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Anomaly Detection in HDFS Logs using Machine Learning Integrated with LLM-Based Mitigation

By

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APPROVED BY: ______________________________

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ABSTRACT

Anomaly detection is essential for managing today's large-scale distributed systems, where system logs are a key resource for identifying unusual behavior. Traditionally, system operators relied on manual inspection methods such as keyword searches and rule-based matching. However, due to the massive volume and complexity of modern system logs, manual approaches are no longer practical. To tackle this, many automated log-based anomaly detection methods have been proposed. Still, developers often struggle to choose a suitable method, as there hasn't been a clear comparison of these approaches.

In this research, I will propose a solution to addresses the fundamental challenge of automated log analysis. Specially, the research tackles three interconnected problems: (1) automated parsing of diverse log formats into structured templates, (2) anomaly detection in high-volume log streams, and (3) generation of contextual, actionable recommendations for identified issues.

Previous research has established some foundational approaches including the algorithms for log parsing and machine learning techniques for anomaly detection. However, existing solutions typically focus on individual components rather than providing end-to-end integration. Most academic implementations lack production-ready deployment architectures, user-friendly interfaces, and the integration of modern Large Language Models (LLMs) for intelligent recommendations—creating a significant gap between theoretical algorithms and practical deployment. Therefore, this research is important since it close the gap between academic log analysis algorithms and production-ready systems.

Furthermore, the research establishes a framework for integrating emerging LLM capabilities into traditional system administration workflows, suggesting broader implications for AI-assisted DevOps practices. The findings indicate that intelligent automation of log analysis is not only technically feasible but can significantly enhance

organizational capabilities in system reliability, security monitoring, and operational efficiency.

CHAPTER 1: INTRODUCTION

1.1 Background of the study

In modern software systems, log files serve as critical sources of information for system monitoring, debugging, troubleshooting, and security analysis. As applications or systems scale and increase its complexity, the volume of generated log data gets bigger exponentially. Therefore, traditional manual approaches for log analysis like manually examine through log files using basic tools such as grep or text editors, has become less efficient and more defective [2]. As the result, it is becoming more difficult to detect anomalies within large scale system.

Over the year, a lot of automated log-based methods have been introduced to help detecting system anomalies. These approaches usually require raw log preprocessing techniques, feature extraction and machine-learning-based algorithms for processing vast amounts of unstructured log data efficiently, identifying potential issues before they escalate into critical failures. Recent advancements in natural language processing and large language models (LLMs) have also increased the potential for intelligent log analysis systems. However, despite these development, traditional machine-learning techniques and LLM-based approaches have yet to be efficiently integrated into a single, cohesive log analysis framework.

This study focuses on leveraging existing machine learning approaches where log parsing and anomaly detected are used, and augmenting them with large language model to provide actionable insights and helpful recommendations.

1.2 Problem Statement

Despite the important role of log analysis that play in making the system more secure and reliable, several significant challenges still persist in current practices:

- *Limited interpretability.* In log anomaly detection, the ability to interpret model's outputs is important for people who work as system administrators or analysts to effectively action to the alerts. They need to understand which log entries may be responsible for the detected abnormality. Yet, many traditional approaches only provide basic classified prediction without any explanation. As a result, engineers still have to perform further manual root cause analysis which in large-scale and complex systems becomes an very time-consuming and heavy task.

- *Poor adaptability.* Many existing methods rely on a predefined set of log event templates during feature extraction phase (This phase will use the set of log event templates generated by log parsing to create numerical features for machine learning models [12]). However, as applications scale up and expand in term of feature, new and unseen log events will definitely appear. Therefore, adapting to these changes require retraining models from scratch which make the systems become less practical in dynamic environments.

- *Poor adaptability.*

1.3 Objectives of the Study

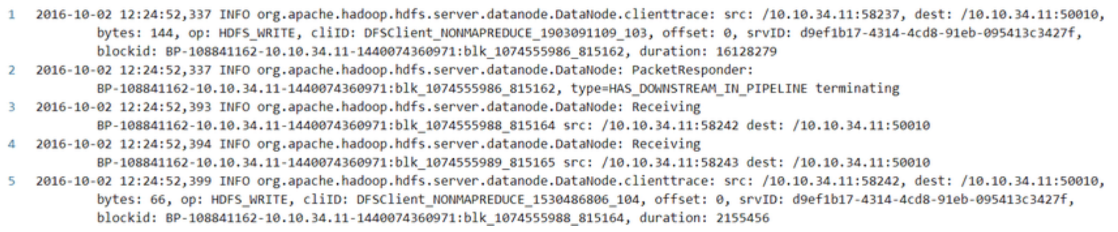
This study will perform the investigation on existing anomaly-detection methodologies, compares the performance of different machine-learning models, and develops a practical framework that integrates large language models (LLMs) to automate and improve anomaly detection in real-world scenario.

1.4 Limitations of the Study

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction to system log

System logs, also known as event logs or audit trails, are automatically generated by a computer system (its operating system, services, applications) that record events, changes and error that occur inside that system. These log files serve an important role in monitoring system health, diagnose failures, detecting anomalies, and ensure system security and compliance [14]. System logs usually follow a semi-structured format which consist of several fields that capture both the context and content of the event.



```
2016-10-02 12:24:52,337 INFO org.apache.hadoop.hdfs.server.datanode.DataNode.clienttrace: src: /10.10.34.11:58237, dest: /10.10.34.11:50010,
        bytes: 144, op: HDFS_WRITE, cliID: DFSClient_NONMAPREDUCE_1903091109_103, offset: 0, srvID: d9ef1b17-4314-4cd8-91eb-095413c3427f,
        blockid: BP-108841162-10.10.34.11-1440074360971:blk_1074555986_815162, duration: 16128279
2016-10-02 12:24:52,337 INFO org.apache.hadoop.hdfs.server.datanode.DataNode: PacketResponder:
        BP-108841162-10.10.34.11-1440074360971:blk_1074555986_815162, type=HAS_DOWNSTREAM_IN_PIPELINE terminating
2016-10-02 12:24:52,393 INFO org.apache.hadoop.hdfs.server.datanode.DataNode: Receiving
        BP-108841162-10.10.34.11-1440074360971:blk_1074555988_815164 src: /10.10.34.11:58242 dest: /10.10.34.11:50010
2016-10-02 12:24:52,394 INFO org.apache.hadoop.hdfs.server.datanode.DataNode: Receiving
        BP-108841162-10.10.34.11-1440074360971:blk_1074555989_815165 src: /10.10.34.11:58243 dest: /10.10.34.11:50010
2016-10-02 12:24:52,399 INFO org.apache.hadoop.hdfs.server.datanode.DataNode.clienttrace: src: /10.10.34.11:58242, dest: /10.10.34.11:50010,
        bytes: 66, op: HDFS_WRITE, cliID: DFSClient_NONMAPREDUCE_1530486806_104, offset: 0, srvID: d9ef1b17-4314-4cd8-91eb-095413c3427f,
        blockid: BP-108841162-10.10.34.11-1440074360971:blk_1074555988_815164, duration: 2155456
```

Figure 2.1: This is the descriptive text that explains the figure.

Figure 2.1 show a log snippet that was generated by HDFS DataNode, one of the core storage components in the Hadoop ecosystem (a more detail explanation of this system will be provided below). These log entries are created from the storage operations of the system such as data writes, packet handling, and communication between DataNodes. A log entry typically follow a structure as follow:

- *Timestamp: 2016-10-02 12:24:52,337.* Indicates the exact moment when the system processed the event.
- *Log level: INFO.* Shows that the entry reports normal operational activity
- *Log message: org.apache.hadoop.hdfs.server.datanode.DataNode.clienttrace:...* Log messages provide a structured description of system behavior, capturing events, performance indicators. This is the most important part of a log entries and therefor become the foundation for monitoring, auditing and anomaly detection.

Given their important role in providing such essential information about the system, logs must be reliably collected, centrally stored and appropriately maintained to enable accurate monitoring, troubleshooting, and subsequent analytical processes.

2.2 Traditional log analysis method

Traditional log analysis have relied on two primary approaches (cite something): manual log inspection and rule-based pattern matching systems. While these techniques are the foundation of the system administrators fields and troubleshooting, it were used during the time when the system complexity and log volumes were much smaller than nowadays modern systems. Understanding the strengths and limitations of these approaches will provide you a better context and insights of logs which will enhance your log analysis systems.

2.2.1 Manual Log Inspection

Manual log inspection is one of the earliest and most straightforward methods used by system administrators to identify issues. In this approach, developers or administrators will directly operate searching on raw log files using command-line tools such as `grep` , `tail`, `less`, to locate error logs or correlate timestamp of the incidents. While feasible for small log volumes, this method is very time-consuming, highly error-prone and relies heavily on an operator's familiarity with the system. Therefore, this approach is no longer a feasible solution for detecting anomalies in large-scale systems which may produce millions of log entries per hour. For instance, in 2013 the Alibaba Cloud system was reported to generate approximately 100 to 200 million log lines in one hour [10].

2.2.2 Rule-Based Systems (Regex and Pattern Matching)

To counter the limitations of manual log review, developers created rule-based system that used fixed rules, regular expressions (regex), and predefined patterns to filter, parse, and identify specific events when a specification conditions are met. For example, system operators can create rules to detect keywords such as ”ERROR”, ”FAILED” or extract key information from log entries. Rule-based methods offer some advantages: they are easy to implement and effective for detecting obvious or recurring errors. Many traditional monitoring tools such as Nagios, Splunk (early versions) [13], and Logstash [3], they are heavily depend on popular pattern-matching techniques to filter, categorize, and index log data.

However, the effectiveness of rule-based approaches highly depend on the completeness and accuracy of the hand-crafted predefined rules. It will become more defective in a constantly evolving environments where logs format change frequently and new types of anomalies will appear which do not match the existing patterns. Maintaining large sets of regex rules is also a labor-intensive action and require continuous manual updates on patterns which is unsuitable for adaptive anomaly detection.

2.3 Log parsing

2.4 Machine learning and deep learning for log anomaly detection

As system continuously scaled and logs volumes grew bigger, manual or rule-based approaches is no longer available. As a result, researchers began to adopt machine learning to automate anomaly detection. These methods are created to enable it to learn the structures, numerical representations, and patterns of logs without depending on predefined rules or templates. These approaches are often categorized as supervised or unsupervised learning.

2.4.1 Supervised learning

a. Support Vector Machine (SVM)

   Support Vector Machine is one of the fundamental methods that proposed by Vapnik [15] which is used for binary classification. The basic idea of this method is as follow. For nonlinear separable data, we can transform it to higher-dimensional space where the data becomes linearly separable. This allows the classifier to construct an optimal separating hyperplane between normal and anomalous log patterns. In log detection context, anomaly logs will be treated as negatives and normal one will be served as positive examples. But using this method for detecting anomalies often often suffers from class imbalance, where the positive examples is outnumber the negatives. As the result, the classifier will overfit the anomalous logs, which make it become weak in detecting new occur, unseen logs.

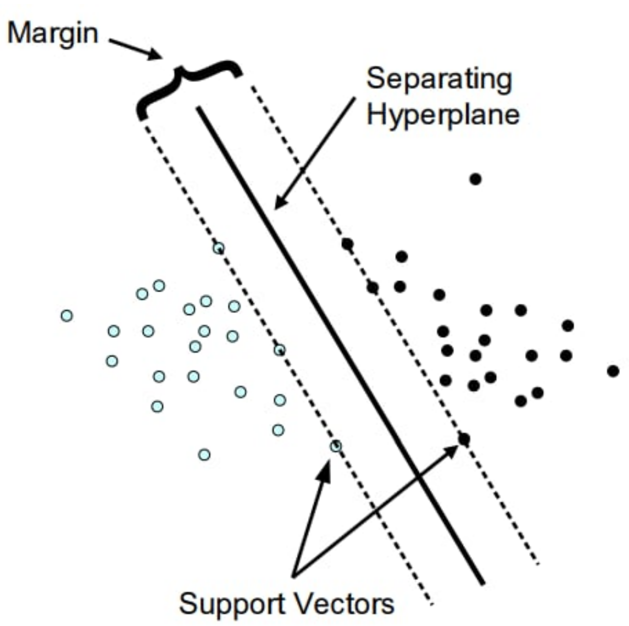


Figure 2.2: SVM classification

b. Decision Tree (DS)

Decision tree is one of the earliest machine learning approaches that apply to anomaly log detection and are defined by Quinlan [11] as ”powerful and common tools for classification and prediction”. This method recursively splitting data based on its features then create a tree-like structure where each leaf node represents a prediction class (normal or abnormal). When apply to log anomaly detection, we have to transform log entries into structured numerical features before feed it into decision tree algorithm. The applications of decision trees to log-based anomaly detection has been proposed in many research with promising results. He et al. [4] did some experiments with anomaly logs in HDFS dataset using decision tree classifier and and prove the effectiveness of it. The approach not only achieve high accuracy but also provide interpretable rules that allows others to validate and refine them as they wish. In context of this research, decision tree served as a foundation machine learning algorithm for detecting anomalies in log data. The specific implementations and results of using this algorithm will be discussed more upon in subsequent sections.

c. The final item summarizes the topic.

2.4.2 Unsupervised learning

In many situation when anomaly data is not labeled or unavailable, the supervised learning is thereby become impractical. As a result, unsupervised learing methods have been adopted widely for log anomaly detection. These approaches aim to analyze data without requiring labeled examples by discovering the characteristics of the data itseft. This section will examine some popular unsupervised approaches that are currently applied to log analysis.

a. Isolation Forrest

   Isolation Forrest is a machine learning algorithm that was introduced by Liu et al [8] in 2012. His core principle of isolation forrest is that anomolies are more accessible to isolate than abnomalous points [9]. The algorithms will construct forrest of random binary trees to separate each data point. Each tree us built by randomly selecting a feature from the dataset and a split value within the feature's range, then repetitive split the data until it reach the maximum depth or the instance is isolated.

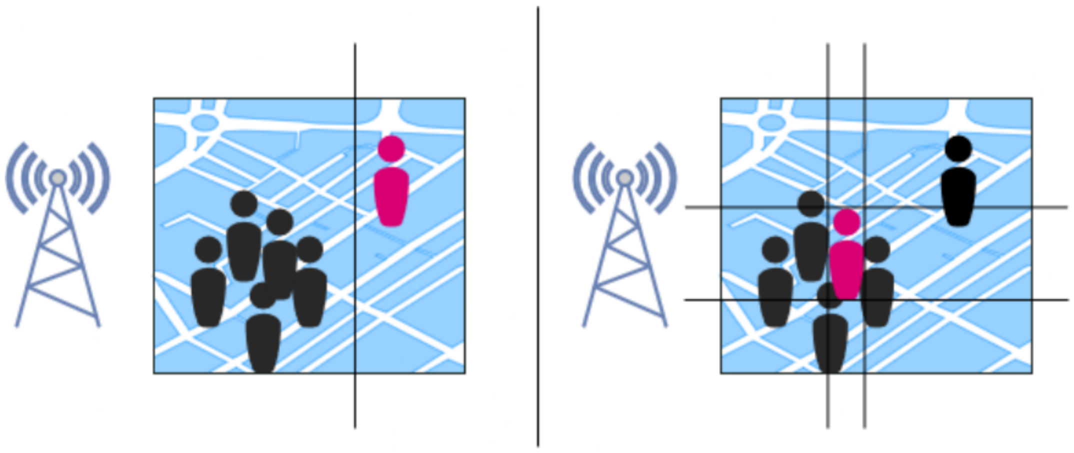


Figure 2.3: Isolation Forest

Figure 2.3 demonstrates the isolation capabilities of Isolation Forest algorithm. In the left, the data point is seperated with only one split, indicating a high anomaly score. On the other hand, data point on the right requires more splits, suggesting it's a nominal data point

b. Principal Component Analysis (PCA)

Principal Component Analysis is a common technique that widely used for dimensionality reduction [1] in a dataset. By doing so, PCA algorithm helps simplifying complex dataset, reducing the redundancy among features, and highlighting the most important patterns in the data [6]. In anomaly detection, it first converts each log sequence into event count vector by counting how many time each type of log event appear in the sequence. Next, the PCA algorithm [7, 1] will capture the main patterns of normal log behavior then project those vectors to a learned space (also known as normal space). However, when a log sequence contains anomaly logs such as missing events or unusual log messages, PCA algorithm will mark it as abnormal behavior by calculating the Square Prediction

[1] Dimensional reduction is the process of reducing the number of input variables (features) in a dataset keeping as much essential information as possible.

Error (SPE) [5] , which measures the deviation from the learned normal patterns.

c. K-Means Clustering

- ml techniques: https://arxiv.org/pdf/2307.16714

2.5 Large Language Models (LLMs) in Log Analysis

Parsing with LLMs instead of templates:

Explainability + anomaly detection:

CHAPTER 3: METHODOLOGIES

3.1 Overview

This chapter describes the methodology that used to design, implement, and evaluate the proposed log anomaly detection framework. The methodology follows a pipeline that begins with data collection and preprocessing, then extract the features and using machine learning techniques to detect anomolies. Large language models (LLMS) are also integrated to address the limitations of the traditional approaches, giving more insights and contextual understanding of detected anomolies. This chapter is organized to present each stage of a framework, from system arichiteture and how data is prepared to model Implementation and evaluation.

3.1.1 Research Approach

In this study, I adopt a design-based experimental research approach that combines traditional machine learning methods with large language model techniques. This approach will focus on constructing a practical, user-friendly and production-ready log anomaly detection framework by integrating proven traditional methods with LLM-based reasoning to addressing both the technical and operational challenges of large-scale log analysis.

The methodology combines well-established components such as the Drain log parsing algorithms to constructs structured log templates from raw log messages, Decision Tree or Isolation Forrest machine learning models are compared to find the most effective one and implemented it as detection instruments.

For data collection, this study relies primarily on secondary collection methods which uses public and available log datasets like HDFS system logs or BGL logs dataset. There will be no primary data involving human participants are collected. The data collection process includes log ingestion, parsing, feature extraction, anomaly labeling (already prepared by experts), and preparation for model training and testing.

This study use a mixed-method of quantitative and qualitative analysis approaches. Quantitative analysis is utilized to evaluate the performance of detection models using real statistics (e.g., detection rates and error rates) and comparison between models. Furthermore, qualitative analysis is applied to the outputs that is generated by LLMs, focusing on their ability to provide root cause explanations and mitigation suggestions.

Ethics are also considered in this study which relate to data usage and research integrity. All datasets that I used are publicly available so it ensures no personal information is exposed. Proper citation and acknowledgment of datasets, tools, and prior research are also maintained. Additionally, this study is responsible for the LLM-generated outputs by put it as only suggestions rather than automated direct action, and thereby preventing unintended operational impact.

3.1.2 System Pipeline Overview

The proposed framework follows a pipeline from transform raw systems logs into structured one and useful recommendations through a sequence of stages. Figure 3.1 illustrates the overall pipeline.

The pipeline begins with log preprocessing, where raw logs are parsed using the Drain algorithm. This step will convert raw and unstructured log into sequence of structured events and extract event templates.

Structured log sequences will be the input for the processing step, where it will be transformed to numerical representations and then fed to machine learning models for anomaly detection.

The final stage integrates large language models (LLMs) to enhance system interpretability. LLMs component will perform semantic analysis based on detected anomalies and generate human-readable explanations about root casues and useful suggestions.

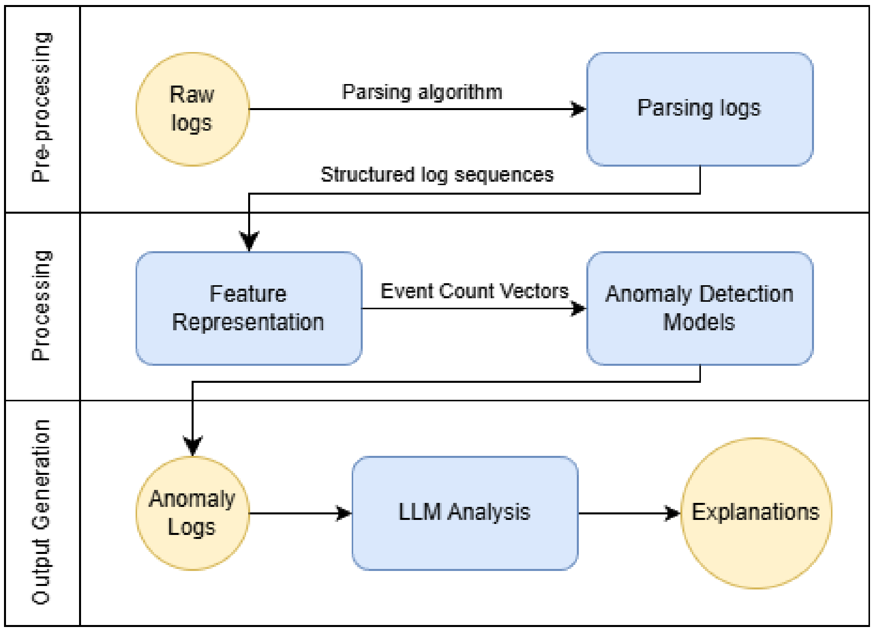


Figure 3.1: System pipeline

3.2 System Architecture and Design

This section presents the system architecture and design of the proposed log anomaly detection framework. We will focus on the structural composition of the system and also show their responsibilities, and interactions. The architecture is designed to make the process of large-scale log data more efficiently while enabling to integrate with traditional anomaly detection techniques and large language models (LLMs).

3.2.1 Architectural Overview and Design Principles

The proposed log analysis system follows a simple architecture but highlight the practicality and ease of integration to support real-world problems. The systems is desgined around some key principles:

1. Asynchronous Processing

   The architecture apply asynchronous task processing to handle computationally heavy workload without affect user interface. Therefore the system can effective process large log files while also maintain good user interaction.

2. Modular Service Design

   Each component in the system is designed as an independent module with clear responsibilities to maintain or test more easily, and also increase the ability of horizontally scaling of individual components.

3. Data Layer Separation

   The system create a clear separation between metadata management and object storage that using MinIO for large-scale objects and PostgreSQL for logs structured metadata. This design optimizes the performance by addressing the data access pattern problem where PostgreSQL is suitable for structured queries and indexing whereas MinIO offer high throughput and cost efficiency for actual log storage.

4. Multi-Stage Processing Pipeline

   In my log analysis system, I implemented a multi-stage pipeline which consists of parsing, anomaly detection, and intelligent analysis phases. This allows me to test and integrate different algorithms and models that is the most suitable for the system without disrupting the entire workflow.

3.2.2 High-Level System Architecture

The system uses a layered, distributed architecture which is designed to support efficient log ingestion and anomaly detection. Each layer is responsible for a distinct functionality ensuring the ease for development and maintenance.

1. Presentation layer

   This layer provides a user-friendly interface between end users and the log analysis system. It is a single-page application (SPA) that built on React framework, allowing users to upload log files, view processing status and final analyzed results. The system also develop authentication through JWT-based mechanism and role-based accesses for better security.

2. API Gateway Layer

   The API gateway layer is responsible for create a communication between the frontend and backend. This layer expose REST API endpoints which will handle request routing, input validation and give back the responses by using FastAPI technologies.

3. Service Layer

   The service layer hold the core business logic of the system. These services include authentication, handling log files, and managing model detection logic. and LLMs analysis. By separating functions into discreate services, the architecture allows each service to work independently and easy to change as you wish.

4. Data Processing Layer

   Data processing is one of the most important steps in the entire workflow, so this layer is built very carefully. Raw log messages are parsed into structured one and extract event templates using Drain algorithm. Then using the structured logs to ingest to machine learning models and save as serialized file for real-time inference. Anomalies is then analyzed by LLMs to generate explanations about how it mark as anomaly and mitigation suggestions.

5. Storage Layer

   The storage layer is designed to handle how log data will be stored and accessed effectively. MinIO is used to store actual raw log files that users upload to the server. I utilized this technology because its object storage allows storing and access large volume of data with high speed and low cost. Whereas PostgreSQL is chosen to manage structured metadata due to its ability to create complex structured queries. An in-memory cache (Redis) is also employed in this system to support fast access to data such as task queues.

6. Task Management Layer

   To support asynchronous processing as I mentioned in section 3.2.1, the system also create a layer for task management. Each step such as parsing, anomaly detection, and LLM inference will be define as tasks and put to message queues. Celery workers will take tasks from queue and execute in the background, thereby parallel execution is made possible.

3.3 Dataset preparation

The HDFS log data set is the most frequently used data set for anomaly detection methods and thus also the main focus point of this study. The logs were collected from the Hadoop Distributed File System (HDFS), which runs on the Amazon EC2 platform. This system is designed to run on commodity hardware and allows users to store and process large files. Each log event have one or more block identifiers which will enable grouping logs into sequence of events. And in fact, the sample logs snippet show in

Figure 2.1 are taken from HDFS data set. The core idea behind the anomaly detection in this dataset is that some data blocks is fail to be processed by the system. When such failures happen, the blocks generate log events that differ from normal processing behavior. Therefore, the entire sequence should be detected as anomalous [16].

The data was originally collected by Xu et al. from a production hadoop cluster comprising more than 200 nodes. The dataset was labeled by domain experts to distinguish normal and anomalous execution flows. In this study the HDFS dataset version is taken from project Loghub [17]. The total lines of log messages in this dataset version is 11,175,629 but a close inspection of the dataset shows that approximately 22,000 lines are missing in comparison to the original data set for unknown reasons. However, the remaining data still provides a sufficient sample for anomaly detection analysis and techniques evaluation.

3.4 Log Parsing Methodology

3.5 Feature Extraction / Representation

3.6 Anomaly Detection Models

3.7 LLM Integration Method

CHAPTER 4: IMPLEMETATIONS

4.1 Implementation Overview

This chapter will present the implementation of the proposed log anomaly detection application. Each components that are described in chapter 3 will be transformed to real functional code and integrate in to the system. The scope of this chapter is focus on implementaion details including configuration, library used, API designs and technologies that are used to build end-to-end system.

4.2 Implementation timeline

The system implementaion is followed a structured timeline that consists of several phases and each phase will focus on a specific tasks and will be described as follow:

- *Phase 1 (Week 1)*

  This initial phase focused on prepare and research background knownledge for the project. Some major activities are:

  - Creating a literature review about log parsing, anomaly detection techniques, and LLMs for log analysis.
  - Understanding about HDFS datatset, how it was generated, and its structure.
  - Defining sytem requirements and architecture.

- *Phase 2 (Week 2): Data Preparation*

  In this phase, raw actual log will be collected, and prepared for use in subsequent steps.

  - Downloading raw HDFS dataset from LogHub repository and validating data.
  - Using a small sample in the data set to understand the event structure.
  - Set up a directories just for data storage purposes.

- *Phase 3 (Week 3-5): Backend Infrastructure Setup*

  The fundamental backend environment was set up carefully for later implementation:

  - Setting up the FastAPI project structure, base routers, and middleware.
  - Configuring PostgreSQL database, Redis, and MinIO containers using Docker.
  - Designing database schema.

- *Phase 4 (Week 6-7): Log Parsing module development*

  This phase mainly focused on implementing a wrapper for Drain parser in order to integrate into the system, which includes some major steps:

  - Developing a Python script to wrap the original Drain algorithm.
  - Creating Celery tasks for asynchronous parsing.
  - Designing storage solution for parsed logs (MinIO + PostgreSQL)

- *Phase 5 (Week 8-9): Log Parsing module development*

  Some popular ML anomaly detection models were utilized and evaluated in this phase:

  - Extracting event count vectors and features.
  - Training and validating models using parsed event sequences.
  - Storing trained models for reusing in the processing pipeline.

- *Phase 6 (Week 10-11): LLM Integration*

  This phase focused on implementing LLM for more understanding of anomalies:

  - Developing the LLM service module for interacting with the model API.
  - Structuring a prompt templates for explanation, and mitigation suggestions.
  - Integrating into the pipeline as the final stage.

- *Phase 7 (Week 12-13): Frontend Development*

  A functional web interface is contructed and delivered in this phase using React technology:

  - Developing the LLM service module for interacting with the model API.
  - Structuring a prompt templates for explanation, and mitigation suggestions.
  - Integrating into the pipeline as the final stage.

- *Phase 8 (Week 14): Testing, Optimization, and Debugging*

  This phase performs several tests and optimization to ensure product stability:

  - Optimizing database queries and model loading.
  - Refining UI responsiveness and user experience flow.
  - Running test with a full datasets to ensure all stages work smoothly.

- *Phase 9 (Week 15-16): Documentation and Thesis writing*

  The final phase will consolidate all the work and prepare the system for thesis writing:

  - Documenting code structure, APIs, preprocessing steps, and models.
  - Preparing visualizations, diagrams, and comparison tables.
  - Create overall structure for thesis and complete the final work.

4.3 Backend Implementation

The backend of the log analysis system was developed using FastAPI due to its ease of use and high performance. The implementation follows the layered architechture that introduced in Chapter 3 and therefore separate the entire system into modular routers and components in order to maintain and scale more easily.

4.3.1 FastAPI Application Architecture

a. Application Initialization

   The main application entry point is defined in ‘src/main.py‘, where all routers and middlewares are registered. The main application is also responsible for initializing CORS middleware and create all database tables that defined in SQLAlchemy models whenever the application start. This setup system features like Auth, Jobs Logs, to be managed by it own route files.

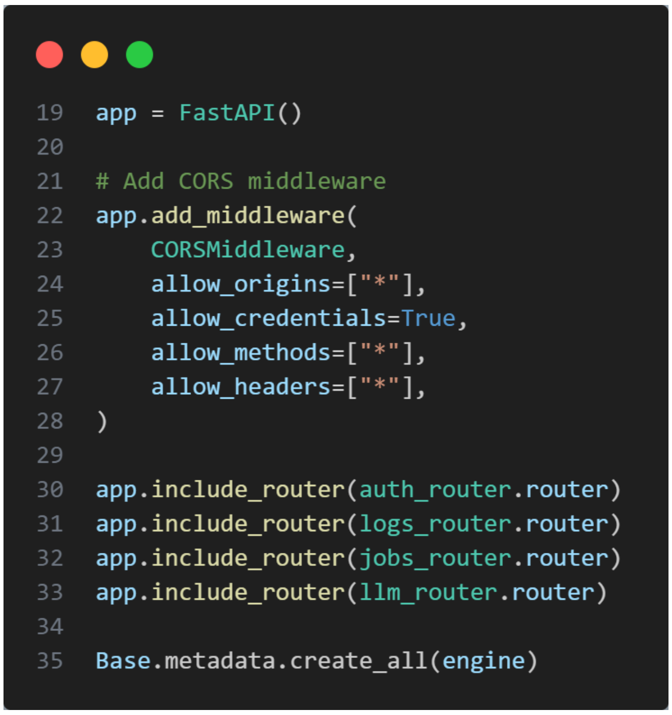

```python
app = FastAPI()

# Add CORS middleware
app.add_middleware(
    CORSMiddleware,
    allow_origins=["*"],
    allow_credentials=True,
    allow_methods=["*"],
    allow_headers=["*"],
)

app.include_router(auth_router.router)
app.include_router(logs_router.router)
app.include_router(jobs_router.router)
app.include_router(llm_router.router)

Base.metadata.create_all(engine)
```

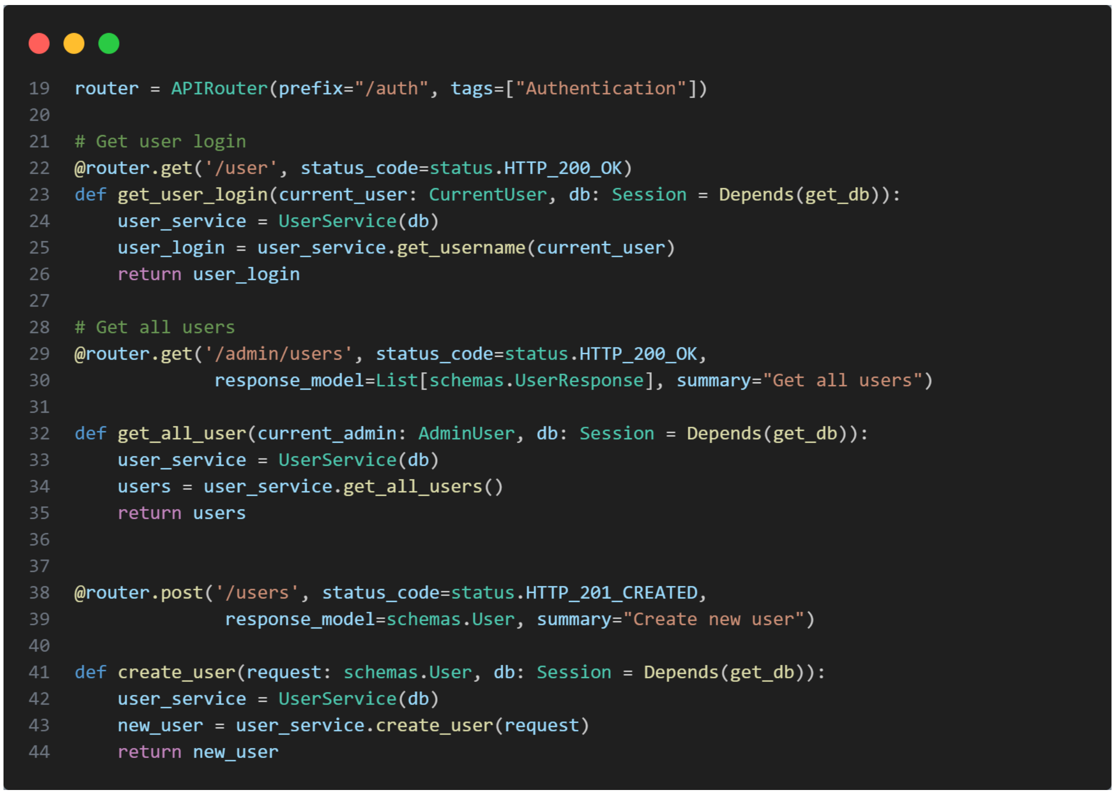
Figure 4.1: main.py file

b. Router Organization

Router	**Responsibilities**
auth_router	Login, registration, token generation
log_router	File upload, metadata retrieval
job_router	Job creation, status queries, result retrieval
ml_router	Model inference endpoints
llm_router	Explanation and mitigation generation

Table 4.1: Router Responsibilities

Each domain in the system is seperated to different router to maintain the ability to scale, be readable when number of features and endpoint grows. The table 4.1 gives information about the total router that are implemented in the systems and their responsibilities. Routers itself will only communicate with service layers to mainin a well and clear application architecture.



```python
router = APIRouter(prefix="/auth", tags=["Authentication"])

# Get user login
@router.get('/user', status_code=status.HTTP_200_OK)
def get_user_login(current_user: CurrentUser, db: Session = Depends(get_db)):
    user_service = UserService(db)
    user_login = user_service.get_username(current_user)
    return user_login

# Get all users
@router.get('/admin/users', status_code=status.HTTP_200_OK,
             response_model=List[schemas.UserResponse], summary="Get all users")

def get_all_user(current_admin: AdminUser, db: Session = Depends(get_db)):
    user_service = UserService(db)
    users = user_service.get_all_users()
    return users


@router.post('/users', status_code=status.HTTP_201_CREATED,
              response_model=schemas.User, summary="Create new user")

def create_user(request: schemas.User, db: Session = Depends(get_db)):
    user_service = UserService(db)
    new_user = user_service.create_user(request)
    return new_user
```

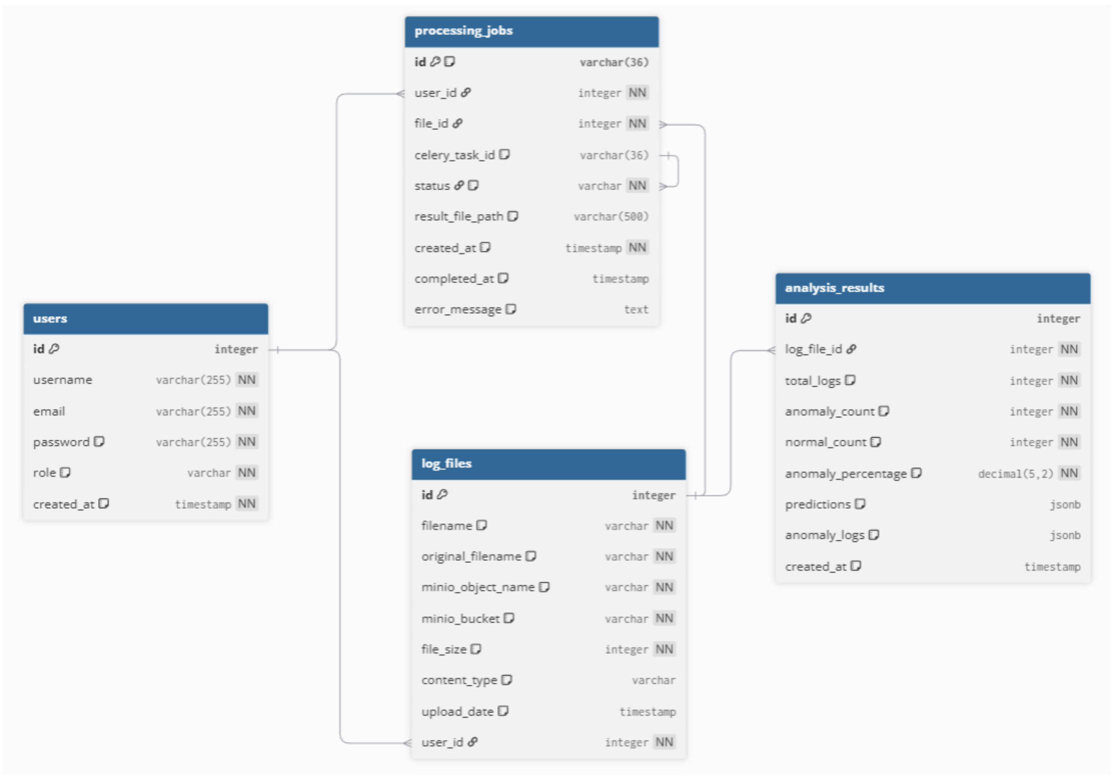
Figure 4.2: Example of a router configuration pattern

Figure 4.2 captures a code snippet that represent a pattern used for implementing router configuration. Each router will contain several endpoints that directly relatect to that functional service layer. For example, the authentication router includes enpoints for user creation, get login users or send access tokens. This approach allows developers to organize the application better and avoid as much as confusion in source code.

4.3.2 Database Layer Implementation

fSupport Vector Machine (SVM) The database layer was built based on PostgreSQL database with SQLAlchemy ORM which allows developers to interact with relational databases using Python classes and objects instead of using raw SQL queries. All entities in the system such as users, logs, jobs and analysis are represented as ORM models ann then mapped to relational database tables.

a. Database schema



processing_jobs		
id	varchar(36)	
user_id	integer	NN
file_id	integer	NN
celery_task_id	varchar(36)	
status	varchar	NN
result_file_path	varchar(500)	
created_at	timestamp	NN
completed_at	timestamp	
error_message	text	

users		
id	integer	
username	varchar(255)	NN
email	varchar(255)	NN
password	varchar(255)	NN
role	varchar	NN
created_at	timestamp	NN

log_files		
id	integer	
filename	varchar	NN
original_filename	varchar	NN
minio_object_name	varchar	NN
minio_bucket	varchar	NN
file_size	integer	NN
content_type	varchar	
upload_date	timestamp	
user_id	integer	NN

analysis_results		
id	integer	
log_file_id	integer	NN
total_logs	integer	NN
anomaly_count	integer	NN
normal_count	integer	NN
anomaly_percentage	decimal(5,2)	NN
predictions	jsonb	
anomaly_logs	jsonb	
created_at	timestamp	

Figure 4.3: System database schema

Figure 4.3 depicts 4 core tables in the anomaly detection system, including `users`, `log_files`, `processing_jobs` and `analysis_results`. Each table serves a distinct pupose and are described as follow:

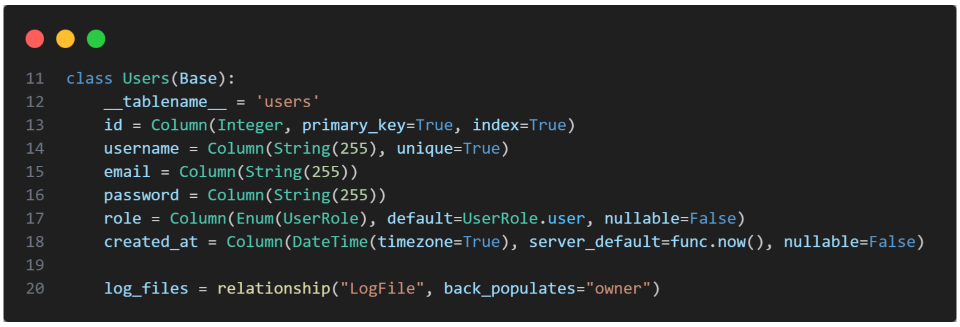
- Table users: This table will manage users information such as user name, password, email adress and their role in the system.

- Table log_files: This table stores metadata of a log file that uploaded by users, and there will be a link to its actual storage location in MinIO.

- Table processing_jobs: This table is primarily used for storing jobs information that create by the system to track the Celery background tasks.
- Table analysis_results: ML anomaly detection results for eacg analyzed log filed are stored in this table with some information such as number of sequences, anomaly and normal sequences count

The database schema also implement logical relationships between entities. Each user can upload multiple log files and create multiple processing jobs. The log file entity is a central reference point to connect both processing jobs and analysis results. This implement means each log file can be associated with multiple processing jobs, which happen when reprocessing is required due to any failures in the pipeline. In addition, each log file can also link to multiple analysis results to support the LLM integration stage.

b. Model implementation



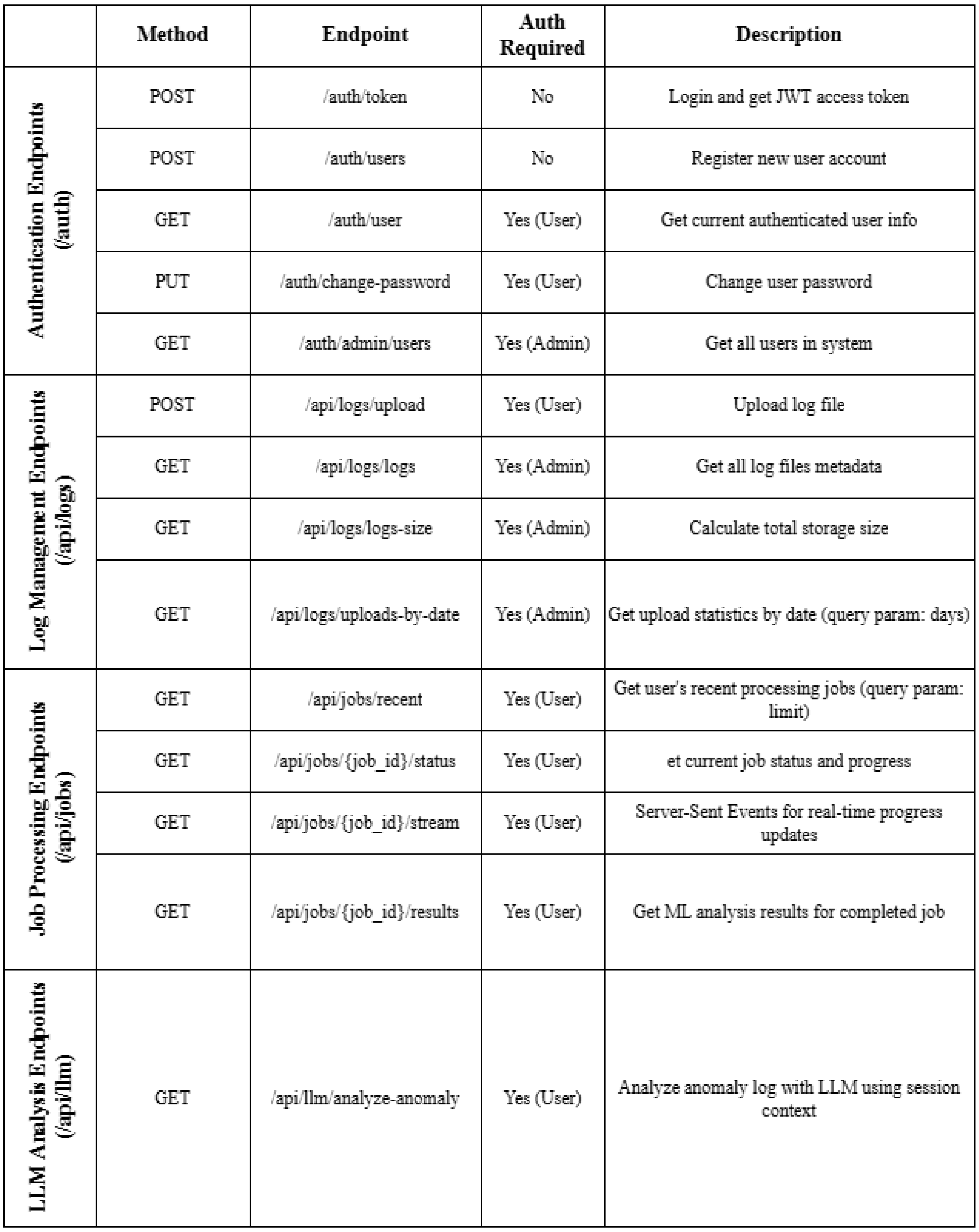
```python
class Users(Base):
    __tablename__ = 'users'
    id = Column(Integer, primary_key=True, index=True)
    username = Column(String(255), unique=True)
    email = Column(String(255))
    password = Column(String(255))
    role = Column(Enum(UserRole), default=UserRole.user, nullable=False)
    created_at = Column(DateTime(timezone=True), server_default=func.now(), nullable=False)

    log_files = relationship("LogFile", back_populates="owner")
```

Figure 4.4: System database schema

In this project SQLAlchemy ORM (Object Relational Mapping) is used to create a clean abstraction over a complex relational database. There are will be four model configuration file for four entities coordinatly. Each file is defined how information of a enity is store and connected within our database. Figure 4.4 shows how a model (Users model) is initialize in the project. The Users entity stores authentication information with server key attributes such as id which is identified for each user, username and password to log into the system. This file also so handle relationship with other entities, in this case, Users model have a one-to-many relationship with the LogFile entity. Each user can upload multiple log files, and each log file link to its owner via a foreign key.

4.3.3 API Endpoints Implementation

Figure 4.2 described all the endpoints that are exposed by the backend of the system that cover authentication, log management, job processing, and LLM results generation. Each endpoint is responsible for a specific functions in the entire processing pipeline.



	Method	Endpoint	Auth Required	Description
Authentication Endpoints (/auth)	POST	/auth/token	No	Login and get JWT access token
	POST	/auth/users	No	Register new user account
	GET	/auth/user	Yes (User)	Get current authenticated user info
	PUT	/auth/change-password	Yes (User)	Change user password
	GET	/auth/admin/users	Yes (Admin)	Get all users in system
Log Management Endpoints (/api/logs)	POST	/api/logs/upload	Yes (User)	Upload log file
	GET	/api/logs/logs	Yes (Admin)	Get all log files metadata
	GET	/api/logs/logs-size	Yes (Admin)	Calculate total storage size
	GET	/api/logs/uploads-by-date	Yes (Admin)	Get upload statistics by date (query param: days)
Job Processing Endpoints (/api/jobs)	GET	/api/jobs/recent	Yes (User)	Get user's recent processing jobs (query param: limit)
	GET	/api/jobs/{job_id}/status	Yes (User)	et current job status and progress
	GET	/api/jobs/{job_id}/stream	Yes (User)	Server-Sent Events for real-time progress updates
	GET	/api/jobs/{job_id}/results	Yes (User)	Get ML analysis results for completed job
LLM Analysis Endpoints (/api/llm)	GET	/api/llm/analyze-anomaly	Yes (User)	Analyze anomaly log with LLM using session context

Table 4.2: API endpoints

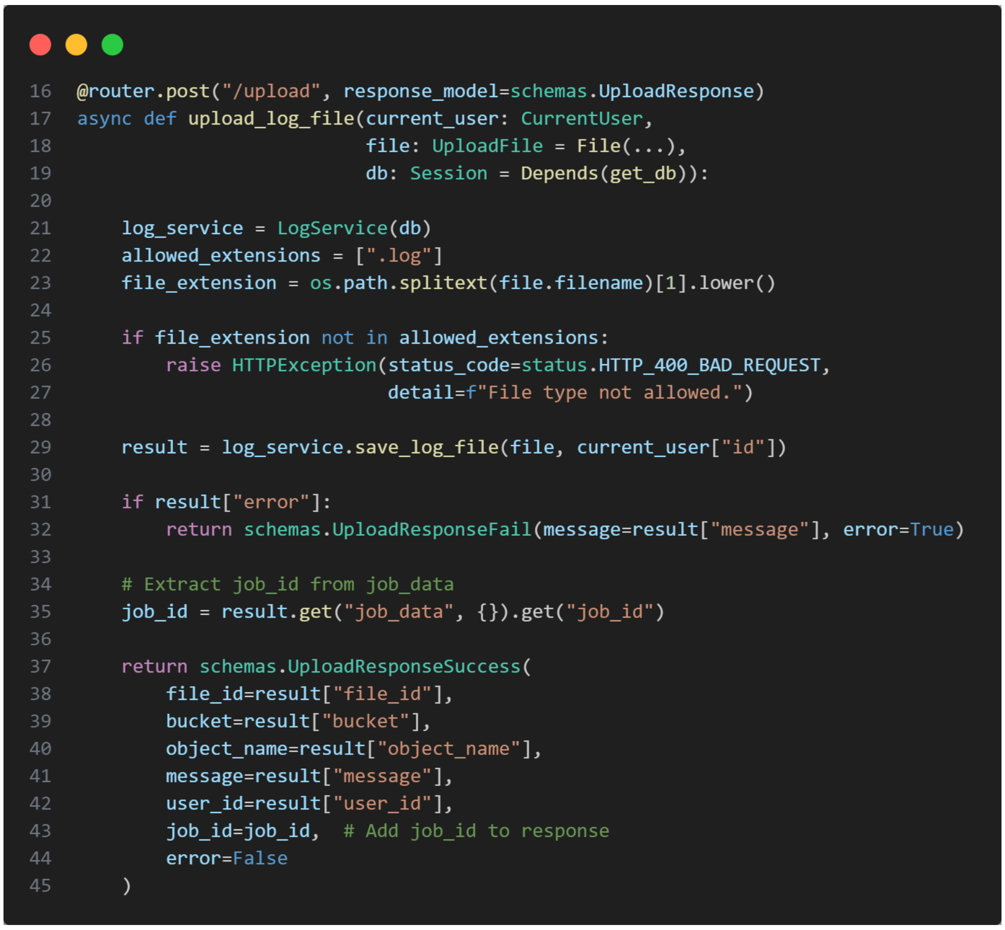
Endpoints implementation detail:

This section will provide detail of technical implementation of some important API endpoints.

1. POST `/api/logs/upload`

   This is the core enpoint that handles the file upload process in the system workflow. It exposes a interface for users to upload their log file, store them in object storage system, register a record in the datase and finally trigger an asynchronous prossing jobs for further analysis.

   The endpoint is implemented as HTTP POST route under path /api/logs/upload. It is defined using FastAPI's router and use asynchronous mechanism to handle request in order to ensure non-blocking I/O operations. When the backend receive a request from this endpoint, it first initialize a `LogService` instance which is a service layer that hold the business logic. The uploaded file is then validated for allowed extension. If the file extension does not match the `.log` extension, the method will immediately return HTTPException with status code 400 which is indicated a bad request error. The endpoint is continue to operate `LogService.save_log_file()` method which is responsible for uploading valid log files to MinIO and save its metadata to the database. Finally, the method return a structured results of several information.

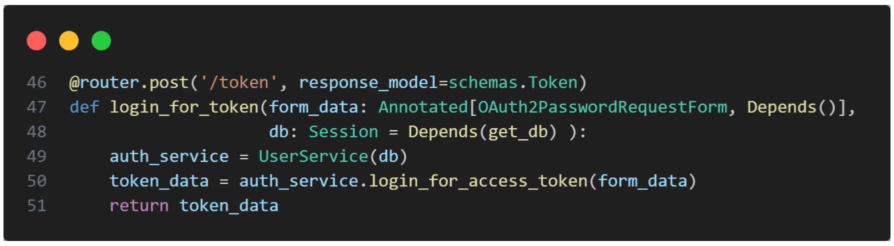


```python
@router.post("/upload", response_model=schemas.UploadResponse)
async def upload_log_file(current_user: CurrentUser,
                          file: UploadFile = File(...),
                          db: Session = Depends(get_db)):

    log_service = LogService(db)
    allowed_extensions = [".log"]
    file_extension = os.path.splitext(file.filename)[1].lower()

    if file_extension not in allowed_extensions:
        raise HTTPException(status_code=status.HTTP_400_BAD_REQUEST,
                            detail=f"File type not allowed.")

    result = log_service.save_log_file(file, current_user["id"])

    if result["error"]:
        return schemas.UploadResponseFail(message=result["message"], error=True)

    # Extract job_id from job_data
    job_id = result.get("job_data", {}).get("job_id")

    return schemas.UploadResponseSuccess(
        file_id=result["file_id"],
        bucket=result["bucket"],
        object_name=result["object_name"],
        message=result["message"],
        user_id=result["user_id"],
        job_id=job_id,  # Add job_id to response
        error=False
    )
```

Figure 4.5: Logs upload endpoints

2. GET `/api/auth/token`

   This endpoint is responsible for handling JSON Web Tokens (JWTs) to verify user within the system. Once the backend receive request, `UserService` will perform user finding, password verification and generate token. When the authentication is successfully done, the service will create JWT which contains user's information and attach it to request header when accessing protected resources.



```python
@router.post('/token', response_model=schemas.Token)
def login_for_token(form_data: Annotated[OAuth2PasswordRequestForm, Depends()],
                    db: Session = Depends(get_db) ):
    auth_service = UserService(db)
    token_data = auth_service.login_for_access_token(form_data)
    return token_data
```

Figure 4.6: Token endpoints

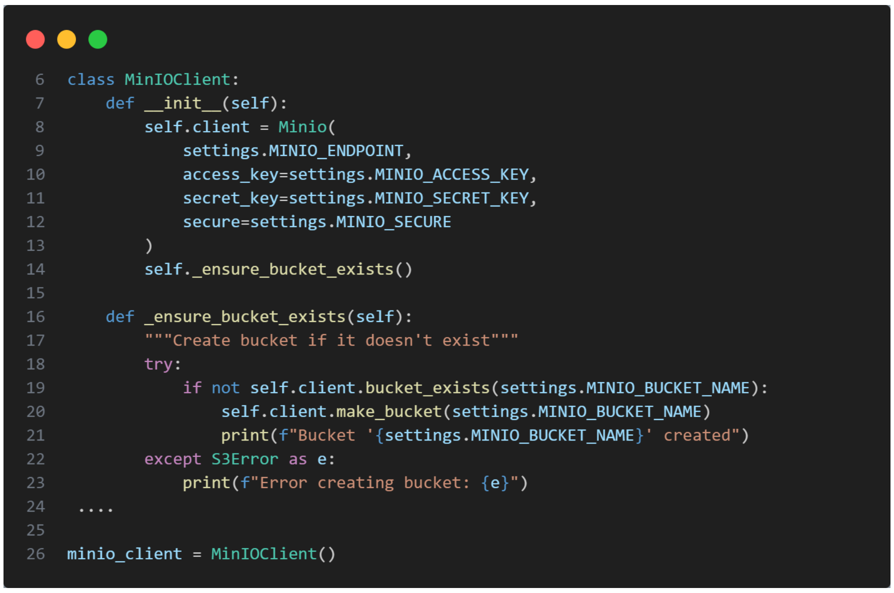
4.4 Log Processing Pipeline

This section provides detail implementations of multi-stage log processing pipeline within the system. This pipeline is responsiple for transform raw logs into structured data and perform anomaly detection with machine learning algorithm.

4.4.1 File Upload and Storage

a. MinIO Client Integration

MinIO was selected as the object storage solution in this project to store raw log data due to its high performance and suitable for containerized deployments. The system implements a Python MinIOClient wrapper class that abstracts from the MinIO Python SDK.



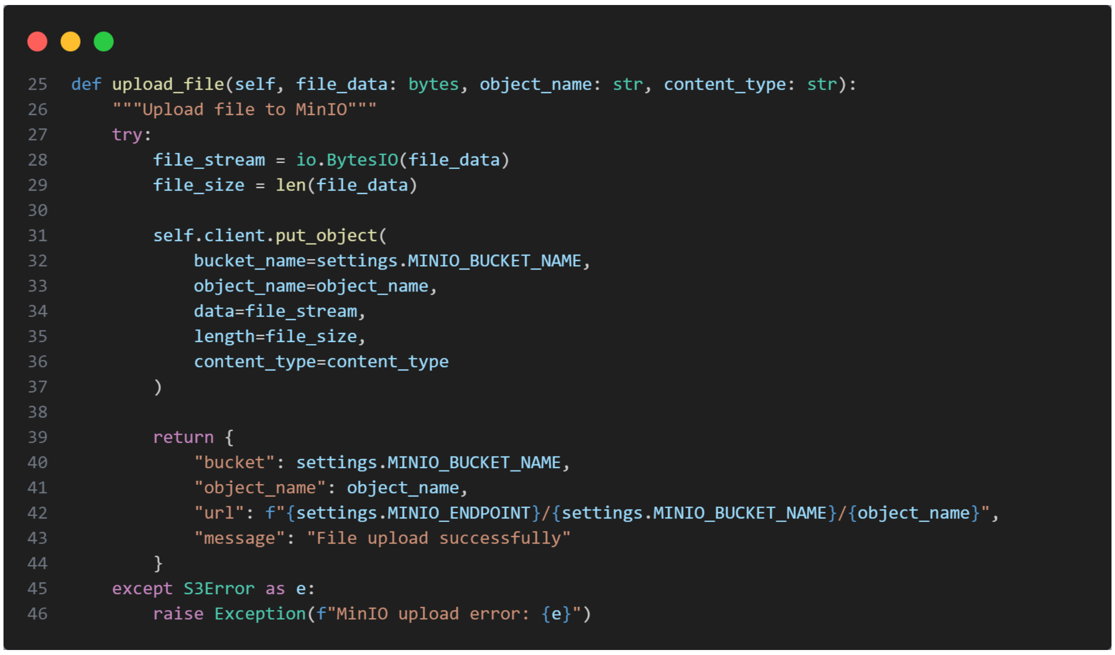
```python
class MinIOClient:
    def __init__(self):
        self.client = Minio(
            settings.MINIO_ENDPOINT,
            access_key=settings.MINIO_ACCESS_KEY,
            secret_key=settings.MINIO_SECRET_KEY,
            secure=settings.MINIO_SECURE
        )
        self._ensure_bucket_exists()

    def _ensure_bucket_exists(self):
        """Create bucket if it doesn't exist"""
        try:
            if not self.client.bucket_exists(settings.MINIO_BUCKET_NAME):
                self.client.make_bucket(settings.MINIO_BUCKET_NAME)
                print(f"Bucket '{settings.MINIO_BUCKET_NAME}' created")
        except S3Error as e:
            print(f"Error creating bucket: {e}")
 ....

minio_client = MinIOClient()
```

Figure 4.7: minio_client.py file

When initializing this class, the client create a connection using predefined access credentials and also vericate bucket with `_ensure_bucket_exists()` method. This ensure the target bucket exist and automatically create it if necessary. The application also implement singleton pattern for MinIO client, where only one instance of `MinIOClient` is created and shared across the entire backend. This design allows system to maintain consistent connection with MinIO that helps uploading and storing operations faster.

b. File Upload Implementation

File upload mechanism is implemented inside `upload_file()` method. The method first wrap log file data in `io.BytesIO` to transform data to file-like interface to that required by MinIO SDK. The the method perform an upload to existing MinIO bucket and a return a response with useful information when the upload is done.

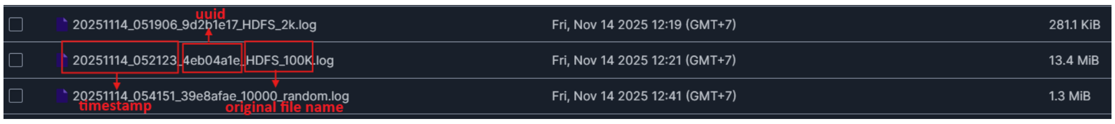


```python
def upload_file(self, file_data: bytes, object_name: str, content_type: str):
    """Upload file to MinIO"""
    try:
        file_stream = io.BytesIO(file_data)
        file_size = len(file_data)

        self.client.put_object(
            bucket_name=settings.MINIO_BUCKET_NAME,
            object_name=object_name,
            data=file_stream,
            length=file_size,
            content_type=content_type
        )

        return {
            "bucket": settings.MINIO_BUCKET_NAME,
            "object_name": object_name,
            "url": f"{settings.MINIO_ENDPOINT}/{settings.MINIO_BUCKET_NAME}/{object_name}",
            "message": "File upload successfully"
        }
    except S3Error as e:
        raise Exception(f"MinIO upload error: {e}")
```

Figure 4.8: File upload method

c. Unique Filename Generation

To ensure files that uploaded to MinIO have the unique object name, the system develop a mechanism to create unique name for each object by combining timestamp, random characters and its original filename. As a result, each log file save to MinIO bucket will have result path as logs/user_id/timestamp_uuid_filename.log. This strategy ensure the object name colision probability is extreme low and therefore reduce the error rate within the system. In addition, objects is store in separate user-scope directories which support better audition and efficient lookup.



```
20251114_051906_9d2b1e17_HDFS_2k.log          Fri, Nov 14 2025 12:19 (GMT+7)    281.1 KiB
20251114_052123_4eb04a1e_HDFS_100K.log        Fri, Nov 14 2025 12:21 (GMT+7)    13.4 MiB
20251114_054151_39e8afae_10000_random.log     Fri, Nov 14 2025 12:41 (GMT+7)    1.3 MiB
```

Figure 4.9: Objects stored in MinIO

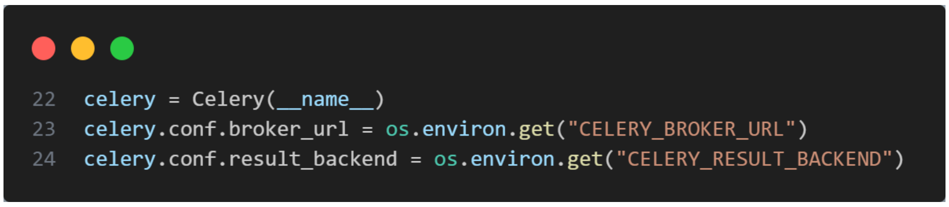
4.4.2 Asynchronous Processing with Celery

a. Introduction to distributed task processing

Distributed task processing has become increasingly imprtant in modern system because this technology allows all tasks are distributed efficiently accross multiple nodes. This approach enhances system scalability, performance, and enable entensive computation can be efficiently execute. Several tools and framework have been proposed to handle distributed task execution such as Apache Hadoop or Apache Spark. However, in this project, Celery is use to handle distributed task processing which is a framework that built on top of the Advanced Message Queuing Protocol (AMQP) paradigm. For the context of log anomaly detection, for example, parsing a 50MB HDFS log file with traditional subsequent methods require 30-100 seconds to finish, this means the entire system have to wait until the process complete. This issue exeed typical HTTP timeou thresholds, therefor degrading user experience and increase the risk of resource exhaustion. With Celery, instead of waiting for the entire processing to finish, the API only submits its task to a queue and immediately returns control to the user. Celery workers then fetch tasks from the message broker, execute them in the background, and update the job status in the database.

b. Celery Implementation and Configuration

This system employs Celery as asynchronous task processing solution and also integrate with Redis as its message broker. This approach is provides a easier and more lightweight solution for task distribution without operational overhead of another message broker is RabbitMQ.



```
celery = Celery(__name__)
celery.conf.broker_url = os.environ.get("CELERY_BROKER_URL")
celery.conf.result_backend = os.environ.get("CELERY_RESULT_BACKEND")
```

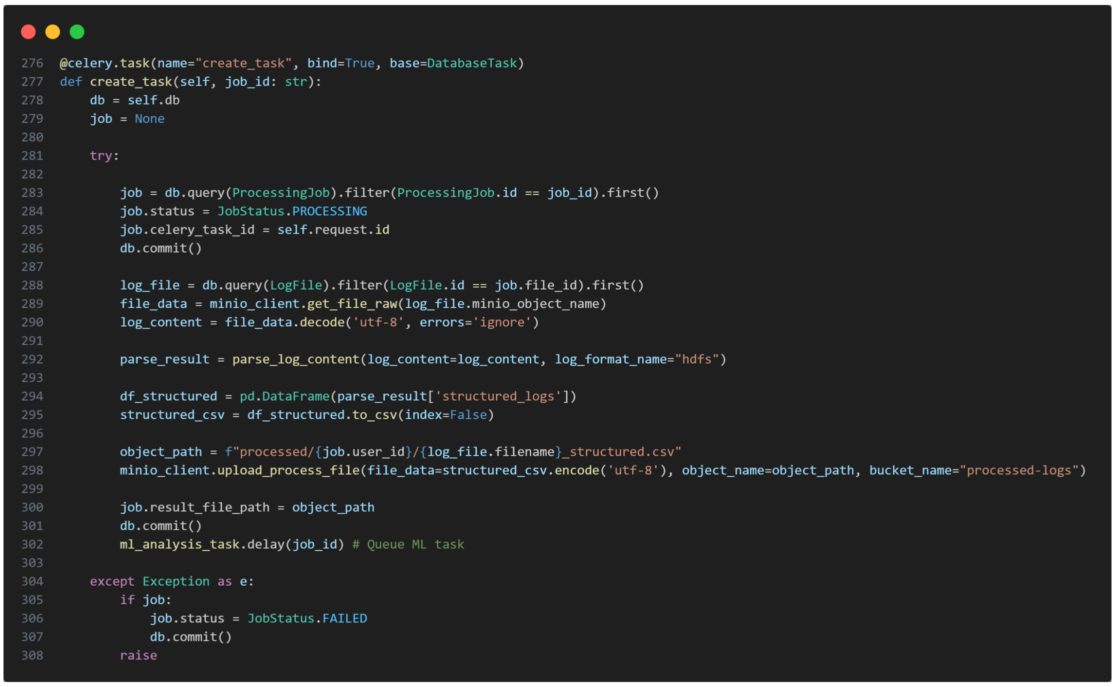
Figure 4.10: Celery application configuration

Figure 4.10 presents a simple configuration to established Celery application and the connection to Redis message broker which is also act as a place to store task results. The architecture follows a standard producer-consumer model: when a use upload a log file through REST API, our FastAPI backend (producer) stores file in MinIO and then publishing a message(task) to Redis queue with an unique ID. Celery workers running in background, continuously poll the queue for pending task. When receiving a task message, a worker executes the processing logic, updates job status in the database, and optionally publishes results back to Redis.

c. Task Implementation

1. Log Processing Task

The system implementes a two-stage processing pipeline through chained Celery task. The first task is `preprocess_task` which is used for log parsing and transform to structured csv file. The detail steps will be described as follow. The Celery worker first retrieve the log file from MinIO object strorage and decode UTF8 centent, then invoke the Drain parser service for template extraction. The parser result is then transform into CSV format to provide human-readable format and serve as a input to machine learning task. The structured CSV is uploaded to other MinIO bucket and save the bucket information to database for retrieving during ML task. Finally, it enqueue the next `ml_analysis_task` to the message queue, this allows the current worker to complete and accept new task while letting other workers to process ML task. All the implements as code is show at Figure 4.11.



```python
@celery.task(name="create_task", bind=True, base=DatabaseTask)
def create_task(self, job_id: str):
    db = self.db
    job = None

    try:

        job = db.query(ProcessingJob).filter(ProcessingJob.id == job_id).first()
        job.status = JobStatus.PROCESSING
        job.celery_task_id = self.request.id
        db.commit()

        log_file = db.query(LogFile).filter(LogFile.id == job.file_id).first()
        file_data = minio_client.get_file_raw(log_file.minio_object_name)
        log_content = file_data.decode('utf-8', errors='ignore')

        parse_result = parse_log_content(log_content=log_content, log_format_name="hdfs")

        df_structured = pd.DataFrame(parse_result['structured_logs'])
        structured_csv = df_structured.to_csv(index=False)

        object_path = f"processed/{job.user_id}/{log_file.filename}_structured.csv"
        minio_client.upload_process_file(file_data=structured_csv.encode('utf-8'), object_name=object_path, bucket_name="processed-logs")

        job.result_file_path = object_path
        db.commit()
        ml_analysis_task.delay(job_id) # Queue ML task

    except Exception as e:
        if job:
            job.status = JobStatus.FAILED
            db.commit()
        raise
```

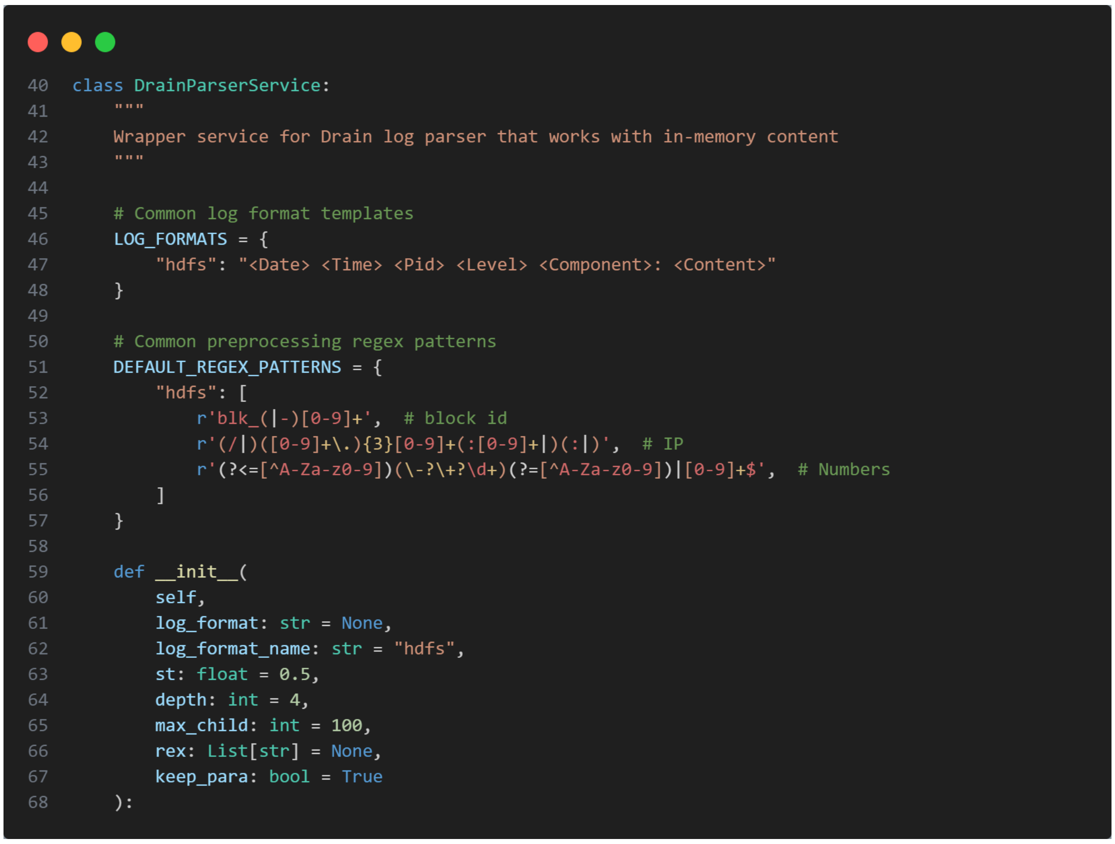
Figure 4.11: Log process task implementation

2. Machine Learning Analysis Task

   This task is responsible for the second stage of the task chain, where it consume CSV input, perform machine learning detection and present output. At the beginning of the task, worker retreive structured log CSV file from MinIO, the pre-trained model is then invoked for prediction. After the prediction successfully done, all the important information such as total logs, anomaly count, and prediction log sequences are stored in to database. Only after the analysis task complete, the entire job will be marked as COMPLETE.

4.4.3 Drain Parser Integration

The system encapsulates the Drain parser algorithm that introduced in previous chapter within a custom python class. The approach wrap the entire original complex Drain algorithm into a clean interface for system to interact with. At the beginning the wrapper defines a format presets for common log types. In the current implementation, the HDFS log format is defined using a fixed template that explicitly separates timestamps, process identifiers, log levels, components, and message content. This structured definition ensures consistent field extraction and reduces ambiguity during parsing. When user invoke the the parser service with a specific log format, these optimized settings wil be applied automatically. In Figure 4.12, the implementation will provide a contructor for `DrainParserService` with several parameters such as similarity threshold (st), parse tree depth (depth), and maximum children per node (max_child). These parameters allow control over parsing behavior which will enable user to customize as they wish. Overall, this approach provides an easy solution and reuseable interface for system to integrate complex algorithm in anywhere.



```python
class DrainParserService:
    """
    Wrapper service for Drain log parser that works with in-memory content
    """

    # Common log format templates
    LOG_FORMATS = {
        "hdfs": "<Date> <Time> <Pid> <Level> <Component>: <Content>"
    }

    # Common preprocessing regex patterns
    DEFAULT_REGEX_PATTERNS = {
        "hdfs": [
            r'blk_(|-)[0-9]+',  # block id
            r'(/|)([0-9]+\.){3}[0-9]+(:[0-9]+|)(:|)',  # IP
            r'(?<=[^A-Za-z0-9])(\-?\+?\d+)(?=[^A-Za-z0-9])|[0-9]+$',  # Numbers
        ]
    }

    def __init__(
        self,
        log_format: str = None,
        log_format_name: str = "hdfs",
        st: float = 0.5,
        depth: int = 4,
        max_child: int = 100,
        rex: List[str] = None,
        keep_para: bool = True
    ):
```

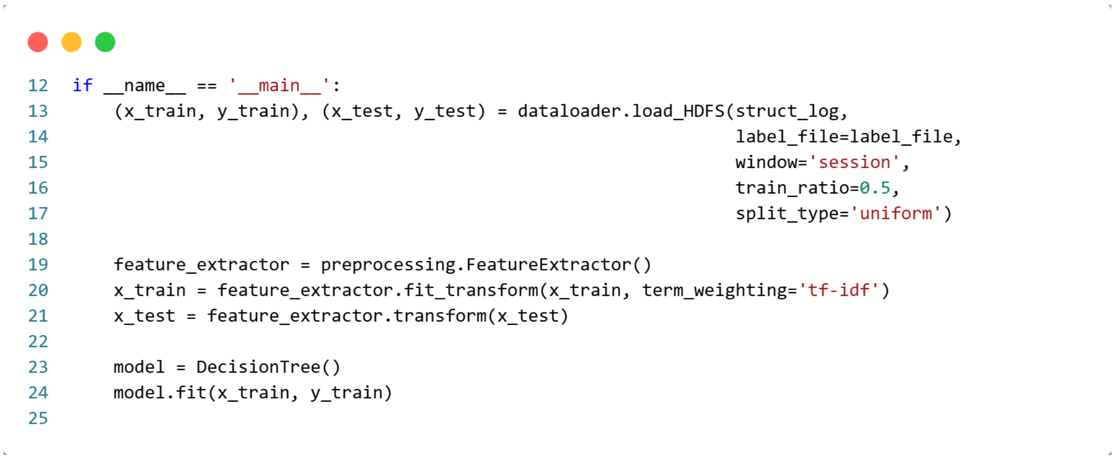
Figure 4.12: Drain algorithm wrapper implementation

4.4.4 Feature Extraction

The next step in the data preprocessing pipeline is feature extraction which transform Drain-parsed data in to numerical feature vectors. This sections presents the implementation of integrating loglizer library's `FeatureExtractor` class to convert event sequences into fixed-dimensional count matrices suitable for machine learning classification. In the proposed system, feature extraction is applied at two distinct phases: (1) During trainning phase, where model learned and serialized for reuse, (2) during online inference, where the same transformation logic is applied to user lof data.

a. Training Phase

Firgure shows the configuration for feature extraction during the offline trainning process. Parse log is first loaded using session-based windowing strategy. This strategy group structured log events by session identifiers and will mark anomalt label at sequence level not entry level. Once the sequences are prepared, `FeatureExtractor` class is invoked to convert event sequences into numerical feature vectors that required by machine learning algorithms. This transform is based of event frequency statistics, which mean that whe count the occurence the number of single log event to form the event count vector. Finally every count vector are formed an event count metrix X, where entry $X_{i,j}$ presents many times the event j occurred in the i-th log sequence [4].



```python
if __name__ == '__main__':
    (x_train, y_train), (x_test, y_test) = dataloader.load_HDFS(struct_log,
                                                                label_file=label_file,
                                                                window='session',
                                                                train_ratio=0.5,
                                                                split_type='uniform')

    feature_extractor = preprocessing.FeatureExtractor()
    x_train = feature_extractor.fit_transform(x_train, term_weighting='tf-idf')
    x_test = feature_extractor.transform(x_test)

    model = DecisionTree()
    model.fit(x_train, y_train)

```

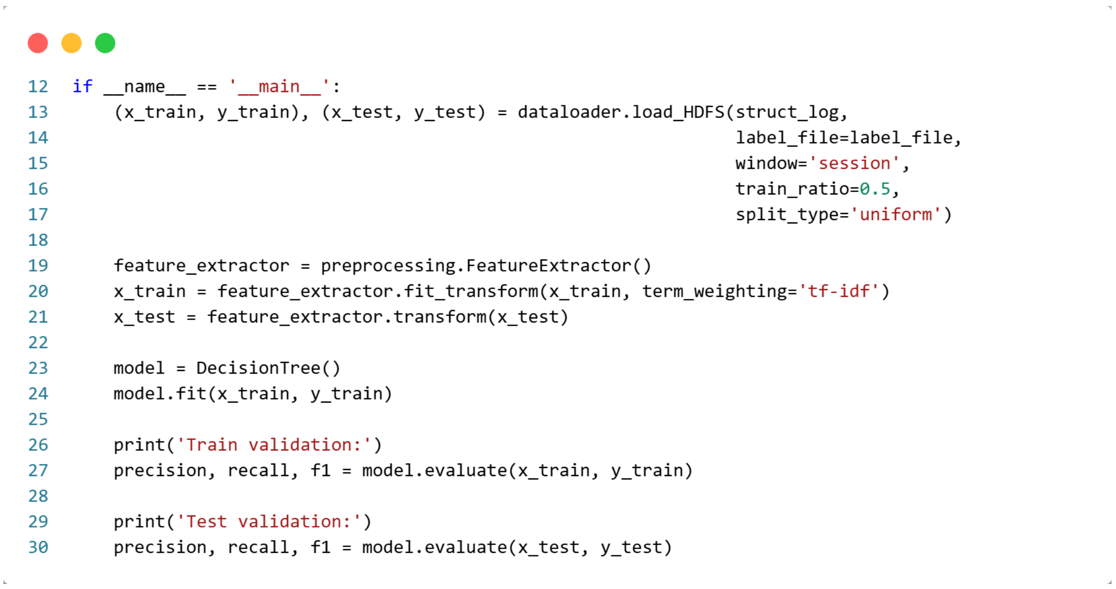
Figure 4.13: Feature extraction implementation

b. Inference Phase

In the inference phase, feature extraction is executed inside Celery background task. Parsed log sequences generate from new logs are transform using pretrained feature extractor. This ensures that the same event vocabulary and weighting scheme learned during training are are consistently applied. This approach helps system avoids feature drift and maintains reliable outcomes.

4.4.5 Machine Learning Implementation for Anomaly Detection

This section will evaluate multiple machine learning models for logs anomaly detection to find the suitable approach that have the most suitable in term of performance and system efficiency for the project. After log parsing and event sequences construction, Several machine learning models were trained and evaluated on the same dataset to ensure fair comparison. The base code for machine learning algorithms were provided by Loglizer project [4] as mentioned erlier in this study. Each algorithm is training with default parameters to establish baseline performance before hyperparameter optimization. The training pattern followed a consistent flow across all models as showing in Figure 4.14.



```python
if __name__ == '__main__':
    (x_train, y_train), (x_test, y_test) = dataloader.load_HDFS(struct_log,
                                                                label_file=label_file,
                                                                window='session',
                                                                train_ratio=0.5,
                                                                split_type='uniform')

    feature_extractor = preprocessing.FeatureExtractor()
    x_train = feature_extractor.fit_transform(x_train, term_weighting='tf-idf')
    x_test = feature_extractor.transform(x_test)

    model = DecisionTree()
    model.fit(x_train, y_train)

    print('Train validation:')
    precision, recall, f1 = model.evaluate(x_train, y_train)

    print('Test validation:')
    precision, recall, f1 = model.evaluate(x_test, y_test)
```

Figure 4.14: Standard training workflow

Finally, anomaly detection results are stored in the database for further analysis and retrieval.

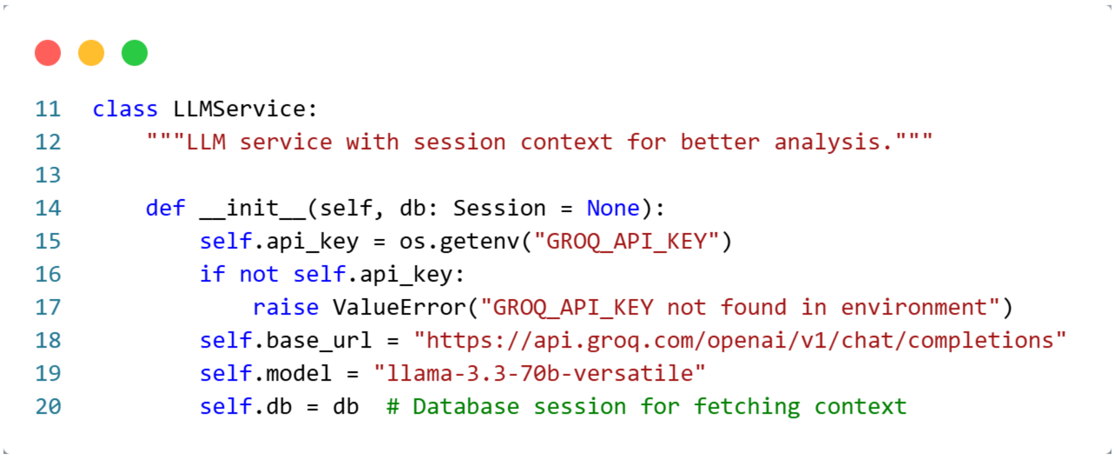
4.5 LLM Integration

Instead of stopping at machine learning detection phase of some previous study, my system extends the ability to detect anomaly with Large Language Model (LLM). This approach will provide human-readable explainations and recommendations for marked anomalies.

4.5.1 API client setup and Context preparation

1. API client setup

   In this study, Groq's cloud-based inference platform is used to provides free hosting Meta's LLaMA 3.3 model. This approach will avoid the computation overhead and the complexity of the system. Figure 4.15 create a API connection through HTTP client. The service configuration includes 3 keys components: (1) API key that used to connect with Groq service, (2) Groq API endpoint URL which specifically targeting its Chat Completion service, and finally (3) the choice of LLaMA 3.3 model that responsible for generating responses. This model is selected because its strong balance between the capability for reasoning and contextual understanding due to its large parameter size (70 billions).

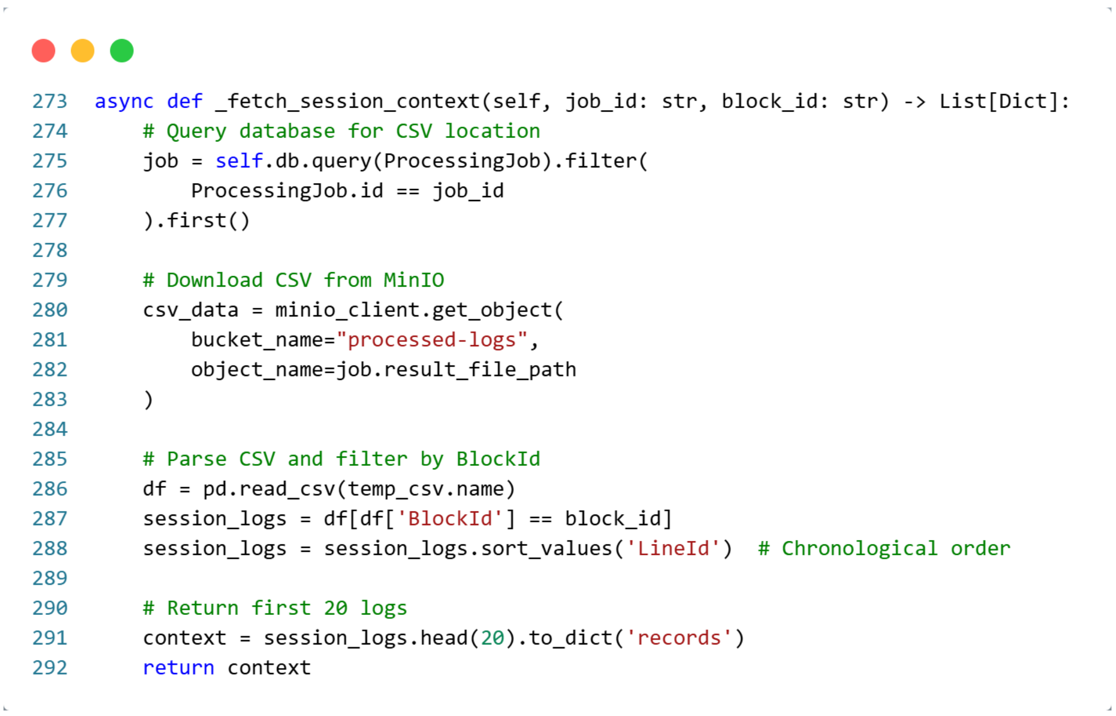


```python
class LLMService:
    """LLM service with session context for better analysis."""

    def __init__(self, db: Session = None):
        self.api_key = os.getenv("GROQ_API_KEY")
        if not self.api_key:
            raise ValueError("GROQ_API_KEY not found in environment")
        self.base_url = "https://api.groq.com/openai/v1/chat/completions"
        self.model = "llama-3.3-70b-versatile"
        self.db = db  # Database session for fetching context
```

Figure 4.15: LLM configurations

2. Context Preparation and Session Retrieval

   To effectively detect anomaly we can not just examin a single log entry, it is depending on the surrounding logs in the same session. To create this context for LLM, I implement the system so that it can retrieve all log entries that sharing the same anomaly's BlockId from the processed CSV file. This process involves four steps which is shown in Firgure 4.16. First, the system queries the database to find the file path of CSV file in MinIO. Next, the CSV is dowloaded from MinIO using chunk approach to prevent unecessary memory usage. The parsed log entries are then filtered to keep the one that match the target BlockId. Finally, the filtered logs are sorted chronologically based on their LineId to ensure the original execution order.



```python
async def _fetch_session_context(self, job_id: str, block_id: str) -> List[Dict]:
    # Query database for CSV location
    job = self.db.query(ProcessingJob).filter(
        ProcessingJob.id == job_id
    ).first()

    # Download CSV from MinIO
    csv_data = minio_client.get_object(
        bucket_name="processed-logs",
        object_name=job.result_file_path
    )

    # Parse CSV and filter by BlockId
    df = pd.read_csv(temp_csv.name)
    session_logs = df[df['BlockId'] == block_id]
    session_logs = session_logs.sort_values('LineId')  # Chronological order

    # Return first 20 logs
    context = session_logs.head(20).to_dict('records')
    return context
```

Figure 4.16: LLM context preparation

4.5.2 Prompt Engineering

Prompt engineers plays an important role on how our Large Language Model understand the context and response. In this system, prompts are designed to guide the model specific for anomaly log reasoning. The system uses two-tier prompting strategy which includes system prompt and user prompt.

1. System Prompt: Role Definition

   The system prompt defines to role and behavior of the LLM before it process tasks. In this project, th prompt instructs the LLM to become a expert in HDFS log analysis and anomaly detection. In addition, the prompt strictly enforce the output format requirment for LLM to JSON format only. This approach is necessary because it will prevent other element like markdown text, emojis, or code blocks that usually be generated by LLMs and keep the response in consistent format for later parsing.

2. User Prompt

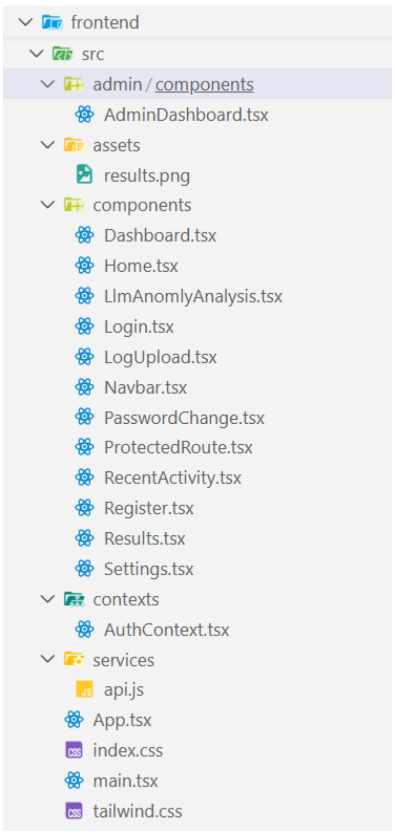
   The user prompt constructs a guide for LLM to analyze the log sequences that are detected as anomaly. Using the context that is prepared, the prompt let the model expore the all the related event to give a more concise explanations and explanations actions.

4.6 Frontend Implementation

This section will describes the implementation of the frontend layer of the system which provides the interface for user to upload log, visualize anomaly and analysis results. The frontend is implemented using React framework which offer the ability to build a responsive and scalable frontend for the system.

4.6.1 React Application Structure

The frontend of the system organizes the components by grouping them by functionality. This aproach improves the scalability and maintainability of the code base. The primary source directory is place under `frontend/src/` and structured as follows.



```
frontend
  src
    admin / components
      AdminDashboard.tsx
    assets
      results.png
    components
      Dashboard.tsx
      Home.tsx
      LlmAnomlyAnalysis.tsx
      Login.tsx
      LogUpload.tsx
      Navbar.tsx
      PasswordChange.tsx
      ProtectedRoute.tsx
      RecentActivity.tsx
      Register.tsx
      Results.tsx
      Settings.tsx
    contexts
      AuthContext.tsx
    services
      api.js
    App.tsx
    index.css
    main.tsx
    tailwind.css
```

Figure 4.17: React frontend structure

Figure 4.17 shows the frontend structure of the system which provides clear seperation between components to make it easy to develop and maintain. For instance, authentication-related components such as Login.tsx, Register.tsx, AuthContext.tsx are seperated from analysis components like LogUpload.tsx or Results.tsx. In addition, the frontend is developed using TypeScript XML (.tsx) in stead of JavaScript XML (.jsx) which provides a better static type checking and support with better with error detection.

4.6.2 Key Components Implementation

a. Authentication Flow

The authentication flow is responsible for verifying user identity, it also manages the session state and restrict access to routes that are protected. This will ensure only authenticated people can access to the system and perform log analysis tasks.

b. Log Upload Component

The log components provides the main interface for user to submit log files for anomaly detection.

CHAPTER 5: RESULT ANALYSIS

This chapter presents a comprehensive evaluation of the proposed log anomaly detection system. The analysis focuses on the overall effectiveness of the machine learing models for log anomaly detection, the overall performance of the system and the quality of LLM generated explainations.

5.1 Machine learing models evaluations

To measures the performance of each model, I use precision, recall and F-measure, which are the most commonly usedme trics, to evaluate the accuracy of anomaly detection methods as we already have the ground truth (anomaly or not) for the dataset. As shown below, precision measures the proportion of how many anomolies are correctly identified in those reported.

$$Precision = \frac{\#Anomalydetected}{\#Anomalyreported}$$

$$Recall = \frac{\#Anomalydetected}{\#Allanomalies}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

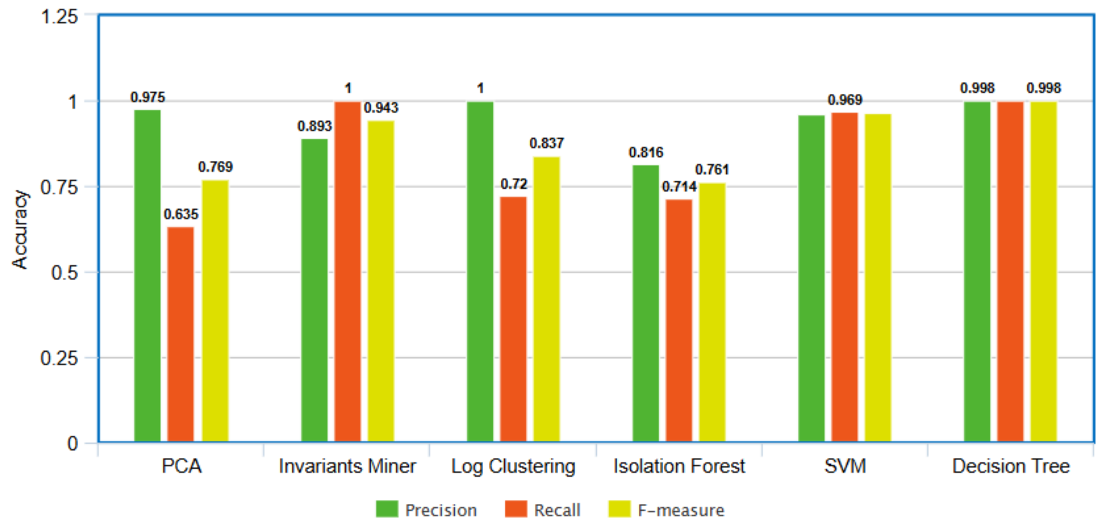


Figure 5.1: Trainning accuracy

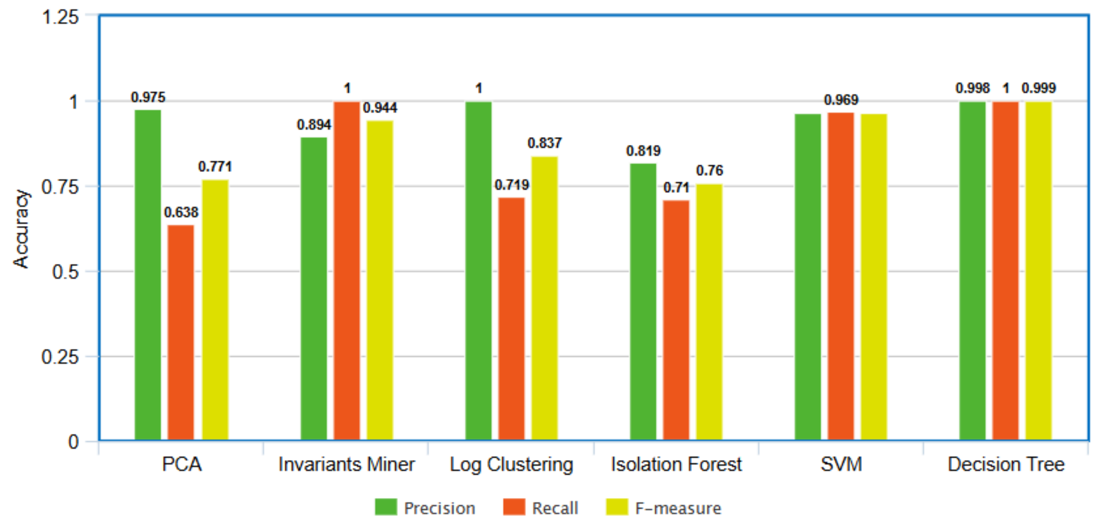


Figure 5.2: Testing accuracy

Based on the experiment results that capsulates in Figure , The Decision Tree model demonstates that most superior performance among all approaches. It achieve near-perfect score for all three evaluated metrics on both training and testing data. SVM algorithm also perform well with F1 score approach 0.964 but the algorithm itself is more complex and harder to understand. Unsupervised methods such as PCA high precision score but low in recall, there for decrease its ability to dectect diverse pattern. Forest and Logistic Regression provide moderate score but much lower than Decision Tree model. As the result, Decision Tree model achieves the optimal accuracy and operational simplicity for my production log anomaly detection framework.

5.2 LLM responses

The LLM is provided with session-level log sequences instead of just a single log entry. This context helps improving the quality of the explanations and allows models to identify root cause more effectively. The LLM responses have a clear consistent structure which contains explanations why a log sequence is lableed anomaly, root causes analysis, severity level and recommended actions. In most cases, the recommendations are sound realiable and detail enough.

5.3 User Interface Effectiveness

The frontend provides a clear and linear workflow: log upload, job monitoring, result visualization, and anomaly explanation review.

5.4 Limitations

Despite the system's promising results, there are still several limitations were identified during development and evaluation.

1. Dataset and Labeling Constraints

   The system is currently relying on HDFS labeled dataset for model training. which can not accurately detect anomalies in real-world log data. If apply the models to non-HDFS logs, the result is would likely to undergo a significant degrade in accuracy. Since the supervised models can only detect patterns present in the training datam unseen or newly failures and anomalies may remain undetected unless new labeled sameples are adding the dataset for the retrain.

2. Limited Explainability

   Another important limitations is the limited explainability of anomaly detection decisions produced by the machine learning models. The Decision Tree classifier determines anomaly based on the decision rules that take from event count vectors. However, these internal decision paths such as which features or rules that triggered the anomalies are not exposed to the users. As a result, the system lack of insights into each decision, making it difficult to actually validate to model behavior. While the integration of Large Language Models may mitgate the issue by providing the human-readable explainations but yet not directly grounded in the root decision logic of the Decision Tree.

3. Manualy Interaction

   The proposed system is relying on manual log upload interaction which is not practical in real-world deployment. This design limits the ability to immediately detect and response in reality where logs are generated continuously and failures must be identified as early as possible. Therefore, in practical production settings, a automated log collection solutions such as log agents or streaming pipeline are highly required to continuous ingestion and near real-time detection.

CHAPTER 6: CONCLUSION AND RECOMMENDATION

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