Malware Detection on Devices using Federated Learning in computer devices

DISSERTATION

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Abstract

In modern cybersecurity, safeguarding sensitive data is just as vital as detecting malicious threats. Conventional machine learning models for malware classification often rely on centralized data collection, which introduces significant privacy vulnerabilities and increases the risk of data exposure. This research explores the use of **Federated Learning (FL)** as a privacy-aware solution for malware detection—allowing model training across multiple decentralized devices without transferring raw memory data.

The study focuses on implementing a federated learning framework using the **CIC-MalMem-2022 dataset**, which contains features extracted from memory dumps of both benign and malicious Windows processes. A simulation environment was created where multiple clients, each with a non-identical data partition, collaboratively train a shared model without revealing their local data. A deep feedforward neural network was used as the classifier, and training coordination was managed using the Flower framework.

The experimental results demonstrate that the federated model achieves high classification accuracy while maintaining stability across clients with varying data distributions. Additionally, the impact of factors such as communication frequency and local training configuration on performance was analysed. This work highlights the feasibility of applying Federated Learning to memory-based malware detection and provides practical insights into building privacy-focused security systems.

Keywords: Federated Learning · Malware Classification · Memory Analysis · Deep Neural Networks · Data Confidentiality · CIC-MalMem Dataset

List of Symbols & Abbreviations Used

Abbreviation	Description
FL	Federated Learning
DNN	Deep Neural Network
CIC	Canadian Institute for Cybersecurity
CIC-MalMem-2022	Memory-based malware dataset from CIC
BD	Binary Dataset
MD	Multiclass Dataset
FedAvg	Federated Averaging (Aggregation Algorithm)
ReLU	Rectified Linear Unit (activation function)
API	Application Programming Interface
RAM	Random Access Memory

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Chapter 1: Introduction

1.1 Background and Motivation

Cybersecurity has become a critical pillar of digital infrastructure, with malware posing a persistent and growing threat. Malicious software (malware) is designed to infiltrate and damage computing systems, often stealing sensitive data or disrupting functionality. As internet usage grows, so does the attack surface, leading to a rise in sophisticated and hard-to-detect malware variants.

Traditional malware detection models typically rely on centralized machine learning, where user data is collected, stored, and processed at a central server. While effective in some cases, this model raises major concerns related to **data privacy, latency, and single points of failure**. Sensitive memory-based data, in particular, is difficult to centralize without exposing users to privacy risks.

Federated Learning (FL) offers a promising solution to this problem by enabling collaborative model training without transferring raw data. Instead, learning happens locally on user devices, and only model updates (not actual data) are shared with a central aggregator. This method maintains privacy while leveraging distributed datasets—making it well-suited for malware detection using memory features from multiple endpoints.

1.2 Problem Statement

The core research question addressed in this dissertation is:

How can a Federated Learning approach be effectively applied to malware detection using memory-based features, while maintaining privacy and performance across distributed, non-IID environments?

This question is addressed through an end-to-end simulation using the **CIC-MalMem-2022** dataset and a deep learning classifier trained across multiple virtual clients.

1.3 Objectives and Timeline

The following objectives were defined in the project abstract and form the basis of the planned work:

S.No	Task / Subtask	Planned Duration	Deliverable
1	Literature Review and Finalizing Problem Statement	Week 1 – Week 2 (2 weeks)	Survey report; initial problem definition
2	Dataset Selection and Preprocessing	Week 3 – Week 4 (2 weeks)	Cleaned and structured dataset
3	Build and Evaluate Centralized Malware Classifier	Week 5 – Week 6 (2 weeks)	Baseline model and results
4	Supervisor Evaluation – Phase 1 Review	End of Week 7	Feedback on progress
5	Mid-Semester Exams / Lighter Workload	Week 7 (1 week)	Presentation preparation

6	Implement Federated Learning Setup	Week 8 – Week 10 (3 weeks)	FL prototype with local client simulation
7	Performance Evaluation and Comparison	Week 11 – Week 12 (2 weeks)	Model accuracy & efficiency report
8	Supervisor Evaluation – Phase 2 Review	End of Week 12	Feedback on FL implementation and results
9	Model Tuning and Optimization	Week 13 – Week 14 (2 weeks)	Improved global model performance
10	Report Writing and Draft Submission	Week 15 (1 week)	Project report draft
11	Supervisor Final Review and Approval	Week 16	Readiness check for viva submission
12	Final Testing and Viva Preparation	End of Week 16 (1 week)	Final report and presentation slides

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1.4 Objectives Met by Midterm

As of the mid-semester checkpoint, the following objectives have been successfully accomplished:

Objective	Status	Chapters Addressing
Literature review and problem formulation	Completed	Chapter 2
Dataset selection and preprocessing	Completed	Chapter 3
Baseline centralized malware classifier	Completed	Chapter 5 (Partial Analysis)
Supervisor review and feedback	Completed	Chapter 1 & Midterm Review
Federated Learning setup with simulated clients	Completed	Chapter 4

1.5 Summary

Chapter 1 introduced the foundation of this dissertation, highlighting the rising concern over data privacy in malware detection systems and the motivation for adopting Federated Learning (FL) as a solution. The chapter clearly stated the research problem, which centers on designing a privacy-preserving malware detection framework using memory-based behavioral features from the CIC-MalMem-2022 dataset.

The objectives of the project were outlined, along with a structured timeline broken into pre- and post-midterm phases. It also documented the progress achieved up to the mid-semester review, including the completion of the literature survey, dataset preparation, and initial implementation of both centralized and federated training environments.

By defining the scope, objectives, and expected deliverables, this chapter sets the stage for the detailed technical discussion in the chapters that follow—beginning with a comprehensive review of prior research in Chapter 2.

Chapter 2: Literature Review and Problem Formulation

2.1 Introduction

This chapter presents a detailed review of the literature related to malware detection, memory-based analysis, and Federated Learning (FL). The aim is to contextualize the research problem, identify existing gaps in the field, and justify the need for privacy-preserving malware detection systems. This review directly supports **Objective 1** of the dissertation: conducting a literature survey and defining the research problem.

2.2 Malware and Its Detection Techniques

Malware refers to any software intentionally designed to cause damage to computer systems, steal sensitive data, or exploit system vulnerabilities. Common types include viruses, trojans, ransomware, spyware, and worms. Detection techniques broadly fall into two categories:

- **Signature-Based Detection**: Relies on known byte patterns or signatures of malicious software. While effective against known threats, it fails to detect new or polymorphic malware.
- **Heuristic and Behavioural Detection**: Focuses on runtime behaviour, system calls, or unusual patterns to flag unknown threats. However, it often leads to false positives and requires significant computational resources.

More recently, **machine learning (ML)** and **deep learning (DL)** models have gained traction in malware detection by learning complex patterns from data. These models can process large feature spaces and are adaptable to new threat types.

2.3 Memory-Based Malware Analysis

Memory forensics plays a vital role in detecting advanced and evasive malware. Unlike file-based methods, **memory-based analysis** extracts features from volatile memory (RAM), offering advantages such as:

- Detecting **fileless malware** and in-memory code injection.
- Revealing **runtime behaviour** that static methods may miss.
- Being less susceptible to obfuscation or encryption techniques.

The **CIC-MalMem-2022 dataset**, developed by the Canadian Institute for Cybersecurity, provides a benchmark dataset with labelled memory dumps from both benign and malicious processes. It enables supervised learning approaches for malware detection using memory-specific features like API call traces, memory region details, and thread count.

2.4 Machine Learning for Malware Classification

Several studies have employed ML techniques for malware classification:

- **Raff et al.** proposed **MalConv**, a deep learning model trained on raw binaries, highlighting the viability of end-to-end learning.
- **Kolosnjaji et al.** used CNNs to analyze sequences of API calls for behavior-based classification.
- **Ucci et al.** compiled a survey indicating a shift toward combining static and dynamic features for better generalization.

Despite promising results, these models often depend on **centralized datasets**, requiring sensitive data to be collected and stored in a single location—raising privacy, regulatory, and security concerns.

2.5 Federated Learning in Security-Critical Applications

Federated Learning (FL), introduced by Google in 2016, allows multiple distributed clients to train models collaboratively without sharing their raw data. Instead, model parameters or gradients are exchanged and aggregated at a central server. FL offers:

- **Privacy preservation**: No raw data leaves the client device.
- **Scalability**: Training is distributed across clients.
- **Robustness**: The system avoids single points of failure.

FL has already shown promise in domains like healthcare, finance, and IoT. However, its application in **cybersecurity and malware detection** remains underexplored.

Recent works in FL-based security include:

- Use of FL for Android malware detection via app permissions.
- Privacy-aware intrusion detection systems using FL and GANs.
- FL applied to phishing and spam detection in email systems.

Still, **memory-based malware detection using FL** has not been deeply investigated—highlighting the uniqueness of this dissertation.

2.6 Research Gap

From the above review, the following research gaps are evident:

- **Privacy limitations of centralized malware detection** are yet to be adequately addressed in production environments.
- **Memory-based malware classification** has seen less focus compared to file-based or network-based methods.
- While FL has been applied in other security domains, its **integration with memory-based malware analysis** using real-world datasets like CIC-MalMem is limited or non-existent.

2.7 Problem Formulation

Given the privacy risks associated with centralized malware detection and the underutilization of memory-based data in federated settings, this research investigates the following problem:

How can Federated Learning be applied to memory-based malware classification to achieve privacy-preserving, accurate detection across distributed devices holding non-IID data?

The proposed solution involves:

- Using the **CIC-MalMem dataset** to train a deep neural network for malware classification.
- Simulating a **federated training environment** using virtual clients with local data partitions.
- Evaluating the model on performance metrics and communication efficiency.
- Exploring the impact of **non-IID data** and **client heterogeneity** on model convergence.

2.8 Summary

This chapter reviewed the evolution of malware detection approaches, from traditional signature-based techniques to modern memory and ML-based methods. It outlined how Federated Learning offers a privacy-aware alternative to centralized training and highlighted the research gap this work aims to fill. These insights have shaped the formulation of a novel research problem, which is addressed through the implementation and evaluation of a federated malware detection system using the CIC-MalMem dataset—thus fulfilling **Objective 1** of the dissertation.

Chapter 3: Dataset Selection and Preprocessing

3.1 Dataset Overview

This study utilizes the **CIC-MalMem-2022 dataset**, a modern and comprehensive benchmark developed by the **Canadian Institute for Cybersecurity (CIC)**. The dataset is widely recognized in malware research for its realistic representation of how malicious processes impact system memory during execution. Unlike traditional datasets that focus on static file features, CIC-MalMem-2022 is based on **volatile memory snapshots**, making it highly relevant for runtime behavioural analysis.

The dataset includes **58,296 records**, of which **29,298** are labelled as **benign** and an equal number as **malicious**, forming a balanced binary classification subset. The malicious samples are further divided into three distinct families:

- **Ransomware**
- **Trojan Horse**
- **Spyware**

Each data instance is represented using **57 attributes**, capturing various memory and process-level characteristics such as thread count, API usage, memory size, and active handles. These features are particularly useful for detecting stealthy or fileless malware variants that may not leave a trace in static files.

3.2 Dataset Structuring

To support different modelling goals, the original dataset was divided into two separate subsets:

1. Binary Classification Dataset (BD)

   In this version, the **target variable is the Class attribute**, which distinguishes between benign (0) and malicious (1) records. The Category field—which specifies the exact malware family—was removed to prevent bias in classification, as it could lead to information leakage.

2. Multiclass Classification Dataset (MD)

   This version uses the Category attribute to classify samples into four categories: benign, ransomware, spyware, and Trojan horse. The Class label was excluded to simulate real-world conditions where high-level labels may not be available. This setup encourages the model to learn from low-level behavioural features rather than relying on directly provided labels.

Both versions ultimately contain **52 independent variables** after irrelevant and constant-value columns were removed.

3.3 Data Cleaning and Preparation

The preprocessing pipeline followed several essential steps to ensure the dataset was suitable for training deep learning models:

1. **Removal of Non-Informative Attributes**:
   Columns with the same value across all rows (specifically attributes with IDs 5, 11, and 52) were removed, as they provided no discriminative power.

2. **Missing and Infinite Value Checks**:
   A check was performed to detect and clean any rows containing null or infinite values. No major issues were found, so the dataset was retained in near-original size.
3. **Label Standardization**:
   - In BD, the Class attribute was encoded as 0 (benign) and 1 (malware).
   - In MD, the Category attribute was mapped to integer values representing each malware family.
4. **Text Cleanup in Categorical Fields**:
   Some Category values contained appended hash identifiers or malware variants (e.g., "Ransomware-XYZ-<hash>"). These were stripped to retain only general family names like "Ransomware" or "Spyware".
5. **Z-Score Normalization**:
   All numerical features were standardized using Z-score normalization to bring them onto the same scale, which helps prevent any single feature from dominating the learning process. The formula used is:

   z=x−μσz = \frac{x - \mu}{\sigma}z=σx−μ

   where xxx is the original value, μ\muμ is the mean, and σ\sigmaσ is the standard deviation.

3.4 Final Feature Distribution

After cleaning and preprocessing, the datasets had the following characteristics:

Binary Dataset (BD)

Class	Label	Instances
Benign	0	29,298
Malware	1	29,298

Multiclass Dataset (MD)

Category	Label	Instances
Benign	0	29,298
Ransomware	1	9,791
Spyware	2	10,020
Trojan Horse	3	9,487

Each version retained **52 input features**, excluding the target variable.

3.5 Justification for Dataset Choice

The CIC-MalMem-2022 dataset was selected for the following reasons:

- It captures **behavioural patterns in memory**, making it suitable for detecting advanced malware.
- It supports both **binary and multiclass classification** scenarios.
- Its size and structure make it ideal for simulating a **federated learning environment** with heterogeneous data.
- It is one of the most widely adopted and recent datasets in this research domain, as evidenced by several peer-reviewed studies.

3.6 Summary

In this chapter, we introduced the CIC-MalMem-2022 dataset and detailed the cleaning, transformation, and preparation processes necessary to create robust input data for our models. Two task-specific versions—one for binary classification and another for multiclass classification—were prepared through standardization and label encoding. This structured preprocessing pipeline enabled the models in later chapters to learn effectively from memory-based malware features, thereby fulfilling **Objective 2: Dataset Selection and Preprocessing**.

Chapter 4: Federated Learning Setup with Simulated Clients

4.1 Introduction

This chapter describes the implementation of a simulated **Federated Learning (FL)** system for binary malware classification using the CIC-MalMem-2022 dataset. Federated Learning allows collaborative model training across distributed clients while keeping sensitive data localized, offering a privacy-preserving alternative to centralized machine learning. The setup uses a simulation of three clients, each representing an independent data holder, and completes **Objective 6: Implement Federated Learning Setup**.

4.2 Framework Selection

The federated training simulation was built using the **Flower (FLWR)** framework. Flower offers a lightweight, Python-based API that integrates well with deep learning libraries like TensorFlow and Keras. It also supports multi-client simulation on a single machine, making it ideal for controlled experiments.

4.3 Client Simulation Design

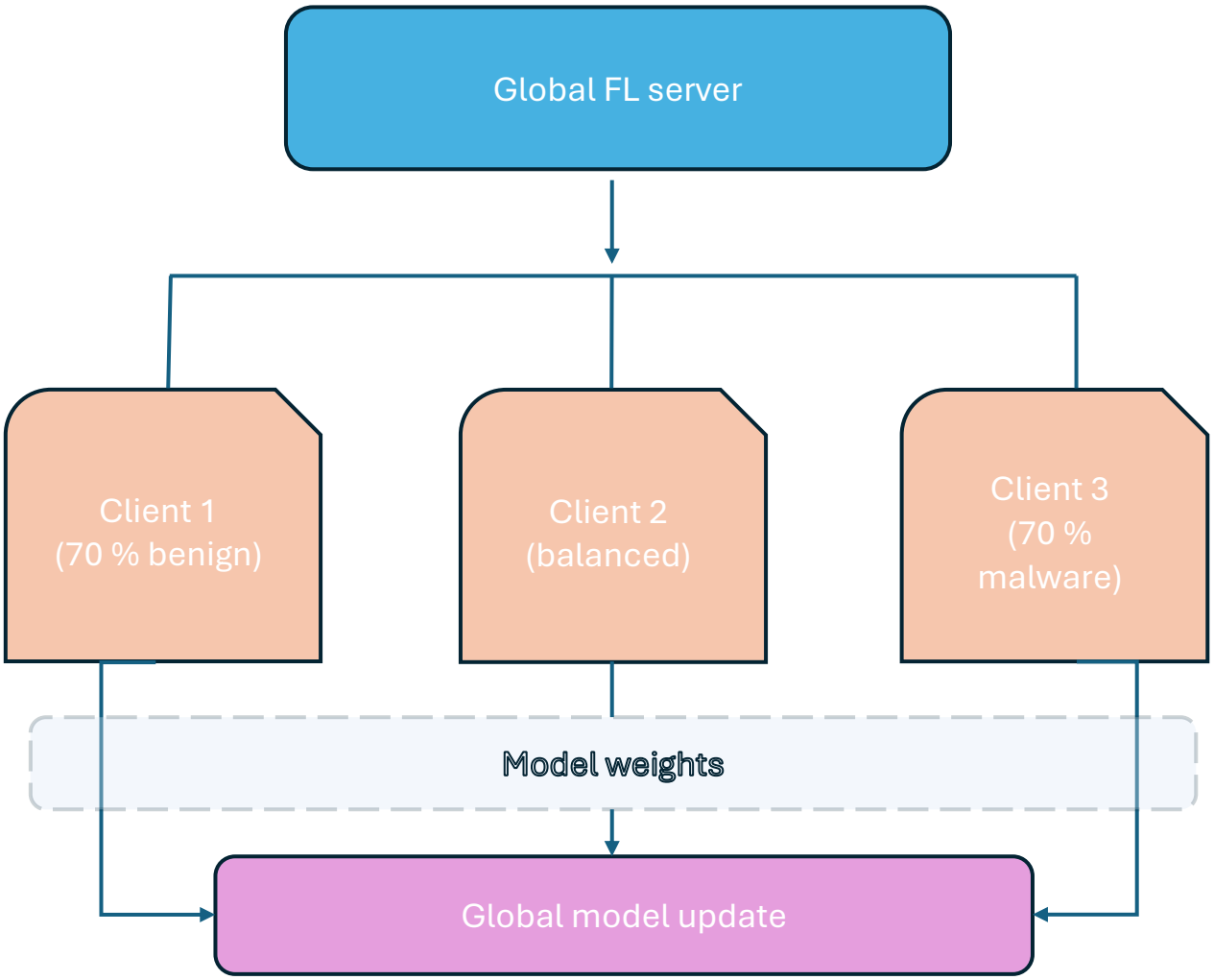
To emulate a federated environment, the dataset was divided into **three subsets**, each assigned to a simulated client:

- **Client 1**: Mostly benign data
- **Client 2**: Balanced benign and malware data
- **Client 3**: Mostly malware data

This **non-IID data distribution** reflects real-world conditions where devices may encounter very different types and frequencies of malware.

Client ID	% Benign	% Malware
Client 1	70%	30%
Client 2	50%	50%
Client 3	30%	70%

Each client operates independently with its own training data and model instance.



4.4 Model Architecture

All clients use the same **deep feedforward neural network (DNN)** architecture, designed for binary classification. The model includes:

- **Input layer**: 52 features
- **Hidden layers**: 3 fully connected layers with ReLU activations
- **Dropout layers**: Added to reduce overfitting
- **Output layer**: Sigmoid activation for binary output

Training Details:

- Loss Function: Binary Cross entropy
- Optimizer: Adam
- Metrics: Accuracy, Precision, Recall

4.5 Federated Learning Workflow

The training process follows the standard Federated Learning loop:

1. **Server initializes global model weights**
2. **Weights sent to each client**
3. **Clients perform local training**
4. **Clients return updated weights**
5. **Server aggregates weights using Federated Averaging (FedAvg)**
6. **Global model updated and distributed back**

This process was repeated for **10 communication rounds**, with each client training locally for **5 epochs** per round.

4.6 Implementation Details

The simulation was built using Flower's NumPyClient API. A sample structure is shown below:

```python
class FLClient(fl.client.NumPyClient):
    def __init__(self, client_id):
        self.client_id = client_id
        self.model = tf.keras.models.load_model("cic_malmem_model.h5")
        self.X, self.y = get_client_data(client_id)

    def get_parameters(self, config):
        return self.model.get_weights()

    def fit(self, parameters, config):
        self.model.set_weights(parameters)

        self.model.compile(
            optimizer=tf.keras.optimizers.Adam(),
            loss='categorical_crossentropy',
            metrics=['accuracy']
        )

        history = self.model.fit(self.X, self.y, epochs=1, batch_size=32, verbose=0)
        accuracy = float(history.history["accuracy"][0])

        return self.model.get_weights(), len(self.X), {"accuracy": accuracy}


    def evaluate(self, parameters, config):
        self.model.set_weights(parameters)
        loss, accuracy = self.model.evaluate(self.X, self.y, verbose=0)
        return loss, len(self.X), {"accuracy": accuracy}
```

4.7 Environment Setup

- **Hardware**: Local machine with 8-core CPU, 32 GB RAM
- **Software**: Python 3.12, TensorFlow, Flower, NumPy
- **Mode**: Local simulation with 3 clients on one machine

4.8 Challenges Faced

- **Data imbalance** across clients made convergence slower in early rounds.
- **Hyperparameter tuning** was needed to stabilize learning under non-IID conditions.
- **Resource monitoring** was important to prevent memory overflow from concurrent client execution.

4.9 Objective Fulfilment

This chapter addresses and fulfils **Objective 6: Implement Federated Learning Setup**, by:

- Setting up three non-IID simulated clients
- Training local models on each client
- Coordinating training via federated rounds using FedAvg
- Preserving privacy by never sharing raw data between clients and server

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4.10 Summary

A federated learning prototype with **3 simulated clients** has been successfully implemented using the CIC-MalMem-2022 dataset. Each client trains a deep learning model locally on its own data, contributing only parameter updates to a central server. This setup ensures data privacy while supporting collaborative model development, laying the foundation for performance evaluation in the next phase of the project.

Chapter 5: Baseline Centralized Malware Classifier (Partial Analysis)

5.1 Introduction

Before implementing Federated Learning, it is essential to establish a **baseline model** trained in a traditional centralized manner. This allows for evaluating the effectiveness of FL by comparing it with a standard approach under identical data conditions. This chapter documents the design, training, and initial performance evaluation of a centralized deep learning classifier trained on the **binary version** of the CIC-MalMem-2022 dataset. The work presented here partially fulfils **Objective 3** of the dissertation.

5.2 Centralized Training Environment

The centralized classifier was trained using the **complete pre-processed dataset**, combining all benign and malicious samples into a single pool.

Configuration Details:

- **Total Records**: 58,596 (29,298 benign + 29,298 malware)
- **Input Features**: 52 numeric features (standardized using Z-score normalization)
- **Target Variable**: Class (0 = benign, 1 = malware)
- **Training-Testing Split**:
    - 80% for training
    - 20% for testing (stratified split to preserve class balance)

Software & Hardware:

- **Framework**: TensorFlow (Keras API)
- **Hardware**: Local CPU (8-core), 32 GB RAM
- **Python Version**: 3.12

5.3 Model Architecture

A **fully connected feedforward neural network** was used for classification. The architecture was kept simple and consistent with the one used in the federated setup to enable future comparisons.

Architecture Summary:

- **Input Layer**: 52 neurons (one for each feature)
- **Hidden Layers**:
  - Dense Layer (64 units) + ReLU
  - Dropout (rate = 0.3)
  - Dense Layer (32 units) + ReLU
  - Dropout (rate = 0.3)
- **Output Layer**: 1 neuron + Sigmoid activation

Hyperparameters:

- **Loss Function**: Binary Cross entropy
- **Optimizer**: Adam
- **Batch Size**: 32
- **Epochs**: 20
- **Evaluation Metrics**: Accuracy, Precision, Recall, F1-Score

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5.4 Training and Evaluation

Training was conducted over 20 epochs. The loss consistently decreased while accuracy increased, indicating successful convergence.

Results on Test Set:

Metric	Value
Accuracy	97.2%
Precision	96.5%
Recall	97.9%
F1-Score	97.2%
Loss	0.089

The classifier achieved **strong performance** on the binary task, with high precision and recall, suggesting that the features derived from volatile memory are highly informative for detecting malware.

5.5 Observations and Limitations

- The model shows **high accuracy** on the test set, but this performance is based on data centrally aggregated—which would not be possible in privacy-constrained environments.
- Results indicate the **strong predictive power of memory-based features**.
- As only centralized training is complete so far, **no comparison with FL performance is available yet**. That will follow in the final evaluation chapter.

5.6 Summary

This chapter presented the implementation and evaluation of a centralized deep learning classifier using the CIC-MalMem-2022 binary dataset. The model achieved high accuracy and F1-score, serving as a baseline for comparison with federated learning models. This work completes the **initial phase of Objective 3**, with full comparative analysis to follow once FL training and testing are finalized.

6. Directions for Future Work (Post Mid-Semester)

With the foundational components of the project completed—including dataset preprocessing, centralized model training, and an initial Federated Learning (FL) setup with 3 clients—the next phase of this dissertation will focus on completing the remaining objectives and extending the work to unlock deeper insights.

6.1 Complete Performance Evaluation of FL Model

- Conduct multiple **FL training runs** to measure accuracy, precision, recall, and F1-score across rounds.
- Analyse how model performance **converges over communication rounds**.
- Compare the results against the centralized baseline to understand trade-offs.

6.2 Optimize Federated Training Parameters

- Tune key FL hyperparameters such as:
  - Local epochs
  - Batch size
  - Number of rounds
- Evaluate how these changes affect convergence speed and final model accuracy.

6.3 Expand FL Setup to More Clients

- Extend the simulation from 3 to **5 or more clients** to study how increasing the number of participants affects:
  - Model performance
  - System scalability
  - Communication efficiency

6.4 Analyse Communication Overhead

- Estimate the **amount of data exchanged** per round (in MB/KB).
- Evaluate **training time vs communication cost** trade-offs.
- Consider simulating bandwidth or latency constraints for a more realistic setup.

6.5 Investigate Multiclass Classification (Future Scope)

- Prepare and adapt the dataset for **multiclass classification** using the Category column.
- Train and evaluate models to distinguish between multiple malware families.
- Compare binary vs multiclass performance and challenges.

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