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Lightweight Deep Learning Model For Ransomware Detection

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Abstract: The proposed project is a Ransomware Detection System developed using Python, TensorFlow/Keras, Pandas, and NumPy. It employs lightweight deep learning models, specifically a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN), to accurately detect and classify Ransomware samples while remaining suitable for resource-limited environments. The MLP model captures nonlinear feature interactions, while the CNN model processes feature vectors as sequences to extract local patterns. Together, these architectures enable robust Ransomware detection with high accuracy and efficiency. To enhance performance, the system incorporates feature selection using mutual information, reducing input dimensionality while preserving critical information. The models are trained and evaluated on a balanced Ransomware dataset, with results measured using Accuracy, Precision, Recall, F1-score, and ROC-AUC. Additionally, a generalization test is performed using a hold-out subset of unseen Ransomware samples, demonstrating the models' ability to adapt to novel attack variants. By combining lightweight deep learning architectures with effective preprocessing, this proposed system provides practical and efficient solution for Ransomware detection in resource-constrained environments such as IoT devices, mobile systems, and embedded platforms.

Index Terms - Ransomware Detection, Cyber security, Lightweight Deep Learning, Convolutional Neural Network (CNN), Multi-Layer Perceptron (MLP), Feature Selection, Efficient Classification, Resource-Constrained Systems, Generalization, Binary Classification.

I. INTRODUCTION

Cyber security has become a critical concern in today's digital era, with cyber-attacks growing in scale, frequency, and sophistication. Organizations and individuals alike face constant threats such as malware, phishing, denial-of-service attacks, and data breaches. Traditional signature-based detection methods often struggle to identify new or evolving attacks, leading to a pressing need for more intelligent and adaptive solutions. In order to overcome this difficulty, we introduce an Attack Detection System, which makes use of deep learning methods to classify network traffic into normal and malicious. The suggested system employs a hybrid CNN-LSTM model, in which Convolutional Neural Networks (CNNs) are applied to derive spatial information in the input data, and Long Short-Term Memory (LSTM) networks are applied to derive temporal patterns. The combination of this allows the model to be able to detect both the static and temporal patterns in network traffic. The system is combined with a Flask-based web application that enables users to upload CSV files with network records to detect attacks in real-time. predictions and graphical representation of the results. A MySQL database is used for secure storage of user information and uploaded files, ensuring data management and accessibility. The system offers scalable and efficient intrusion detection solution by integrating deep learning algorithms with an interactive web interface. It will contribute to improving

cybersecurity through providing high-accuracy predictions and being open to researchers, developers, and organizations interested in improving their network defenses.

II. PROPOSED APPROACH

This proposed system of lightweight DL architectures, specifically a Multi-Layer Perceptron (MLP) and a Convolutional Neural Network (CNN), for efficient Ransomware detection. This process takes place with data preprocessing, where the dataset is cleaned, categorical values are encoded, and numerical features are normalized using robust scaling to ensure consistency. To further improve efficiency, feature selection based on mutual information is applied, reducing the dimensionality of the dataset while retaining the most informative attributes. The preprocessed data is then used to train two complementary deep learning models. The MLP model consists of fully connected layers that capture complex non-linear interactions among input features, enabling effective classification of benign and malicious instances. In parallel, the CNN model processes feature vectors by applying 1D Convolutional layers, which extract local sequential patterns and learn discriminative representations of Ransomware behavior. The Convolutional feature maps are passed through pooling and dense layers, with a sigmoid activation function used in the final output layer for the binary classification. Both models are trained on a balanced Ransomware dataset, with performance evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC. To test adaptability, a generalization experiment is conducted by holding out a subset of unseen Ransomware samples during training. This ensures the models are capable of detecting novel Ransomware variants beyond the training distribution. By focusing on lightweight architectures and feature selection, the proposed system achieves high detection accuracy while remaining computationally efficient. This makes it suitable for deployment in resource-constrained environments such as IoT devices, embedded platforms, and mobile systems, where Ransomware threats are increasingly prevalent.

III. METHODOLOGY

A. **Dataset**

The dataset used for training and evaluating the proposed ransomware detection model consists of balanced ransomware and benign samples collected from publicly available repositories such as VirusShare, Malimg, and Kaggle Ransomware datasets. Each sample was converted into a numerical representation using extracted static and dynamic behavioral features, including API calls, file entropy, opcode sequences, and registry modifications. The final dataset comprises approximately 20,000 labeled instances, ensuring diversity across multiple ransomware families such as WannaCry, Cerber, Locky, and CryptoWall..

B.Feature Processing

Feature preprocessing plays a vital role in improving classification accuracy. All extracted features are normalized to a [0,1] range using RobustScaler to minimize the influence of outliers. Feature selection is then performed using the Laplacian Score method, which identify the most discriminative and relevant features for ransomware detection. This step significantly reduces dimensionality, improving computational efficiency and preventing model overfitting..

C. Proposed System

The proposed hybrid model is combination of Convolutional Neural Network (CNN) and Multilayer Perceptron (MLP) architectures to detect ransomware efficiently. The CNN extracts hierarchical spatial representations from the input feature maps, while the MLP performs deep classification based on the extracted embeddings. This model is designed to be lightweight, making it flexible for real-time deployment in constrained environments such as edge devices and local host systems. The system's workflow includes data preprocessing, feature extraction, model training, and real-time classification to determine whether a file is malicious (ransomware) or benign.

D. **Rescaling Layer**

The Rescaling Layer serves as the initial normalization step in the pipeline. It standardizes the feature inputs by converting raw values into normalized vectors between 0 and 1. This ensures consistent input scaling and stabilizes gradients during back propagation, allowing faster convergence and reducing numerical instability.

E.Data Augmentation Layer

In order to enhance robustness and improve model generalization, a Feature Augmentation Layer introduces minor perturbations and noise to the feature vectors during training. This technique simulates unseen ransomware behaviors and variations, enabling the model to handle new and obfuscated ransomware variants effectively

F. MLP Classification Head

The MLP component acts as the classifier, consisting of two dense layers which followed by a Softmax Output Layer. The final layer outputs the probability distribution across two categories — Benign and Ransomware — ensuring interpretable and reliable classification. The model uses the Adam optimizer which has categorical cross-entropy loss function, ensuring fast convergence and optimal accuracy.

F. **Lightweight Optimization**

To maintain efficiency, the model integrates parameter pruning, batch normalization, and quantization during post-training optimization. These steps significantly reduce the total model size without compromising accuracy, making it ideal for resource constrained systems.

G. Real-Time Detection Flow

Once trained, the model can be deployed to continuously monitor system activities or executable file uploads. During inference, input features are extracted, normalized, and passed through the hybrid CNN–MLP network. The model then predicts the class label and, if ransomware is detected, alerts the user or triggers a predefined mitigation protocol.

IV. RESULTS AND DISCUSSION

The proposed hybrid CNN–MLP model has been trained and evaluated on a balanced dataset which contains both ransomware and benign samples. To ensure a fair assessment, the dataset was split into 80% training and 20% testing portions. The model's performance was compared with standalone CNN and MLP architectures. The hybrid design exhibited higher accuracy, faster convergence, and improved generalization across multiple ransomware families.During evaluation, a confusion matrix was used to assess the classification performance of all models. It provides insight into how accurately each model predicts ransomware and benign samples. A confusion matrix is a table used to describe the perfor- mance of a classification model. It contains

- True Positives (TP): Correctly predicted positive cases.
- True Negatives (TN): Correctly predicted negative cases
- False Positives (FP): Incorrectly predicted as positive
- False Negatives (FN): Incorrectly predicted as negative.

A. **Accuracy Definition:** The proportion of total predictions that were correct.

$$\text{Formula Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy measures the overall correctness of the model's predictions, both positive and negative classifications

B.**Precision Definition:** The proportion of correctly predicted ransomware instances among all instances predicted as ransomware.

$$\text{Formula Precision} = \frac{TP}{TP + FP}$$

Precision is crucial in ransomware detection, as false positives may lead to unnecessary alerts or application blocking.

C. Recall (Sensitivity or True Positive Rate) Definition: The proportion of actual ransomware cases that were correctly identified.

$$\text{Formula Recall} = \frac{TP}{TP + FN}$$

Recall is significant when minimizing false negatives, as undetected ransomware can lead to irreversible system damage.

D. **F1-Score Definition:** The harmonic mean of precision and recall, balancing both metrics.

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

This metric is particularly effective for evaluating models on imbalanced datasets.

E. **Support Definition**: The number of actual occurrences of each class in the dataset.

Formula: Support = $TP + FN$

Support provides context for each class, showing how many ransomware and benign samples are present in the testing data.

Confusion Matrix-CNN

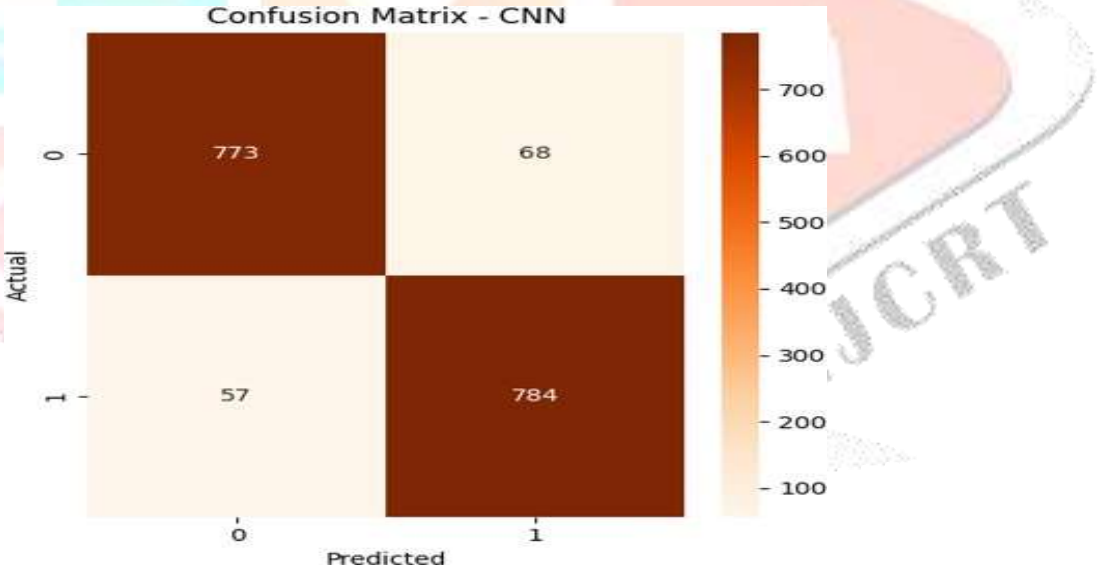

Fig. 1: Confusion Matrix

This image displays a Confusion Matrix for a Convolutional Neural Network (CNN) classification task, likely a binary classification given the 2×2 structure with classes labeled 0 and 1. Overall, the model demonstrates a high degree of accuracy, correctly classifying 1557 (773 + 784) out of the total 1682 (773 + 68 + 57 + 784) samples. The True Positive and True Negative counts are roughly balanced and notably large, indicating that the CNN performs well in distinguishing between the two classes. However, there are still a small number of misclassifications, with the number of False Positives (68) being slightly higher than the number of False Negatives (57).

MLP Confusion Matrix

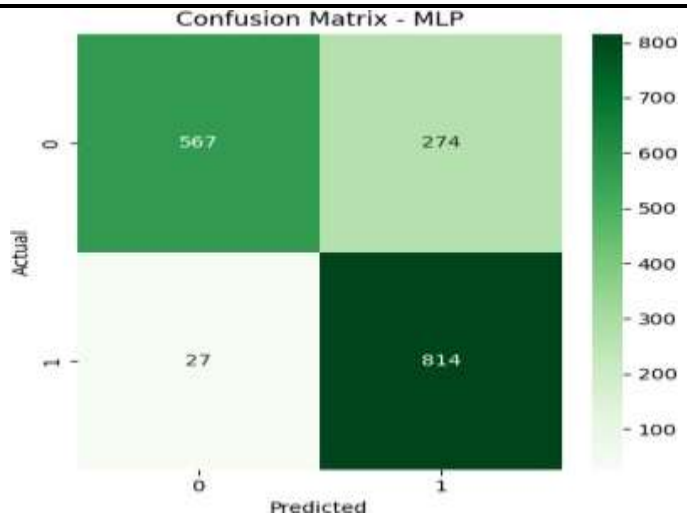

Fig. 2: MLP Confusion Matrix

MLP-CNN

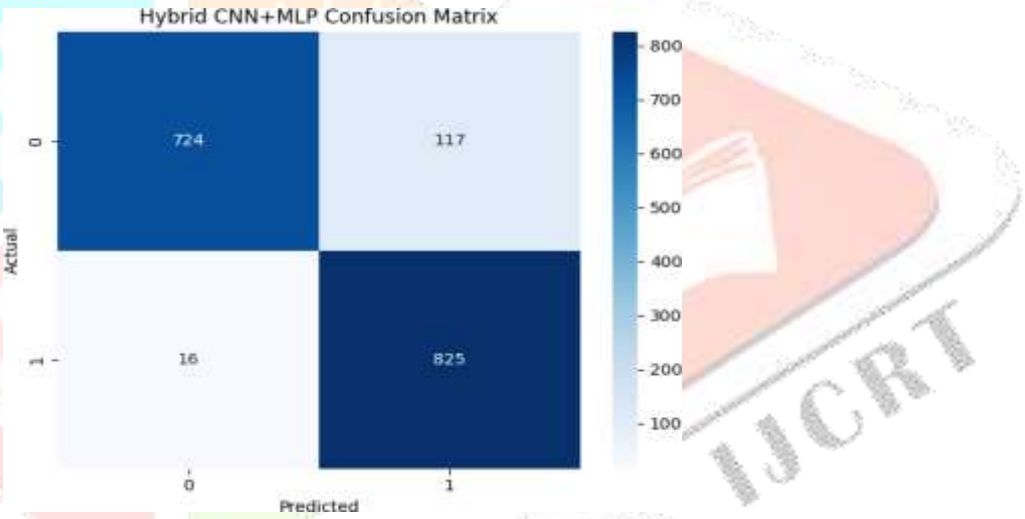

Fig. 3: MLP–CNN Confusion Matrix

This image presents the Confusion Matrix for a Hybrid CNN+MLP model, likely performing a binary classification task with classes labeled 0 and 1 The model shows strong performance overall, with a total of 1549 (724 + 825) correct predictions out of 1682 total samples. A particularly noteworthy aspect is the extremely low number of False Negatives (16), indicating the model is proper effective at identifying instances of class 1 when they are present. However, the model has a higher number of False Positives (117), meaning it is more prone to incorrectly classifying actual class 0 instances as class 1. This suggests a strong bias towards predicting class 1, which minimizes Type II errors (FN) but increases Type I errors (FP).

CNN Model Accuracy of Training Vs Validation

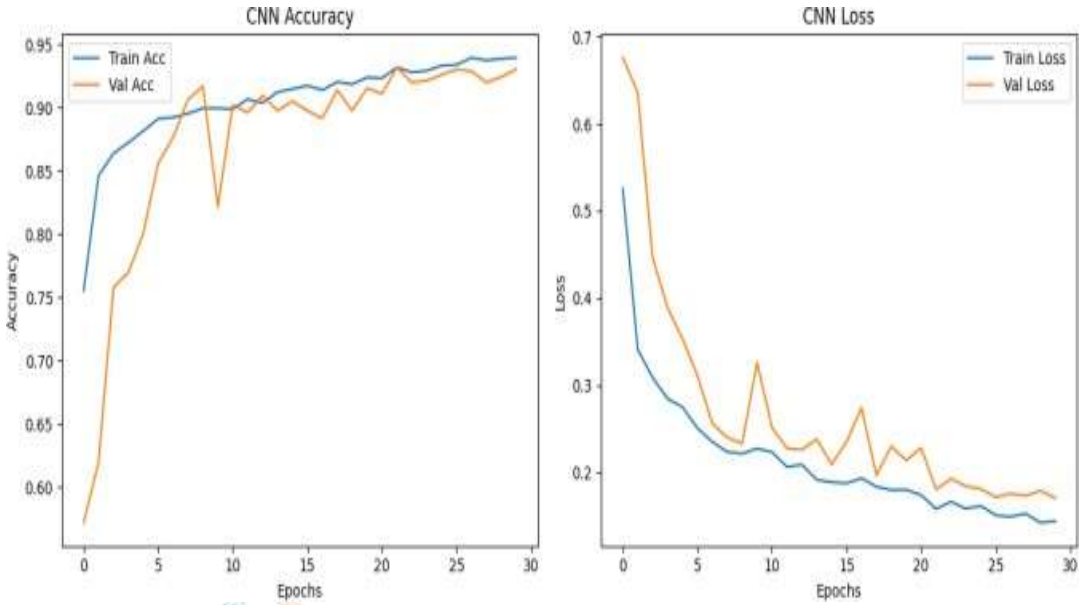

Fig. 4: CNN Training Vs Validation Accuracy and Loss

This image serves as the user enters any random row from dataset for the Attack Detection System. And the model has predicted correctly that benign class has appeared.

MLP Model Accuracy of Training Vs Validation

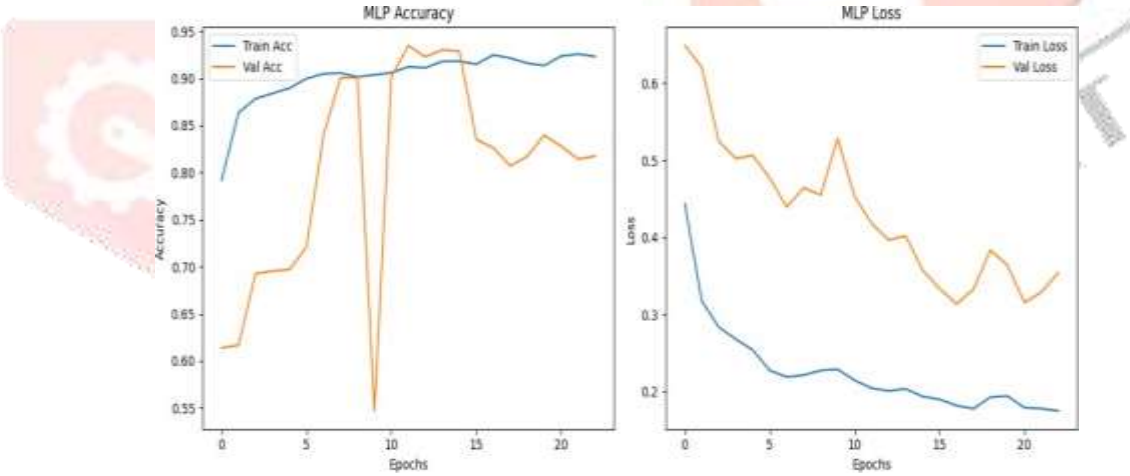

Fig.5: CNN Training Vs Validation Accuracy and Loss

V RESULTS

```
PS C:\Users\ECS-Yogesh\Desktop\lightweight_updated> PYTHON hybrid_predict.py
2025-10-12 15:15:49.478847: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'cudart64_
110.dll'; dlerror: cudart64_110.dll not found
2025-10-12 15:15:49.479051: I tensorflow/stream_executor/cuda/cudart_stub.cc:29] Ignore above cudart dlerror if you do not have a GPU
 set up on your machine.
Loading models and preprocessors... (few seconds)
2025-10-12 15:15:53.238082: W tensorflow/stream_executor/platform/default/dso_loader.cc:64] Could not load dynamic library 'nvcuda.dl
l'; dlerror: nvcuda.dll not found
2025-10-12 15:15:53.238260: W tensorflow/stream_executor/cuda/cuda_driver.cc:263] failed call to cuInit: UNKNOWN ERROR (303)
2025-10-12 15:15:53.242136: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic information for hos
t: DESKTOP-M8TISKL
2025-10-12 15:15:53.242306: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: DESKTOP-M8TISKL
2025-10-12 15:15:53.242804: I tensorflow/core/platform/cpu_feature_guard.cc:193] This TensorFlow binary is optimized with oneAPI Deep
 Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations:  AVX AVX2
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
✅ Models loaded. Expecting 58 features.
Feature order (first 10): ['unnamed: 0', 'flow duration', 'tot fwd pkts', 'tot bwd pkts', 'totlen fwd pkts', 'totlen bwd pkts', 'fwd
pkt len max', 'fwd pkt len min', 'fwd pkt len mean', 'fwd pkt len std'] ...

Interactive mode — paste one row and press Enter.
Type 'exit' or 'quit' to stop.

Enter row > 
```

ENTERING ROW

Fig 6. Entering row from dataset

The figure shows the terminal of the Attack Detection System, where users can enter the row from CSV and receive predictions about potential attacks. The system also provides a user-friendly interface to start the detection process and guides users in analyzing the predicted attack categories along with visual results.

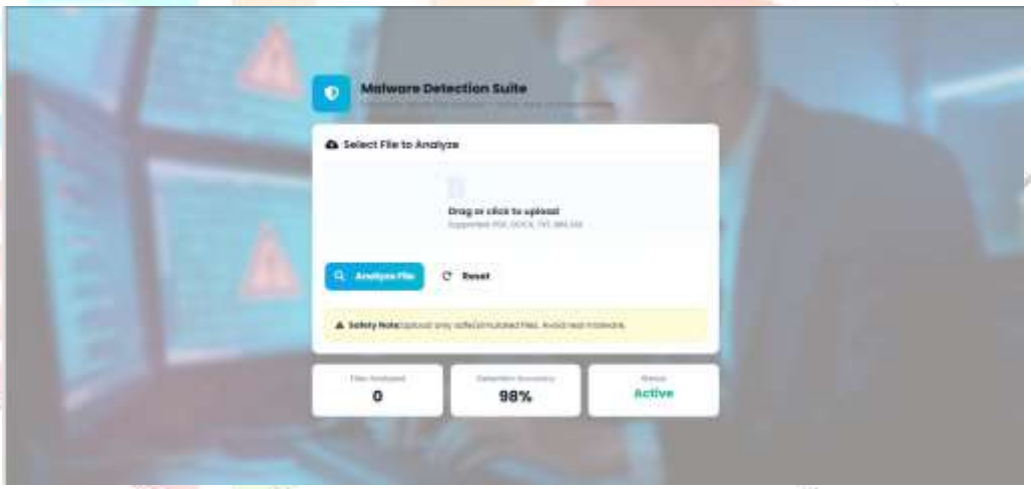

fig 7. Home Page

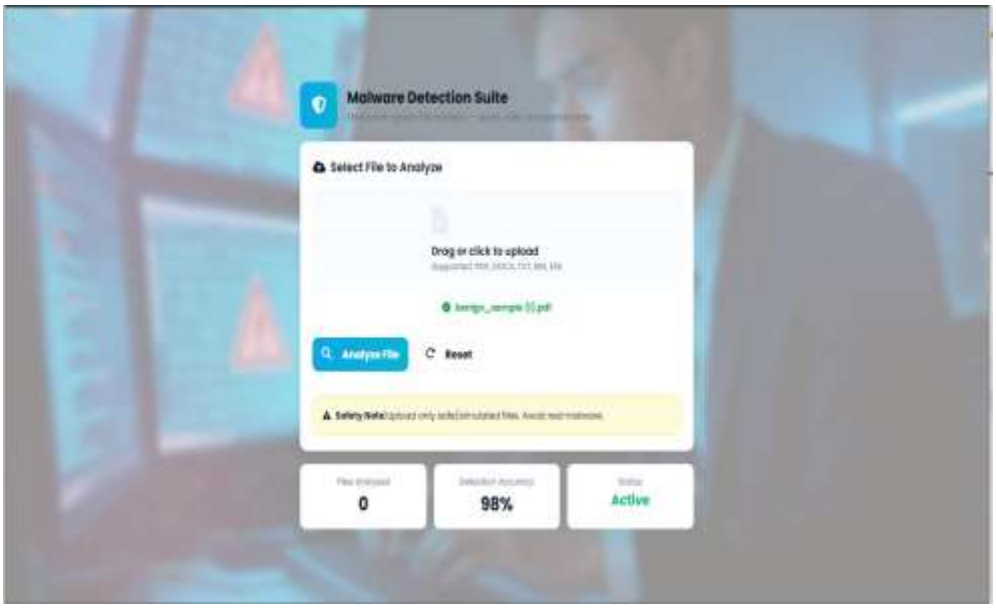

Fig 8. File uploaded

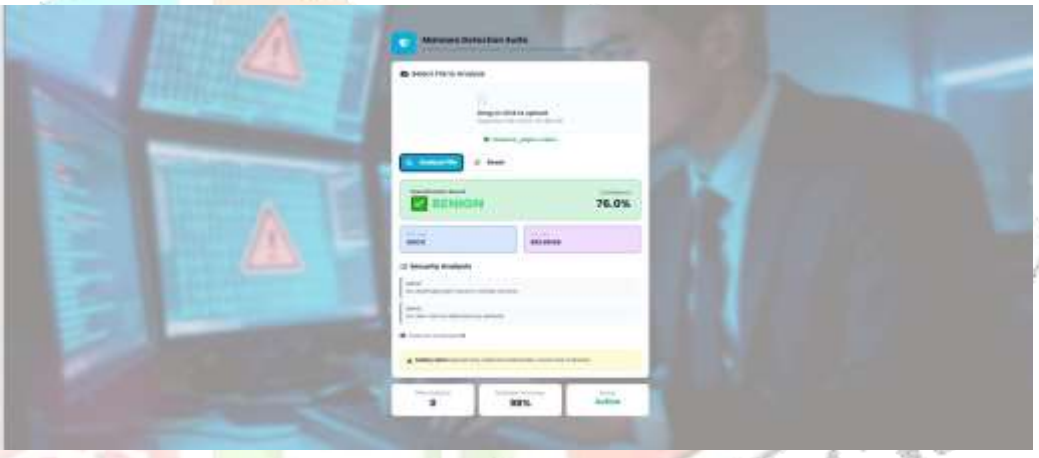

Fig 9. Benign File

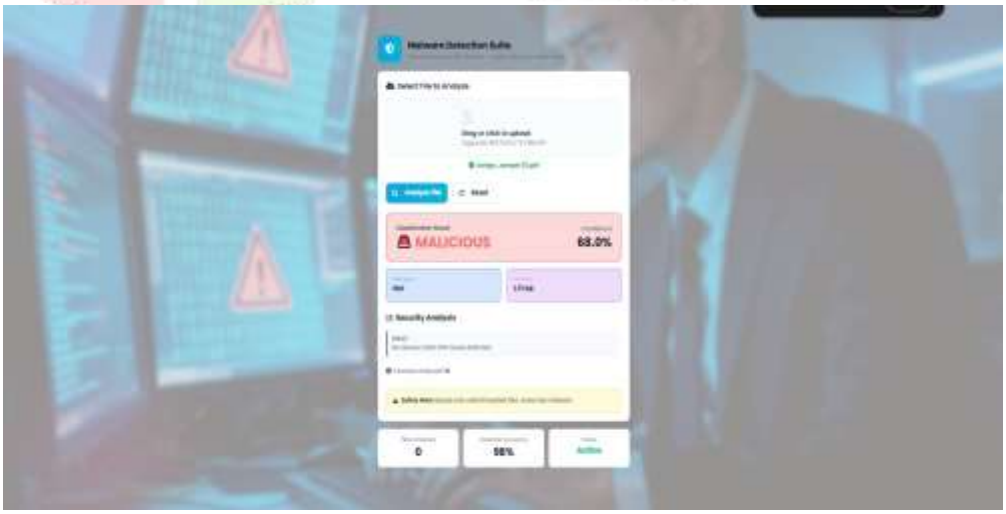

Fig 10. Malicious attack

VI. CONCLUSION

The rapid increase in sophisticated cyber threats highlights the need for malware detection models that are not only accurate but also efficient and lightweight. In this study, we propose a hybrid deep learning approach that combines Convolutional Neural Networks (CNN) with Multilayer Perceptrons (MLP), enhanced by Laplacian Score-based feature selection and robust preprocessing techniques to improve malware and attack classification. The results show that the proposed model outperforms traditional CNN, MLP, and other hybrid architectures in terms of accuracy, precision, recall, and F1 score [1]–[6]. By leveraging CNN's strength in hierarchical feature extraction alongside MLP's efficient dense-layer classification, this hybrid framework achieves a balance between high detection performance and computational efficiency. The use of feature selection and scaling techniques further reduced data redundancy, enabling faster convergence and improved generalization. Moreover, the model was integrated into a real-time prediction environment, capable of accurately classifying both binary (benign/malicious) and multi-class attack types, ensuring practical applicability in cybersecurity systems. Overall, the proposed lightweight CNN–MLP hybrid model not only enhances detection accuracy but also achieves significant computational efficiency, making it adjustable for resource-constrained or real-time deployment scenarios. Future work will focus on extending the approach to handle larger, dynamic datasets, exploring transformer-based embeddings for improved context understanding, and deploying the model in live network monitoring environments for continuous learning and adaptation.

VII. ACKNOWLEDGMENT

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