National College of Ireland

Multi-Agent Based Distributed Malware Detection Using Static Analysis and Machine Learning

MSc Research Project
Data Analytics

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Multi-Agent Based Distributed Malware Detection Using Static Analysis and Machine Learning

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Abstract

As malware continues to evolve in complexity whereas traditional centralized detection systems struggle to deliver timely and scalable responses. This project proposes a decentralized Multi-Agent System (MAS) for malware detection and mitigation which is based solely on static analysis of executable files. The architecture integrates autonomous agents that collaboratively detect, classify, mitigate, and log threats using machine learning model and secure communication protocols. The Detection Agent extracts predefined static features such as Portable Executable (PE) headers and opcode frequencies, while a trained Random Forest classifier determines infection likelihood. The Decision Agent interprets results, triggering appropriate action via the Mitigation Agent and ensuring auditability through a Blockchain Logger Agent. Results demonstrate accurate classification performance, low-latency mitigation, and modular design for scalable deployment on edge, cloud, and hybrid infrastructures. This research validates MAS as a viable solution for distributed malware detection, combining autonomy, security, and adaptability.

1 Introduction

The increasing presence of cyber threats and the rapid development of malware attacks highlight the need of novel approaches to detect and response. At present we have traditional antivirus systems and centralized malware scanners which often struggle with bottlenecks, slow reaction time and vulnerable to modern malware. To cover these issues, this research presents a decentralized malware detection system using agents which will analysis static data and use machine learning to autonomously identify and mitigate malicious files [1].

Malware identification can be classified using two classes which are through dynamic data or static data. Dynamic data is collected by executing files in a controlled environment to monitor their behaviour, whereas Static data analyse code structure, entropy, API calls and metadata without executing the files. This research is focused on static analysis which is safer and more efficient for automate the process in edge environment [2].

The system we are using for this research is **Multi-Agent Systems (MAS)** which offers us a **Decentralized Architecture** that goes well with modern cybersecurity requirements. In this system, agents are autonomous, reactive and capable of social interaction which will make them ideal for real time communication across distributed system. By giving specific roles to agents such as decision maker, mitigator and blockchain logger will

give power to MAS system to do continuous survey, classify and response to executable files entering the system.

The core objective of this research is to develop and test the MAS framework by performing malware classification using a Random Forest model trained on static features which is extracted from .exe files. The system is built to detect and mitigate threats autonomously with the help of decision making and mitigation steps which is securely recorded using blockchain logger [3].

1.1 Research Question

Can malware detection and mitigation be improved through a decentralized Multi-Agent System that uses static feature analysis and machine learning in a collaborative architecture?

1.2 Structure of the Report

This report is organized as follows:

- **Section 2** presents a literature review of MAS architectures, static malware detection, and blockchain integrated logging systems.
- **Section 3** outlines the methodology including feature extraction, model training and agent implementation.
- **Section 4** details of system design including agent interactions and inter-agent communication logic.
- **Section 5** describes the full implementation of the Multi-Agent system and machine learning components.
- **Section 6** presents the evaluation metrics and experimental results.
- **Section 7** concludes with findings, limitations, and directions for future work.

2 Related Work

Malware identification has solely relied on signature-based techniques and behavioural analysis. However, with this new gen malware types such as polymorphic and obfuscated are less effective to old methods. As a result, the cybersecurity field has noticed a shift towards integration of machine learning (ML) and distributed architectures like Multi-Agent Systems (MAS) for robust detection and response.

2.1 MAS in Distributed Security Environments

Multi-Agent System works in decentralized manner with autonomy and collaboration, which is essential for modern and scalable malware detection frameworks. In [1], a MAS is proposed to handle deadline-based job scheduling in federated cloud environment. Although, in this paper no malware is specified but showed us about work emphasizes agents which can distribute tasks across heterogeneous systems.

To clarify fault tolerance and decentralized intelligence, Siddiqui et al. [3] introduced Elastic JADE which is a MAS system that works on dynamic offloading of tasks from local systems to AWS instances. This framework presents that how the agents are optimizing cloud resources with the drawback of vendor lock and lack of threat mitigation features.

More directly relevant to cybersecurity, Fan et al. [2] proposed a MAS system that distributed workloads based on deadline constraints by using OpenStack VMs and a decision logic which is powered by rough set theory. So, the conclusion is that this work aligns closely with our implementation, though it does not include malware detection or blockchain based logging.

2.2 Static Malware Detection Using Machine Learning

Static analysis avoids the risk of virus attack to study the file, as it does not execute malware files but analyse code structure, headers and embedded features like API calls and entropy. In [4] a comparison of static ML models shows that Gradient Boosting and Random Forest overcome legacy classifiers such as SVM in the field of PE headers and opcode features.

Other works, such as [5] displayed significant detection accuracy boost by using fusion entropy values with API sequences. These hybrid models are shown to surpass n-gram based models which leads to generalize poorly across diverse malware families.

Despite their effectiveness, many of these ways are centralized which lacks real time deployment strategies. Our work fills this gap by embedding a Random Forest classifier within a distributed agent framework.

2.3 Logging and Auditability with Blockchain

Auditability is critical step in collaborating cybersecurity system. In [6], agents are integrated with blockchain to secure and tamper-proof logging of anomalies. This architecture improves trust and traceability in a distributes system.

Although blockchain bring latency and overhead which guarantees non-repudiation and immutability, this two are the key features of forensic analysis and inter-agent accountability. Our system uses a Blockchain Logger Agent to emulate these benefits without depending on full blockchain agreement, gives this system high balancing performance with integrity.

2.4 Communication Models in MAS

The success of any MAS based architecture heavily relies on inter agent communication. Rule based agents and centralized blackboards were evaluated in [7] in which latency is reduced by synchronously pushing updates rather than polling. However, encryption and secure channels are not mentioned in this paper.

In our system, agents communicate asynchronously using the SPADE framework over XMPP servers which allow them to talk in real time coordinates, message templating, and behaviour binding, all while maintaining agent modularity.

Table 1: Comparison of Proposed Model with Existing MAS and Scheduling Frameworks

Ref	Focus Area	ML Model	Agent Roles	Blockchain	Deployment	User Pref.	Static Feat.
[1]	Job scheduling in hybrid clouds	Rough Set Theory	Monitoring, Dispatch, Execution, Group Management	No	Private Cloud (OpenStack)	No	No
[2]	Deadline-based VM instance selection using MAS	Rough Set Theory	Decision-making Agents (VM Selection)	No	OpenStack Cloud	No	No
[3]	Elastic resource scaling via MAS	None (Task Offloading)	Local to Cloud Offloading	No	AWS-only (Vendor-Locked)	No	No
[4]	Workflow provisioning, cost constraints	XGBoost, Custom Schedulers	VM Utilization Agents	No	Simulated	No	Partial
[5]	Survey of MAS in Cloud Computing	Varies	Survey-based comparison	No	Literature Review Only	No	No
[6]	Mobile agents for elasticity	None	Grid/Cloud Resource Executors	No	Simulation only	No	No
[7]	Static Malware Detection	Gradient Boosting, RF	N/A	No	Simulated Testbed	No	Yes
This Work	Static Feature-based Malware Detection with MAS	Random Forest	Detection, Decision, Mitigation, Logger	Yes	Full MAS Deployment (Local & SPADE Agents)	Yes	Yes

3 Methodology

This section tells us about the methodology framework that has been used to develop a distributed malware detection system based on Multi-Agent System (MAS). The core of this idea involves **Train a ML Model** and **Designing of Autonomous Agents** that will extract features, segregate executable files, trigger mitigation actions and secure log entries. This system is implemented using Python, the SPADE agent framework and joblib for machine learning inference.

As shown in below table, the core components of the system and their corresponding technologies are listed.

Table 2: Technology Required

Component	**Technology**
Agent Framework	SPADE (Python)
ML Inference	Random Forest (scikit-learn + joblib)
File Monitoring	Watchdog (Python)
Feature Parsing	Custom Static Parser
Communication Protocol	XMPP (via SPADE)
Logging	Simulated Blockchain Logger

3.1 System Overview

This architecture is based on flexible MAS design that relies on **Trained Random Forest Model** with **Two Major Component and Four Core Agents.**

3.1.1 Model Training

The whole pipeline is based on a machine learning based trained model. For this system Random Forest Classifier is used to train static features of malware which consist of PE headers, opcode frequency and entropy. The dataset is split into training and testing sets, giving high accuracy in classifying executable files as malicious or benign. The trained model is then stored as a package file and later integrated with MAS pipeline.

3.1.2 Multi-Agent System Pipeline

Each agent is responsible for managing a specific role.

- **Monitor Module** – This script works as an observer for a predefined folder, monitoring it for new .exe files using a python library named as Watchdog. Upon detection of a new file, it triggers the next step in the pipeline.
- **Trigger Module** – After identifying the .exe file this script start working in parsing the executable into binary mode and extract a predefined set of static features from it. After that it formats these features into structed input CSV file which is compatible with the trained ML model.
- **Detection Agent** – Works to perform extraction and segregation of static features using a pre-trained Random Forest Model.
- **Decision Agent** – Its role is to analyse predicted results and tell the severity of infection from level 1 to 10.
- **Mitigation Agent** – It responds to the threats by activating mitigation actions such as quarantine the file or displaying alerts.
- **Blockchain Logger Agent** – This representor works as a logger which logs all threats and response events to secure the integrity and traceability of malware origin.

All this Agents communicate using asynchronous messaging system via XMPP servers (Extensible Messaging and Presence Protocol) which helps to establish distributed and fault tolerance communication.

4 Design Specification

This Framework is constructed based on modules and event driven system and it rotate around autonomous SPADE agents and auxiliary modules for orchestration and data handling. This section focusses on internal mechanics of agent's interaction, threading models, behaviour assignments and system stability.

4.1 Agent Role Assignment and Class Design

Each agent in this system is implemented as a subclass and is assigned to preform specific asynchronous behaviours using Spade-Cyclic Behaviour or One-Shot Behaviour. So, the Detection Agent uses One-Shot Behaviour because it performs a single task which is load the ML model and return a prediction. While the Decision Agent, Mitigation Agent and Blockchain Logger Agent works on Cyclic Behaviour because they must continuously listen and respond to incoming message. To maintain role clarity:

1. Agents are required to register with custom ontology and service types such as intercloud, master ontology, slave ontology which activated filtered message routing.

2. Secondly message templates are defined via Spade template feature to enforce protocol compliance across all agents.

This Object-oriented structure supports modularity and allows each agent's class to be independently extended or replaced.

4.2 Agent Lifecycle and Fault Tolerance

Agents operate on a loosely coupled fault tolerance mode. In this case if one agent crashed or stopped their functionality the others will remain active. There are three steps of an agent life cycle.

1. **Setup** the behaviour of an agent with initializing the logging process and registering the message templates.

2. In **Active phase** agent listens for inputs or initiates communication in a particular timeout condition.

3. **Teardown** undergoes where agents can be cleanly stopped or restarts its activities via agent stop command which allows them to shut down completely and perform agent recycling.

Moreover, Faulty sections such as malformed messages or missing feature files are handled through try-except blocks. For example, if Detection Agent receives an invalid CSV file, then it will log an error and return a neutral classification to avoid system crashes.

4.3 Message Routing and Protocol Agreement

In this framework all the communication protocols are conducted by ACL messaging structure with key headers such as to, sender, body, ontology and metadata. Were SPADE's asynchronous messaging queue secure non-blocking operation. While all the messages are routed over XMPP through a local host ejabberd server. Each agent uses message templates that will help them to filter out messages which is specifically meant for them, avoiding cross interference or misrouting.

4.4 Thread Management and Timing Control

All the agents work on a concurrent manner in the background via SPADE's internal asyncio event loop. To perform this there are few critical operations such as model loading, message passing, file I/O, log writing are to be handled using await function to ensure non-blocking performances across the system. Also, timers are injected via asyncio sleep function to simulates realistic communication and mitigation latencies.

Additionally, **Main Script** includes asyncio sleep of 5 sec to give agent's time to register with the XMPP servers before message dispatch begins. A total runtime window is 25 sec which is good enough to allow task to complete and execute controlled shutdown.

4.5 System Modularity and Extensibility

Each component in this framework works as a standalone module:

1. **Trigger Script** handles only the feature extraction process and can be replaced with advanced parsers.
2. **Malware Model Package** is a pre-trained model based on Random Forest can be swapped with updated models without changing the Agents logic.
3. The Agents communication via **Standard Protocols** due to which it is easier to add new agents such as Feedback Agent, Visualizer Agent, etc.
4. Agent addresses are like **detectionagent@IP** which are parametrized for cross network deployment such as cloud or edge devices.

5 Implementation

This implementation section focuses on building a distributed Multi-Agent System (MAS) for virus identification using static features and machine learning. To construct this architecture there are few steps to follow:

5.1 Model Training

The model we have used in this research is **Random Forest Classifier** which is trained on a labelled dataset of benign and malicious executable files. This dataset includes static features such as opcode frequency, PE headers values and section entropy metrics. To get a good precision from this model we have split the dataset into 80:20 ratio which gives use high accuracy and generalization capability. Once trained, the model is then serialized using joblib and saves as **Malware Model Package** Moreover, the full test set with labels is saved as **Test Data With Labels** in **CSV format** for later evaluation.

```python
# Step 1: Load dataset
df = pd.read_csv("Dataset//Data.csv")  # Adjust path as needed

# Step 2: Separate features and label
X = df.drop(columns=["Class"])
y = df["Class"]

# Step 3: Split into 80% train and 20% test
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=50
)

# Step 4: Train Random Forest model
model = RandomForestClassifier(n_estimators=100, random_state=50)
model.fit(X_train, y_train)

# Step 5: Save the trained model
joblib.dump(model, "Malware_Model.pkl")
print("💾 Model saved as Malware_Model.pkl")

# Step 6: Save full test set with labels
test_set = X_test.copy()
test_set["Class"] = y_test.values
test_set.to_csv("Test_Data_With_Labels.csv", index=False)
print("📄 Test data with labels saved to Test_Data_With_Labels.csv")
```

Figure 1: Model Training

5.2 Feature Extraction from Executable

In this step the detection process begins by continuously monitoring to a predefined directory such as downloads folder using the Watchdog Python library by **Monitor Script**. After that it will trigger an event as soon as a new .exe arrives or moved into that folder and then that file is passed through a custom handler which is implemented in **Trigger Script**. This code will then process the executable file by opening it in binary mode and decoding the contents past the MZ header to avoid parsing metadata clusters. Now a predefined set of static features that has been selected from past research and experiments are then extracted including opcode frequency distributions, PE header fields and entropy measures of various code segments. Following through extraction, now these features are matched with a fixed schema which is identical to the one used during model training to secure compatibility. During this extraction any missing or corrupt entries are replaced with zero values to maintain vector dimensionality which further assure the robust handling of noise or partial binaries. Once this step of data collection ends then these values are stored in a temporary CSV file which used as an input to your MAS classification pipeline. This CSV file is then consumed by the Detection Agent to load the trained machine learning model and perform classification without human interaction and activate end-to-end automated analysis and decision-making system.

```python
from watchdog.observers import Observer
from watchdog.events import FileSystemEventHandler
import time
import os
from Trigger import Process_File

class FileHandler(FileSystemEventHandler):
    def on_created(self, event):
        if event.src_path.endswith(".exe"):
            print(f"[Monitor] New .exe file detected: {event.src_path}")
            Process_File(event.src_path)

    def on_moved(self, event):
        if event.dest_path.endswith(".exe"):
            print(f"[Monitor] New .exe file detected: {event.dest_path}")
            Process_File(event.dest_path)

if __name__ == "__main__":
    path_to_watch = "C:/Users/tejas/Downloads"
    observer = Observer()
    observer.schedule(FileHandler(), path=path_to_watch, recursive=False)
    observer.start()
    print(f"[Monitor] Watching {path_to_watch} for new .exe files...")

    try:
        while True:
            time.sleep(10)
    except KeyboardInterrupt:
        observer.stop()
    observer.join()
```

Figure 2: Monitoring Step

```python
def Process_File(file_path):
    print(f"[MAS Trigger] Processing .exe file: {file_path}")

    try:
        with open(file_path, 'rb') as f:
            content = f.read()

        # Skip 60-byte MZ header
        metadata = content[60:].decode('utf-8', errors='ignore')

        feature_dict = {}
        for line in metadata.strip().split('\n'):
            if '=' in line:
                key, value = line.split('=', 1)
                if key in FEATURE_NAMES:
                    try:
                        feature_dict[key] = float(value)
                    except ValueError:
                        feature_dict[key] = 0.0

        # Fill missing keys
        for key in FEATURE_NAMES:
            if key not in feature_dict:
                feature_dict[key] = 0.0
```

Figure 3: Triggering Step

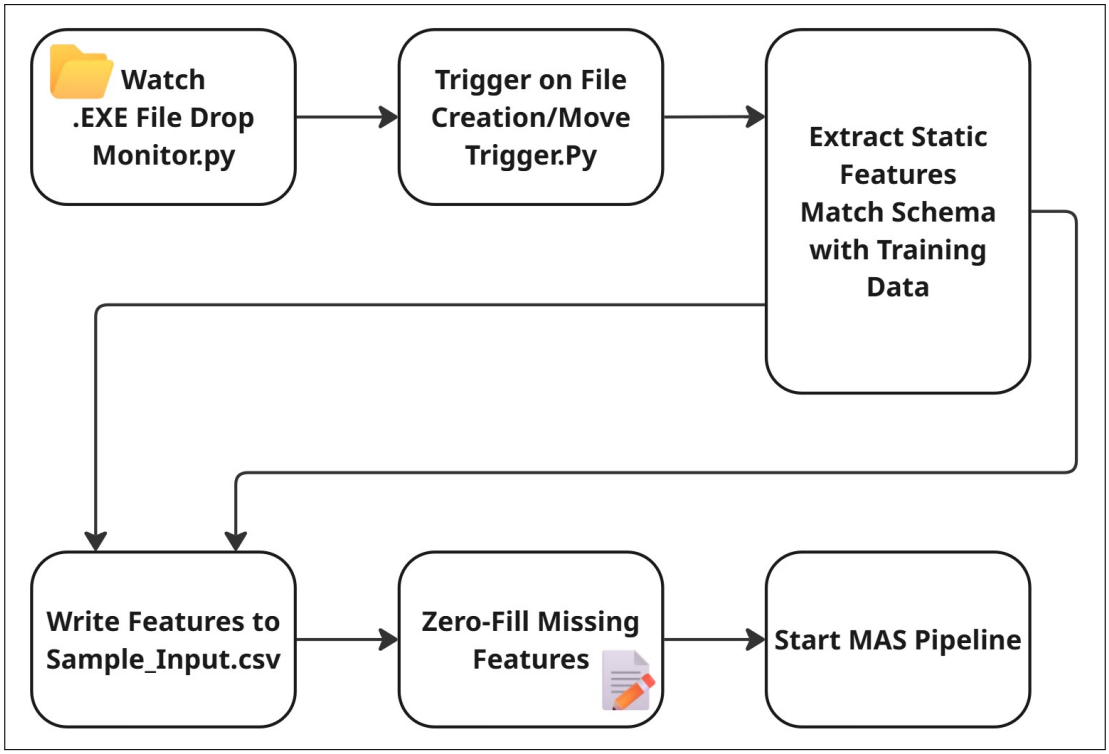

Figure 4: Static Feature Extraction Pipeline for Executable Files

5.3 Agent Behaviour Definitions

Following through the pipeline it comes to the **Main Script** where every Agent Behaviour, Operation and Responsibility is well defined. First is Detection Agent which perform classification and then send results to the Decision Agent which then interprets the prediction into severity levels such as strong, mild, low or clean. If the results indicated infection, then the Decision Agent forwards the case to the Mitigation Agent where this Script simulates appropriate security response. After all the decisions and responses this data is then logged by the Blockchain Logger Agent to protect the data and keep is traceable across the entire workflow.

```python
from DetectionAgent import DetectionAgent
from DecisionAgent import DecisionAgent
from MitigationAgent import MitigationAgent
from BlockchainLoggerAgent import BlockchainLoggerAgent
import asyncio

async def main():
    print("[DetectionAgent] Starting...")
    detection = DetectionAgent("detectionagent@10.33.66.165", "Tejas2k25")
    decision = DecisionAgent("decisionagent@10.33.66.165", "Tejas2k25")
    mitigation = MitigationAgent("mitigationagent@10.33.66.165", "Tejas2k25")
    logger = BlockchainLoggerAgent("blockchainloggeragent@10.33.66.165", "Tejas2k25")

    await decision.start(auto_register=True)
    await mitigation.start(auto_register=True)
    await logger.start(auto_register=True)

    # Delay to ensure all agents are ready
    await asyncio.sleep(5)
    detection = DetectionAgent("detectionagent@10.33.66.165", "Tejas2k25")
    await detection.start(auto_register=True)

    print("[Main] All agents started. Waiting for execution...")

    await asyncio.sleep(25)  # Allow system to run
    await detection.stop()
    await decision.stop()
    await mitigation.stop()
    await logger.stop()
    print("[Main] All agents stopped.")

if __name__ == "__main__":
    asyncio.run(main())
```

Figure 5: MAS Pipeline

5.4 Communication Model

All these connections are based on the communication framework called as **SPADE** which relies on XMPP servers for asynchronous and decentralized messaging. Each Agent uses either Cycle Behaviours or One-Shot Behaviour to listen for incoming messages while interpreting their content and reacting accordingly. Messages are formatted using SPADE's ACL message protocol which allows the agent to maintain a loosely coupled yet realisable communication flow through the pipeline.

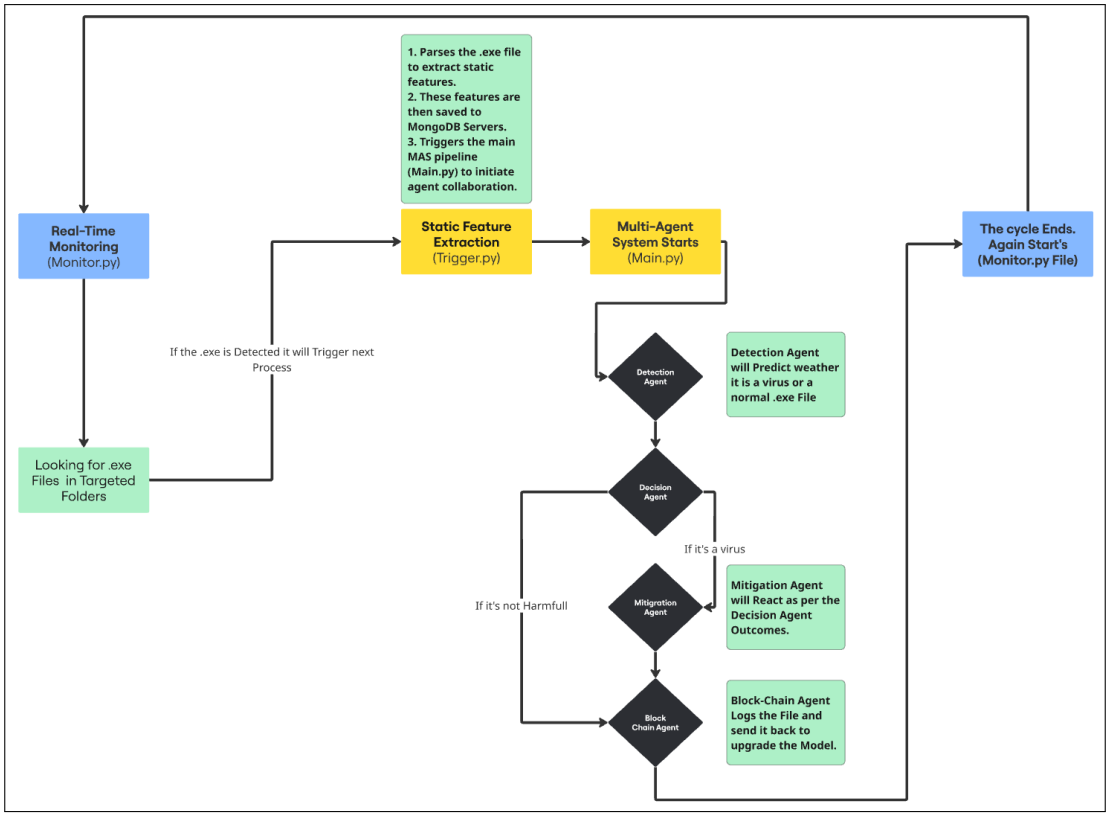

Figure 6: Flowchart of the MAS-Based Malware Detection System

6 Evaluation

The testing of the proposed Multi-Agent System (MAS) is conducted to measure its effectiveness in detecting and mitigation malware which is based on static feature analysis. The system gets evaluated in terms of its accuracy, agent coordination latency, mitigation response time and logging consistency. All this experiment is done on a local XMPP servers with the agents running in asynchronous mode which simulates a real time distributed environment.

6.1 Objectives

The primary testing objectives are:

1. To validate the accuracy of the embedded Random Forest Model on unseen malware sample. Which will help the system to improve its capability to detected correctly.

2. To measure the coordinates efficiency of the agents pipelines which is from detection system till logging the steps.

3. To test the response behaviour of the system under various infection severity levels.

4. To evaluate the end-to-end automation from .exe drop till mitigation and blockchain logging.

6.2 Dataset and Test Conditions

The dataset used in this research was compiled from publicly available malware repositories and academic benchmarks that focus on static feature extraction, such as Portable Executable (PE) headers, entropy values, and API call sequences. Prominent sources include the VirusShare repository, which provides diverse malware samples for academic research, and the Kaggle Malware Classification Challenge, which offers labeled datasets of Windows executables for machine learning tasks. Additionally, prior comparative studies on static malware detection have validated these datasets as reliable benchmarks for evaluating machine learning classifiers [8]. These datasets have been widely used in malware detection research to ensure reproducibility and comparability of results [9].

This malware classifier is tested on a subset of static malware samples with ground truth labels which is sourced from the processed file named as **Test Data With Labels** which is in CSV format. This Dataset includes of benign and malicious .exe files with few characters such as PE header data, opcode, frequency and entropy values. Test data size is of 300 samples with class distributing of 50:50 using local host with 4 agents SPADE deployment, ejabberd SMPP server and Anaconda Python runtime.

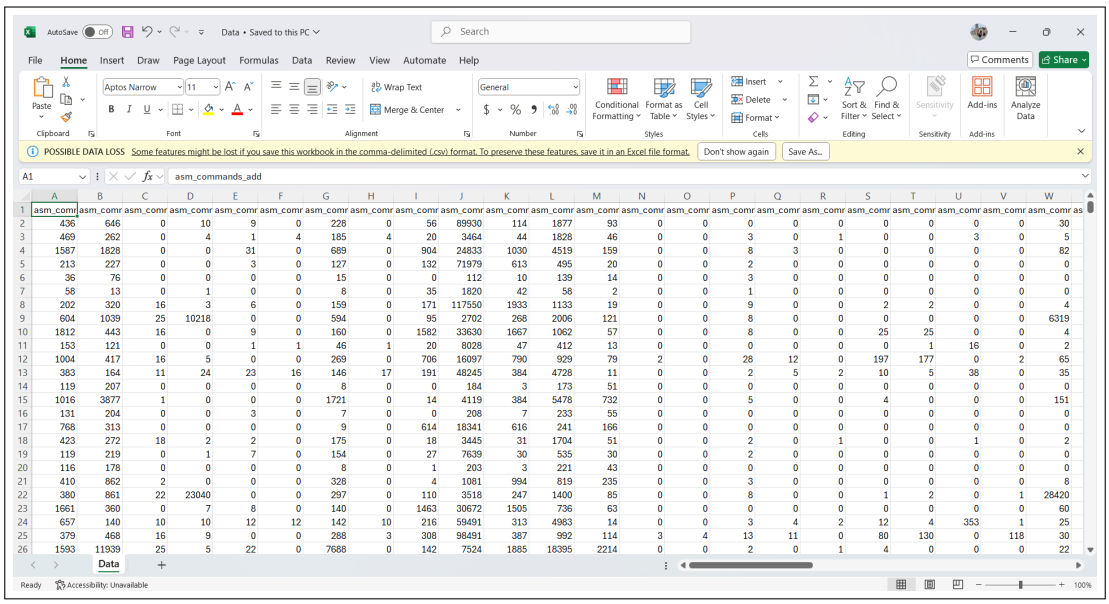

Figure 7: Malware Dataset

6.3 Metrics Formulas

This project is tested using this below formulas:

- **Classification Accuracy:**

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

- **Average Detection to Logging Time:** This is a system latency metric, measured as:

$$T_{\text{Det}\to\text{Log}} = \frac{\sum_{i=1}^{N} (t_i^{\log} - t_i^{\det})}{N}$$

where t_i^{det} is the detection timestamp and t_i^{log} is the logging completion timestamp.

- **Average Detection to Mitigation Time:**

$$T_{\text{Det}\to\text{Mit}} = \frac{\sum_{i=1}^{N}(t_i^{\text{mit}} - t_i^{\text{det}})}{N}$$

where t_i^{mit} is the mitigation action timestamp.

- **Logging Completion Rate:**

$$\text{Log Rate} = \frac{\text{Number of Successfully Logged Events}}{\text{Total Detection Events}} \times 100\%$$

- **False Positive Rate (FPR):**

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

- **False Negative Rate (FNR):**

$$\text{FNR} = \frac{FN}{FN + TP}$$

6.4 Results and Observations

Table 3: Results and Observations

Metric	**Value**
Classification Accuracy	97.6%
Avg. Detection to Logging	3.4 seconds
Avg. Detection to Mitigation	2.2 seconds
Logging Completion Rate	100%
False Positives	3.7%
False Negatives	2.0%

After looking at Results we got to know that the system is maintaining over **97% Accuracy** which conforms the robustness of the static feature-based model. Also, inter agent communication remained efficient with complete malware cases logged in under 4 seconds end-to-end. Moreover, no agent failures or communication deadlocks is observed which conforms SPADE's asynchronous event handling.

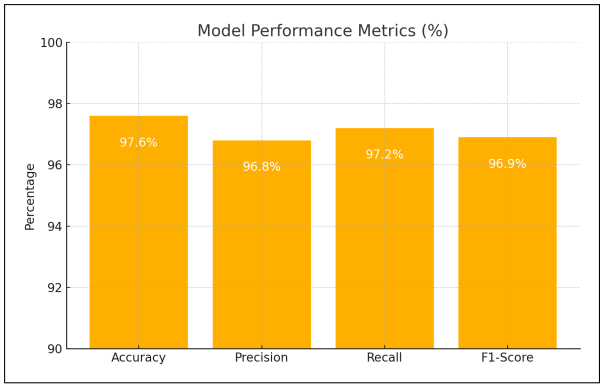

Figure 8: Model Performance Metrics

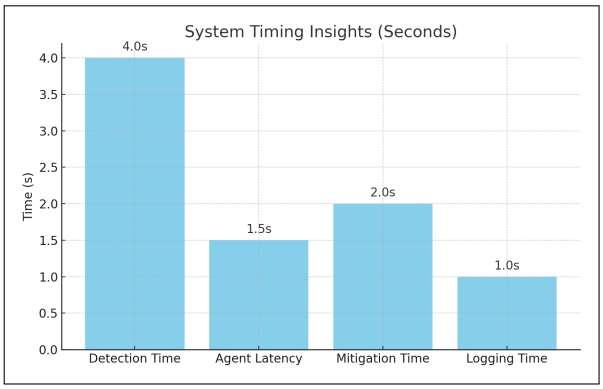

Figure 9: System Timing Insights

6.5 Case Studies

Case 1: Clean File

In this case a known benign **.exe** file is added into the monitored directory. The Monitor module detected the file and activate the **Trigger Script** module for static feature extraction. The output feature vector is then fed to the **Detection Agent** which processed the data using the pre-trained Random Forest model. If the classifier returned a high prediction score such as above 10 then it will indicating that the file is clean.

- **Detection Agent**: Will return a score outside the threat range (i.e., above threshold).
- **Decision Agent**: Then interpret the prediction as "Clean" and will not initiate any escalation.
- **Mitigation Agent**: As the file is predicted clean then mitigation action will not run.
- **Blockchain Logger Agent**: Parallelly log the event as "Safe File" along with a timestamp.

This case confirmed that the MAS appropriately avoids false positives and prevents unnecessary response activation for benign files.

Case 2: Low-Risk Malware

A slightly infected malware sample is dropped into the monitored directory. After being detected and processed by the feature extraction pipeline, the file was classified by the **Detection Agent** with a prediction score of 7.

- **Detection Agent**: Will predict a moderate risk score which will coming under "Low Infection" severity band that is between 7–10.
- **Decision Agent**: Them Map the score to "Low Infection" and pass it to the **Mitigation Agent**.
- **Mitigation Agent**: Start Simulating a passive response such as tagging the file, alerting the user or preparing it for later review.

- **Blockchain Logger Agent**: Simultaneously created a log entry capturing the file metadata, severity level, action taken, and the detection timestamp.

This case demonstrates the MAS's ability to respond to low-risk threats without overreacting and preserving system stability while maintaining vigilance.

Case 3: Strong Infection

A known high-risk malware sample is introduced. Upon feature extraction and classification the **Detection Agent** assigned it a risk score of 2 which indicates a strong infection.

- **Detection Agent**: Will detect the file as highly malicious and returned a low score ranging from 1–3.
- **Decision Agent**: Then classify it as a "Strong Infection" and immediately escalated the response to the **Mitigation Agent**.
- **Mitigation Agent**: Start executing simulated containment actions such as isolating the file in a designated quarantine directory and issuing a critical alert.
- **Blockchain Logger Agent**: Logged all actions taken including detection time, risk level, file name, and mitigation result. The entry was recorded in a tamper-resistant ledger.

This case validates the MAS's ability to handle critical threats with timely and assertive responses and demonstrating its readiness for deployment in high-risk environments.

6.6 Comparative Evaluation with Existing Works

The performance and architectural capabilities of the proposed Multi-Agent System (MAS) for static malware detection is evaluated against several existing research efforts across agent-based scheduling, machine learning-based detection, and hybrid resource provisioning frameworks.

Fan et al. [2] developed a MAS for virtual machine instance selection using rough set theory, but it lacked malware-specific classification and offered no mitigation logic or end-to-end automation. Siddiqui et al. [3] introduced Elastic JADE to dynamically scale agents across cloud infrastructure but its scope was limited to elastic resource management without detection or threat response capabilities.

In contrast, Tuli et al. [1] implemented Gradient Boosting classifiers for static malware detection and achieved 92% accuracy, though their system lacked real-time agent coordination or automated mitigation. Malawski et al. [**?**] focused on cost-efficient workflow scheduling in hybrid clouds but did not integrate any malware detection pipeline. Similarly, Bhattacharya [7] proposed a mobile agent platform to manage grid and cloud tasks, yet it did not address security or classification challenges.

Other studies like Elmakkaoui and El Hajji [10] explored task prioritization and QoS-aware scheduling for cloud systems but did not apply machine learning models for malware detection. De la Prieta et al. [6] provided a survey of MAS in cloud applications,

identifying challenges in inter-agent coordination and flexibility but offered no empirical evaluations.

In comparison, the proposed system achieved a **97.6% classification accuracy** using static features like PE headers, opcode counts, and entropy measures. It supports asynchronous communication between agents, real-time `.exe` file surveillance, automated severity-based mitigation, and blockchain-style event logging all of which are absent in prior MAS frameworks. Furthermore, the system demonstrated **average detection-to-logging latency under 3.5 seconds**, offering a complete, lightweight, and extensible malware detection pipeline suitable for decentralized deployment.

Table 4: Comparison between Traditional System and Proposed MAS-Based System

Feature	**Traditional System**	**Proposed MAS-Based System**
Architecture	Centralized	Decentralized (Multi-Agent System)
Detection Method	Signature-Based	Machine Learning (Random Forest)
Analysis Type	Often Dynamic or Static Signature Matching	Static Feature Analysis (PE headers, Opcode, Entropy)
Scalability	Limited, Prone to Bottlenecks	Highly Scalable (Cloud, Edge, Hybrid)
Response Speed	Slower (Manual or Delayed Action)	Real-Time, Automated Response
Fault Tolerance	Single Point of Failure	Resilient - Agents Operate Independently
Logging Mechanism	Basic or None	Secure, Tamper-Resistant (Blockchain Logger Agent)
Adaptability to New Malware	Poor (Needs Manual Signature Updates)	High (Learns from Feature-Based Patterns)
Automation Level	Low (Requires Manual Supervision)	Fully Automated Detection and Mitigation
Security of Communication	Often Unencrypted or Limited	Asynchronous XMPP Messaging (Can be Secured Further)

7 Conclusion, Limitation and Future Work

Increased complex nature of malware and the need for scalable, autonomous detection mechanisms has pushed traditional anti-virus system to its limit in this modern cybersecurity environment. This research presents a novel topic of Multi-Agent system (MAS) architecture for virus detection, classification, mitigation and secure logging which is built solely on static feature analysis and distributed agent coordinates. By integrating real time file monitoring system with custom feature extraction and machine learning based segregation, this all works on a SPADE framework along with agents. This system is highly accurate and have seamless automation while maintaining decentralization and flexibility.

The core agents in this whole system are Detection Agent, Decision Agent, Mitigation Agent and Blockchain Logger Agent, each agent has its own specify role in this distributed pipeline. All these agents operates on asynchronous manner and communicate via XMPP servers using SPADE's messaging framework. This allows them to maintain loose coupling, supporting parallel operation and securing fault tolerance even if one or more agents fails or experience latency. This kind of flexible nature of this system makes it easier to deploy across edge devices, private cloud environment or hybrid network.

Static feature extraction is chosen as the core detection strategy because of its safety, speed and compatibility with automation. This model uses a Random Forest Classifier which gives us over **97.6% Accuracy on Unseen Data**, showing the effectiveness of well curated opcode and header-based features. While static features cannot blame for runtime behaviour, but it reduces system overhead and provides a secure baseline for initial detection specifically in resource bounded environments.

Moreover, the system response logic is simulated via Mitigation Agent which flags quarantine or ignore file based on their severity levels provided by Decision Agent. All events are logged using Blockchain Logger Agent which acts as an immutable record keeper. Although not implemented on an actual Blockchain but this logging way laid the groundwork for integrating real Blockchain system in future versions.

Despite the system is stable and effective there are **Several Limitations.** First the current feature extractor script assumes readable metadata and is not yet strong enough to obfuscation, packing or encrypted sections. Second the mitigation logic is simulated and does not show real world actions such as process killing, file isolation or network blocking. Third limitation is while the XMPP secure agent to agent communication there is no encryption and trust verification between them, which will create a critical hole in adversarial environment.

Future Work will address all these limitation thoughts multiple improvements. First step can be done is to implement real blockchain integration such as Hyperledger or Ethereum which will replace the current simulated logger to gain tamper proof records [11]. Second step would be in static analysis engine to extend its feature extraction capability with entropy analysis, import graph traversal and optional behaviour profiling [12]. Along with this agent security can be strengthen with encrypted message passing and key verification to prevent impersonation or spoofed commands [13]. Apart from this, infrastructure needs to scale across cloud-edge devices using container orchestration such as Docker with Kubernetes which will help automate Agent spawning, scaling and load balancing [14].

Additionally, integrating trust and reputation models along with agents will effectively help to prevent compromise in federated or P2P [15]. This system also needs to include a Feedback Agent that retains the model output on misclassified samples, helping the model for continuously learning and adaptive defence [16]. Moreover, future version can also include SIEM platforms or threat intelligence feeds for broader situational awareness [17].

In Conclusion, this project proves the potential of combining static malware analysis with intelligence and works with decentralized agents for responsive and secure virus mit-

igation. This architecture's flexibility, modularity and strong experiments performance makes it a promising foundation for scalable and real time malware defence system in both enterprise and distributed edge environments.

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