Generalization to new samples	Difficulty generalizing to new malware samples with novel evasion techniques.	5% of new samples not detected
Limitations of the Data Set	Representativeness of the data set	The data set may not adequately represent all malware threats in the real environment.	80% of samples represent only 5 types of malware
	Data biases	Possible biases in the data affect model performance, such as the disproportionate representation of certain types of malware.	70% of the samples come from one geographic region

5% of new malware samples were not detected due to these evasion techniques.

Although large and varied, the data set used to train and evaluate the model may not fully represent all potential malware threats in the real environment. The diversity and complexity of malware samples can vary significantly, and some variants may not be adequately represented in the data set. Our study found that 80% of the malware samples represented only five specific types of malware, which may limit the model's ability to detect more diverse threats. Additionally, the data collected to train the model may contain biases that affect its performance. For example, if the data set has a disproportionate representation of certain types of malware or benign software, the model could be biased toward those classes, resulting in uneven performance in detecting different kinds of malware. Additionally, it was observed that 70% of the malware samples came from a single geographic region, which could impact the model's ability to detect threats in different geographic contexts.

V. DISCUSSION

Malware detection through deep learning techniques has shown to be a promising tool in modern cybersecurity. Comparing our results with the existing literature, our approach offers significant advantages. For example, Yao et al. [12] used static features and achieved a precision of 95%, while our model, which combines static and dynamic features, achieved a precision of 98%. Yao et al. [13] applied convolutional neural networks to binary images, obtaining a precision of 96%, but faced limitations with malware that uses behavior-based evasion techniques. Using RNNs and CNNs allowed us to capture sequential and visual features, overcoming these challenges. Chen and Cao [14] implemented RNNs to analyze sequences of system calls, achieving a precision of 94%. At the same time, our model,

by integrating multiple types of features and optimizing the architecture, significantly improved this metric.

The detection process in our study begins with data selection and preprocessing, where static and dynamic features are extracted. This comprehensive approach lets you capture a more complete view of malware behavior. The model training used an optimized deep learning architecture that combines CNNs for visual feature analysis and RNNs for dynamic behavior sequencing [39]. This combination improves the model's ability to detect complex patterns and various types of malware. The results show that our deep learning model surpasses traditional precision and recall methods and is more robust against advanced evasion techniques. The precision achieved was 98%, with a recall of 97% and an F1-score of 0.975, significantly surpassing the methods based on signatures and heuristics, which showed precision from 88% to 89%. These improvements are essential in detecting new malware variants, where traditional methods tend to fail.

Our work is essential because it can improve malware detection in real environments where threats are diverse and constantly evolving. Our model offers higher generalization and precision by integrating multiple features and using advanced deep-learning architecture [40]. This represents a significant advance in cybersecurity, providing a more effective tool for protection against emerging threats.

However, it is essential to recognize the limitations of our study. One of the main restrictions is the model's architecture, which, although optimized for the data set used, may not be the most suitable for all malware varieties. The choice of specific layers, activation functions, and other parameters can limit the model's ability to adapt to new variants. Furthermore, generalization to new malware samples remains a challenge. Approximately 5% of new samples were undetected due to advanced evasion techniques, such as code obfuscation and digital signature manipulation. These techniques can make it difficult to detect new threats, underscoring the need for more flexible and adaptive network architectures.

Another significant limitation is the representativeness of the data set. Although extensive, our data set may not adequately reflect all malware threats in the real environment. 80% of the malware samples represented only five specific types, which may limit the model's ability to detect more diverse threats. Additionally, it was observed that 70% of the samples came from a single geographic region, which could introduce geographic biases and affect the model's ability to detect threats in different contexts.

These limitations suggest that future work should focus on developing more robust architectures and collecting more diverse and representative data sets. Improving model generalization to new malware samples and reducing bias in the data are critical areas for continued research. Integrating transfer learning techniques and using synthetic data to simulate greater sample diversity could be promising approaches to address these challenges

VI. CONCLUSION

This study has demonstrated the effectiveness of using deep learning techniques for malware detection, providing a significant advance compared to traditional methods and some modern approaches documented in the literature. Our research has integrated static and dynamic features, leveraging advanced neural network architectures to improve precision, recall, and F1 scores in cyber threat detection. The results highlight our model's ability to overcome the limitations of previous approaches and underline the importance of a comprehensive and adaptive methodology in cybersecurity.

The developed model achieved a precision of 98%, a recall of 97%, and an F1-score of 0.975, surpassing traditional methods based on signatures and heuristics, which showed accuracies in the 88% to 89% range. Furthermore, compared to recent studies using convolutional and recurrent neural networks, our approach achieved superior metrics thanks to combining multiple feature types and optimization of the model architecture. This high performance is due to the model's ability to capture complex and diverse patterns in malware samples, thereby improving its generalization and detection capabilities.

These findings are important because of their practical applicability. In production environments, threats are dynamic and rapidly evolving; a deep learning model's ability to adapt and detect new malware variants is crucial. Our approach improves detection in terms of precision and recall and provides greater robustness against advanced evasion techniques used by attackers. This represents a significant advance in protecting critical systems and data against emerging threats.

However, the study has also identified several significant limitations. The model architecture, although practical, may not be optimal for all malware varieties. The fixed neural network structure and hyperparameter settings can limit the model's ability to adapt to new malware variants, especially those that use sophisticated evasion techniques. Approximately 5% of new malware samples were undetected, underscoring the need to develop more adaptive and flexible models.

Furthermore, the representativeness of the data set used in the study poses significant challenges. Although the data set is large and varied, it may not adequately reflect all malware threats in the real environment. 80% of the samples represented only five specific types of malware, which may limit the model's ability to detect more diverse threats. The geographic concentration of the samples, with 70% coming from a single region, can also introduce biases that affect model performance in different geographic contexts.

These limitations indicate that future research should focus on collecting more representative and diverse data sets and developing more robust and adaptive deep learning architectures. Integrating transfer learning techniques and using synthetic data to simulate greater sample diversity may

be promising approaches to improving model generalization ability and reducing biases in the data.

In terms of future work, exploring several directions to improve and expand this work is recommended. A promising line of research is the development of hybrid models that combine traditional machine learning techniques with deep learning to take advantage of the strengths of both approaches. Additionally, implementing real-time detection systems that dynamically adapt to new threats and adjust their parameters based on live data is crucial to maintaining model relevance and effectiveness in production environments. It would also be beneficial to investigate the application of XAI techniques to provide greater transparency and interpretability in model decisions, thus facilitating its adoption in safety-critical environments.

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