

# **Project Report**

**Vulnerability Assessment & Reverse Engineering**

## **Automated Vulnerability Scanner with AI-Powered Classification and Remediation**

**Team Members:** Muhammad Umer Farooq, Jalil Ahmad, Aleena Fatima

**Roll Numbers:** I221661, I221635, I222353

**Class:** CY-D

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# 1. Introduction

## 1.1 Background

As cyber threats grow in complexity and frequency, automated systems that not only detect but also assess and remediate vulnerabilities are critical. Traditional vulnerability scanners like OpenVAS (Greenbone Vulnerability Management) are effective at detection but lack automated reasoning and response generation capabilities.

## 1.2 Objective

This project aims to build a comprehensive vulnerability scanning framework that integrates:

- OpenVAS for detection
- Machine learning for severity classification
- Natural language generation (NLG) for remediation recommendations

The system streamlines the vulnerability management process, providing actionable insights in addition to detection.

# 2. System Overview

## 2.1 Core Modules

The system is composed of three core modules:

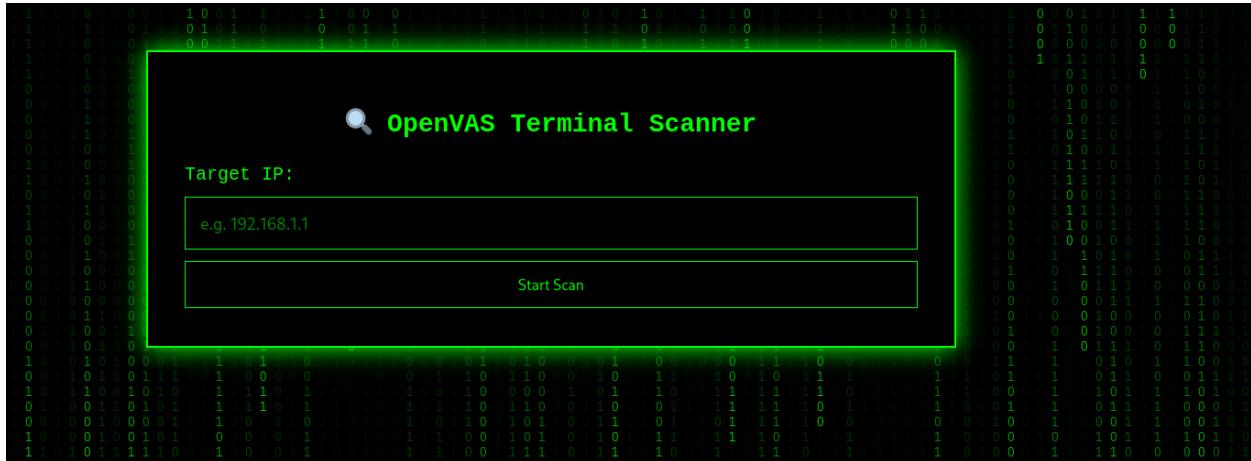
Module	Function
Vulnerability Scanning	Conducts system scans using OpenVAS
Severity Classification	Predicts vulnerability severity using ML models
Remediation Recommendation	Generates remediation steps via a fine-tuned T5 model

## 2.2 Pipeline

Target IP → [OpenVAS Scan] → [Cleaned Report] → [Severity Classifier] → [Remediation Generator] → [Final Output]

## 3. Technical Components

### 3.1 Vulnerability Scanning



#### 3.1.1 Tool Used: OpenVAS

OpenVAS is an open-source vulnerability scanner that performs a wide range of network checks against known CVEs.

#### 3.1.2 Workflow

- Scan tasks are initiated using gvm-cli via Unix socket.
- The scan is configured to use "Full and fast" policy.
- Results are fetched in CSV format and parsed using pandas.

#### 3.1.3 Data Enrichment

- Extracted data includes CVE ID, CVSS score, solution, impact, and affected software.
- A secondary lookup (if available) is used to enrich the data with:
  - access\_vector
  - access\_complexity
  - exploit

## 3.2 Severity Classification

cve_id	cvss_score	description	access_vector	access_complexity	exploit	predicted_severity
cve-2008-5305	10.0	twiki, twiki version prior to 4.2.4. Successful exploitation could allow execution of arbitrary script code or commands. this could let attackers steal cookie-based authentication credentials or compromise the affected application.	network	low	exploits/php/webapps/32645.txt	high
cve-1999-0618	10.0	the vsftpd 2.3.4 source package downloaded between 20110630 and 20110703 is affected. attackers can exploit this issue to execute	network	low	NaN	high
cve-2011-2523	9.8		network	low	exploits/unix/remote/17491_rh	high

### 3.2.1 Problem Framing

Severity classification is treated as a supervised classification task with multi-class output (e.g., Low, Medium, High).

### 3.2.2 Model Architecture

- **Base Classifier:** Random Forest
- **Text Embedding:** SBERT (all-MiniLM-L6-v2) is used to convert descriptions to numerical vectors.

### 3.2.3 Feature Set

- Encoded categorical fields: access\_vector, access\_complexity, exploit
- Continuous fields: cvss\_score
- Text embeddings: SBERT vectors from the vulnerability description

### 3.3 Remediation Generation

The screenshot shows a Kali Linux VM interface. A browser window displays a remediation report for IP 192.168.59.130. The report table has columns for CVE ID, CVSS Score, Solution, and Remediation Steps.

CVE ID	CVSS Score	Solution	Remediation Steps
cve-2008-5305	10.0	upgrade to version 4.2.4 or later.	(1)- upgrade twiki to version 424 or later to eliminate the eval injection vulnerability in the search variable (2)- sanitize user inputs to prevent the execution of arbitrary perl code (3)- review and restrict the use of twiki variables that can execute code such as search (4)- educate users on the risks of executing untrusted code within twiki
cve-1999-0618	10.0	disable the rexec service and use alternatives like ssh instead.	(1)- disable the rexecd service if not required as it poses a security risk by allowing remote command execution without proper authentication (2)- configure the rexecd service to restrict access to trusted hosts only (3)- regularly audit and monitor services running on the system for unauthorized access attempts (4)- consider replacing rexec with more secure alternatives that provide better authentication mechanisms
cve-2011-2523	9.8	the repaired package can be downloaded from the referenced vendor homepage. please validate the package with its signature.	(1)- upgrade vsftpd to version 235 or later to remove the backdoor that opens a shell on port 6200tcp (2)- monitor network traffic for unusual activity on port 6200tcp to detect potential exploitation attempts (3)- implement firewall rules to block unauthorized access to port 6200tcp (4)- regularly audit and update ftp server configurations to adhere to security best practices

Remediation is not fetched from a database but generated using a **fine-tuned T5 (Text-to-Text Transfer Transformer)** model. The model generates contextual, human-readable remediation steps tailored to each CVE and its description.

## 4. Implementation Details

### 4.1 Backend

- Framework:** Flask
- Task Management:** Dictionary-based tracking of running/completed scans
- Data Handling:** pandas, joblib, torch, transformers

### 4.2 Frontend

Implemented using HTML/CSS/JavaScript with a consistent hacker-themed visual identity (Matrix-style green-on-black). Each stage has a dedicated UI:

- index.html: Scan initiation
- results.html: Scan data

- classification.html: Severity predictions
- remediations.html: Final output with recommendations

## 5. User Workflow

### Step Action

- 1 User enters target IP on the web interface
- 2 OpenVAS scan begins in background
- 3 Upon completion, results are shown in a table
- 4 User can trigger severity classification
- 5 Final step generates AI-powered remediation suggestions

## 6. Datasets Utilised

The data for training severity classification model is gathered from NVD database and ExploitDB for corresponding exploits. A corpus of 200,000 entries is created. Following is the glimpse of it:

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	cve_id	description	access_vector	access_complexity	exploit	cvss_score	severity								
2	cve-1999-0095	the debug command in sendmail network	low	exploits/lir	10	critical									
3	cve-1999-0082	cwd+root command in ftpd allow network	low	null	10	critical									
4	cve-1999-1471	buffer overflow in passwd in bsc local	low	null	7.2	high									
5	cve-1999-1122	vulnerability in restore in sunos : local	low	null	4.6	medium									
6	cve-1999-1467	vulnerability in rcp on sunos 4.0 network	low	null	10	critical									
7	cve-1999-1506	vulnerability in smi sendmail 4.C network	low	null	7.5	high									
8	cve-1999-0084	certain nfs servers allow users : local	low	null	7.2	high									
9	cve-2000-0388	buffer overflow in freebsd libmy network	low	null	7.5	high									
10	cve-1999-0209	the sunview (suntools) selector network	low	exploits/sc	5	medium									
11	cve-1999-1198	builddisk program on next syste : local	low	null	7.2	high									
12	cve-1999-1391	vulnerability in next 1.0a and 1.1c : local	low	null	7.2	high									
13	cve-1999-1392	vulnerability in restore0.9 instl : local	low	null	7.2	high									
14	cve-1999-1057	vms 4.0 through 5.3 allows loca : local	low	null	4.6	medium									
15	cve-1999-1554	/usr/sbin/mail on sgi irix 3.3anc : local	low	null	2.1	low									
16	cve-1999-1197	tioccoms in sunos 4.1.1 does no : local	low	null	7.2	high									
17	cve-1999-1115	vulnerability in the /etc/suid_exi : local	low	null	7.2	high									
18	cve-1999-1258	rpc_pwindauthd in sunos 4.1.1 an : network	low	null	5	medium									
19	cve-1999-1438	vulnerability in /bin/mail in suno : local	low	null	7.2	high									
20	cve-1999-1211	vulnerability in in.telnetd in sun : local	low	null	7.2	high									
21	cve-1999-1212	vulnerability in in.rlogind in sun : local	low	null	7.2	high									
22	cve-1999-1194	chroot in digital ultric 4.1 and 4.1 : local	low	exploits/ai	7.2	high									
23	cve-1999-1193	the "me" user in next nextstep 2 : network	low	null	10	critical									
24	cve-1999-1123	the installation of sun source : si : local	low	exploits/sc	7.2	high									
25	cve-1999-1034	vulnerability in login in at&t syste : local	low	null	7.2	high									
26	cve-1999-1415	vulnerability in /usr/bin/mail inc : local	low	null	4.6	medium									
27	cve-1999-1090	the default configuration of ncsi : network	low	null	7.5	high									

The dataset for remediations is gathered through web scraping and contains remediation steps for over 14000 vulnerabilities. It is as follows:

## 7. Model Evaluation and Testing

This section presents the evaluation results for both core models developed as part of the vulnerability scanning framework: the **Severity Classification Model** and the **Remediation Generation Model**. Each model was rigorously tested to ensure accuracy, generalization, and utility in a real-world cybersecurity context.

## 7.1 Severity Classification Model

The severity classification model is a Random Forest classifier trained on enriched CVE metadata. Input features included the cvss\_score, access\_vector, access\_complexity, and SBERT-encoded descriptions of vulnerabilities. The model was trained using 100 trees and evaluated on a held-out test set.

## Evaluation Metrics

<b>Class</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-Score</b>	<b>Support</b>
Critical	0.99	0.89	0.94	3489
High	0.96	0.99	0.97	7878
Low	1.00	0.95	0.97	3816
Medium	0.99	1.00	0.99	20834
<b>Accuracy</b>			<b>0.98</b>	36017

Class	Precision	Recall	F1-Score	Support
<b>Macro Avg</b>	0.98	0.96	0.97	36017
<b>Weighted Avg</b>	0.98	0.98	0.98	36017

```

train.ipynb
File Edit View Insert Runtime Tools Help
Commands + Code + Text
building tree 99 of 100
building tree 100 of 100
[INFO] Training completed in 362.73 seconds
[Parallel(n_jobs=1)] Done 100 out of 100 | elapsed: 6.0min finished

[12]: print("[INFO] Evaluating model performance...")
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))

[INFO] Evaluating model performance...
[Parallel(n_jobs=2)] Using backend ThreadingBackend with 2 concurrent workers.
[Parallel(n_jobs=2)] Done 37 tasks | elapsed: 0.9s
[Parallel(n_jobs=2)] Done 100 out of 100 | elapsed: 2.0s finished
precision    recall    f1-score   support
critical      0.99      0.89      0.94     3489
high          0.96      0.99      0.97     7878
low           1.00      0.95      0.97     3816
medium         0.99      1.00      0.99    20834
accuracy       0.98      0.98      0.98     36017
macro avg     0.98      0.96      0.97     36017
weighted avg   0.98      0.98      0.98     36017

[13]: import joblib
joblib.dump(model, 'severity_predictor.pkl')
print("[INFO] Model saved as severity_predictor.pkl")

[INFO] Model saved as severity_predictor.pkl

[14]: from google.colab import files
files.download('severity_predictor.pkl')

```

## 7.2 Remediation Generation Model

The remediation model is a fine-tuned T5 transformer trained on a custom dataset containing CVE IDs, descriptions, and corresponding remediation steps. The model is tasked with generating human-readable, context-specific mitigation recommendations from structured inputs.

Metric	Score
<b>ROUGE-1</b>	0.597
<b>ROUGE-2</b>	0.566
<b>ROUGE-L</b>	0.618
<b>ROUGE-Lsum</b>	0.618

The screenshot shows a Jupyter Notebook interface with several tabs open. The active tab is 'remediations\_model.ipynb'. The code cell contains Python code for generating predictions from a T5 model and computing ROUGE scores. The terminal output shows the download of a builder script and the creation of a zip file named 'final\_t5\_remediation\_model.zip' containing various model files like config.json, special\_tokens\_map.json, spiece.model, and added\_tokens.json. The status bar at the bottom indicates it's 30°C Heavy rain, the date is 04/05/2025, and the time is 3:04 pm.

```

[9] for example in tqdm(eval_dataset):
    input_ids = torch.tensor([example["input_ids"]], dtype=torch.long).to(device)
    labels = torch.tensor([example["labels"]], dtype=torch.long).to(device)

    with torch.no_grad():
        output_ids = model.generate(input_ids, max_new_tokens=50)

    pred_text = tokenizer.decode(output_ids[0], skip_special_tokens=True)
    label_text = tokenizer.decode(labels[0], skip_special_tokens=True)

    preds.append(pred_text)
    targets.append(label_text)

# Compute ROUGE
rouge = evaluate.load("rouge")
results = rouge.compute(predictions=preds, references=targets)

# Show results
import pprint
pprint.pprint(results)

[10] model.save_pretrained("final_t5_remediation_model")
tokenizer.save_pretrained("final_t5_remediation_model")

[11] !zip -r final_t5_model.zip final_t5_remediation_model

```

## 8. Limitations and Future Work

### 8.1 Current Limitations

- OpenVAS may miss zero-day vulnerabilities.
- The classifier's accuracy is bounded by the training data and SBERT embeddings.
- The T5 model may generate plausible but non-authoritative remediations.

### 8.2 Proposed Enhancements

- Integrate NVD API for real-time vulnerability enrichment.
- Replace SBERT with a domain-specific LLM fine-tuned on MITRE CVE data.
- Build a dashboard for multi-host scanning and vulnerability trend analytics.

## 9. Conclusion

This project bridges the gap between detection and response by combining the strengths of traditional vulnerability scanners and modern AI models. It provides:

- End-to-end automation
- Human-like remediation suggestions
- An intuitive UI to manage scan workflows

This system is a step toward building **smart cybersecurity assistants** that can reason and recommend—automatically.