An industrial oriented mini project report

on

APPROACHES FOR BENIGN AND RANSOMEWARE ATTACKS DETECTION USING XGBOOST

Submitted in partial fulfilment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING
(ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)
By

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Under the guidance of
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CSE (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

MALLA REDDY COLLEGE OF ENGINEERING
(Approved by AICTE-Permanently Affiliated to JNTU-Hyderabad)
Accredited by NBA & NAAC, Recognized section 2(f) & 12(B) of UGC New Delhi
ISO 9001:2015 certified Institution
Maisammaguda, Dhulapally (Post via Kompally), Secunderabad500100

2024 - 2025

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CERTIFICATE

This is to certify that the Minor Project report on **"APPROACHES FOR BENIGN AND RANSOMEWARE ATTACKS DETECTION USING XGBOOST"** is successfully done by the following students of Department of Computer Science & Engineering Artificial Intelligence and Machine Learning of our college in partial fulfilment of the requirement for the award of B. Tech degree in the year 2023-2024. The results embodied in this report have not been submitted to any other University for the award of any diploma or degree.

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Submitted for the viva-voce examination held on: ____

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External Examiner

DECLARATION

We, Akula Ganesh, Sai Mokshitha , Palle Ramyasri, Purushottam Rajpurohith with Regd. no. 22Q91A6667, 22Q91A6678, 22Q91A66B0, 22Q91A66B5 are hereby declaring that an industrial oriented mini project report entitled **"APPROACHES FOR BENIGN AND RANSOMEWARE ATTACKS DETECTION USING XGBOOST"** has done by us under the guidance of **Mrs. Anju Gopi,** Assistant Professor, Department of CSE (Artificial Intelligence and Machine Learning) is submitted in the partial fulfilment of the requirements for the award of degree of **BACHELOR OF TECHNOLOGY** in **CSE (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING).**

The Results embedded in this project report have not been submitted to any other University or institute for the award of any degree or diploma.

Signature of the Candidate

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ABSTRACT

Ransomware often evades antivirus tools, encrypts files, and renders the target computer and its data unusable. The current approaches to detect such ransomware include monitoring processes, system calls, and file activities on the target system and analysing the data collected. Monitoring multiple processes has a very high overhead; newer ransomware may interfere with the monitoring and corrupt the collected data. This project presents a robust and practical approach to detecting ransomware in execution on a virtual machine (VM). We collect data for selected processor and disk I/O events for the entire VM from the host machine and use a machine learning (ML) classifier to develop a detection model. This approach avoids the overhead of continuously monitoring every process on the target machine and prevents the risk of data contamination by ransomware. Furthermore, it is resilient to variations in user workloads. It provides fast detection with a high probability for known (used for training the ML model) and unknown (not used for training) ransomware. The random forest (RF) classifier performed the best of the seven ML classifiers we tested. Over six different user loads and 22 ransomwares, the RF model detected ransomware within 400 milliseconds with a 0.98 probability.

Keywords: ML,VM,ransomeware

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF SCREEN SHOTS

CHAPTER: 1

INTRODUCTION

1.1 Motivation

The motivation for this project arises from the rapidly escalating threat posed by ransomware attacks, which have become one of the most significant and pervasive challenges in the field of cybersecurity. Ransomware is a particularly destructive form of malware that encrypts user files or locks entire computer systems, rendering them unusable until a ransom is paid.

Over the past decade, ransomware has evolved from targeting individual users to orchestrating large-scale attacks on businesses, healthcare institutions, and even critical infrastructure, resulting in substantial financial losses and operational disruptions. Recent statistics underscore the gravity of the situation: in 2022, approximately 70% of businesses reported being victimized by ransomware, and projections indicate that by 2031, a ransomware attack could occur every two seconds globally, with damages potentially exceeding $265 billion annually.

These attacks are often compounded by the exfiltration of sensitive data, with attackers threatening to leak or sell this information on the dark web if their demands are not met, thereby amplifying the pressure on victims and the potential for harm.

1.2 Problem Definition

The core problem addressed by this project is the reliable, timely, and efficient detection of ransomware attacks on computer systems, particularly in virtualized environments. As ransomware continues to evolve, traditional detection methods such as signature-based antivirus solutions and process-level monitoring have proven increasingly inadequate. Signature-based systems rely on known malware signatures or hash values, making them ineffective against new, polymorphic, or metamorphic ransomware variants that can easily alter their code to evade detection.

Another significant challenge lies in the fact that ransomware, in its attempt to encrypt as many files as possible in the shortest amount of time, exhibits a unique pattern of elevated processor and disk activity.

While this behavior can potentially be used to distinguish ransomware from benign applications, accurately capturing and analyzing these patterns without impacting system performance is a complex task. Monitoring at the process level is not only resource-intensive but also susceptible to evasion tactics employed by sophisticated ransomware. Additionally, changes in user workloads or the presence of multiple applications can significantly affect the accuracy of detection models that are not robust to such variations.

1.3 Objective of Project

The primary objective of this project is to develop a robust, practical, and efficient approach for detecting ransomware attacks in execution on virtual machines. The proposed solution involves:

- Collecting processor and disk I/O event data for the entire VM from the host machine, avoiding the need to monitor individual processes.
- Employing machine learning classifiers—specifically, Random Forest (RF), which demonstrated the best performance among tested algorithms—to build a detection model capable of identifying ransomware activity with high accuracy and speed.
- Achieving rapid detection (within approximately 400 milliseconds) with a high probability of success (up to 98%) across diverse ransomware samples and user loads.

1.4 Limitations

Despite its advantages, the propose detection approach has certain limitations:

- Resource Requirements: While less intrusive than process-level monitoring, collecting and analyzing processor and disk I/O data at the VM level still requires computational resources, which may impact performance in resource-constrained environments.
- Detection Scope: The approach relies on detecting anomalous behavior based on elevated processor and disk activity. Ransomware that is specifically engineered to mimic benign application behavior or that encrypts data very slowly may evade detection.

CHAPTER: 2

LITERATURE SURVEY

‘‘Behavior-based malware analysis and detection,’’

Malware, such as Trojan Horse, Worms and Spy ware severely threatens Internet. We observed that although malware and its variants may vary a lot from content signatures, they share some behavior features at a higher level which are more precise in revealing the real intent of malware. This project investigates the technique of malware behavior extraction, presents the formal Malware Behavior Feature (MBF) extraction method, and proposes the malicious behavior feature based malware detection algorithm. Finally we designed and implemented the MBF based malware detection system, and the experimental results show that it can detect newly appeared unknown malwares.

‘‘RanStop: A hardwareassisted runtime crypto-ransomware detection technique,’’

Among many prevailing malware, crypto-ransomware poses a significant threat as it financially extorts affected users by creating denial of access via unauthorized encryption of their documents as well as holding their documents hostage and financially extorting them.

This results in millions of dollars of annual losses worldwide. Multiple variants of ransomware are growing in number with capabilities of evasion from many anti-viruses and software-only malware detection schemes that rely on static execution signatures. In this project, we propose a hardware-assisted scheme, called Rain Stop, for early detection of crypto-ransomware infection in commodity processors. Rain Stop leverages the information of hardware performance counters embedded in the performance monitoring unit in modern processors to observe micro-architectural event sets and detects known and unknown crypto-ransomware variants.

In this project, we train a recurrent neural network-based machine learning architecture using long short-term memory (LSTM) model for analyzing micro-architectural. We create time series to develop intrinsic statistical features using the information of related HPCs and improve the detection accuracy of Rain Stop and reduce noise by via LSTM and global average pooling. As an early detection scheme, Rain Stop can accurately and quickly identify ransomware

This detection time is too early for a ransomware to make any significant damage, if none. Moreover, validation similarity with that of a crypto-ransomware shows that Ran Stop can detect ransomware with an average of 97% accuracy for fifty random trials.

‘‘On the feasibility of online malware detection with performance counters,’’

The proliferation of computers in any domain is followed by the proliferation of malware in that domain. Systems, including the latest mobile platforms, are laden with viruses, rootkits, spyware, adware and other classes of malware. Despite the existence of anti-virus software, malware threats persist and are growing as there exist a myriad of ways to subvert anti-virus (AV) software. In fact, attackers today exploit bugs in the AV software to break into systems. In this project, we examine the feasibility of building a malware detector in hardware using existing performance counters. We find that data from performance counters can be used to identify malware and that our detection techniques are robust to minor variations in malware programs. As a result, after examining a small set of variations within a family of malware on Android ARM and Intel Linux platforms, we can detect many variations within that family. Further, our proposed hardware modifications allow the malware detector to run securely beneath the system software, thus setting the stage for AV implementations that are simpler and less buggy than software AV. Combined, the robustness and security of hardware AV techniques have the potential to advance state-of-the-art online malware detection.

‘‘Unsupervised anomaly based malware detection using hardware features,’’

Recent works have shown promise in using microarchitectural execution patterns to detect malware programs. These detectors belong to a class of detectors known as signature-based detectors as they catch malware by comparing a program's execution pattern (signature) to execution patterns of known malware programs. In this work, we propose a new class of detectors - anomaly-based hardware malware detectors - that do not require signatures for malware detection, and thus can catch a wider range of malware including potentially novel ones. these profiles to detect significant deviations in program behavior that occur as a result of malware exploitation.The proposed detector is complementary to previously proposed signature-based detectors and can be used together to improve security.

CHAPTER:3

SYSTEM ANALYSIS

3.1. Overall Description

A Software Requirements Specification (SRS) – a requirements specification for a software system is a complete description of the behaviour of a system to be developed. It includes a set of use cases that describe all the interactions the users will have with the software.

System requirements specification: A structured collection of information that embodies the requirements of a system. A business analyst, sometimes titled system analyst, is responsible for analysing the business needs of their clients and stakeholders to help identify business problems and propose solutions. Within the systems development lifecycle domain, the BA typically performs a liaison function between the business side of an enterprise and the information technology department or external service providers. Projects are subject to three sorts of requirements:

- Business requirements describe in business terms what must be delivered or accomplished to provide value.
- Product requirements describe properties of a system or product (which could be one of several ways to accomplish a set of business requirements.)
- Process requirements describe activities performed by the developing organization. For instance, process requirements could specify .Preliminary investigation examine project feasibility, the likelihood the system will be useful to the organization. There are aspects in the feasibility study portion of the preliminary investigation:

- **ECONOMIC FEASIBILITY**

A system can be developed technically and that will be used if installed must still be a good investment for the organization. In the economical feasibility, the development cost in creating the system is evaluated against the ultimate benefit derived from the new systems. Financial benefits must equal or exceed the costs. The system is economically feasible. It does not require any addition hardware or software. Since the interface for this system is developed using the existing resources and technologies available at NIC, There is nominal expenditure and economical feasibility for certain.

- **OPERATIONAL FEASIBILITY**

Proposed projects are beneficial only if they can be turned out into information system. That will meet the organization’s operating requirements. Operational feasibility aspects of the project are to be taken as an important part of the project implementation. This system is targeted to be in accordance with the above-mentioned issues. Beforehand, the management issues and user requirements have been taken into consideration

- **TECHNICAL FEASIBILITY**

Earlier no system existed to cater to the needs of ‘Secure Infrastructure Implementation System’. The current system developed is technically feasible. It is a web-based user interface for audit workflow at NIC-CSD. Thus, it provides an easy access to. the users. The database’s purpose is to create, establish and maintain a workflow among various entities in order to facilitate all concerned users in their various capacities or roles. Permission to the users would be granted based on the roles specified. Therefore, it provides the technical guarantee of accuracy, reliability and security.

3.2 User Requirements

The effectiveness of a ransomware detection system hinges on a clear understanding of user requirements, which can be categorized into functional and non-functional aspects.

Functional Requirements:

- The system must be capable of real-time detection of ransomware activity, ensuring minimal data loss and rapid response.
- It should accurately differentiate between benign and malicious behaviors, reducing false positives and negatives.
- The detection process should operate with low overhead, ensuring that system performance is not adversely affected.

- The system must be resilient to evasion tactics employed by sophisticated ransomware, such as attempts to disable monitoring processes or corrupt collected data.
- Users require an intuitive interface for receiving alerts, viewing logs, and managing responses to detected threats.

Non-Functional Requirements:

- Scalability is essential, allowing the solution to function effectively across varying workloads and in both standalone and virtualized environments.
- The system should be maintainable and adaptable, facilitating updates as new ransomware variants emerge.
- Security of collected data and system integrity must be ensured, preventing unauthorized access or tampering1.

3.3 Content Diagram of The Project

A content diagram, or system architecture diagram, visually represents the main components and their interactions within the ransomware detection system.

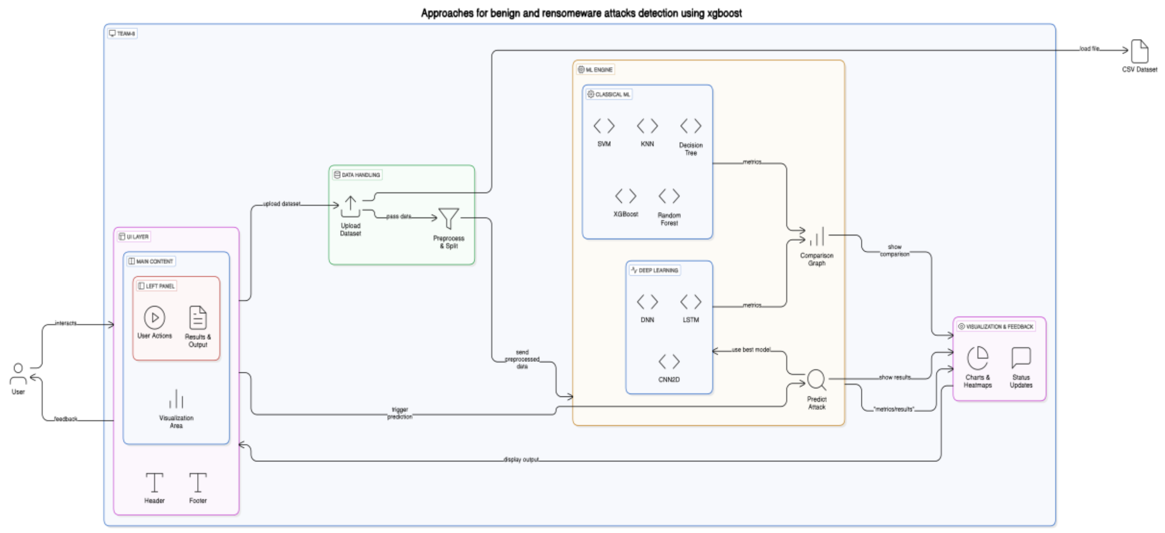


Fig 3.3(content Diagram)

Component Descriptions:

- **User Interface:** Provides access for users and administrators to receive alerts, view logs, and manage system responses.
- **Data Collection:** Gathers processor and disk I/O event data from the host machine, targeting the entire virtual machine to avoid process-level overhead.
- **Feature Extraction:** Processes raw event data to generate meaningful features for analysis.
- **ML/DL Detection:** Utilizes machine learning and deep learning models (such as Random Forest, XGBoost, DNN, and LSTM) to classify activity as benign or ransomware.
- **Alert & Response:** Generates alerts and may initiate automated mitigation actions upon detection.
- **Logging & Report:** Maintains detailed records for post-incident analysis and compliance

3.4 Algorithms and Flowchart

Algorithms Used: The proposed system employs a range of machine learning and deep learning algorithms to enhance detection accuracy and efficiency:

- **Random Forest:** An ensemble learning method that builds multiple decision trees and merges their outputs for robust classification.
- **XGBoost:** A high-performance gradient boosting algorithm known for its speed and accuracy.
- **SVM, KNN, Decision Tree:** Other traditional algorithms evaluated for comparative analysis.
- **Deep Neural Networks (DNN) and LSTM:** These deep learning models capture complex and sequential patterns in system behavior, improving detection of sophisticated ransomware.

- **CNN2D (Extension):** As an advanced extension, 2D Convolutional Neural Networks are used for feature optimization, extracting relevant data across multiple layers to further improve detection performance1.

Detection Workflow:

1. **Data Collection:** Continuously monitor and collect processor and disk I/O metrics from the VM host.
2. **Feature Extraction:** Preprocess and extract relevant features such as instruction counts, cache misses, and disk access frequency.
3. **Model Prediction:** Feed the extracted features into the trained machine learning or deep learning model.
4. **Classification:** The model outputs a prediction, classifying the activity as benign or ransomware.
5. **Alert Generation:** If ransomware is detected, the system triggers alerts and initiates response protocols.
6. **Logging:** All events and decisions are recorded for future analysis and reporting.

3.5 Existing System

Traditional Detection Approaches

1. Signature-Based Detection

Signature-based approaches are the most commonly used in commercial antivirus products. These systems maintain a database of known malware signatures (hashes or code patterns) and scan files for matches. While effective against known threats, this method fails to detect new or modified ransomware variants that do not match existing signatures.

2. **Process and File Activity Monitoring**

   Some systems monitor running processes or file system activities (such as file creation, modification, or deletion) to identify suspicious behavior. These methods can detect some forms of ransomware but have significant drawbacks:

   - High Resource Overhead: Monitoring every process or file operation in real time can degrade system performance, especially on resource-constrained devices.
   - Evasion Techniques: Advanced ransomware may terminate or corrupt monitoring processes before launching an attack, or mimic benign behavior to avoid detection.
   - Detection Delays: These approaches may only identify ransomware after significant damage has occurred.

3. **Behavior-Based Analysis**

   Behavioral analysis focuses on the sequence of actions performed by software. For ransomware, this often involves detecting rapid, widespread file encryption or abnormal system resource usage.

Disadvantages of Existing Systems

- Lower accuracy for unknown or modified ransomware variants.
- Resource-intensive monitoring that can degrade system performance.
- Delayed detection, allowing ransomware to inflict significant damage.
- Susceptibility to evasion, as sophisticated ransomware can disable

3.6 Proposed System

In proposed system, experimented with various machine learning algorithms such as SVM, KNN, Decision Tree, Random Forest and XGBOOST and then employed two deep learning models called DNN and LSTM. In all algorithms Random Forest, XGBOOST is giving accuracy.

Advantages:

1. High Accuracy
2. Takes less time

Extension Concept

In propose work author has used all traditional algorithms but not used any advance features optimization algorithms so as extension we have experimented with CNN2D which will optimized dataset features in multiple layers which help in getting relevant data for training and can improve detection accuracy.

PROCESS MODEL USED WITH JUSTIFICATION

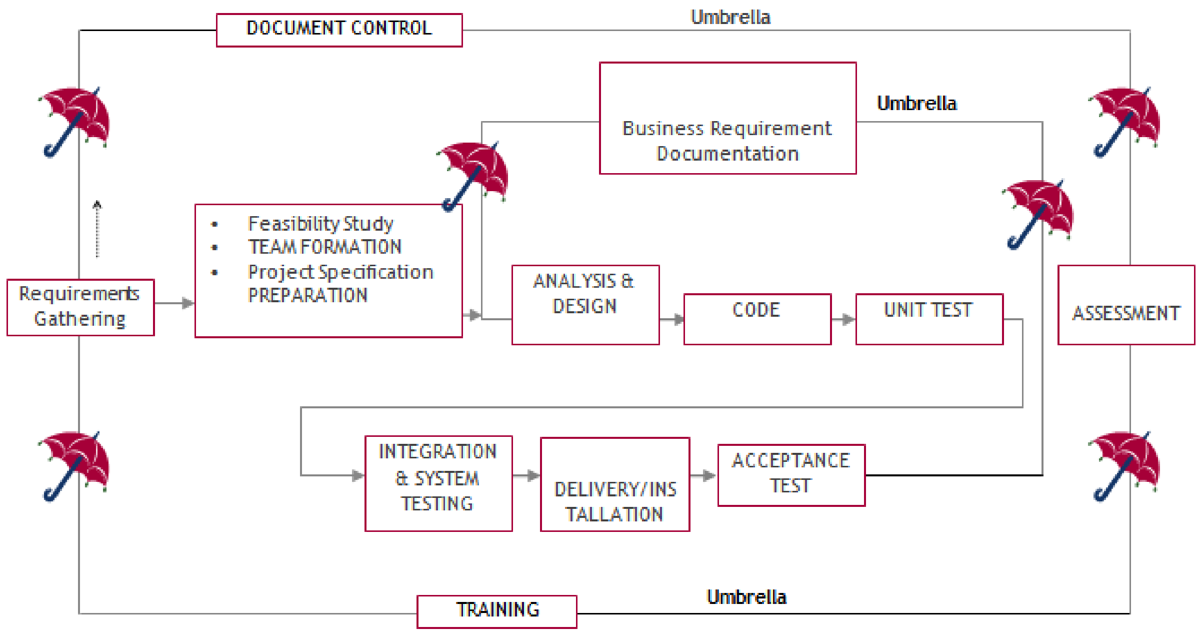


Fig3.6.1(SDLC Model)

SDLC is nothing but Software Development Life Cycle. It is a standard which is used by software industry to develop good software.

Stages in SDLC:

- Requirement Gathering
- Designing
- Coding
- Testing

- Maintenance

Requirements Gathering stage:

Major functions include critical processes to be managed, as well as mission critical inputs, outputs and reports. A user class hierarchy is developed and associated with these major functions, data areas, and data entities. Each of these definitions is termed a Requirement. Requirements are identified by unique requirement identifiers and, at minimum, contain a requirement title and textual description.

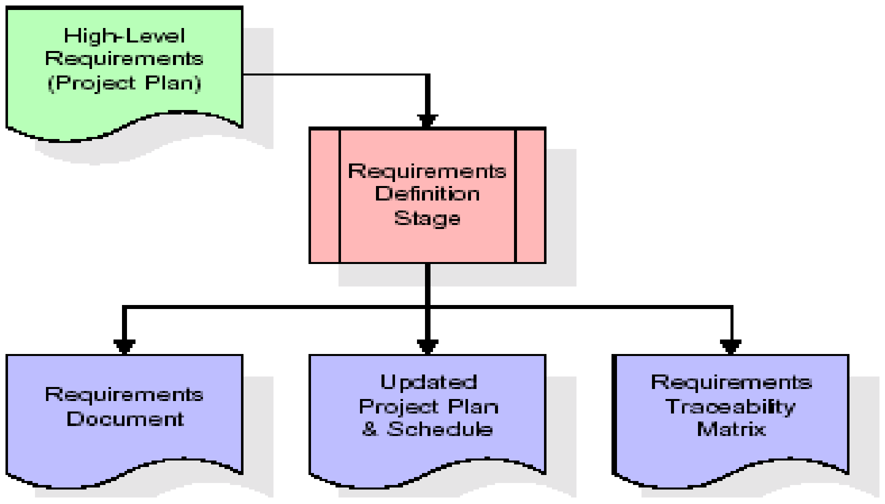

High-Level Requirements (Project Plan)
Requirements Definition Stage
Requirements Document
Updated Project Plan & Schedule
Requirements Traceability Matrix

Fig3.6.2(Requirement gathering stage)

These requirements are fully described in the primary deliverables for this stage: the Requirements Document and the Requirements Traceability Matrix (RTM)Note that detailed listings of database tables and fields are *not* included in the requirements document.

In the requirements stage, the RTM consists of a list of high-level requirements, or goals, by title, with a listing of associated requirements for each goal, listed by requirement title. the RTM shows that each requirement developed during this stage is formally linked to a specific product goal. In this format, each requirement can be traced to a specific product goal, hence the term requirements traceability

The outputs of the requirements definition stage include the requirements document, the RTM, and an updated project plan.

- Feasibility study is all about identification of problems in a project.
- No. of staff required to handle a project is represented as Team Formation, in this case only modules are individual tasks will be assigned to employees who are working for that project.
- Project Specifications are all about representing of various possible inputs submitting to the server and corresponding outputs along with reports maintained by administrator.

Analysis Stage:

The planning stage establishes a bird's eye view of the intended software product, and uses this to establish the basic project structure, evaluate feasibility and risks associated with the project, and describe appropriate management and technical approaches.

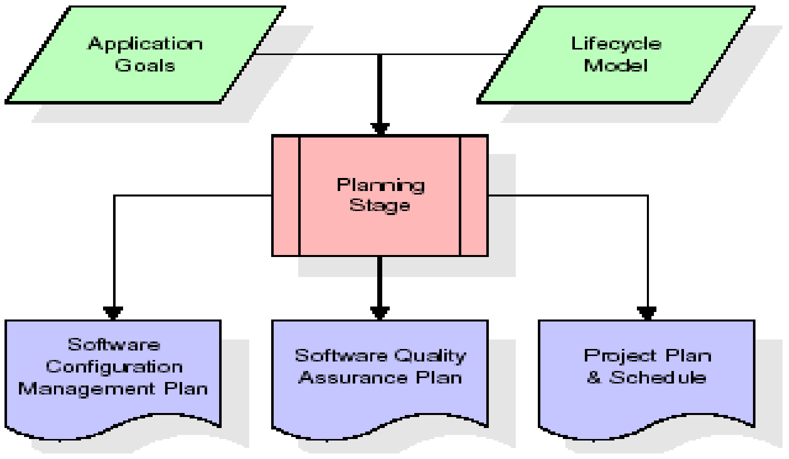

Application Goals
Lifecycle Model
Planning Stage
Software Configuration Management Plan
Software Quality Assurance Plan
Project Plan & Schedule

Fig3.6.3(Analysis Stage)

Designing Stage:

The design stage takes as its initial input the requirements identified in the approved requirements document. For each requirement, a set of one or more design elements will be produced as a result of interviews, workshops, and/or prototype efforts.

Design elements describe the desired software features in detail, and generally include functional hierarchy diagrams, screen layout diagrams, tables of business rules, business process diagrams, pseudo code, and a complete entity-relationship diagram with a full data dictionary. These design elements are intended to describe the software in sufficient detail that skilled programmers may develop the software with minimal additional input.

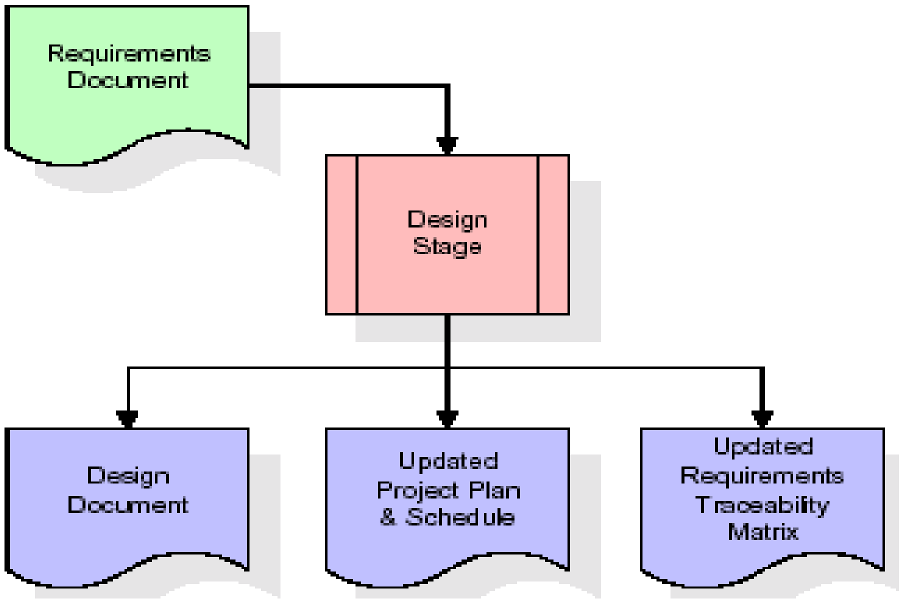

Requirements Document
Design Stage
Design Document
Updated Project Plan & Schedule
Updated Requirements Traceability Matrix

Fig 3.6.4(**Designing Stage)**

When the design document is finalized and accepted, the RTM is updated to show that each design element is formally associated with a specific requirement. The outputs of the design stage are the design document, an updated RTM, and an updated project plan.

Development (Coding) Stage:

The development stage takes as its primary input the design elements described in the approved design document. For each design element, a set of one or more software artifacts will be produced.

Software artifacts include but are not limited to menus, dialogs, and data management forms, data reporting formats, and specialized procedures and functions. Appropriate test cases will be developed for each set of functionally related software artifacts, and an online help system will be developed to guide users in their interactions with the software.

Software artifacts include but are not limited to menus, dialogs, and data management forms, data reporting formats, and specialized procedures and functions.

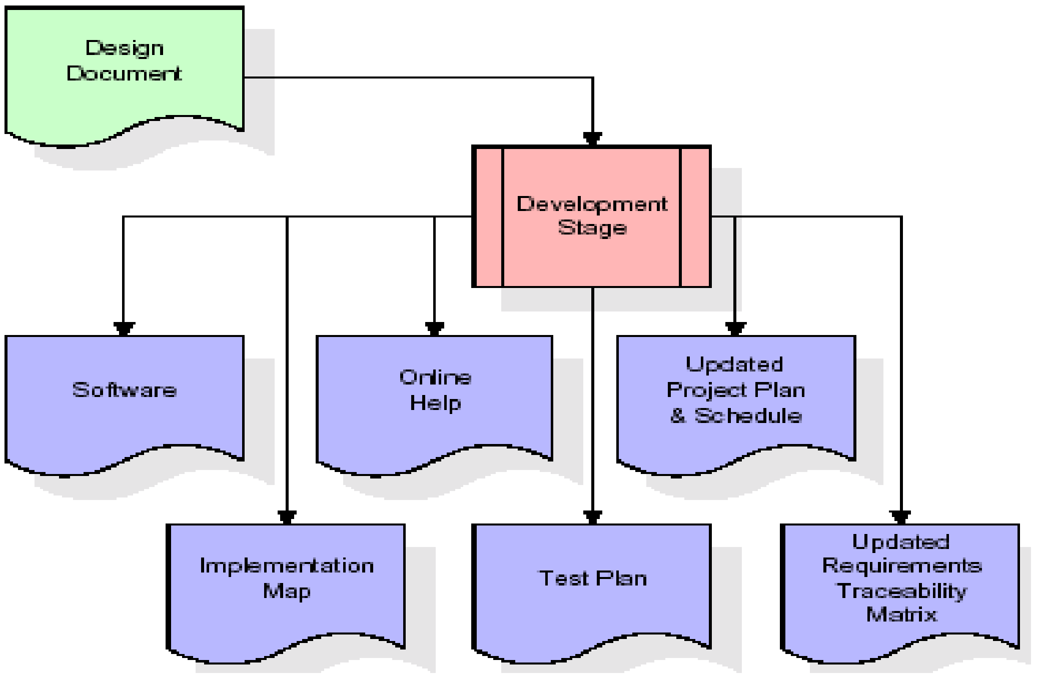


Fig 3.6.5(**Development Stage)**

Integration & Test Stage:

During the integration and test stage, the software artifacts, online help, and test data are migrated from the development environment to a separate test environment. At this point, all test cases are run to verify the correctness and completeness of the software. Successful execution of the test suite confirms a robust and complete migration capability.

During this stage, reference data is finalized for production use and production users are identified and linked to their appropriate roles. The final reference data (or links to reference data source files) and production user list are compiled into the Production Initiation Plan.

During the integration and test stage, the software artifacts, online help, and test data are migrated from the development environment to a separate test environment

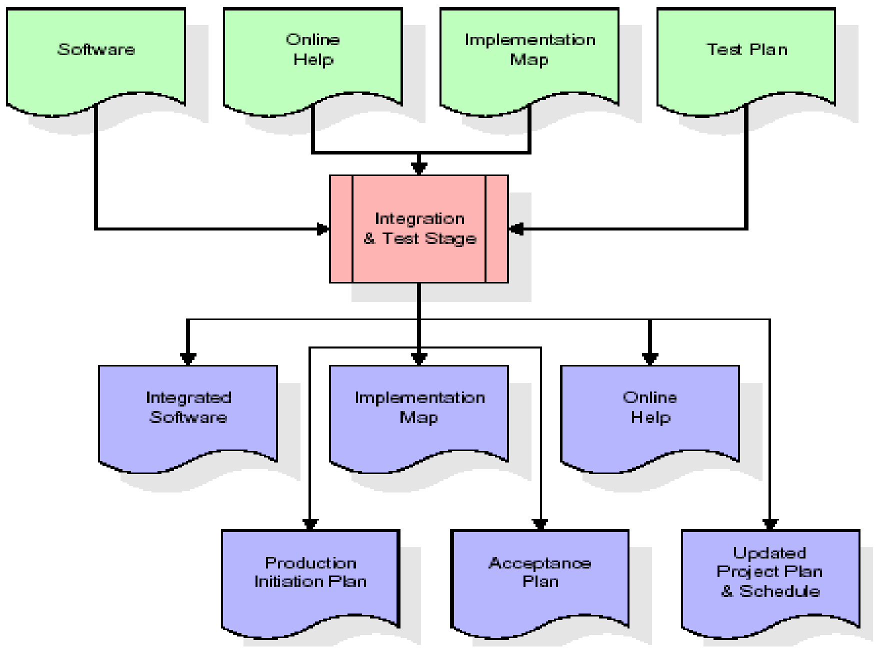


Fig3.6.6**(Integration & Test Stage)**

The outputs of the integration and test stage include an integrated set of software, an online help system, an implementation map, a production initiation plan that describes reference data and production users, an acceptance plan which contains the final suite of test cases, and an updated project plan.

♦ **Installation & Acceptance Test:**

During the installation and acceptance stage, the software artifacts, online help, and initial production data are loaded onto the production server. At this point, all test cases are run to verify the correctness and completeness of the software. Successful execution of the test suite is a prerequisite to acceptance of the software by the customer.

Outer rectangle represents maintenance of a project, Maintenance team will start with requirement study, understanding of documentation later employees will be assigned work

The primary outputs of the installation and acceptance stage include a production application, a completed acceptance test suite, and a memorandum of customer acceptance of the software.

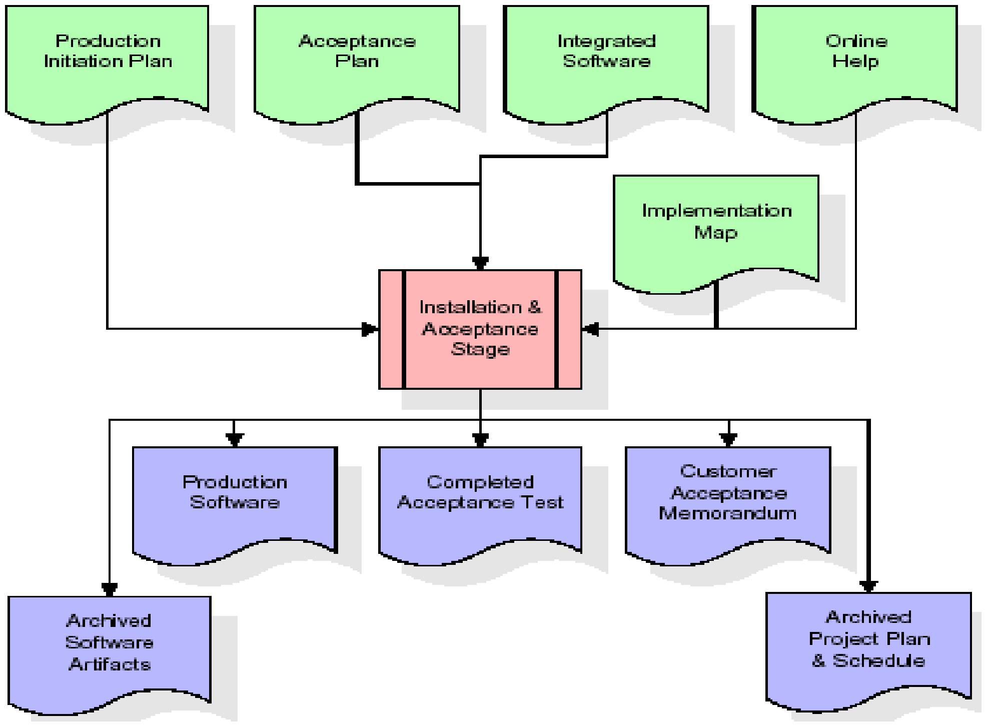

Production Initiation Plan
Acceptance Plan
Integrated Software
Online Help
Implementation Map
Installation & Acceptance Stage
Production Software
Completed Acceptance Test
Customer Acceptance Memorandum
Archived Software Artifacts
Archived Project Plan & Schedule

Fig3.6.7(Installation Test)

Finally, the PDR enters the last of the actual labor data into the project schedule and locks the project as a permanent project record. At this point the PDR "locks" the project by archiving all software items, the implementation map, the source code, and the documentation for future reference.

Maintenance:

Outer rectangle represents maintenance of a project, Maintenance team will start with requirement study, understanding of documentation later employees will be assigned work and they will undergo training on that particular assigned category. For this life cycle there is no end, it will be continued so on like an umbrella (no ending point to umbrella sticks).

3.7External Interface Requirements

User Interface:

The user interface of this system is a user friendly python Graphical User Interface.

Hardware Interfaces:

The interaction between the user and the console is achieved through python capabilities.

Software Interfaces:

The required software is python.

SYSTEM REQUIREMENT:

HARDWARE REQUIREMENTS:

• Processor	-	Intel i5(min)
• Speed	-	1.1 GHz
• RAM	-	4GB(min)
• Hard Disk	-	256 GB

SOFTWARE REQUIREMENTS:

• Operating System	-	Windows10(min)
• Programming Language	-	Python with Jupiter notebook

CHAPTER:4

SYSTEM DESIGN

4.1. Introduction to System Design

System design is a crucial phase in the development of any software project, serving as the blueprint that transforms user requirements and analytical insights into a structured, actionable plan for implementation. In the context of ransomware detection, system design involves defining the architecture, components, data flows, and interactions necessary to create an effective and efficient defense mechanism against rapidly evolving threats. This phase bridges the gap between high-level problem understanding and practical realization, ensuring that every aspect of the system—from data collection and feature extraction to machine learning-based detection and user response—is thoughtfully planned and cohesively integrated.

4.2. Data Flow(uml) Diagram:

The Unified Modelling Language allows the software engineer to express an analysis model using the modelling notation that is governed by a set of syntactic semantic and pragmatic rules.

A UML system is represented using five different views that describe the system from distinctly different perspective. Each view is defined by a set of diagram, which is as follows.

- **User Model View**
    i. This view represents the system from the users perspective.
    ii. The analysis representation describes a usage scenario from the end-users perspective.
- **Structural Model view**
    i. In this model the data and functionality are arrived from inside the system.
    ii. This model view models the static structures.
- **Behavioural Model View**

  It represents the dynamic of behavioural as parts of the system, depicting the interactions of collection between various structural elements described in the user

4.2.1.Class Diagram:

The class diagram is the main building block of object oriented modeling. It is used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class diagram represent both the main objects, interactions in the application and the classes to be programmed. In the diagram, classes are represented with boxes which contain three parts:

- The upper part holds the name of the class
- The middle part contains the attributes of the class
- The bottom part gives the methods or operations the class can take or undertake.

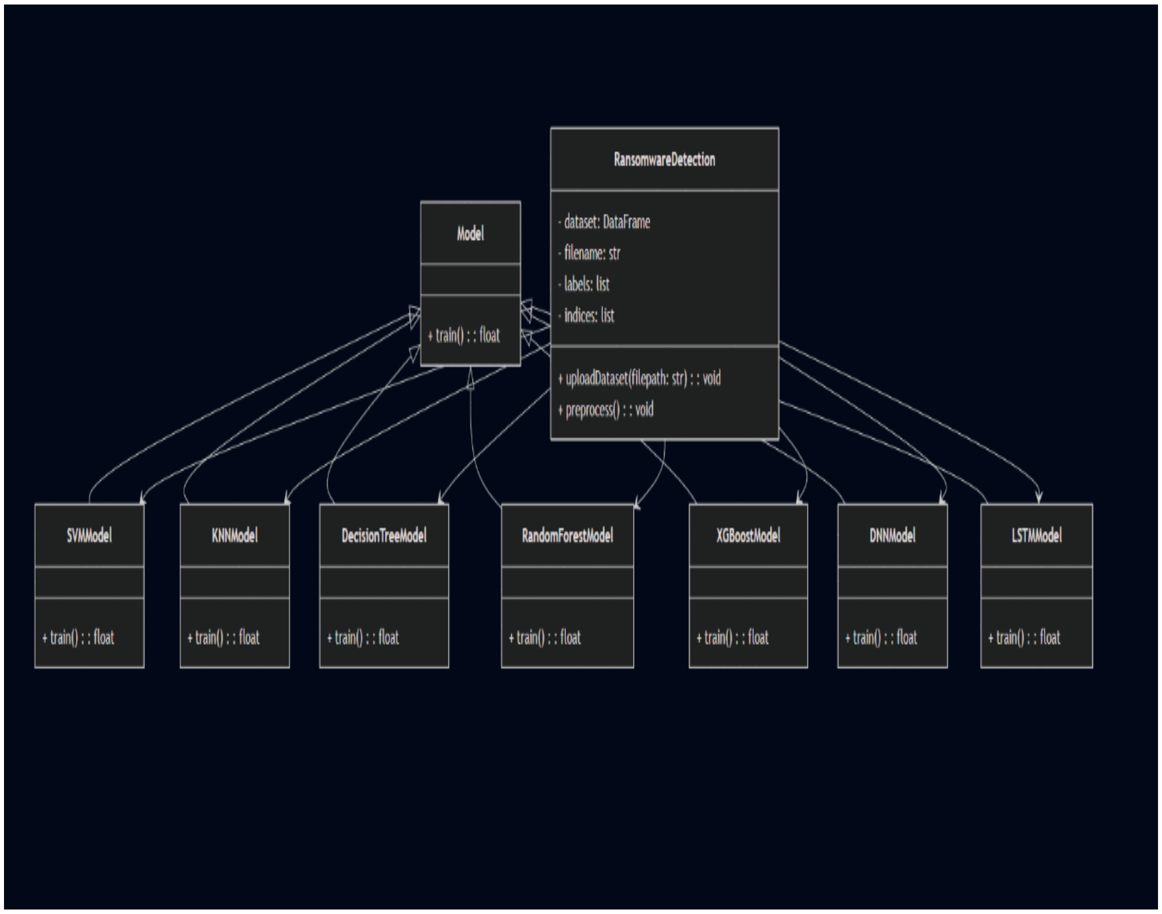


Fig4.2.1:(class Diagram)

4.2.2.Use case Diagram:

A **use case diagram** at its simplest is a representation of a user's interaction with the system and depicting the specifications of a use case. A use case diagram can portray the different types of users of a system and the various ways that they interact with the system. This type of diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as well.

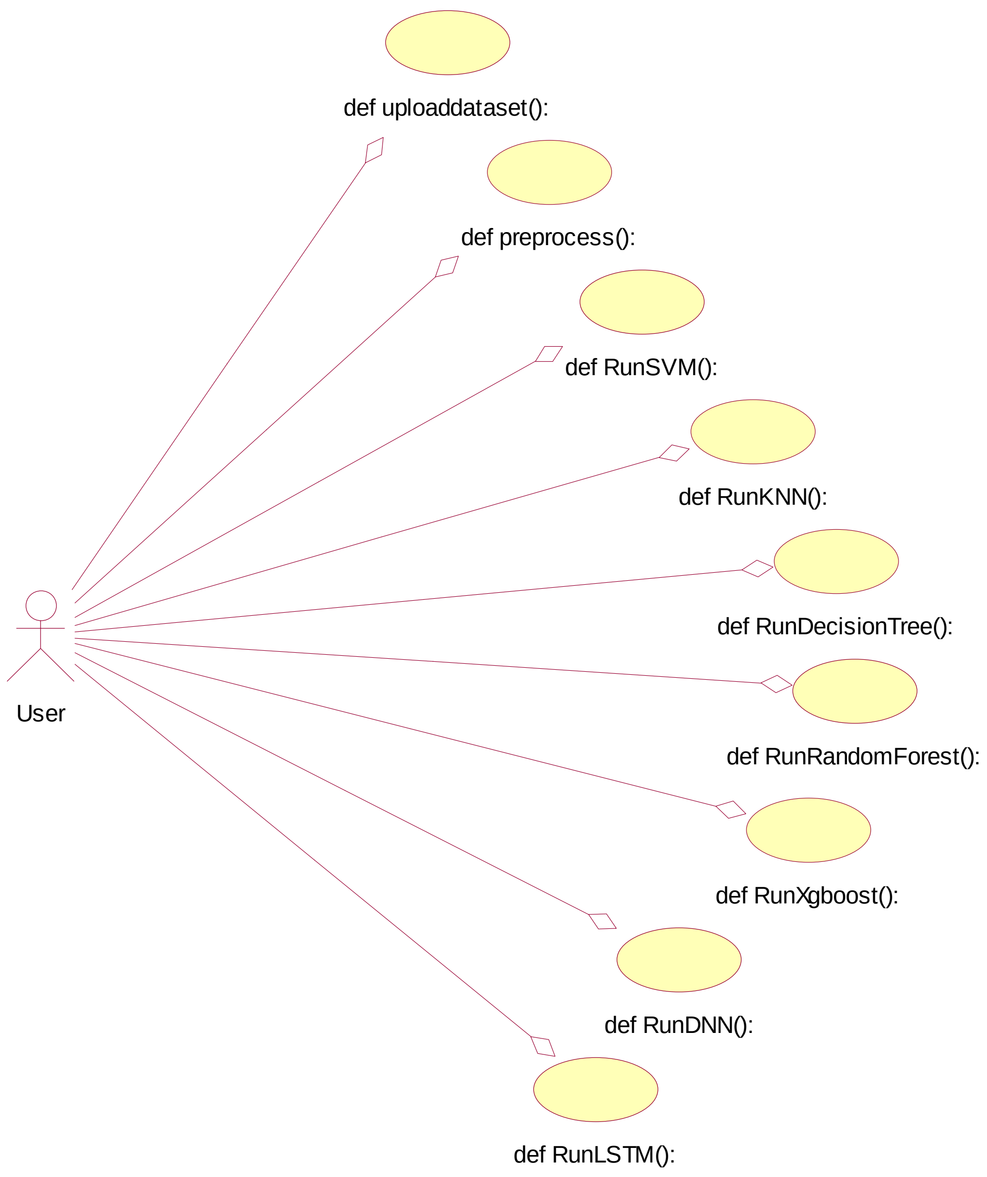


Fig4.2.2:(Use case Diagram)

4.2.3.Sequence diagram:

A sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

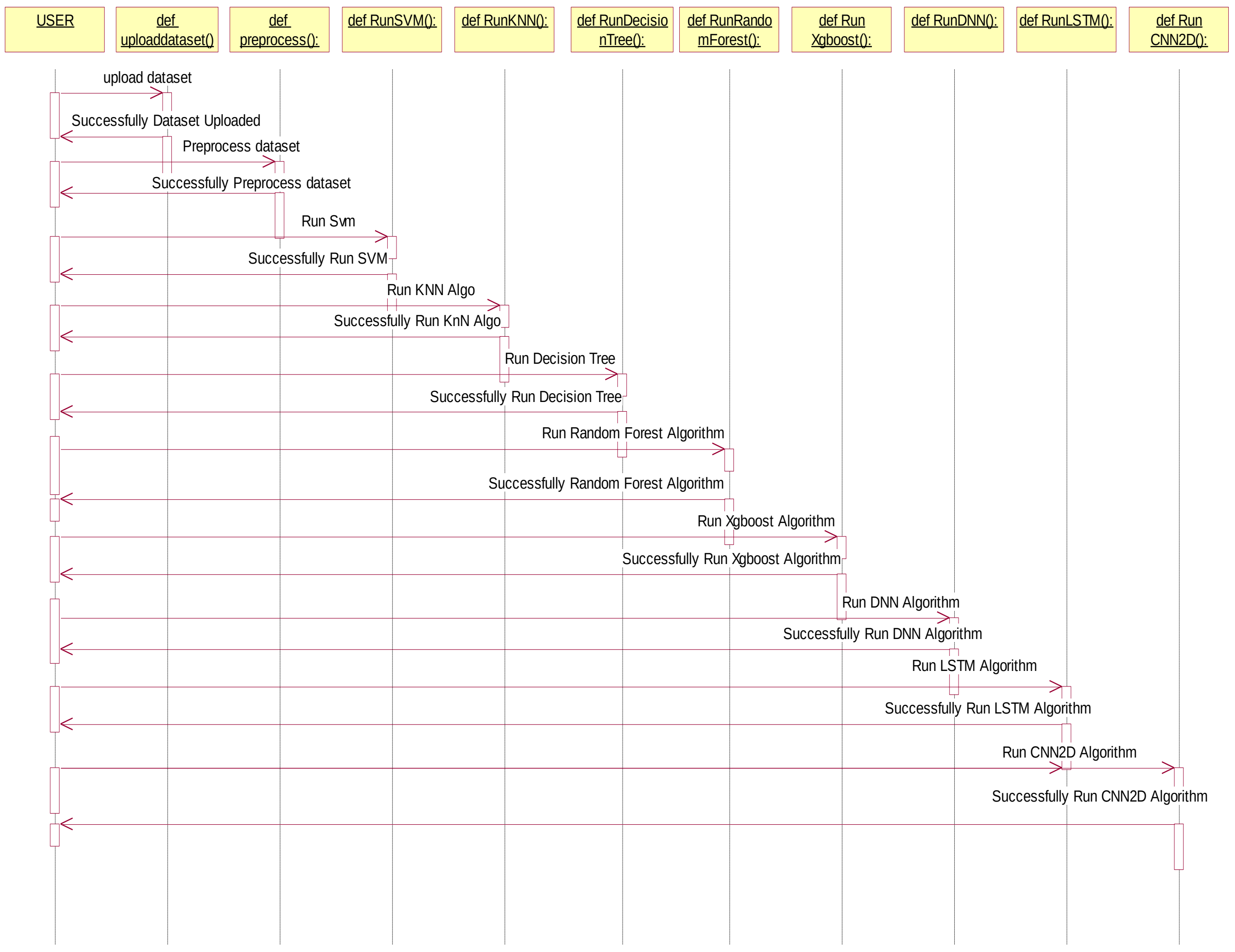


Fig**4.2.3(Sequence diagram)**

4.2.4. Collaboration diagram:

A collaboration diagram describes interactions among objects in terms of sequenced messages. Collaboration diagrams represent a combination of information taken from class, sequence, and use case diagrams describing both the static structure of a system.

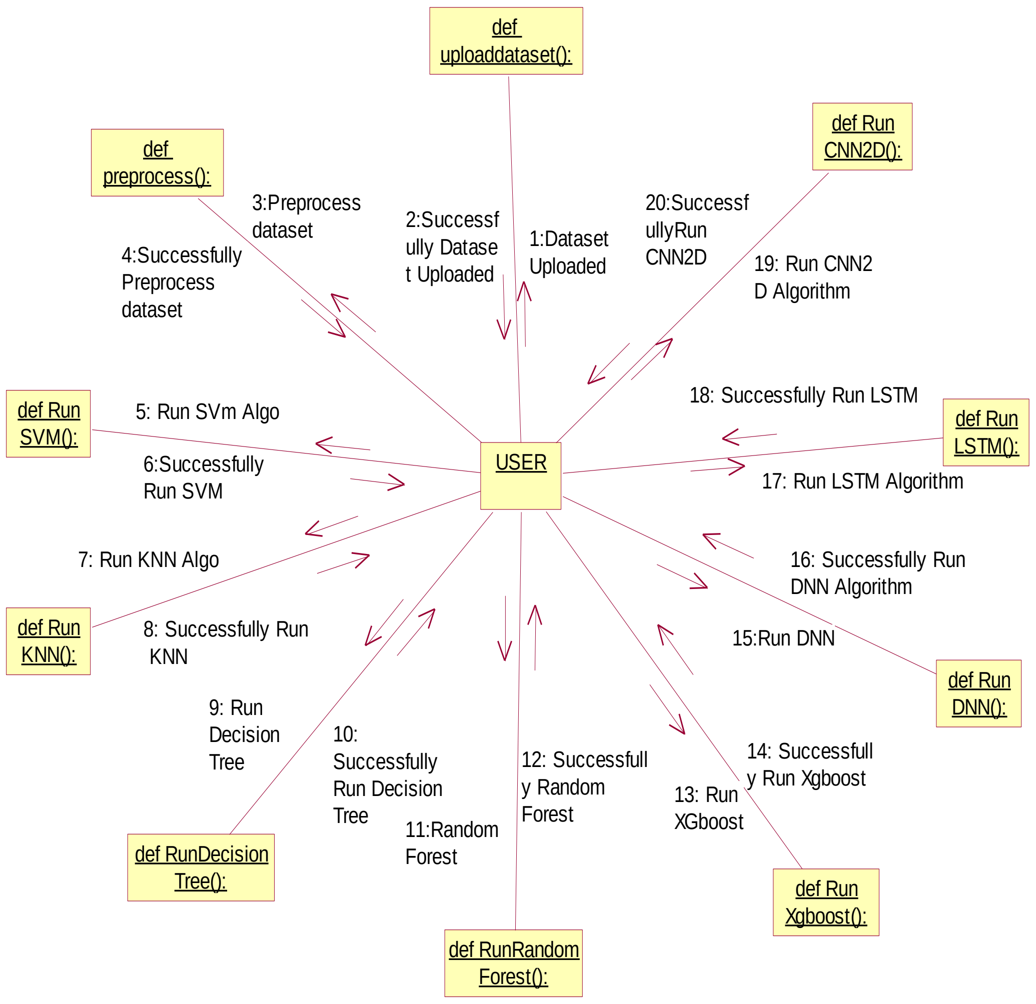


Fig4.2.4:(**Collaboration diagram)**

4.2.5.Component Diagram:

In the Unified Modelling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems.

Components are wired together by using an assembly connector to connect the required interface of one component with the provided interface of another component. This illustrates the service consumer - service provider relationship between the two components.

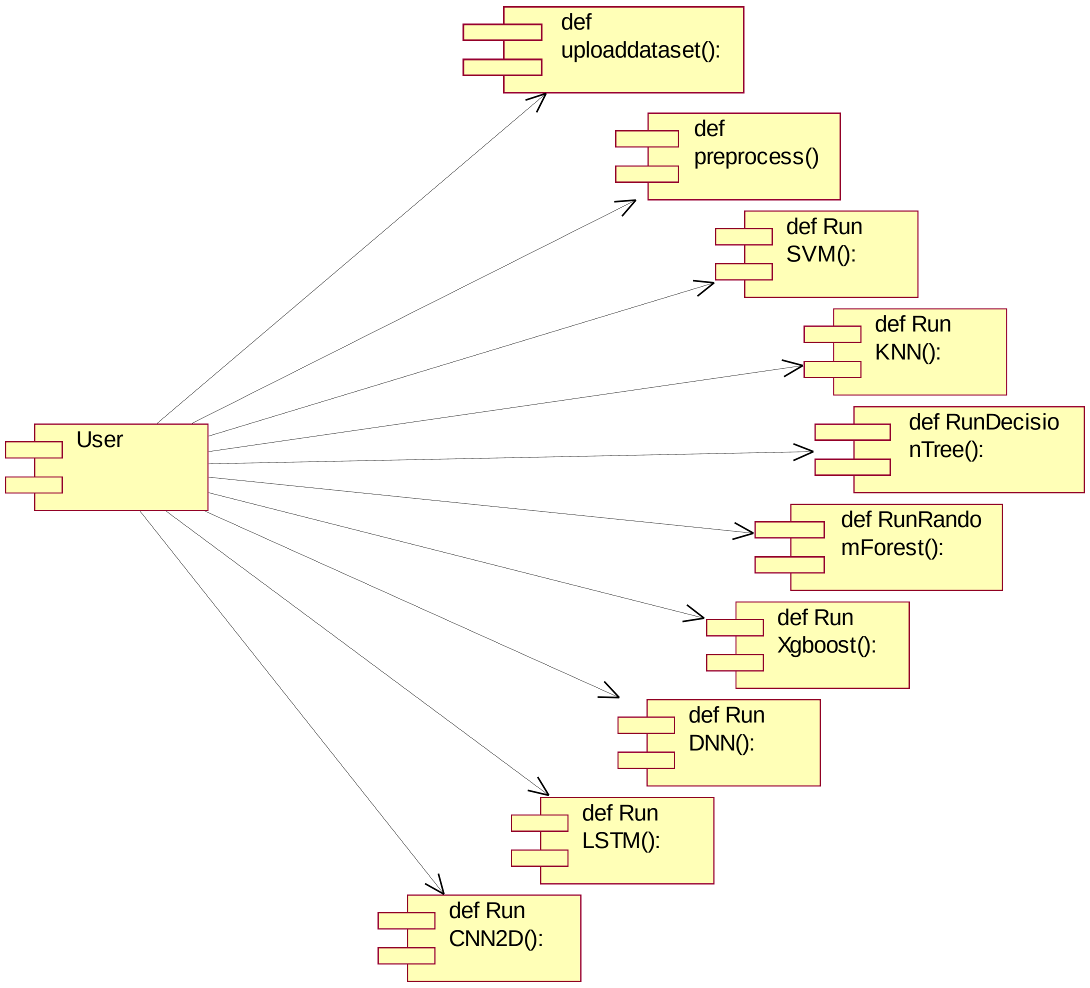


Fig4.2.5:(Component Diagram

4.2.6.Deployment Diagram:

A **deployment diagram** in the Unified Modeling Language models the *physical* deployment of artifacts on nodes. To describe a web site, for example, a deployment diagram would show what hardware components ("nodes") exist (e.g., a web server, an application server, and a database server), what software components ("artifacts") run on each node (e.g., web application, database), and how the different pieces are connected (e.g. JDBC, REST, RMI).

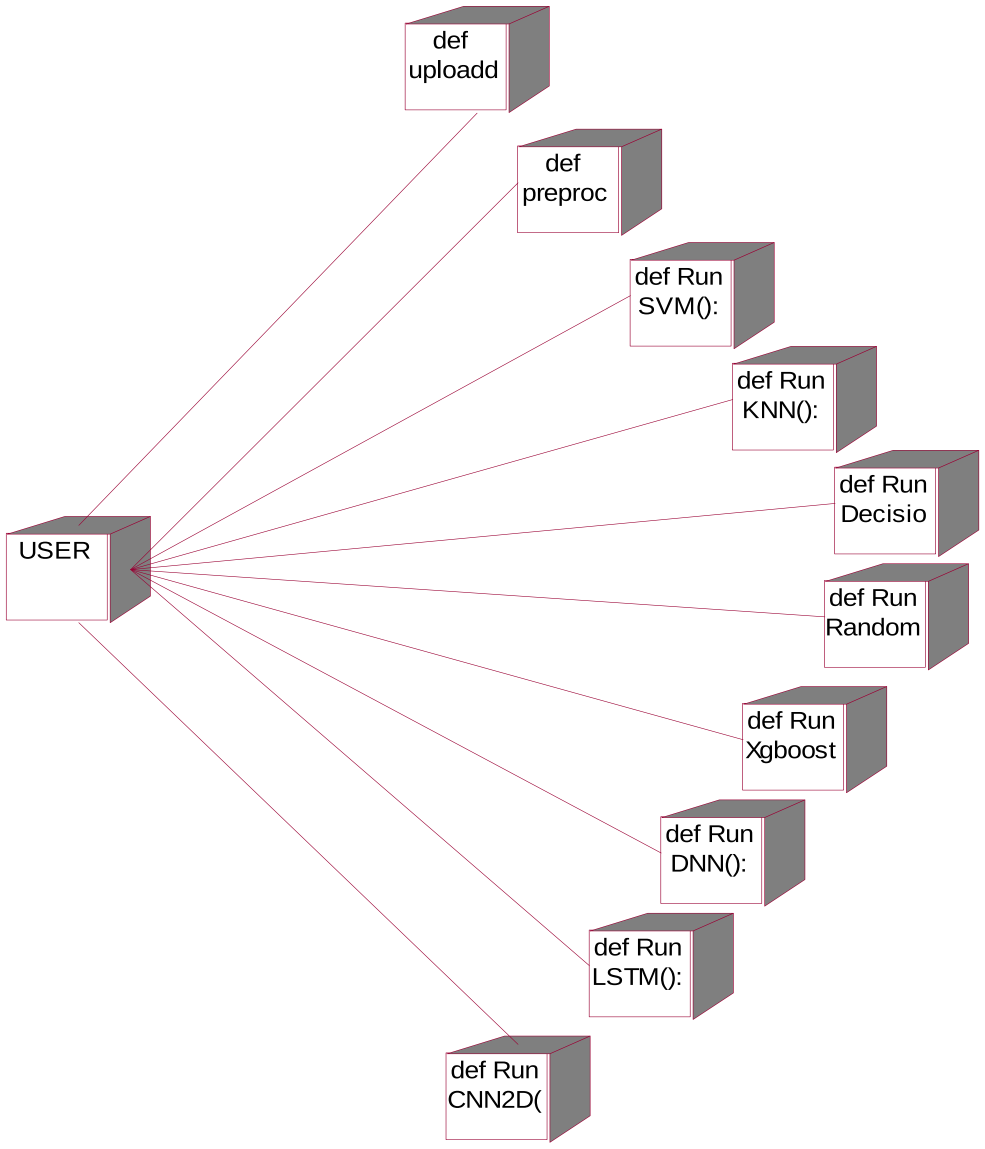


Fig4.2.6:(Deployment Diagram)

4.2.7.Activity Diagram:

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flow chart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. So the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent

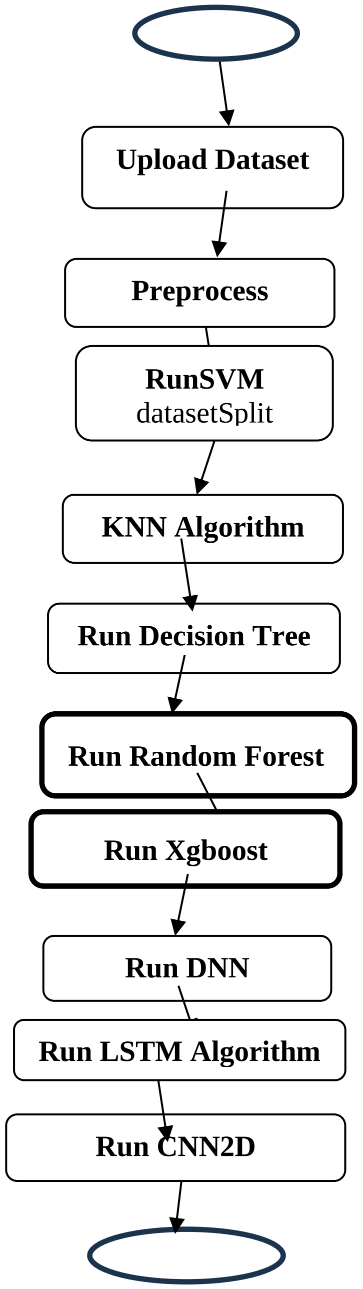


Fig4.2.7:(Activity Diagram

4.2.8.Data Flow Diagram:

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Data flow diagrams can be used to provide a clear representation of any business function. The technique starts with an overall picture of the business and continues by analyzing each of the functional areas of interest. This analysis can be carried out in precisely the level of detail required. The technique exploits a method called top-down expansion to conduct the analysis in a targeted way.

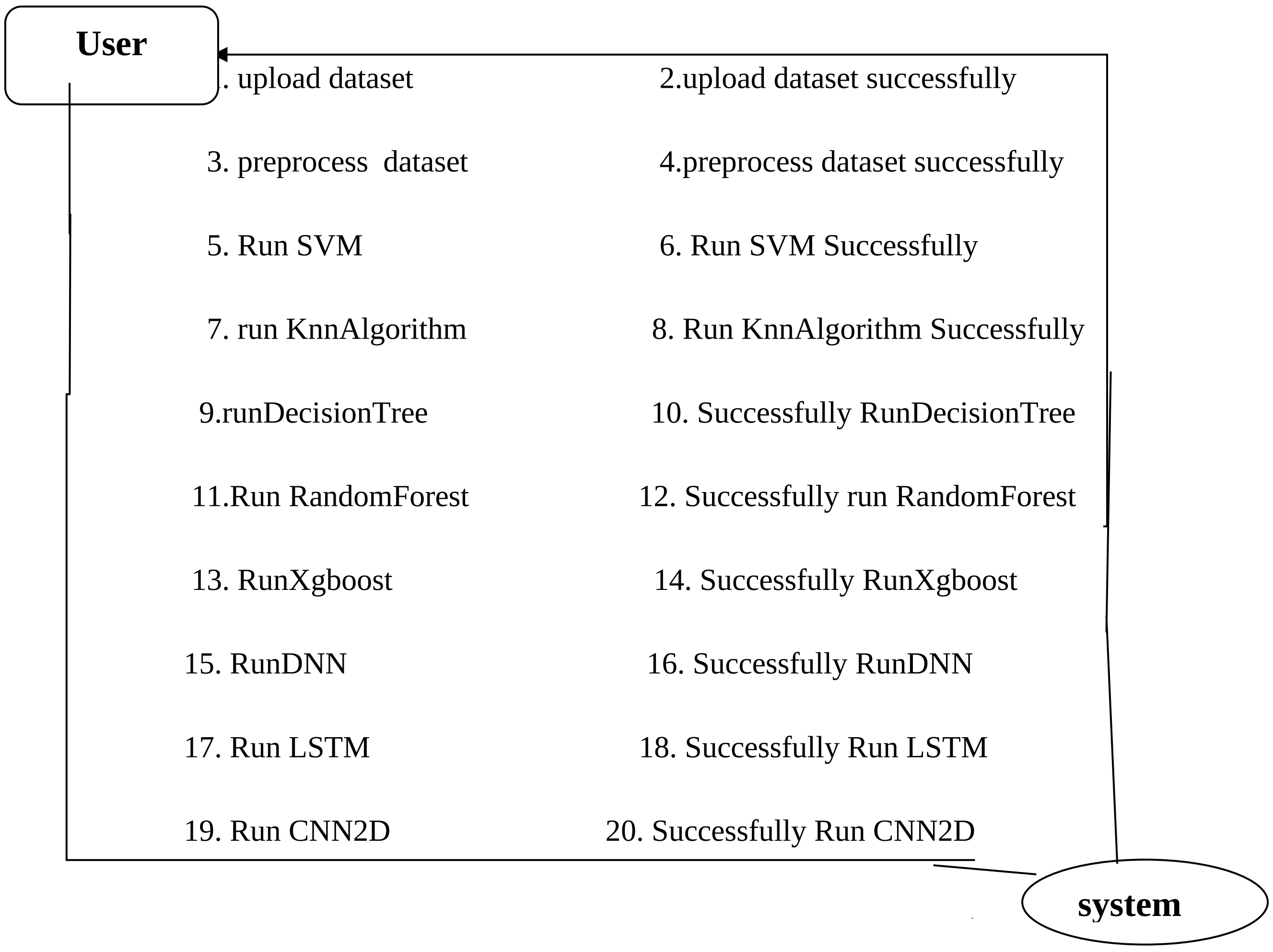

User
1. upload dataset
2.upload dataset successfully
3. preprocess dataset
4.preprocess dataset successfully
5. Run SVM
6. Run SVM Successfully
7. run KnnAlgorithm
8. Run KnnAlgorithm Successfully
9.runDecisionTree
10. Successfully RunDecisionTree
11.Run RandomForest
12. Successfully run RandomForest
13. RunXgboost
14. Successfully RunXgboost
15. RunDNN
16. Successfully RunDNN
17. Run LSTM
18. Successfully Run LSTM
19. Run CNN2D
20. Successfully Run CNN2D
system

Fig: 4.2.8:(Data Flow Diagram)

CHAPTER:5

IMPLEMENTATIONAND RESULTS

5.1 INTRODUCTION

PYTHON

One of the most popular languages is Python. Guido van Rossum released this language in 1991. Python is available on the Mac, Windows, and Raspberry Pi operating systems. The syntax of Python is simple and identical to that of English. When compared to Python, it was seen that the other language requires a few extra lines.

Here are some key features and characteristics of Python:

- Extensible and Modular: Python supports modular programming, enabling developers to organize code into reusable modules and packages. Additionally, Python allows integrating modules written in other languages, such as C or C++, providing flexibility and performance optimizations.
- Wide Range of Libraries and Frameworks: Python has a vibrant ecosystem with numerous third-party libraries and frameworks. These libraries, such as NumPy, pandas, TensorFlow, and Django, extend Python's capabilities for specific domains, making it a powerful tool for diverse applications.
- Object-Oriented: Python supports object-oriented programming (OOP) principles, allowing developers to create and work with classes and objects. OOP provides a structured approach to code organization, promoting code reuse and modularity.
- Dynamic Typing: Python is dynamically typed, meaning variable types are determined at runtime. Developers do not need to declare variable types explicitly, which enhances flexibility and simplifies code writing.

5.2 Installation

To install Python on your computer, follow these basic steps:

- Step 1: Visit the Python website Go to the official Python website at https://www.python.org/.
- Step 2: Select the operating system Choose the appropriate installer for your operating system. Python supports Windows, macOS, and various Linux distributions. Make sure to select the correct version that matches your operating system.
- Step 3: Check which version of Python is installed; if the 3.7.0 version is not there, uninstall it through the control panel and

- Step 4: Install Python 3.7.0 using Cmd.
- Step 5: Install the all libraries that required to run the project
- Step 6: Run

5.2.1 Python GUI (Tkinter)

- Tkinter is the easiest and quickest way to write Python GUI programs.
- Using Tkinter, creating a GUI is simple.
- A part of Python's built-in library is Tkinter. The GUI programs were created.
- Python and Tkinter together give a straightforward and quick way. The Tk GUI toolkit's object-oriented user interface is called Tkinter.

5.2.2 Python IDLE

- ❖ Python IDLE offers a full-fledged file editor, which gives you the ability to write and execute Python programs from within this program. The built-in file editor also includes several features, like code completion and automatic indentation, that will speed up your coding workflow.
- ❖ Guido Van Rossum named Python after the British comedy group Monty Python while the name IDLE was chosen to pay tribute to Eric Idle, who was one of the Monty Python's founding members. IDLE comes bundled with the default implementation of the Python language since the 01.5. 2b1 release
- ❖ IDLE is used to execute statements similar to Python Shell. IDLE is used to create, modify, and execute Python code. IDLE provides a fully-featured text editor to write Python scripts and provides features like syntax highlighting, auto-completion, and smart indent.
- ❖ IDLE has two modes: interactive and script. We wrote our first program, "Hello, World!" in interactive mode. Interactive mode immediately returns the results of commands you enter into the shell. In script mode, you will write a script and then run it.

5.2.3 Libraries

In Python, libraries (also referred to as modules or packages) are collections of pre-written code that provide additional functionality and tools to extend the capabilities of the Python language. Libraries contain reusable code that developers can leverage to perform specific tasks without having to write everything from scratch.

Python libraries are designed to solve common problems, such as handling data, performing mathematical operations, interacting with databases, working with files, implementing networking protocols, creating graphical user interfaces (GUIs), and much more. They provide ready-to-use functions, classes, and methods that simplify complex operations and save development time.

Libraries in Python offer various advantages:

- Code Reusability:
- Efficiency:
- Collaboration
- Domain-Specific Functionality
- To use a Python library, you need to install it first.

There are some libraries following

- **Pandas:**

Pandas are a Python computer language library for data analysis and manipulation. It offers a specific operation and data format for handling time series and numerical tables. It differs significantly from the release3-clause of the BSD license. It is a well-liked open-source of opinion that is utilized in machine learning and data analysis.

- It has functions for analysing, cleaning, exploring, and manipulating data.
- The name "Pandas" has a reference to both "Panel Data", and "Python Data Analysis" and was created by Wes McKinney in 2008.
- Pandas allow us to analyse big data and make conclusions based on statistical theories.
- Pandas can clean messy data sets, and make them readable and relevant.

- **NumPy:**

The NumPy Python library for multi-dimensional, big-scale matrices adds a huge number of high-level mathematical functions. It is possible to modify NumPy by utilizing a Python library. Along with line, algebra, and the Fourier transform operations, it also contains several matrices-related functions.

NumPy can be used to perform a wide variety of mathematical operations on arrays. It adds powerful data structures to Python that guarantee efficient calculations with arrays and matrices and it supplies an enormous library of high-level mathematical functions that operate on these arrays and matrices.

- NumPy is a Python library used for working with arrays.
- In Python we have lists that serve the purpose of arrays, but they are slow to process.
- NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.
- The array object in NumPy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy.
- Arrays are very frequently used in data science, where speed and resources are very important.

- **Matplotlib:**

Matplotlib is a popular Python library for creating static, animated, and interactive visualizations. It provides a flexible and comprehensive set of tools for generating plots, charts, histograms, scatter plots, and more. Matplotlib is widely used in various fields, including data analysis, scientific research, and data visualization.

Here are some key features and functionalities of the Matplotlib library:

- Plotting Functions
- Customization Options
- Multiple Interfaces
- Integration with NumPy and pandas
- Subplots and Figures:
- Saving and Exporting

- **Scikit-learn:**

Scikit-learn (also referred to as sklearn) is a widely used open-source machine learning library for Python. It provides a comprehensive set of tools and algorithms for various machine learning tasks, including classification, regression, clustering, dimensionality reduction, model selection, and pre-processing.

Here are some key features and functionalities of the Scikit-learn library:

- Easy-to-Use Interface:
- Broad Range of Algorithms:
- Data Pre-processing and Feature Engineering:
- Model Evaluation and Validation:
- Integration with NumPy and pandas:
- Robust Documentation and Community Support:

- **h5py:**

* The h5py Python module offers an interface for the binary HDF5 data format. Thanks to p5py, the top can quickly halt the vast amount of numerical data and alter it using the NumPy library. It employs common syntax for Python, NumPy, and dictionary arrays.

h5py is a Python library that provides a simple and efficient interface for working with datasets and files in the Hierarchical Data Format 5 (HDF5) format. HDF5 is a versatile data format commonly used for storing and managing large volumes of numerical data.

Here are some key features and functionalities of the h5py library:

- HDF5 File Access
- Dataset Handling:
- Group Organization:
- Attributes:
- Compatibility with NumPy
- Performance

- **Tensor flow**

TensorFlow is a popular open-source library for machine learning and deep learning. It provides a comprehensive set of tools, APIs, and computational resources for building and training various types of machine learning models, especially neural networks.
Here are some key features and functionalities of TensorFlow:

  - Neural Network Framework:
  - Computational Graphs
  - Automatic Differentiation

- **Tkinter**

Tkinter is a standard Python library used for creating graphical user interfaces (GUIs). It provides a set of modules and classes that allow you to develop interactive and visually appealing desktop applications.
Here are some key features and functionalities of Tkinter:

  - Cross-Platform Compatibility
  - Simple and Easy-to-Use
  -
  - Widgets and Layout Management

- **NLTK**

NLTK (Natural Language Toolkit) is a Python library widely used for working with human language data and implementing natural language processing (NLP) tasks. It provides a set of tools, corpora, and resources for tasks such as tokenization, stemming, tagging, parsing, sentiment analysis, and more.

Here are some key features and functionalities of NLTK:

- Text Processing
- Part-of-Speech Tagging
- Named Entity Recognition

➢ **Scipy**

SciPy is a collection of mathematical algorithms and convenience functions built on the NumPy extension of Python. It adds significant power to the interactive Python session by providing the user with high-level commands and classes for manipulating and visualizing data.

- Numerical Integration:
- Optimization and Root Finding
- Linear Algebra
- Signal and Image Processing

5.3 Sample Code:

RansomewareDetection.ipynb

```
#importing pythom classes and packages

import numpy as np

import pandas as pd

import seaborn as sns

from sklearn.preprocessing import LabelEncoder

import os

from keras.callbacks import ModelCheckpoint

import pickle

from keras.layers import LSTM #load LSTM class

from keras.utils.np_utils import to_categorical

from keras.layers import  MaxPooling2D
from keras.layers import Dense, Dropout, Activation, Flatten #load DNN dense layers

from keras.layers import Convolution2D #load CNN model

from keras.models import Sequential, Model

from sklearn.preprocessing import MinMaxScaler

from sklearn.metrics import accuracy_score

from sklearn.model_selection import train_test_split

from sklearn.feature_selection import RFECV

from sklearn.svm import SVR

from sklearn.metrics import precision_score

from sklearn.metrics import recall_score

from sklearn.metrics import f1_score

from sklearn.metrics import confusion_matrix

import matplotlib.pyplot as plt

from xgboost import XGBClassifier #load ML classes

from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn import svm

from sklearn.ensemble import RandomForestClassifier

#define minmax object for features normalization

scaler = MinMaxScaler(feature_range = (0, 1)) #use to normalize training data
```

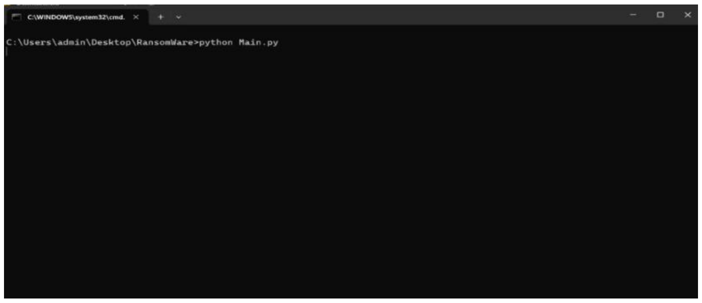
```
#load and display dataset values

dataset = pd.read_csv("Dataset/hpc_io_data.csv")

dataset.fillna(0, inplace = True)#replace missing values

dataset

#find and plot graph of ransomware and benign from dataset where 0 label refers as benign and 1 refer as ransomware

#plot labels in dataset

labels, count = np.unique(dataset['label'], return_counts = True)

labels = ['Benign', 'Ransomware']

height = count

bars = labels

y_pos = np.arange(len(bars))

plt.bar(y_pos, height)

plt.xticks(y_pos, bars)

plt.xlabel("Dataset Class Label Graph")

plt.ylabel("Count")

plt.show()
```

CHAPTER:6

OUTPUT SCREENS

6.1 screens:-

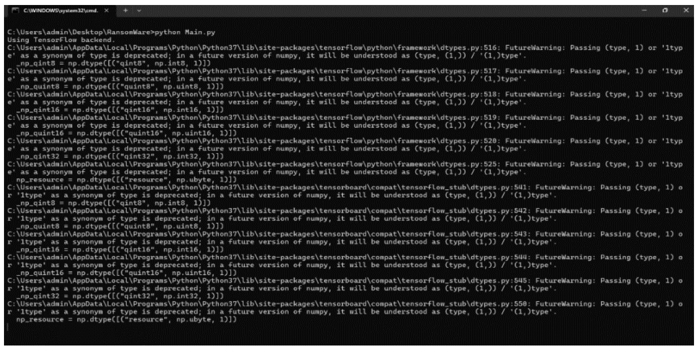
Python script (Main.py) for the ransomware detection system is being executed via the command prompt.



```
C:\Users\admin\Desktop\RansomWare>python Main.py
```

Fig6.1:(**Run File)**

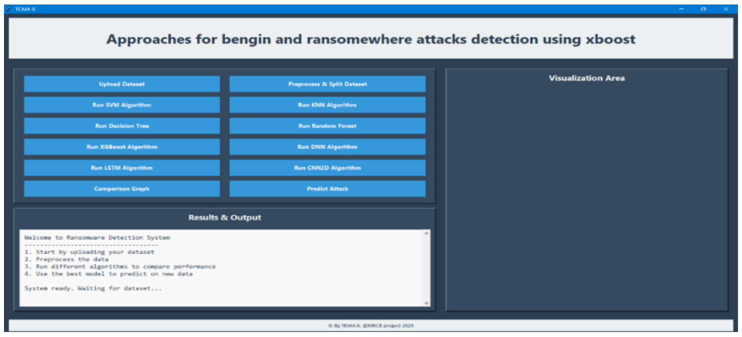
TensorFlow and NumPy compatibility warnings are displayed, but the script continues execution



```
C:\Users\admin\Desktop\RansomWare>python Main.py
Using TensorFlow backend.
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:516: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:517: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:518: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:519: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:520: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorflow\python\framework\dtypes.py:525: FutureWarning: Passing (type, 1) or '1typ
e' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:541: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:542: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:543: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:544: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550: FutureWarning: Passing (type, 1) o
r '1type' as a synonym of type is deprecated; in a future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

Fig6.2:(**CMD Execution)**

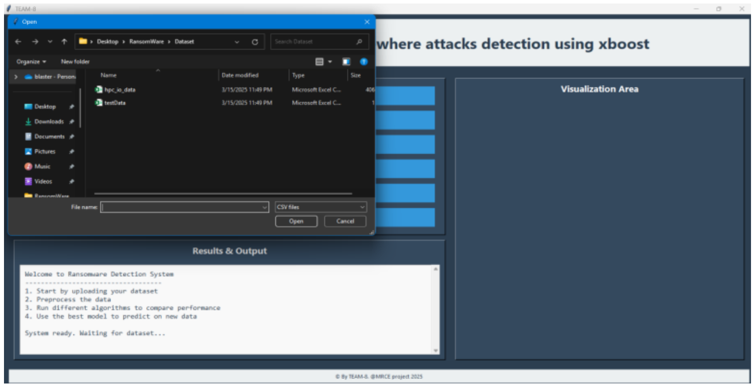
The GUI application titled is successfully launched**.**



```
Welcome to Ransomware Detection System
----------------------------------
1. Start by uploading your dataset
2. Preprocess the data
3. Run different algorithms to compare performance
4. Use the best model to predict on new data

System ready. Waiting for dataset...
```

Fig6.3:(**Interface)**

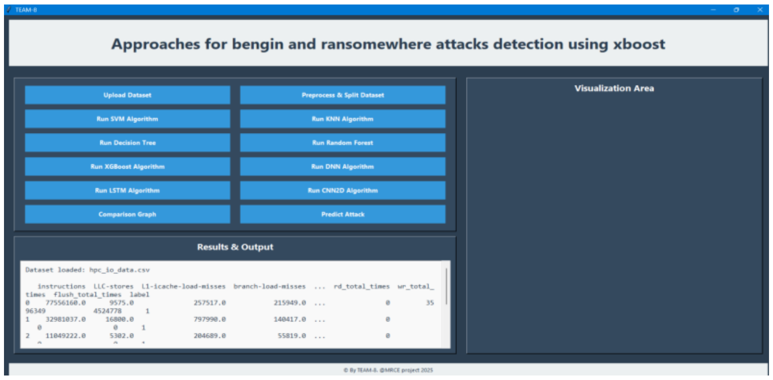
File dialog window appears for uploading a CSV dataset to the application.



```
Welcome to Ransomware Detection System
-----------------------------------
1. Start by uploading your dataset
2. Preprocess the data
3. Run different algorithms to compare performance
4. Use the best model to predict on new data

System ready. Waiting for dataset...
```

Fig6.4:(**Dataset Loading)**

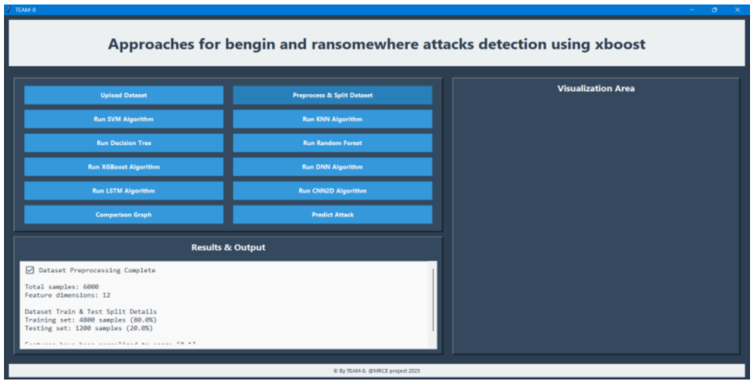
Dataset hpc_ko_data.csv is loaded and previewed within the application.



```
Dataset loaded: hpc_io_data.csv

   instructions  LLC-stores  L1-icache-load-misses  branch-load-misses  ...  rd_total_times  wr_total_
times  flush_total_times  label
0    77556160.0      9575.0               257517.0            215949.0  ...               0         35
96349            4524778      1
1    32981037.0     16800.0               797990.0            140417.0  ...               0
   0                 0      1
2    11049222.0      5302.0               204689.0             55819.0  ...               0
```

Fig6.5**:(data show)**

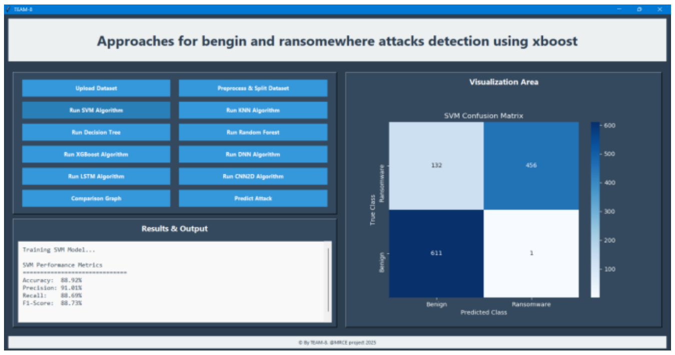
Dataset preprocessing is completed with training and test data split summary shown**.**



```
☑ Dataset Preprocessing Complete

Total samples: 6000
Feature dimensions: 12

Dataset Train & Test Split Details
Training set: 4800 samples (80.0%)
Testing set: 1200 samples (20.0%)
```

Fig6.6**:(preprocessing)**

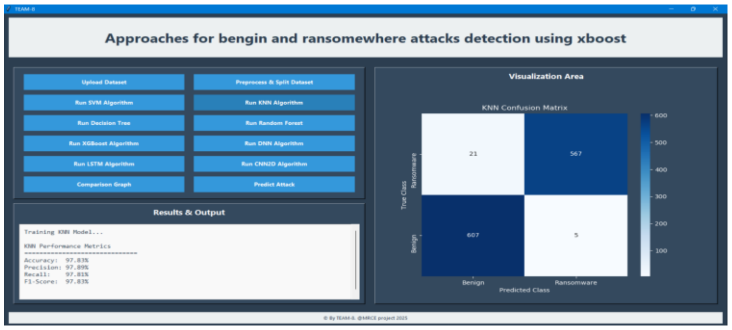
SVM algorithm is run and confusion matrix with performance metrics is displayed (Accuracy: 88.92%).



```
Training SVM Model...

SVM Performance Metrics
==============================
Accuracy:  88.92%
Precision: 91.01%
Recall:    88.69%
F1-Score:  88.73%
```

Fig6.7**(SVM Model)**

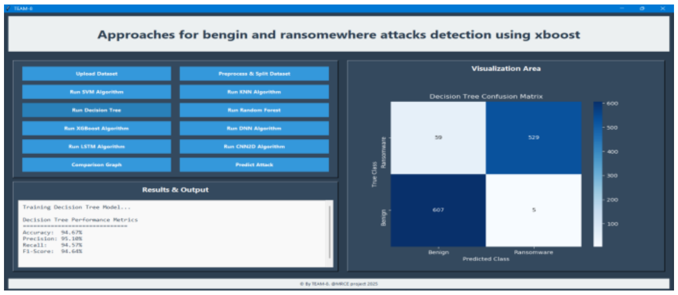
KNN algorithm results are shown with high accuracy (97.83%) and corresponding confusion matrix



```
Training KNN Model...

KNN Performance Metrics
==============================
Accuracy:  97.83%
Precision: 97.89%
Recall:    97.81%
F1-Score:  97.83%
```

Fig6.8:**(KNN Model)**

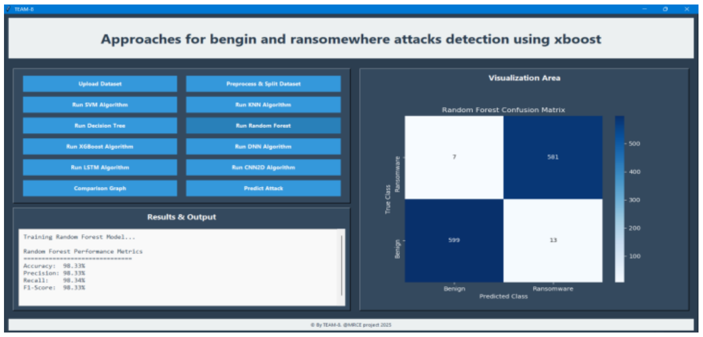
Decision Tree model performance is displayed with moderate accuracy (94.62%) and confusion matrix.



```
Training Decision Tree Model...

Decision Tree Performance Metrics
==============================
Accuracy:  94.67%
Precision: 95.10%
Recall:    94.57%
F1-Score:  94.64%
```

Fig6.9:**(Decision Tree Model)**

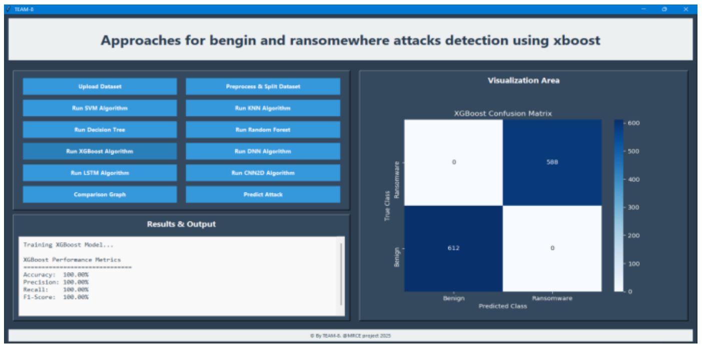
Random Forest classifier results shown with an accuracy of 98.33% and its confusion matrix



```
Training Random Forest Model...

Random Forest Performance Metrics
==============================
Accuracy:  98.33%
Precision: 98.33%
Recall:    98.34%
F1-Score:  98.33%
```

Fig6.10:(**Random Forest Model)**

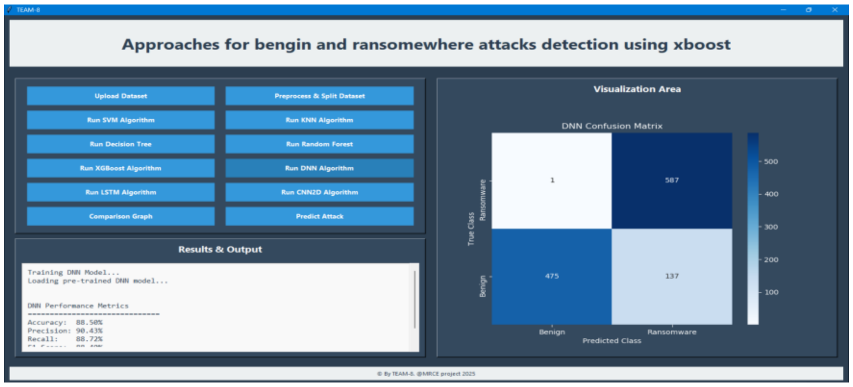
In below screen XGBOOST also got 98% accuracy



```
Training XGBoost Model...

XGBoost Performance Metrics
==============================
Accuracy:  100.00%
Precision: 100.00%
Recall:    100.00%
F1-Score:  100.00%
```

Fig6.11**(XGBoost Model)**

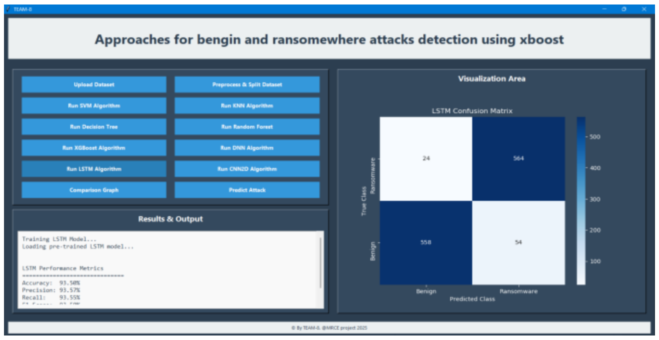
In below screen training DNN algorithm and below is the DNN output got 88%accuracy



```
Training DNN Model...
Loading pre-trained DNN model...


DNN Performance Metrics
==============================
Accuracy:  88.50%
Precision: 90.43%
Recall:    88.72%
```

Fig6.12**:(DNN Model)**

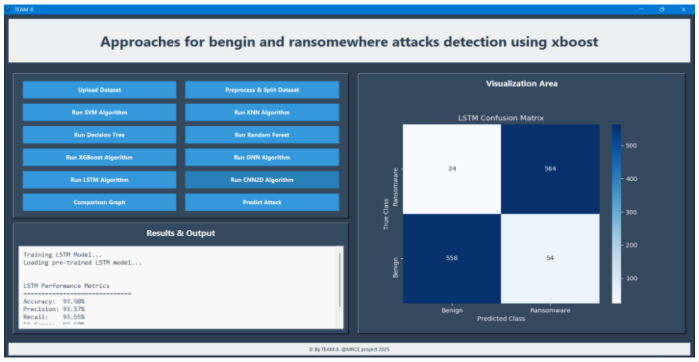
LSTM algorithm and after executing above block will get below output LSTM got 93% accuracy



```
Training LSTM Model...
Loading pre-trained LSTM model...


LSTM Performance Metrics
==============================
Accuracy:  93.50%
Precision: 93.57%
Recall:    93.55%
```

Fig6.1.13:(**LSTM Algorithm)**

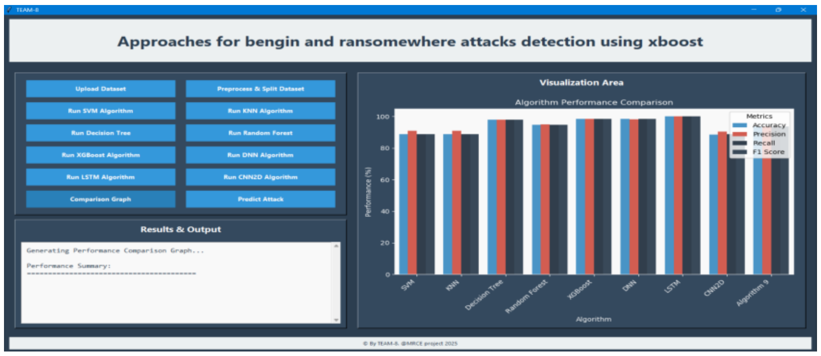
screen defining CNN2D algorithm and this block will get 98.83% accuracy



```
Training LSTM Model...
Loading pre-trained LSTM model...

LSTM Performance Metrics
==============================
Accuracy:  93.50%
Precision: 93.57%
Recall:    93.55%
```

Fig6.1.14**:(CNN2D Algorithm)**

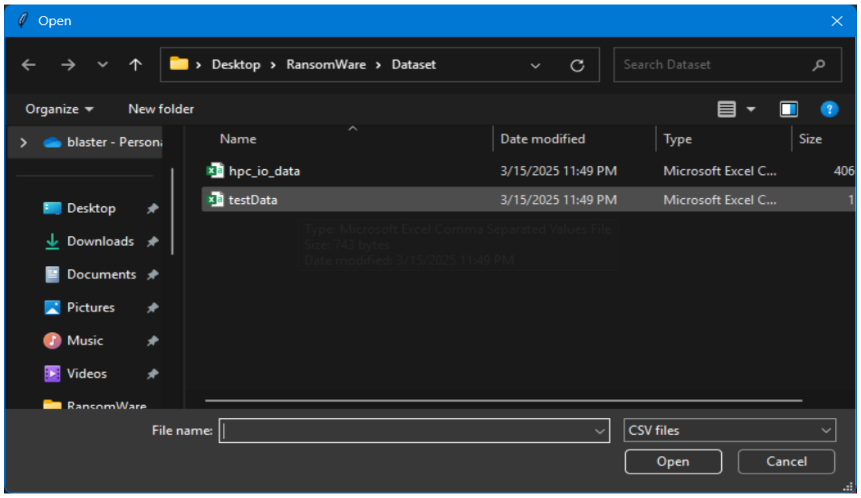
graph x-axis represents algorithm names and y-axis represents accuracy.



```
Generating Performance Comparison Graph...

Performance Summary:
========================================
```

Fig6.15:(comparision graph)

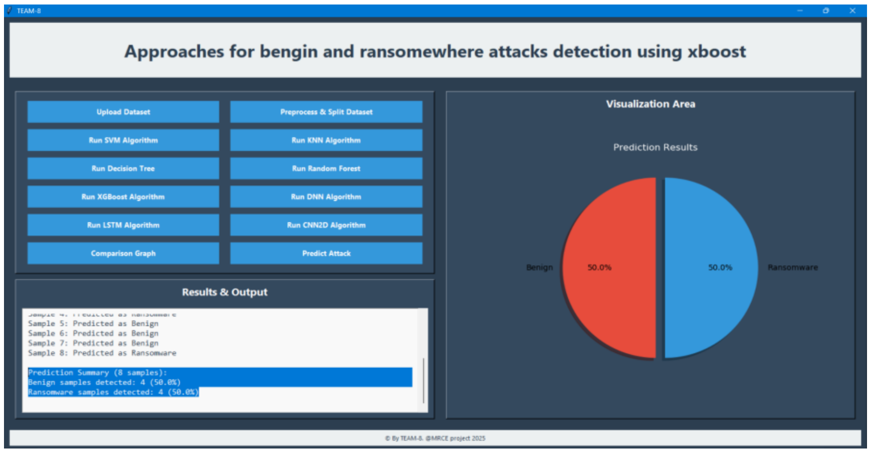
We have to provide an test data to check ransomeware.



Name	Date modified	Type	Size
hpc_io_data	3/15/2025 11:49 PM	Microsoft Excel C...	406
testData	3/15/2025 11:49 PM	Microsoft Excel C...	1

Fig6.16**:(test data sample)**

In below screen reading test data and then using extension CNN algorithm object performing prediction on test data and then in output before arrow symbol =➔ we can see Test data values and after arrow symbol we can see predicted values as ‘Ransomware or Benign’.



```
Sample 4: Predicted as Ransomware
Sample 5: Predicted as Benign
Sample 6: Predicted as Benign
Sample 7: Predicted as Benign
Sample 8: Predicted as Ransomware

Prediction Summary (8 samples):
Benign samples detected: 4 (50.0%)
Ransomware samples detected: 4 (50.0%)
```

Fig6.17**:(Attack Prediction)**

CHAPTER:7

TESTING AND VALIDATION

7.1 Introduction

Implementation is one of the most important tasks in project is the phase in which one has to be cautions because all the efforts undertaken during the project will be very interactive. Implementation is the most crucial stage in achieving successful system and giving the users confidence that the new system is workable and effective. Each program is tested individually at the time of development using the sample data and has verified that these programs link together in the way specified in the program specification. The computer system and its environment are tested to the satisfaction of the user.

7.2 Implementation

The implementation phase is less creative than system design. It is primarily concerned with user training, and file conversion. The system may be requiring extensive user training. The initial parameters of the system should be modifies as a result of a programming. A simple operating procedure is provided so that the user can understand the different functions clearly and quickly. The different reports can be obtained either on the inkjet or dot matrix printer, which is available at the disposal of the user. The proposed system is very easy to implement. In general implementation is used to mean the process of converting a new or revised system design into an operational one.

Testing

Testing is the process where the test data is prepared and is used for testing the modules individually and later the validation given for the fields. Then the system testing takes place which makes sure that all components of the system property functions as a unit. The test data should be chosen such that it passed through all possible condition. Actually testing is the state of implementation which aimed at ensuring that the system works accurately and efficiently before the actual operation commence. The following is the description of the testing strategies, which were carried out during the testing period.

7.3 System Testing

Testing has become an integral part of any system or project especially in the field of information technology. The importance of testing is a method of justifying, if one is ready to move further, be it to be check if one is capable to with stand the rigors of a particular situation cannot be underplayed and that is why testing before development is so critical. When the software is developed before it is given to user to use the software must be tested whether it is solving the purpose for which it is developed. This testing involves various types through which one can ensure the software is reliable. The program was tested logically and pattern of execution of the program for a set of data are repeated. Thus the code was exhaustively checked for all possible correct data and the outcomes were also checked.

Module Testing

To locate errors, each module is tested individually. This enables us to detect error and correct it without affecting any other modules. Whenever the program is not satisfying the required function, it must be corrected to get the required result. Thus all the modules are individually tested from bottom up starting with the smallest and lowest modules and proceeding to the next level. Each module in the system is tested separately. For example the job classification module is tested separately. This module is tested with different job and its approximate execution time and the result of the test is compared with the results that are prepared manually. The comparison shows that the results proposed system works efficiently than the existing system. Each module in the system is tested separately. In this system the resource classification and job scheduling modules are tested separately and their corresponding results are obtained which reduces the process waiting time. **Integration Testing**

Acceptance Testing

When that user fined no major problems with its accuracy, the system passers through a final acceptance test. This test confirms that the system needs the original goals, objectives and requirements established during analysis without actual execution which elimination wastage of time and money acceptance tests on the shoulders of users and management, it is finally acceptable and ready for the operation

7.4 Testing table

Test Case Name	**Test Case Desc.**	**Test Steps**			**Test Case Status**	**Test Priority**
		Step	**Expected**	**Actual**		
Upload Dataset	Test whether Dataset is uploaded or not into the system	If the Dataset may not uploaded	We cannot do further operations	Dataset uploaded we will do further operations	High	High
Preprocess& Normalized Dataset	Test whether the Pre-process & Normalized Dataset Successfully or not	If the Pre-process & Normalized Dataset may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Train run SVM Algorithm	Test whether SVM Algorithm Run Successfully or not	If the **SVM** Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Run Decision Tree	Test whether Decision Tree Algorithm Successfully or not	If the Decision Tree Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Run Random Forest	Test whether Random Forest Algorithm Run Successfully or	If the Random Forest Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High

Run Xgboost	Test whether Run Xgboost Algorithm Run Successfully or not	If the Run Xgboost Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Run DNN	Test whether DNN Algorithm Run Successfully or not	If the DNN Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Run LSTM	Test whether LSTM Algorithm Run Successfully or not	If the LSTM Algorithm may not Run Successfully	We cannot do further operations	we will do further operations	High	High
Run CNN2D	Test whether CNN2D Algorithm Run	If the CNN2D Algorithm may not Run	We cannot do further operations	we will do further operations	High	High

7.5 Validation

Validation is a crucial phase in ensuring the reliability, robustness, and practical applicability of the ransomware detection system presented in this documentation. The primary goal of validation in this project is to rigorously assess the effectiveness of the machine learning (ML) and deep learning (DL) models in accurately and rapidly detecting ransomware attacks under realistic and diverse user workloads on virtual machines (VMs).

Methodology

The validation process begins with the systematic collection of processor and disk I/O event data from the host machine while various workloads and ransomware samples are executed on the target VM. Processor-event data is gathered using the perf tool and hardware performance counters (HPCs), while disk I/O data is collected using virsh domblkstats. The dataset comprises both benign activities (such as productivity software usage, web browsing, and multimedia playback) and malicious activities (ransomware encryption operations).

Each data sample is labeled accordingly to facilitate supervised learning and evaluation.

To ensure a comprehensive assessment, multiple ML and DL classifiers—including Random Forest, XGBoost, SVM, KNN, Decision Tree, DNN, and LSTM—are trained and validated. For each classifier, three models are constructed: one using only HPC data, one using only disk I/O data, and an integrated model using both. Recursive feature elimination with cross-validation is employed to select the most relevant features from the available events, optimizing model performance and reducing overfitting.

Experimental Setup

Validation is conducted under several scenarios:

- Known Ransomware: Models are tested on ransomware samples included in the training data to evaluate their ability to detect familiar threats.
- Unknown Ransomware: Models are tested on ransomware samples not included in the training data to assess generalization to new, previously unseen attacks.
- Multiple User Workloads: The system’s performance is evaluated under various background workloads, such as document editing, web browsing, and media playback, to ensure robustness in real-world conditions.

CHAPTER:8

CONCLUSION

This project presents a comprehensive and innovative approach for detecting ransomware executing on virtual machines (VMs) by leveraging processor and disk I/O activity events collected from the host machine and applying advanced machine learning (ML) techniques to analyze this data.

The core motivation stems from the increasing frequency and sophistication of ransomware attacks, which are capable of bypassing traditional signature-based detection methods through polymorphic and metamorphic techniques. As ransomware continues to evolve, there is a pressing need for detection mechanisms that are both rapid and resilient to evasion, especially in cloud and virtualized environments where the attack surface is broad and dynamic.

To address these challenges, this study utilizes the Linux perf tool and hardware performance counters (HPCs) to collect processor-event data for five carefully selected events out of more than forty candidates, using recursive feature elimination with cross-validation to ensure only the most relevant features are included1. Disk I/O-event data is simultaneously gathered for eight distinct events using the virsh domblkstats utility.

By collecting these metrics at the VM level from the host, the system avoids the significant overhead and risk of interference associated with process-level monitoring on the target machine. This architecture ensures that the data collection process is both efficient and secure, as ransomware operating within the VM cannot detect or disrupt the monitoring activities.

Another area for future research is the extension of the methodology to monitor and detect data exfiltration activities by analyzing network traffic in conjunction with HPC and I/O data. Furthermore, while the current models are tailored for VMs, the authors plan to adapt and validate their approach for standalone machines and to assess the transferability of models across different hardware configurations.

In summary, this project advances the state of the art in ransomware detection by introducing a host-level, machine learning-driven approach that is both efficient and resilient. It demonstrates that combining processor and disk I/O activity data enables rapid and accurate detection of ransomware, even under realistic and varied workloads.

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