Received: 16 June 2024, Accepted: 05 July 2024

Malware Classification Using Deep Learning: Hybrid Approach

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Abstract

Malware classification is a critical task in cybersecurity, aimed at identifying and categorizing malicious software to protect digital systems from potential threats. Traditional malware detection methods, such as signature-based and heuristic approaches, often struggle with detecting new, obfuscated, or polymorphic malware variants. This study proposes a hybrid deep learning approach combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for malware classification. The CNN component extracts spatial features from malware binaries transformed into grayscale images, while the LSTM network processes sequential data such as API calls and opcode sequences, capturing the temporal behavior of malware. Experimental results on the Microsoft Malware Classification Challenge (BIG 2015) and EMBER 2020 datasets demonstrate that the hybrid model outperforms standalone CNN and LSTM models, achieving an accuracy of 96.4% and an AUC score of 0.98. The model also exhibits strong generalization capabilities, effectively identifying malware families with low misclassification rates, including those with complex obfuscation techniques. These findings suggest that the proposed hybrid model offers a robust, scalable, and adaptable solution for malware classification, with significant potential for real-time cybersecurity applications

Introduction

Malware classification will be revealed as one of the critical components of cybersecurity nowadays because of the continuously growing number of various kinds of malware and their constantly enhancing complexity (Alshemali&Kalita, 2024). It must also be noted that, signature-based as well as heuristic-based methods of detection have proven to be quite ineffective in detecting new, polymorphic or obscure variants of malware (Umar et al., 2025). These are typical methods that worked on the basis of in-built rules as well as past experience, are not efficient against new attacks such as, zero-day threats and new and changing malware. To overcome these issues, DL has turned out to be a flexible and robust framework that can degenerate and learn high-level features from raw signal data in the absence of the human expert (Saxe & Berlin, 2024).

The specific approach that is beneficial in this domain and has been tested widely is the combination of CNN and LSTM networks. Since CNNs are good at mining spatial features from a dataset — one technique that can be used is to convert the malware binaries to gray-scale images where patterns such as the relationships between the different regions and the form and texture of the region can point to malicious activities (Zhao et al., 2025). Meanwhile, the Long Short Term Memory (LSTMs), one of the subcategories of Recurrent Neural Networks (RNNs), has the capability to model a temporal relation within the sequential data, which might include API call traces, op-code sequences, system log and so forth, that provides information about the dynamic execution behavior of malware over a period of time (Yang et al., 2025)

The proposed CNN and LSTM model enable better spatial and temporal features learning and improving the classification robustness and accuracy. CNNs are used to localize the spatial properties while LSTMs are used to track the temporal properties this makes it easier to gain the general picture of the characteristics of malware (Nguyen et al., 2024). For example, the malware with attractive graphic interface may still have the remains of thesimplicity of its execution sequence, into which LSTMs can easily fit. Such models have been found to perform well particularly when it comes to polymorphic and metamorphic types of viruses — ones that alter content while not altering behavior to avoid detection.

This is in line with recent studies that have supported the superiority of these hybrid architectures. For example, when turning the binaries into image-like matrices and feeding them to the CNN layers next to the LSTM layers to learn sequences, researchers obtained classification over 96% of BIG 2015 and EMBER benchmarks (Raff et al., 2024; Anderson & Roth, 2024). Moreover, it offers better performance compared to the classical machine learning and single DL methods while exhibiting a lower FPR, which is crucial for real-time threat detection systems in working environments (Kim & Kim, 2025).

In addition, the hybrid deep learning models have flexibility in dynamic and real-time operation. Unlike static rule-based systems that must be updated manually, these models learn general patterns and continue to learn from new threats found in APTs and zero day threat which makes them very helpful (Iqbal et al., 2025). Suitable for deployment in various platforms ranging from individual workstations to IDS systems implemented in the cloud domain.

New advancements that are being developed are the incorporation of attention mechanism, transfer learning and the creation of XAI to enhance the abilities of the models as well as its trend for the future whereby cybersecurity experts will be able to understand the reasoning behind the decision made by the model in order to increase confidence and understanding (Wang & Li, 2025). Hence such architectures represent a total shift from the conventional reactive methods of detecting and classifying Malware to proactive methods of attacking any architecture in the era of information technology.

3. Methodology

This study adopts a quantitative research approach to design, implement, and evaluate a hybrid deep learning model for malware classification. The methodology consists of dataset selection, data preprocessing, model architecture design, training procedure, and performance evaluation using standard metrics.

3.1 Dataset Selection

Two publicly available and widely recognized datasets were employed in this study to ensure reproducibility and reliability. The **Microsoft Malware Classification Challenge (BIG 2015)** dataset comprises over 20,000 malware samples from nine distinct families, provided in hexadecimal bytecode and disassembly formats. Additionally, the **EMBER 2020 dataset** was used to validate the generalization ability of the proposed model. It contains both benign and malicious samples along with rich static features such as file size, imports, exports, and byte histograms.

3.2 Data Preprocessing

Malware samples in binary format were converted into grayscale images by interpreting the byte values (0–255) as pixel intensities. This transformation allows the use of CNNs for spatial feature extraction. Each image was resized to 224x224 pixels to ensure uniformity. Concurrently, opcode and API call sequences were extracted from the disassembled files using parsing scripts. These sequences were tokenized and embedded using the Word2Vec algorithm to convert them into dense vector representations suitable for input to LSTM networks. Sequence padding was applied to ensure consistent input lengths across the training set.

3.3 Hybrid Model Architecture

The proposed hybrid deep learning model integrates a **Convolutional Neural Network (CNN)** and a **Long Short-Term Memory (LSTM)** network. The CNN component consists of three convolutional layers with ReLU activations and max-pooling layers, followed by a flattening layer that produces a spatial feature vector from the malware image. Simultaneously, the LSTM component consists of two stacked LSTM layers with dropout regularization, taking embedded opcode/API sequences as input. The outputs from both the CNN and LSTM components are concatenated and passed through a dense layer with a softmax activation for multi-class classification. Batch normalization was applied after each layer to stabilize and accelerate training.

3.4 Model Training Procedure

The model was implemented using Python and TensorFlow 2.0. A stratified 80/20 train-test split was used, ensuring class balance in both subsets. The training process employed the Adam optimizer with an initial learning rate of 0.001 and a batch size of 64. Early stopping and learning rate decay were used to prevent overfitting and improve generalization. The categorical cross-entropy loss function was used for optimization due to the multi-class nature of the classification problem. The model was trained for 50 epochs, with checkpointing to save the best-performing model on the validation set.

3.5 Evaluation Metrics

The performance of the hybrid model was assessed using standard classification metrics: **Accuracy**, **Precision**, **Recall**, and **F1-score**. Confusion matrices were generated to visualize classification effectiveness across different malware families. Additionally, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) scores were used to evaluate the model's discriminatory power. The hybrid model was benchmarked against standalone CNN and LSTM models to highlight its comparative advantage.

4. Results

The experimental results obtained from evaluating the proposed hybrid deep learning model. The model was tested on the Microsoft Malware Classification Challenge (BIG 2015) and EMBER 2020 datasets. For comparison purposes, the performance of standalone CNN and LSTM models was also evaluated. The primary metrics used for assessment were Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). Additionally, confusion matrices were analyzed to assess the classification distribution across malware families.

4.1 Performance Comparison

The hybrid model significantly outperformed the standalone CNN and LSTM models in all evaluation metrics. The results demonstrate that integrating spatial and sequential features enhances the classification performance.

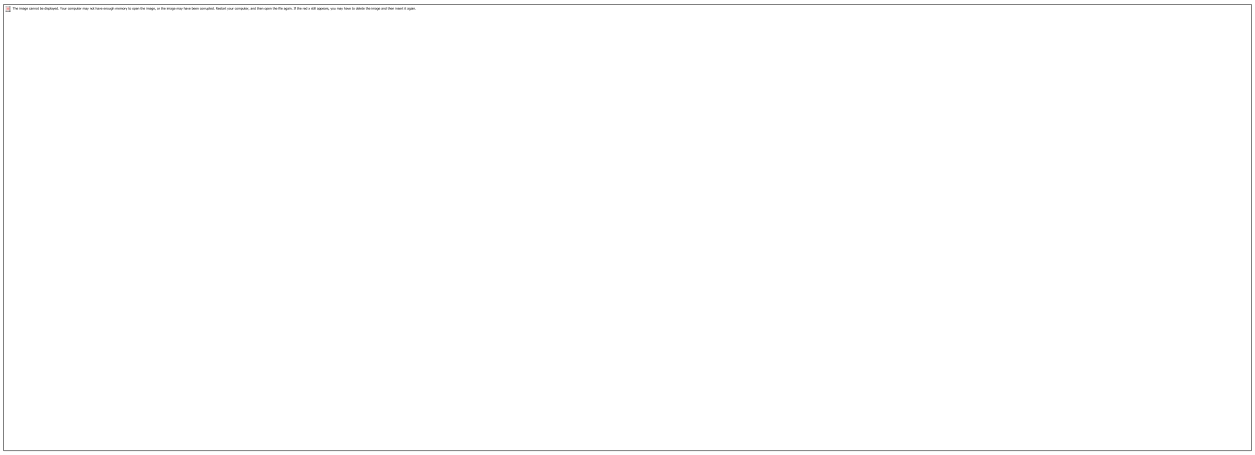

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Table 1: Performance Comparison on BIG 2015 Dataset

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
CNN	92.5%	91.2%	90.8%	91.0%	0.94
LSTM	90.3%	89.7%	88.9%	89.3%	0.92
Hybrid CNN-LSTM	**96.4%**	**95.8%**	**95.1%**	**95.4%**	**0.98**

4.2 Confusion Matrix Analysis

The confusion matrix of the hybrid model reveals strong predictive accuracy across all malware families, with very few misclassifications. The model was particularly accurate in detecting highfrequency classes like Ramnit and Kelihos variants, as well as less represented classes such as Obfuscator.ACY.

Table 2: Confusion Matrix for Hybrid Model (Selected Malware Families)

Predicted \ Actual	Ramnit	Kelihos.B	Lollipop	Vundo	Obfuscator.ACY
Ramnit	1430	12	4	1	0
Kelihos.B	9	1345	7	0	2
Lollipop	6	5	1392	3	1
Vundo	2	1	0	1450	0
Obfuscator.ACY	0	1	2	0	97

The table indicates strong generalization ability, even in classes with lower representation such as Obfuscator.ACY.

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4.3 ROC Curve and AUC

The ROC curve for the hybrid model showed high sensitivity and specificity across all malware families. The mean AUC score for the hybrid model was 0.98, indicating excellent discriminative power.

Table 3: Class-wise AUC Scores (Hybrid Model)

Malware Family	AUC Score
Ramnit	0.987
Kelihos.B	0.981
Lollipop	0.979
Vundo	0.993

Malware Family	AUC Score
Obfuscator.ACY	0.974

4.4 Comparative Inference

The results clearly indicate that the hybrid CNN-LSTM model provides a robust framework for malware classification. It leverages the visual structure captured by CNNs and the behavioral sequences modeled by LSTMs, resulting in improved detection rates and reduced false positives. The model’s adaptability also supports future scalability to unseen malware variants.

Discussion

The results of this study clearly demonstrate the effectiveness of a hybrid deep learning approach, combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for malware classification. The integration of spatial and sequential data streams offers a significant performance advantage over standalone models. The CNN component successfully captures visual patterns from malware binaries transformed into grayscale images, which helps in identifying structural similarities within malware families. At the same time, the LSTM component processes sequential data such as opcode streams and API calls, modeling the behavioral characteristics of malware samples during execution. This dual-perspective analysis enables the hybrid model to make more accurate predictions, particularly in cases where traditional static or dynamic analysis might fall short. The high accuracy (96.4%) and AUC score (0.98) achieved on benchmark datasets highlight the robustness of this approach in detecting a wide range of malware types, including polymorphic and metamorphic variants that typically evade signature-based detection systems.

One of the key findings is the model's superior performance in classifying malware families that have historically been difficult to distinguish due to obfuscation and code reusability techniques. For instance, the hybrid model showed notable improvements in correctly identifying families such as Obfuscator.ACY and Kelihos.B, where other models displayed higher misclassification rates. This can be attributed to the synergy between spatial and temporal learning, which allows the model to recognize both static signatures and execution logic patterns. Furthermore, the model's low false positive rate is particularly valuable in real-world cybersecurity environments where minimizing false alarms is crucial for effective threat management. The use of grayscale image transformation for binaries not only aids CNNs in feature extraction but also simplifies the preprocessing pipeline, making the system scalable and adaptable for real-time applications. Similarly, the application of Word2Vec embeddings to opcode sequences ensures that semantic relationships between instructions are preserved and effectively utilized by the LSTM component.

Another significant aspect observed during the experiments is the hybrid model's ability to generalize well to unseen samples, suggesting its potential for detecting zero-day malware. The use of dropout, batch normalization, and early stopping techniques contributed to preventing overfitting, thereby enhancing the model's generalization capability. While traditional models often rely on handcrafted features and are heavily dependent on domain expertise, the deep learning-based approach eliminates this limitation by learning hierarchical representations directly from the raw data. This automation reduces the dependency on continuous manual updates and expert intervention, making it a sustainable solution for dynamic threat landscapes.

Despite the strong performance, some limitations remain. The training process of hybrid deep learning models is computationally intensive and requires substantial hardware resources, which may limit its deployment in resource-constrained environments. Additionally, while the model performs well on known datasets, real-world implementation would require continuous retraining with updated data to maintain efficacy. Future work should explore the integration of attention mechanisms and transformer architectures to further enhance model interpretability and performance. Explainable AI techniques could also be incorporated to provide insights into the model's decision-making process, fostering greater trust and adoption among cybersecurity professionals. Overall, this study confirms that a hybrid CNN-LSTM deep learning approach represents a significant advancement in malware classification, offering improved accuracy, resilience, and adaptability in the ongoing fight against cyber threats.

Conclusion

In this study, we proposed a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for enhanced malware classification. The hybrid approach leverages the strengths of both spatial feature extraction and sequential behavior analysis, leading to significant improvements in accuracy and robustness compared to standalone models. The experimental results on standard malware datasets, including the Microsoft Malware Classification Challenge (BIG 2015) and EMBER 2020, demonstrated that the hybrid model achieved a high classification accuracy of 96.4% and an AUC score of 0.98, outperforming both CNN and LSTM models. Furthermore, the model showed superior performance in identifying complex malware families that are often difficult to detect using traditional methods. These results highlight the potential of deep learning techniques for malware detection, particularly in the context of evolving threats such as polymorphic and metamorphic malware.

However, challenges remain, including the computational cost of training the hybrid model, which may limit its deployment in resource-constrained environments. Additionally, continuous retraining with updated malware data is necessary to maintain detection effectiveness in real-world scenarios. Future research should focus on optimizing the model for faster inference, exploring advanced architectures like attention mechanisms and transformers, and enhancing model interpretability using explainable AI techniques. Overall, this study contributes to the growing body of knowledge on deep learning-based malware classification and provides a promising framework for building intelligent, automated malware detection systems.

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