

CLASSIFY DATA LEAKAGE LEVEL WITH MACHINE LEARNING

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Final Report documentation in partial fulfillment of the requirements for the Bachelor
of Science (Hons) in Information Technology Specializing in Cyber Security

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DECLARATION OF CANDIDATE AND SUPERVISOR

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

.....

Signature of the Supervisor :

(Mr. Amila Senarathne)

.....

Date

ABSTRACT

As our final year research project, we have chosen a research topic which is directly related with information security. Since from the very beginning of the digital data era, data leakages have been a very common problem for most of the organizations & people. However, with the gradual development of the modern technology, various types of Data Leakage Prevention solutions were introduced to the market. However, most of those data leakage prevention solutions had 2 main issues with them which are the lack of user friendliness and the lack of automation capabilities. Although with the time being some of those issues were solved up to some extent, still there are major security loop holes and considerable amount of unreliability associated with the current generation data leakage prevention solutions. So, as a research team, we did a thorough investigation on currently existing DLP solutions in order to identify the potential research gaps within them.

Furthermore mentioned, most of the DLP solutions that are in the current market are completely based on traditional outdated technology. Most of those DLP solutions do not provide full visibility into user actions. Not only that, through the initial research we have carried out, we have discovered that most of the DLP solutions that are currently existing in the market are not capable of identifying user behaviors beforehand. Additionally, we have also discussed with an industry professional who is working for a well-reputed company in Sri Lanka, in order to find out a specific research problem that is actually existing within the modern day DLP solutions. After gathering all those knowledge, we got to know that most of the current day DLP solutions generate a huge number of false positive alerts that really has become a huge burden for the SOC Team of an organization. So, as the research team, together we proposed with a brand-new solution for this particular research problem. Our main objective out of this research project is to design an Unified DLP Solutions for Email System.

In order to achieve this objective, we are going to use several methods & techniques which are heavily dependent on machine learning (ML) and Neural Language Processing (NLP). In order to make our research progress more effective & productive, we have divided 4 research components within the team members. Those 4 research components are Abnormal Login Analysis for Email-Based DLP Systems, Natural Language Processing for Phishing Email Detection, Utilizing NLP Techniques for Content Analysis in Email Systems, Classify data leakage level with machine learning. When all those 4 research components are successfully completed & merged together, it enables in identifying a user who is susceptible for potential data leakage based on our own classifying and giving unified DLP solutions for Email System.

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LIST OF ABBREVIATIONS

Abbreviation	Description
DLP	Data Loss Prevention
ML	Machine Learning
SOC	Security Operations Center
CIS	Center for Internet Security
UI	User Interface

1. INTRODUCTION

The spread of data and leakage risks have become major concerns for businesses across all industries in today's digital environments. The detection and resolution of data leaks are frequently insufficient to keep up with the evolving cyber risks. As a result, there is an increasing need for sophisticated methods that employ machine learning (ML) approaches to effectively classify data leakage levels. The goal of this study is to address this need by emphasizing the development and use of artificial intelligence-based classifiers to assess data leakage levels. This study aims to provide proactive and flexible tools for businesses to identify, categorize, and minimize data leak circumstances through the use of machine learning algorithms.

The uniqueness of this study is in its focus on using machine learning techniques to assess data leakage levels, enabling businesses to prioritize their response activities based on the severity and effect of events. This study aims to increase the accuracy and efficiency of classifications by integrating machine learning algorithms with exhaustive datasets that cover various data leak instances. Using machine learning to classify data leakage levels requires creating advanced algorithms that can rank security responses according to the risk of possible breaches. Machine learning algorithms are capable of risk-scoring individual data leakage occurrences and enabling prompt response by examining patterns and trends in the incidents. With the help of this research component, companies will be able to minimize the effects of security events on their day-to-day operations and improve their response efforts by creating machine learning-based categorization models particularly designed for email DLP systems.

A proactive method of data protection is to use machine learning to classify data leakage levels. This allows businesses to prioritize their responses according to the severity of the released information. By classifying data breaches into varying degrees of severity using advanced machine learning algorithms, this technique enables firms to more efficiently spend resources and react quickly to high-risk situations. A key component of this methodology is creating an interactive categorization dashboard that offers immediate email sensitivity monitoring. Administrators can observe and measure the severity of each event as it happens using this dashboard, which acts as a centralized platform for tracking and evaluating data leakage issues. This dashboard enables enterprises to enhance their incident reaction times and lessen the impact of data breaches by offering actionable information and notifications. Additionally, this research advances data security by modifying machine learning models and natural language processing (NLP) methods to address changing risks associated with data leaks. Organizations may keep ahead of cyberattacks and successfully reduce the risks of data breaches by regularly updating and improving these models with the addition of new information and emerging threats.

Index Terms— Data Loss Prevention (DLP), Machine Learning (ML), Email System, Cyber Attack.

2. BACKGROUND & LITERATURE SURVEY

2.1 What is Data Classification?

According to J. Petters in [1], data classification is considered as the general process for analyzing structured or unstructured data and organizing it into categories based on file type, contents, and other metadata. The data classification process has always become a very crucial procedure for the organizations specially to assess the value of various kinds of data, determine the risk levels & to implement the necessary mitigation mechanisms in order to prevent any potential risks. Furthermore mentioned, data classification has actually become a mandatory process for the organizations in order to comply with modern data privacy regulations such as SOX, HIPAA, PCI DSS, and GDPR.

2.2 Significance of Data Classification

Currently, data classification process has become a mandatory task for almost all the organizations in the world. According to J. Petters in [1], there are multiple reasons for an organization to implement a proper data classification process. The main reason behind implementing a data classification process is to mitigate the potential risks towards the organization. When a particular organization is considered, it is possible to achieve the above-mentioned goal using multiple techniques. Some of them are limiting the access to Personally Identifiable Information (PII), controlling the location & access to intellectual property and reducing the attack surface area for the sensitive information.

The next main reason behind the significance of data classification is the governance & compliance. A proper data classification mechanism can achieve this in various methods. Some of them are identifying the data that are governed by GDPR, HIPAA, CCPA, PCI, SOX etc. and applying the metadata-related tags towards protected data in order to enable additional tracking and controls [7]. The next most important usage of a data classification process is to improve the efficiency and optimization of the system. A well-defined data classification mechanism has the ability to achieve this in multiple different ways. Some of them are enabling the efficient access to content based on type, usage etc., discovering & eliminating the redundant data and moving the heavily utilized data into faster devices or cloud-based infrastructure.

2.3 Types of Data Classification

According to an article in Imperva in [2], data classification process can be performed based on content, context, or user selections.

- **Content-Based Classification** - In here, the classification process is done by reviewing the content of files & documents.
- **Context-Based Classification** - In here, the classification process is dependent on meta data such as the applicatio / software that is being used, the person who created the document, the stored location of the sensitive data etc.

- User-Based Classification - In here, the classification process is done manually by a knowledgeable user. Additionally, the user itself can specify the sensitivity of the documents that they have been working on.

2.4 Main Steps in Data Classification Procedure

According to J. Petters in [1], the data classification procedure consists with 7 main steps.

- As the very 1st step, you need to clearly define all the necessary required objectives. In here, it is mandatory to define the relevant reasons for those selected objectives as well. Additionally, this particular step should also clearly indicate your scope for the initial classification phase.
- As the 2nd step, you need to categorize the data types correctly. In here, it is expected for you to clearly identify the types of data that your organization generates (**Customer information, financial records, source codes, project plans**). Since this is the very early stages, it might become very effective if the proprietary & public data are separated clearly. After performing those, then you need to check whether you are able to find any kind of regulated data such as GDPR & CCPA.
- As the 3rd step, you need to establish the necessary classification levels. In here, it is very much important to clearly define the number of classification levels that you need. For the better understanding, it is required to clearly document each level separately with the examples. As the final process in this step, if the approach is a manual (user-based) classification procedure, it is required to train the users in properly classifying data.
- As the 4th step, you need to clearly define the automated classification process. In here, it is mandatory to include the prioritization plan in scanning the data. Additionally, you need to decide on the required resources that are needed for the automated data classification approach.
- As the 5th step, you need to correctly define the categories & classification criteria. In here, it is necessary for you to clearly define your high-level categories and the related examples (PII, PHI). After performing it you need to enable the suggested classification labels & patterns. As the final process in this step, you need to establish a procedure in order to review and validate both user classified and automated results.
- As the 6th step, you need to clearly define the outcomes & usage of classified data. In here, you need to clearly document the necessary risk mitigation steps & automated policies. Then it is necessary for you to define a process in order to apply analytics to classification results. After the analytic analysis is fully completed, you need to establish the expected outcomes from it.
- As the 7th and the last step, you need to always monitor & maintain your data classification mechanism. In here, the main task is to review the classification

procedure in a regular basis and to update the necessary changes according to the regulatory standard.

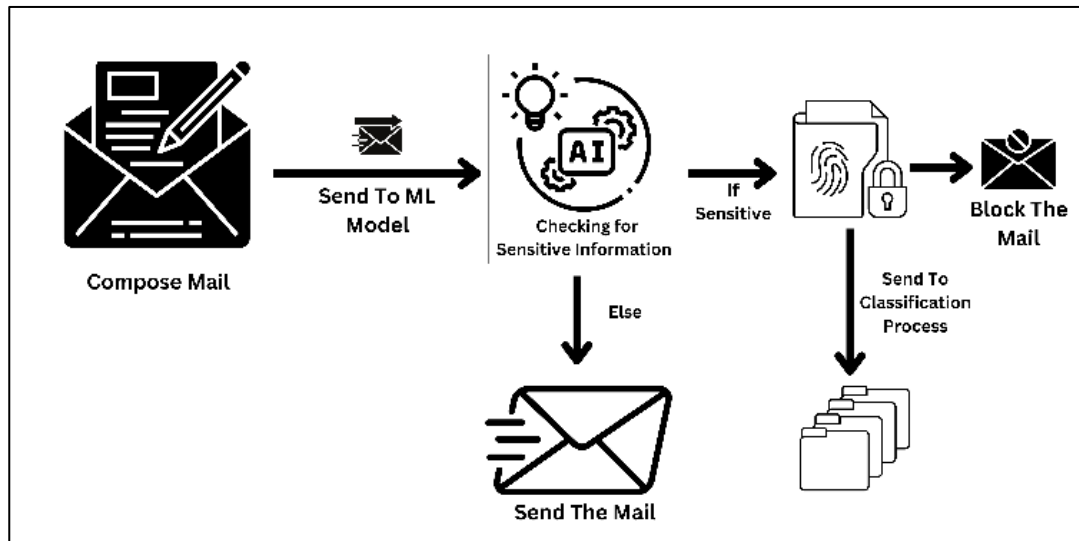


Figure 1 : Data Classification Procedure

2.5 Data Sensitivity Levels

According to Center for Internet Security (CIS) [8], most of the organizations are currently using a data classification mechanism which contains 3 levels of data sensitivity. Although it is possible to add more than just 3 levels of data sensitivity, practically it's going to be more difficult when maintaining those systems due to the added complexity. However, reducing the data sensitivity levels more than 3 is also not recommended as it could lead to insufficient privacy and protection.

According to I. Sotnikov in [3], mainly there are 3 data sensitivity levels.

- i. **High Sensitivity Data** → If compromised it will bring significant harm the organization or individuals. Since most of the times, data is protected by regulatory standards, violating them may result in penalties & fines.

Examples: - *financial records, intellectual property, authentication data*

- ii. **Medium Sensitivity Data** → Those data are usually intended for internal use only. Although, those data are compromised, it won't bring a catastrophic impact on the organization or individuals.

Examples : - *emails and documents with no confidential data, non-identifiable personnel data*

- iii. **Low Sensitivity Data** → Usually, those data are intended for public use. So, those data won't be needing any kind of access restrictions.

Examples : - *public website content, job postings, and blog posts*

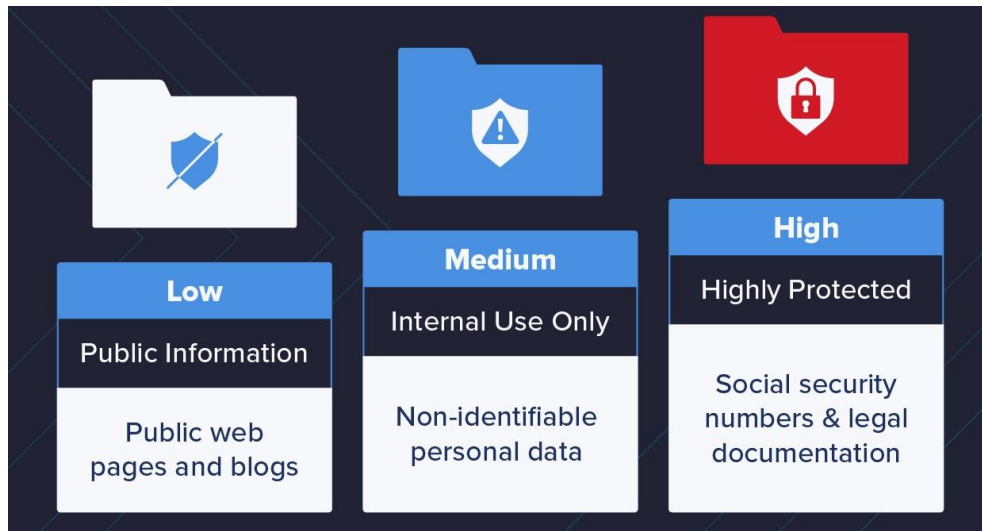


Figure 2 : Data Sensitivity Levels

2.6 Primary Paradigms in Data Classification Process

According to J. Petters in [1], mainly there are 2 primary paradigms to be followed when implementing a data classification process.

i. Manual (User based) Procedure

- In here, the users itself have to classify their own data based on pre-defined sensitivity levels. So, it is necessary for all the users to be trained properly in order to identify the correct level of data sensitivity & to assign the correct classification tags for all the new files they create. However, since the tagging process is done manually, most of the users always forget or neglect that procedure. Furthermore mentioned, this approach becomes bit of unpractical specially when dealing with large amounts of pre-existing data (**Machine-generated data**).

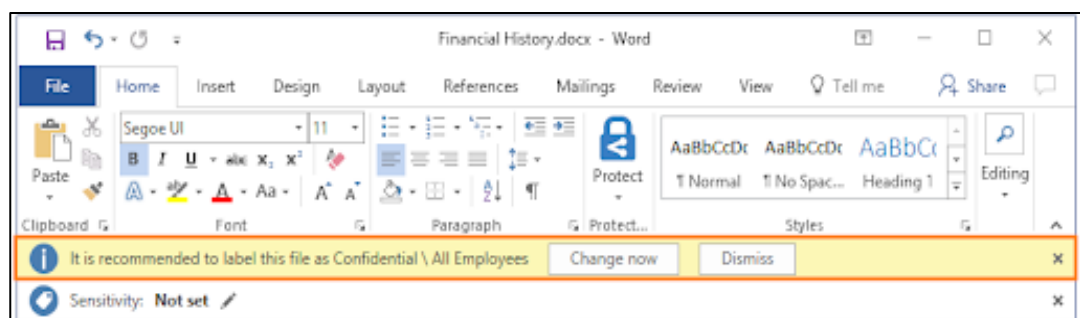


Figure 3 : Manual (User based) Procedure

Automated Procedure

- In here, the built-in data classification engines are capable of employing a file parser combined with a string analysis system to find data in files. The main purpose of this file parser is to allow the data classification engine to read the contents of several different types of files. After it is completed, then those data are matched with the necessary files using a string analysis system. When compared to the User-based procedure, automated classification procedure is much more efficient & productive. However, the accuracy factor in this particular system may heavily depend on the quality of the parser. So, when this automated data classification procedure is concerned, there are several added features as well such as accuracy, scalability, reliability etc.

The screenshot shows the 'Edit Rule' window for a rule named 'GDPR Austria'. The rule is enabled and its description is '[Policy Pack] Detects National Identification Numbers for Austria.'. It is classified as 'GDPR' and is considered sensitive. The conditions section shows a list of filters: 'AT SSN', 'AT Driver's License', 'AT PIC', and 'AT Passport', each with a 'validate with' dropdown and an 'Advanced' link. The actions section has a checkbox for 'Save matches for review' and a field for 'Assign Global Flag(s):'.

Section	Field/Option	Value/State
General	Rule Name	GDPR Austria
	Enabled	<input checked="" type="checkbox"/>
	Rule Description	[Policy Pack] Detects National Identification Numbers for Austria.
Classification	Files classified by this rule are considered sensitive	<input checked="" type="checkbox"/>
	Classification category	GDPR
Conditions	Any of (OR)	<input type="checkbox"/>
	Match range	10
	words	words
	Pattern	AT SSN
	validate with	AT SSN
	Advanced	Advanced
	or	
	Pattern	AT Driver's License
	validate with	(none)
	Advanced	Advanced
Actions	Save matches for review	<input checked="" type="checkbox"/>
	Assign Global Flag(s):	

Figure 4 : Automated Procedure

3. RESEARCH GAP

According to E. Costante in [5] most of the DLP solutions that are currently existing in the market, do not have the capability of determining whether a particular alert is a false positive or not. As a result of that, most of the legitimate transactions that are performed by the users are marked as suspicious activities. Furthermore mentioned, according to A. Chatterjee in [6], due to the higher false positive rate, it generates a huge number of unwanted alerts just for the legitimate actions. According to most organizational policies, such kind of alerts needs to be addressed in a more regular manner. However, since each & every alert has to be analyzed by a human itself, it results a massive operational cost for the organization as well. According to a survey by Computer Weekly / TechTarget, Figure 2 shows the disadvantages of traditional

DLP tool [10]. The chart also shows a false-positive ratio of 28%, which is a huge disadvantage of the DLP tool.

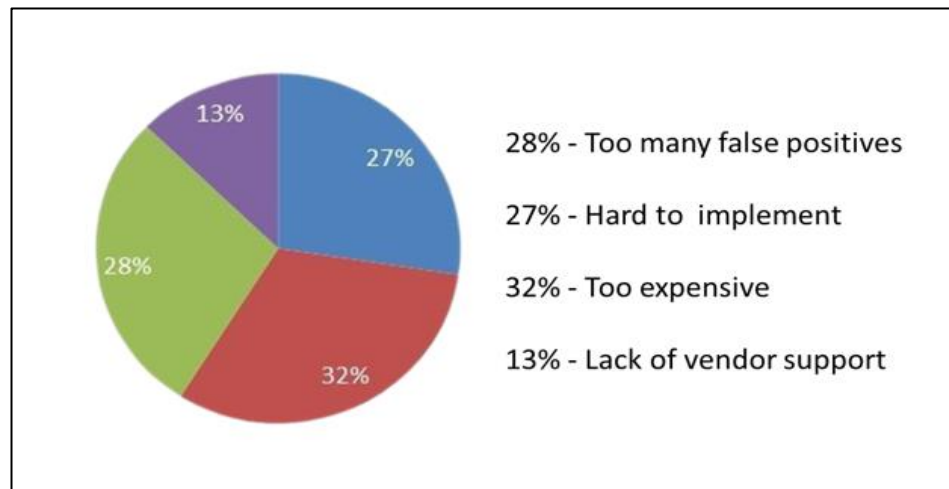


Figure 5 : Disadvantages of Traditional DLP Tool

DLP tools detect data breaches. However, it does not provide a list of users who may disclose data within the organization in the future. Our proposed scoring system will give the organization with a list of high-risk users who may perform a data leak in the future. The benefit of maintaining a list of susceptible users is that it allows an organization to take proper action prior to a data breach. As a result, our proposed evaluation methodology uses predictive analytics and machine learning algorithms to estimate future data leakage occurrences based on prior user behaviour and contextual data. The system may detect high-risk users who are likely to participate in illegal data disclosure activities by studying patterns and anomalies in user interactions with sensitive data.

	DLP Solutions Lack False Positive Detection	DLP Tools Lack User Risk Identification	Admin Penal	Lack of Scalability and Adaptability
Research A	X	X	X	X
Research B	X	✓	X	✓
Research C	X	✓	✓	X

Data Classification using ML	✓	✓	✓	✓
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Table 1 : Research Gap

4. RESEARCH PROBLE

Most of the DLP solutions that are in the current market are completely based on traditional outdated technology. Most of those DLP solutions do not provide full visibility into user actions. According to Bitglass in [4], most of the current day DLP solutions in the market are only capable of scanning files only at the send time. Those DLP solutions do not contain the ability of self-learning & identifying the user behaviors.

For example, in most of the current day DLP solutions, it generates a huge number of false positive alerts that really has become a huge burden for the SOC Team of an organization. Those people have to spend at least 10-15 hours weekly in order to check for the false positives (**This process is also known as “Fine Tuning”**).

According to E. Costante in [5], most of the DLP solutions that are currently existing in the market, do not have the capability of determining whether a particular alert is a false positive or not. As a result of that, most of the legitimate transactions that are performed by the users are marked as suspicious activities. Furthermore mentioned, according to A. Chatterjee in [6], due to the higher false positive rate, it generates a huge number of unwanted alerts just for the legitimate actions. According to most organizational policies, such kind of alerts needs to be addressed in a more regular manner. However, since each & every alert has to be analyzed by a human itself, it results a massive operational cost for the organization as well.

Due to their dependence on fixed thresholds or static criteria, which may not fully reflect the changing character of data leakage patterns, effective feature selection approaches frequently lack resilience. Moreover, the lack of automated feature selection processes adds to the process' complexity by necessitating human interaction and specialized knowledge, which restricts its scalability and efficiency. The primary cause of current systems' difficulties in attaining real-time monitoring and alerting capabilities is latency in data processing and analysis. This issue is made worse by the time-consuming nature of conventional detection techniques like rule-based pattern matching, which leads to longer incident response times and more vulnerability to possible data breaches.

Existing systems are not as scalable or adaptable as they may be when it comes to adjusting machine learning models and natural language processing approaches to changing data leak threats. The adoption and optimization of sophisticated ML-based solutions may be hampered by legacy architectures and infrastructure's inability to

handle the increasing volume and complexity of data due to a lack of computing power and adaptability. In addition, the fast advancement of cyber dangers necessitates constant modifications and enhancements to machine learning models and algorithms, creating difficulties in staying in sync with new developments in data leak trends and patterns.

5. RESEARCH OBJECTIVES

5.1 Main Objective:

Create a system that uses NLP and machine learning approaches to categorize the severity of data breach incidents. Minimizing harm and efficiently prioritizing responses are the objectives. This entails developing a framework for event analysis and severity level classification. By integrating with current incident response procedures, the technology will allow for prompt and focused action. The model is continuously improved to guarantee that it can respond to new threats. The ultimate goal is to provide enterprises with useful information for improved data security in Email System.

5.2 Sub-Objectives:

- Validate and optimize machine learning models for data leakage level classification.

Machine learning algorithms are frequently used in current research to categorize email data leakage situations into various levels of severity. To categorize incidents, these models often make use of information taken from email text, metadata, and user activity patterns. However, common methods like cross-validation and hyperparameter modifying are frequently used in the validation and improvement of these models. To evaluate the effectiveness of their categorization models across various subsets of email data, researchers may, for instance, employ k-fold cross-validation. Although these methods work in some situations, they might not fully capture the subtleties of email data breach incidents.

Specifically designed for data leakage level categorization in email systems, we provide in this research unique validation and optimization methodologies. To enhance the categorization model over time, we provide a novel technique called dynamic validation, which integrates feedback loops from incident response teams. To further optimize our machine learning models for email data leakage detection, we automatically adjust their parameters using sophisticated optimization methods like genetic or Bayesian optimization. We hope that by including these new strategies, our classification model will perform better than current techniques in terms of accuracy and resilience.

- Create an interactive classification dashboard for user-friendly monitoring and management.

Many of the data leakage prevention email solutions on the market today provide rudimentary reporting features for tracking and handling events. It might be difficult for users to modify or engage with the data in these systems in a way that best suits their needs because they usually offer static dashboards with predetermined metrics and visuals. Users might not be able to drill down into individual event details or change the visualization parameters, for instance, and instead only be able to see preset charts or tables.

In this study, we provide an interactive categorization dashboard created especially to track and handle email system data leaks. Users may personalize the way incident data is shown on our dashboard by applying filters based on severity level, time frame, or impacted email content. In addition, we provide interactive elements like dynamic data tables and clickable charts that let users examine event details in real time and act quickly when necessary. Compared to current methods, our dashboard improves the usability and efficacy of data leakage monitoring and management in email systems by offering a simple and adaptable interface.

- Implement real-time alerting to respond promptly to potential data leak threats and generate a report.

Basic alerting features are provided by a large number of data leakage prevention email systems now in use to inform users of potential dangers or accidents. Frequently, pre-established rules or thresholds—such as identifying questionable email attachments or peculiar sender behavior—are what set off these notifications. These warnings are helpful markers of possible data breaches, but they could not be timely or detailed enough, leading to false positives or a delay in responding.

In our work, we put into practice real-time warning systems designed especially to identify and address the risks of data leaks in email systems. Our technology tracks user activities and email traffic in real-time, looking for unusual trends that might point to instances of data leaks. Our technology instantly provides notifications with comprehensive details regarding incidents, such as the severity level, impacted email content, and suggested actions, once a possible danger is identified. We also automate the creation of thorough incident reports, which give stakeholders information about the incident's impact, cause, and mitigation techniques.

6. METHODOLOGY

6.1 System Diagram for Individual Research Component (Classify Data Leakage Level with Machine Learning)

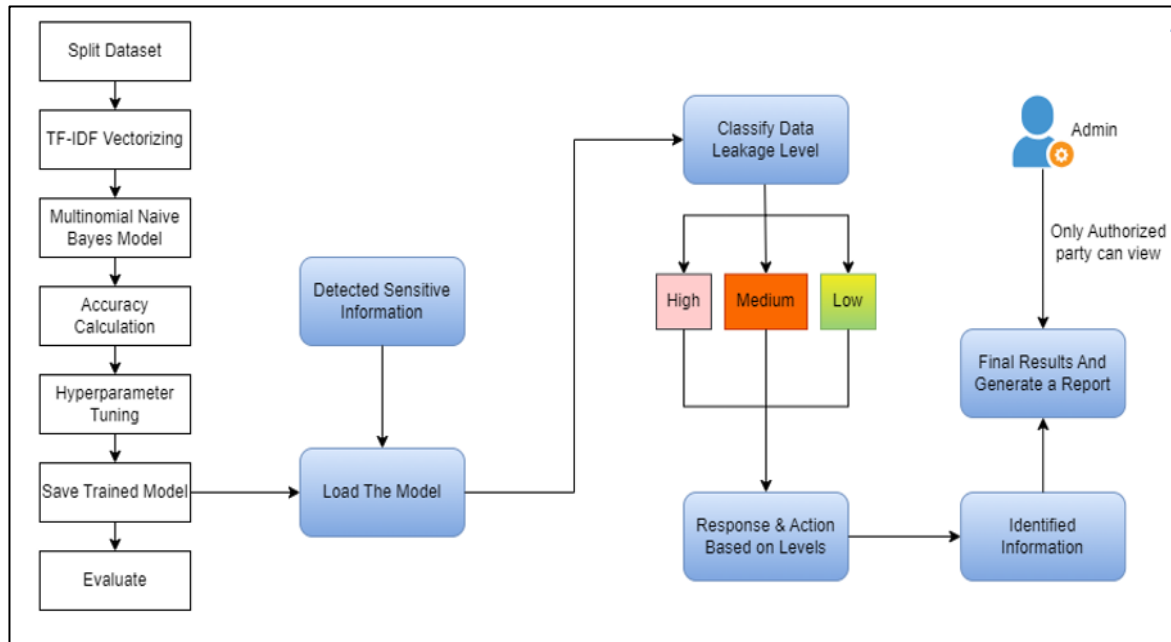


Figure 6 : System Diagram for Individual Research Component

6.2 System Diagram for Overall System

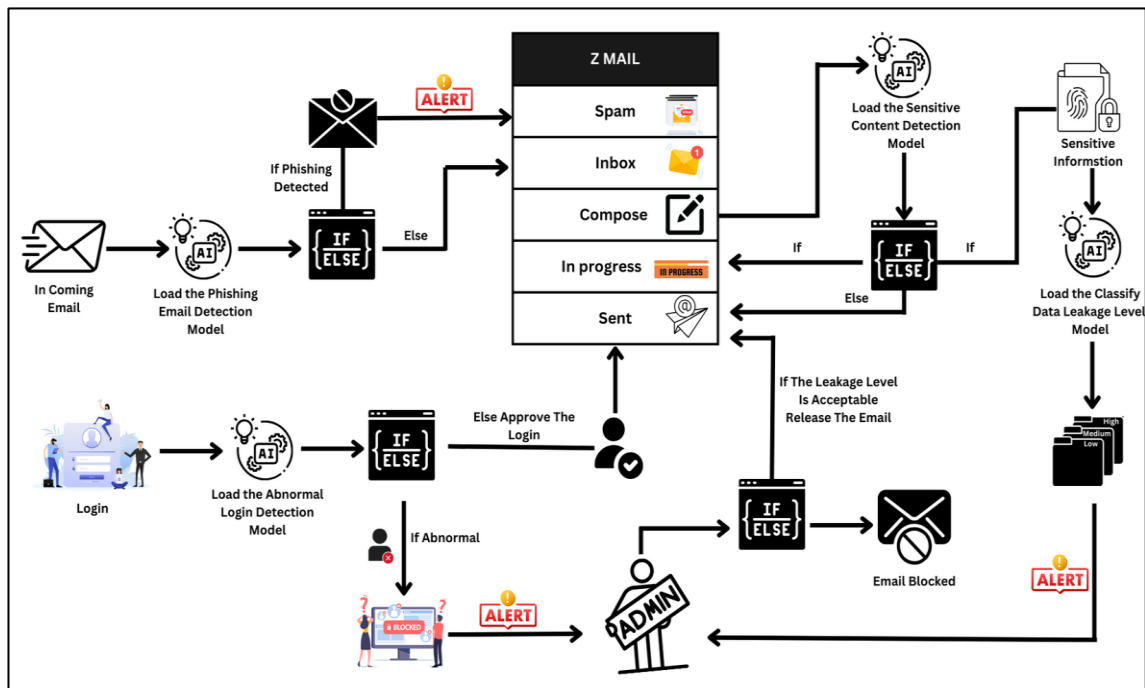


Figure 7 : System Diagram for Overall System

Due to the explosive growth of modern technology, data leaks occur often in the majority of companies. But given the importance of the information being released, there might be some serious consequences from this. Many companies have taken action to reduce data leaks since they have become increasingly frequent during the past few years. Those organizations developed the concept of Data Leakage Prevention Solution, but their effectiveness against modern data leaks was limited. When a certain set of words/terms matches in standard DLP solutions, an alarm is raised. We have used a different approach in our suggested DLP solution. Our machine learning-based prediction system is capable of identifying whether a particular set of data is sensitive or not & the probability of it.

6.3 User Interface Design

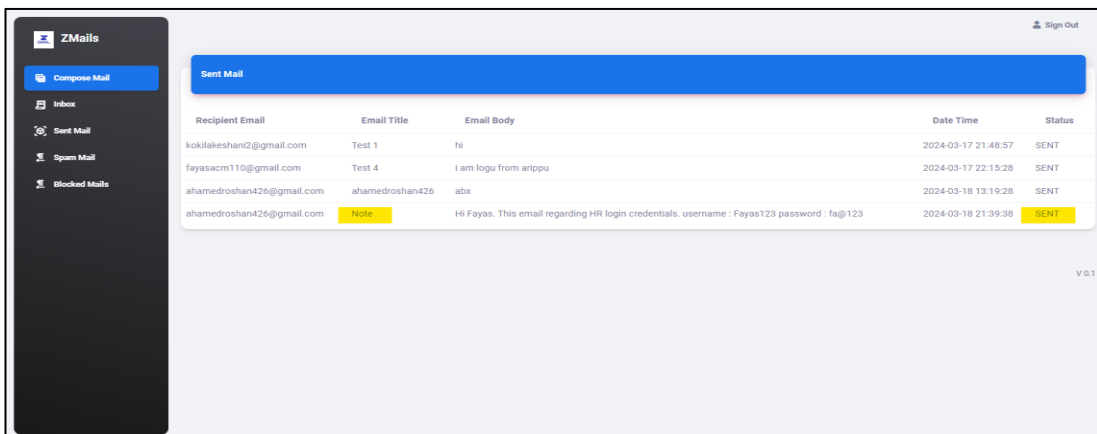


Figure 8 : Client UI Panel

6.4 Admin Interface Design

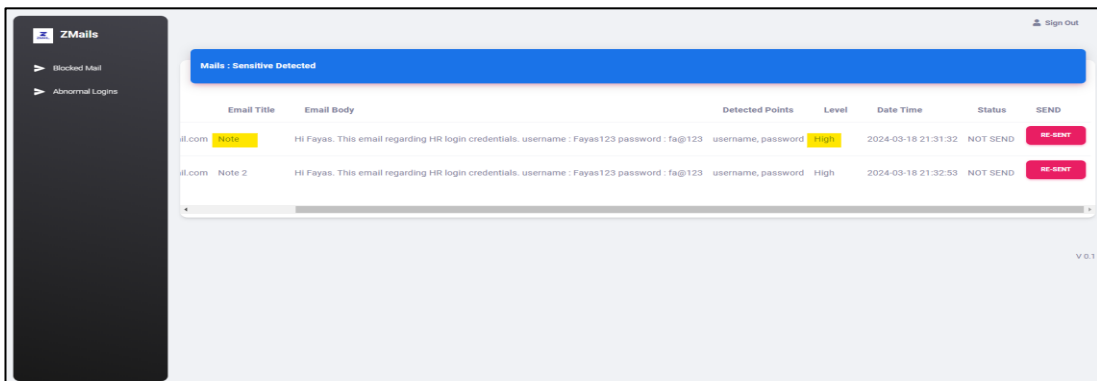


Figure 9 : Admin UI Panel

6.5 SOFTWARE SPECIFICATIONS & DESIGN COMPONENTS

6.5.1 Functional Requirements

Analysis of Email Content: Capacity to examine email text for trends, attachments, or sensitive phrases that could be signs of data leaking. Using content analysis and machine learning algorithms, emails are categorized into various leakage levels.

Monitoring in real time: Real-time, ongoing email monitoring is done to spot any suspicious activity or any data leaks. Quick detection of irregularities or departures from typical email correspondence.

Monitoring User Activity: Keeping a record of user interactions and behaviors by monitoring and recording user activity within the email system. recording actions like sending, forwarding, or reading attachments in emails in order to do additional analysis.

Assigning a Risk Level: Each email is given a risk score that is determined by the seriousness and probability of data leaking. a weighted rating system that takes into account a number of variables, including the recipient, attachment types, and email content.

Automated Notification: System administrators or other designated persons will get automated alerts when suspicious activity or high-risk emails are detected. systems for instant alerting in order to provide prompt mitigation and reaction.

Adaptive Education: Utilizing adaptive learning techniques to raise the categorization of data leakage's efficacy and accuracy over time. Machine learning models are continuously improved in response to input from events involving detected data leaks.

Combining DLP Policies : Seamless connection to enforce organizational data security regulations with current Data Loss Prevention (DLP) setups and policies. Compliance with DLP rule sets to ensure uniform application of email data protection regulations.

Admin Panel: Capacity to add, edit, or delete user accounts in the DLP system that correspond to certain rights. Roles and permissions are assigned to users, including normal users and administrators, to manage activities and access inside the system.

6.5.2 Non - Functional Requirements

Performance: Even at times of high usage, the system must function well and be responsive in order to guarantee prompt categorization of data leakage levels in emails.

Safety: Strict security protocols have to be put in place to protect user information and stop illegal access or disclosure to other parties.

Sensitive data inside the DLP system should be protected using encryption methods and access controls.

Mobility: The DLP system should have capabilities that make it portable, enabling easy deployment across many platforms or scenarios. It is imperative to provide compatibility with many operating systems and architectures to facilitate a smooth integration into pre-existing IT infrastructures.

Reliability: In order to minimize downtime and guarantee the continued availability of data leakage categorization services, the system must maintain high dependability and uptime.

In order to prevent data loss or corruption and to gracefully handle failures, robust error handling methods must be in place.

Scalability : It is important to plan for future development and extension of the DLP system in terms of both user base and data volume. System scaling to meet rising workload needs should be made easy by scalable design and resource allocation techniques.

Availability: High user availability is required to guarantee that services for classifying data leaks are available whenever they're needed. Redundancy and failover measures should be built to limit the effect of hardware or network failures and preserve uninterrupted service availability.

6.6 System Requirements

Processor	Intel Core i7 (10th Gen)
Clock Speed of CPU	2.80 GHz
Operating System	Windows 10 Home / Professional
RAM	16 GB
Storage	512 GB SSD
GPU	NVIDIA GEFORCE

Table 2 : System Requirements

6.7 Work Breakdown Structure

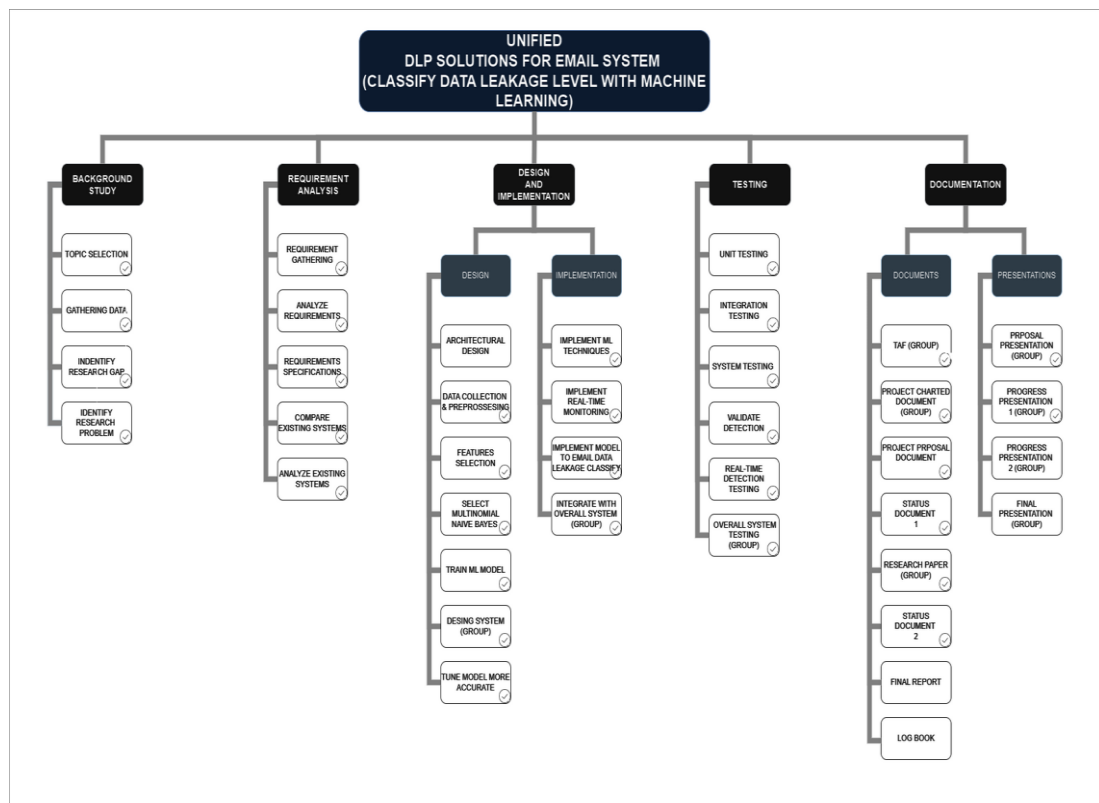


Figure 10 : Work Breakdown Structure

6.8 GANTT CHART

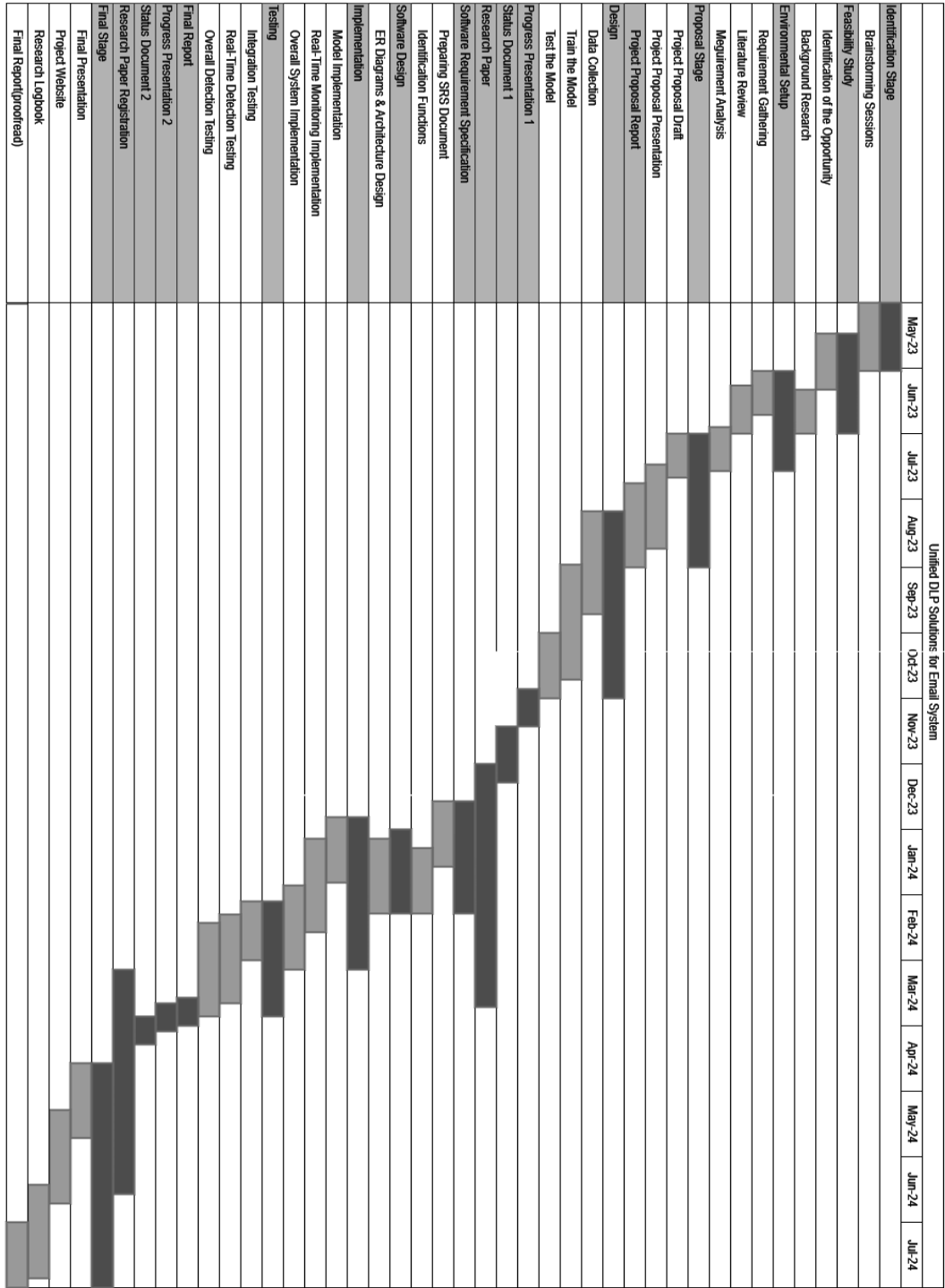


Figure 11 : GANTT CHART

6.9 BUDGET & BUDGET JUSTIFICATION

Following table demonstrates the total amount of money that were spent when developing our DLP product.

Resources	Price (LKR)
Purchasing Software License	35000.00
Purchasing a cooling pad for laptop. <i>(In order to prevent damaging my laptop because of overheating)</i>	6,000.00
Team Travel Costs	10000.00
Internet <i>(We had regular meetings weekly in order to complete our DLP product for Email System)</i>	20000.00
Stationary Materials	8000.00
Research Paper Submission Costs	75,000.00
Total Amount	Rs. 154,000.00/=

Table 3 : BUDGET

When we first started the research project, we had an approximate total expenditure of Rs. 125,000.00/=. But when our research project came to a finish, the entire cost went up from Rs. 29,000/=. Since we are all still employed and getting paid a sufficient salary, the team was able to handle the additional expense.

6.10 Commercialization Aspect of the Product

When compared to other countries in the world, Sri Lanka is still a 3rd world developing country. As a result of that, our country hesitates in adapting to newer technologies due to various budget limitations. When compared to government sector, private sector organizations show much higher interest towards adapting into newer technologies. However, most of the organizations within the private sector also won't give enough attention towards the security aspect of the products that they purchase. Due to various budget limitations, most of the organizations tend to use cheaper & outdated traditional tools in order to carry out their tasks. But this has eventually lead the pathway for serious security consequences. If we consider a medium company, only one security incident is more than enough to lose both money & the customer confidence.

So, when it comes to our DLP product, it consists with lot of advanced security features when compared to those traditional DLP solutions for Email system out there in the market. Furthermore mentioned, due to machine learning mechanisms that are integrated into our DLP product, it has the ability to predict whether users are performing any suspicious activity or not.

We have developed our DLP product mainly targeting the medium industry. However, organizations within other industries also have the ability to experience our DLP product by implementing it to their own organization.

We allow users to experience our product for free during the first 30-day trial period. We have created a 3 package like (Silver, Gold, and Platinum) In order to purchase the Gold version of our product, for one user it costs \$100 only for six months subscription. However, for government organizations such as hospitals & police departments, we have decided to provide our product for a discounted price. For the above government organizations, for one user it only costs \$85 for six months subscription.

Furthermore mentioned, there is also a professional version of our DLP product as well. It is a Platinum. It contains more advanced end-to-end device protection mechanism & a cloud-based protection mechanism also. If any organization is interested in purchasing the pro version, then for one user it only costs \$175 for one-year subscription.

If an organization needs further clarification, they can contact us using our email: edlp.g082@gmail.com

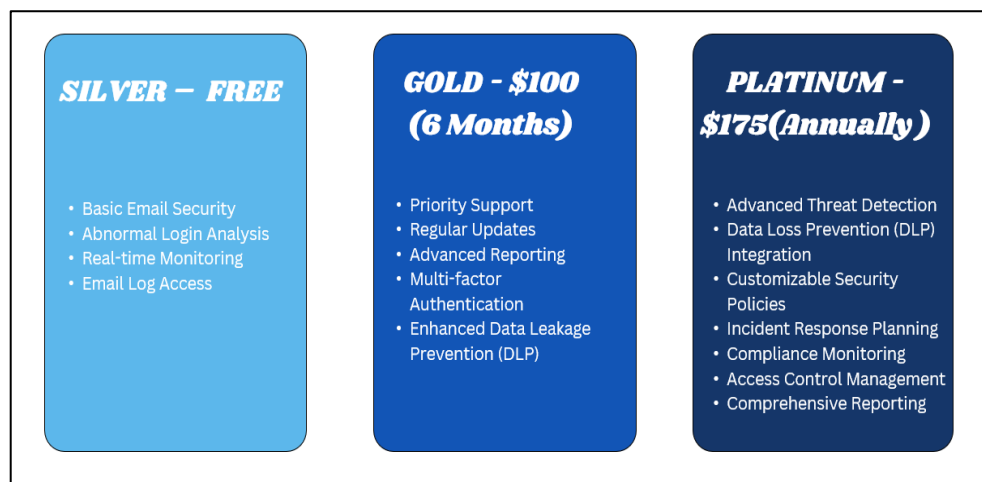


Figure 12 : Commercialization Packages

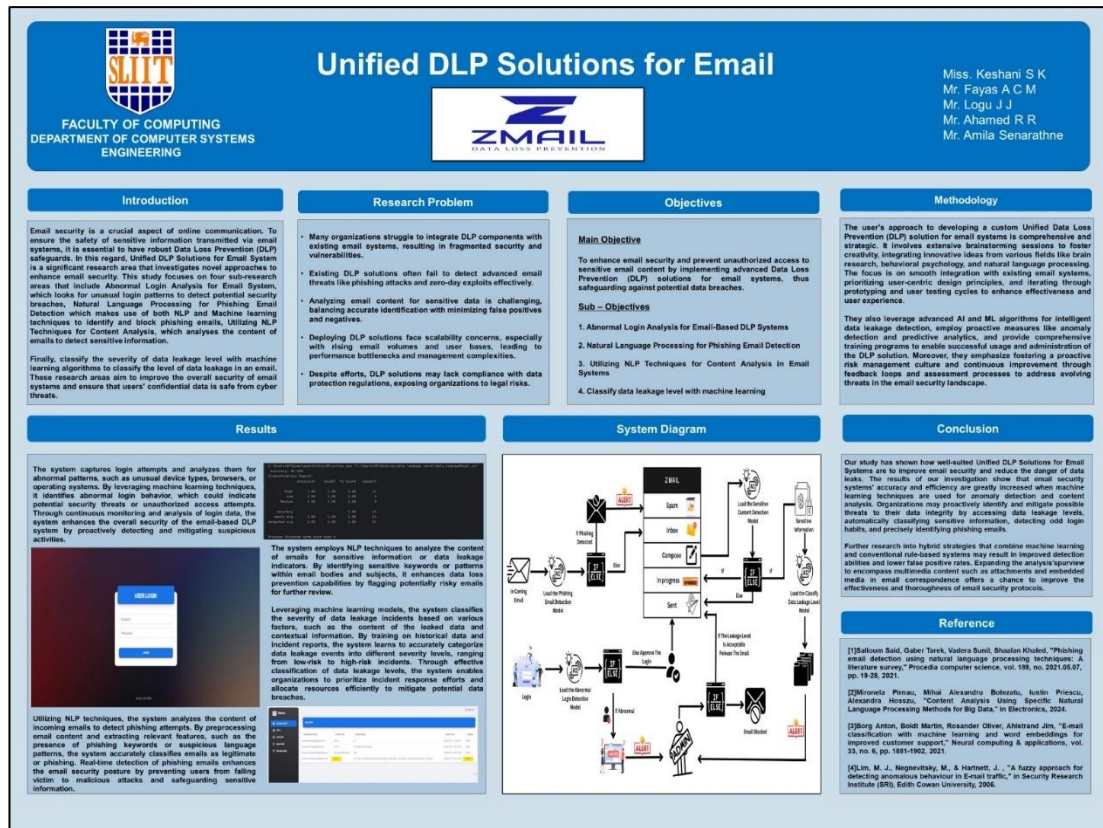


Figure 13 : Commercialization Poster

7. TESTING AND IMPLIMENTATION

In this research, we provide the testing procedure for our suggested Data Loss Prevention (DLP) solution for Email systems' Data Leakage Level. The classification of outgoing emails according to their content and the assessment of the possible degree of data leakage are handled by the Data Leakage Level. Our testing attempts to guarantee the performance, accuracy, and constancy of this essential component in protecting sensitive information.

7.1 Necessary Package Installation

```

1 import pandas as pd #data manipulation and analysis
2 from sklearn.feature_extraction.text import TfidfVectorizer #
3 from sklearn.naive_bayes import MultinomialNB
4 from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
5 from sklearn.metrics import accuracy_score, classification_report
6 import joblib
7

```

Figure 14 : Package Installation

pandas: pandas is a widely used Python library for data manipulation and analysis. It provides data structures and functions for efficiently handling structured data, such as tables and time series. In here, pandas is used to read and manipulate the dataset stored in a CSV file.

sklearn: scikit-learn (sklearn) is a popular machine learning library for Python. It provides tools and algorithms for various machine learning tasks, including classification, regression, clustering, and dimensionality reduction. In here we used for implementing machine learning algorithms, data preprocessing, model evaluation, and hyperparameter tuning.

joblib: joblib is a utility library in Python for saving and loading Python objects, such as machine learning models, efficiently. It provides functions for serializing objects to disk and reloading them into memory. In here we used to save and load the trained machine learning model and the TF-IDF vectorizer.

sklearn.naive_bayes.MultinomialNB: MultinomialNB is a classification algorithm based on the multinomial naive Bayes theorem. It is commonly used for text classification tasks, particularly when dealing with discrete features such as word counts. In here, MultinomialNB is used as the machine learning model for classifying the severity levels of data leakage incidents.

sklearn.model_selection.train_test_split: `train_test_split` is a function in scikit-learn used for splitting datasets into training and testing sets. It randomly divides the dataset into two subsets: one for training the machine learning model and the other for evaluating its performance. In here code, `train_test_split` is used to split the dataset into training and testing sets for model training and evaluation.

7.2 Training the Machine Learning Model

Data Set

```
10
11 csv_file = "incidents.csv"
12 df = pd.read_csv(csv_file)
13
```

Figure 15 : Data Set csv file

In this code snippet, the contents of the CSV file "incidents.csv" are read to establish a pandas DataFrame called `df`. The location of the CSV file on the file system should be indicated by the supplied file path. Once read, the DataFrame makes it simple to manipulate and analyze the dataset included in the CSV file, which helps with a number of data processing work.

Split

```
14
15 X = df['incident_description']
16 y = df['leakage_level']
17 X_train, X_test, y_train, y_test = train_test_split(*arrays: X, y, test_size=0.2, random_state=42)
18
```

Figure 16 : Split the data set

The characteristics (X) and labels (y) of the dataset are divided into two sections using this code. Then, using a split ratio of 80% for training and 20% for testing, it further splits them into training and testing sets (X_train, X_test, y_train, y_test). This section enables the machine learning model to be trained on some of the data and its efficacy is evaluated by measuring its performance on data that has not yet been seen.

TF-IDF Vectorizer

```
17
20 tfidf_vectorizer = TfidfVectorizer(max_features=5000, stop_words='english', ngram_range=(1, 2))
21 X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
22 X_test_tfidf = tfidf_vectorizer.transform(X_test)
23
```

Figure 17 : TF-IDF Vectorizer

A TF-IDF (Term Frequency-Inverse Document Frequency) vectorizer is created by this code segment, and it transforms text input into numerical representations that are appropriate for machine learning. It analyzes both single words and word pairs in the text, takes into account up to 5000 characteristics, and disregards frequently used stop words in English.

The training data ({X_train}) is then subjected to this vectorizer, which turns it into a TF-IDF matrix ({X_train_tfidf}). Similarly, it creates a TF-IDF matrix ({X_test_tfidf}) using the test data ({X_test}). By doing this, it is made sure that the testing and training data are represented numerically so that machine learning algorithms may use them.

Multinomial Naive Bayes algorithm

```
24
25 classifier = MultinomialNB()
26 classifier.fit(X_train_tfidf, y_train)
27
```

Figure 18 : Train the Algorithm

A Multinomial Naive Bayes classifier, a popular approach for text classification applications, is initialized in this section of code. Next, it fits this classifier to the appropriate labels ({y_train}) and the TF-IDF converted training data ({X_train_tfidf}).

By doing this, the classifier picks up features and labels from the training data, allowing it to predict unknown data using the patterns it has obtained.

Accuracy of the incident

```
28
29 y_pred = classifier.predict(X_test_tfidf)
30 accuracy = accuracy_score(y_test, y_pred)
31 cv_scores = cross_val_score(classifier, X_train_tfidf, y_train, cv=5)
32 print(f" Accuracy: {cv_scores.mean() * 100:.2f}%")
33
```

Figure 19 : Train the Algorithm

This section of code uses the newly acquired classifier to predict labels for the test data. Next, by contrasting these predictions with the real labels, it determines how accurate these predictions were. To provide a reliable assessment of the model's performance, it also applies cross-validation to the training set of data. The classifier's mean accuracy over all cross-validation folds is printed at the end.

Hyperparameter tuning

```
35 param_grid = {'alpha': [0.1, 1.0, 10.0]}
36 grid_search = GridSearchCV(classifier, param_grid, cv=5, scoring='accuracy')
37 grid_search.fit(X_train_tfidf, y_train)
38 best_classifier = grid_search.best_estimator_
39
```

Figure 20 : Hyperparameter tuning

Using grid search, the Multinomial Naive Bayes classifier's alpha hyperparameter is adjusted in this code blocks. It looks for the best setting by testing three alpha values: 0.1, 1.0, and 10.0. The configuration with the greatest accuracy on the training set is chosen by the grid search after each configuration is assessed using 5-fold cross-validation. `best_classifier` is the name of the best-performing model that is obtained and saved for further usage.

Save Model

```
40
41 model_filename = "incident_classifier_model.joblib"
42 vectorizer_filename = "incident_vectorizer.joblib"
43 joblib.dump(best_classifier, model_filename)
44 joblib.dump(tfidf_vectorizer, vectorizer_filename)
45
```

Figure 21 : Save the Model

Using the Joblib library, this code segment saves the TF-IDF vectorizer and the best classifier model to disk. "incident_classifier_model.joblib" is the file containing the trained classifier model, and "incident_vectorizer.joblib" is the file containing the TF-IDF vectorizer. There is no need to retrain the model or recompute the vectorizer when using these stored files to make predictions or conduct additional analysis.

Evaluate

```

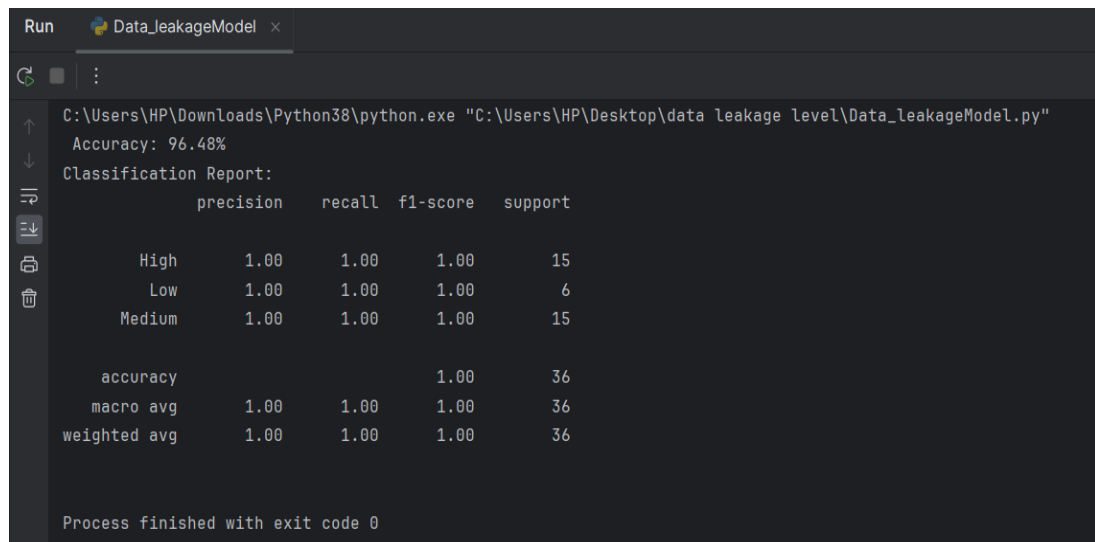
49
50 y_pred_best = best_classifier.predict(X_test_tfidf)
51 print("Classification Report:")
52 print(classification_report(y_test, y_pred_best))
53

```

Figure 22 : Evaluate

Using the best classifier ({best_classifier}), this code segment creates predictions ({y_pred_best}) for the test data ({X_test_tfidf}). The model's performance is then thoroughly assessed by computing many metrics, including precision, recall, F1-score, and support for every class in the test data, and this is printed as a classification report. This report can pinpoint areas for development and aid in evaluating the model's performance across several classes.

Data Leakage Level Accuracy Check



```

Run Data Leakage Model x
C:\Users\HP\Downloads\Python38\python.exe "C:\Users\HP\Desktop\data leakage level\Data Leakage Model.py"
Accuracy: 96.48%
Classification Report:

```

	precision	recall	f1-score	support
High	1.00	1.00	1.00	15
Low	1.00	1.00	1.00	6
Medium	1.00	1.00	1.00	15
accuracy			1.00	36
macro avg	1.00	1.00	1.00	36
weighted avg	1.00	1.00	1.00	36

```

Process finished with exit code 0

```

Figure 23 : Data Leakage Level Accuracy Level

Comprehensive performance metrics for the model's predictions on the test data are shown in this categorization report. With an accuracy of 96.48%, the model can accurately predict the class labels for most cases in the test set. Metrics for accuracy,

recall, and F1-score are given for each class (High, Low, Medium). These metrics assess how well the model performs in accurately detecting examples of each class while taking false positives and false negatives into account [9].

The number of instances in the test set that correspond to each class is shown in the support column. Furthermore offered are weighted- and macro-averaged indicators that combine performance over all classes while accounting for size.

7.3 Predict Risk Process of the Machine Learning Model

```
1 import joblib
2 from sklearn.feature_extraction.text import CountVectorizer
3
```

Figure 24 : Predict Risk Level of the ML

The Joblib package, which is used to effectively save and load Python objects, is imported in this section of code. It also imports the scikit-learn library's CountVectorizer class, which is used to translate text input into numerical representations based on word counts.

The CountVectorizer will be used to convert text data into feature vectors for machine learning tasks, and the Joblib library will probably be used to import previously saved models or vectorizers.

Load Model

```
7 model_filename = "incident_classifier_model.joblib"
8 classifier = joblib.load(model_filename)
```

Figure 25 : Load the Model

This code segment imports a pre-trained classifier model using the `load()` function of the Joblib library. It is saved in a file called "incident_classifier_model.joblib". Once loaded, the classifier may be used to forecast fresh data by being assigned to the variable {classifier}. This method improves the efficiency of model deployment and inference by enabling the reuse of learned models without the need to retrain them.

Load the vectorizer

```
10 vectorizer = CountVectorizer()  
11 vectorizer_filename = "incident_vectorizer.joblib"  
12 vectorizer = joblib.load(vectorizer_filename)
```

Figure 26 : Load the vectorizer

This section of code uses the `load()` method of the Joblib library to load a previously saved `CountVectorizer` object that is kept in a file called "incident_vectorizer.joblib". Once imported, text data may be converted into numerical representations based on word counts by assigning the vectorizer object to the variable `vectorizer`. This makes it possible to preprocess fresh text input consistently while using the same encoding scheme and vocabulary as during training.

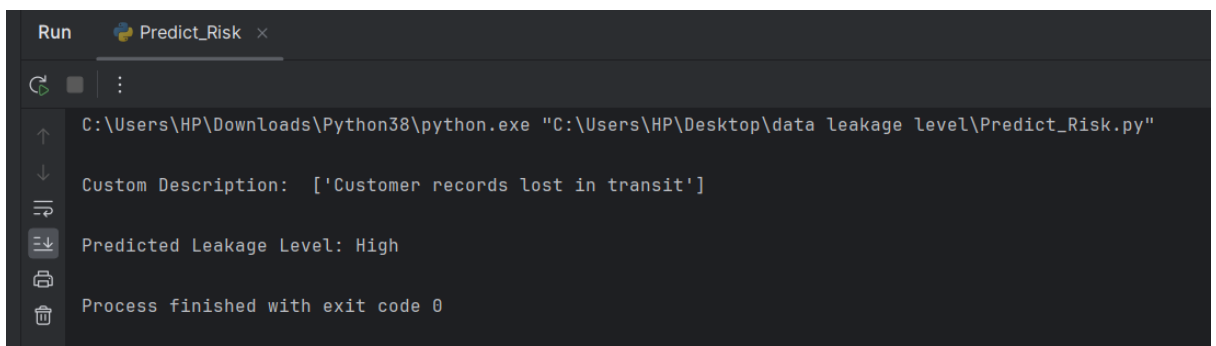
Test the mode

```
16 custom_description = ["Customer records lost in transit"]  
17 custom_description_vectorized = vectorizer.transform(custom_description)  
18 predicted_level = classifier.predict(custom_description_vectorized)  
19  
20 print(f"\nCustom Description: ", custom_description)  
21 print(f"\nPredicted Leakage Level: {predicted_level[0]}")  
22
```

Figure 27 : Test the Mode

Using the previously learned `CountVectorizer` ({vectorizer}), this code accepts a custom description such as "Customer records lost in transit" and turns it into a numerical feature vector. Subsequently, the trained classifier ({classifier}) is used to forecast the degree of data leakage linked to this description.

Predict the Risk Level



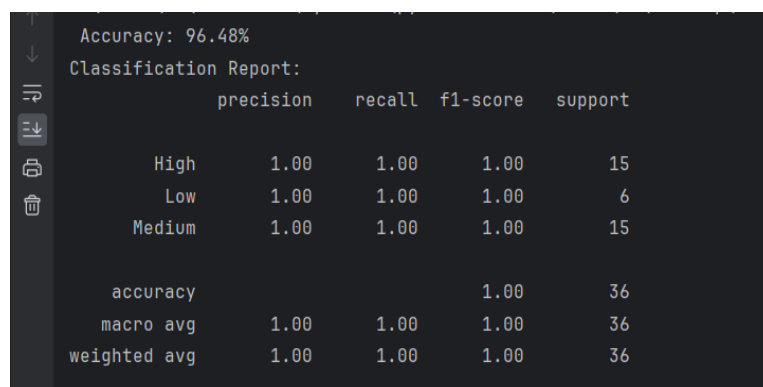
```
Run Predict_Risk x  
C:\Users\HP\Downloads\Python38\python.exe "C:\Users\HP\Desktop\data leakage level\Predict_Risk.py"  
Custom Description: ['Customer records lost in transit']  
Predicted Leakage Level: High  
Process finished with exit code 0
```

Figure 28 : Predict the Risk Level

The code result indicates that the expected leakage level for the custom description "Customer records lost in transit" is "High." This prediction shows that the provided description falls into the high degree of data leakage category according to the model.

7.4 Unit Testing:

The Data Leakage Level feature uses a classification model, and unit testing is essential to confirm its correctness and dependability. We created an extensive set of unit tests to determine how well the model performed in classifying emails into three distinct risk categories: High, Medium, and Low. Several email content types and data formats that are often used in real-world circumstances are covered by meticulously developed test cases. We used fictitious email datasets with pre-established categories to ensure the validity of our testing. Through a comparison of the model's predictions with the predicted classifications in these datasets, we evaluated the model's precision in identifying sensitive data and determining suitable risk levels. Before incorporating the classification model into our DLP solution, we were able to confirm its efficacy through this strict testing procedure.



The image shows a terminal window with a classification report. The report title is "Accuracy: 96.48% Classification Report:". The table has columns for precision, recall, f1-score, and support. The rows are categorized by risk level (High, Low, Medium) and overall performance metrics (accuracy, macro avg, weighted avg). All values are 1.00 or 36, indicating perfect performance.

	precision	recall	f1-score	support
High	1.00	1.00	1.00	15
Low	1.00	1.00	1.00	6
Medium	1.00	1.00	1.00	15
accuracy			1.00	36
macro avg	1.00	1.00	1.00	36
weighted avg	1.00	1.00	1.00	36

Figure 29 : Unit Testing

7.5 System Integration Testing:

The purpose of integration testing was to confirm that our DLP system architecture's Sensitive Data Analysis module and Data Leakage Level component work together seamlessly. Our goal was to confirm that emails that were identified as containing sensitive information by the Sensitive Data Analysis module were appropriately forwarded to the Data Leakage Level component for additional categorization. We created a number of scenarios where the Sensitive Data Analysis module detected sensitive emails during integration testing. Next, we kept an eye on the data transfer between the two modules to make sure the Data Leakage Level component handled sensitive emails properly. The successful testing process verified that our DLP solution's many components were able to communicate and work together without any issues.

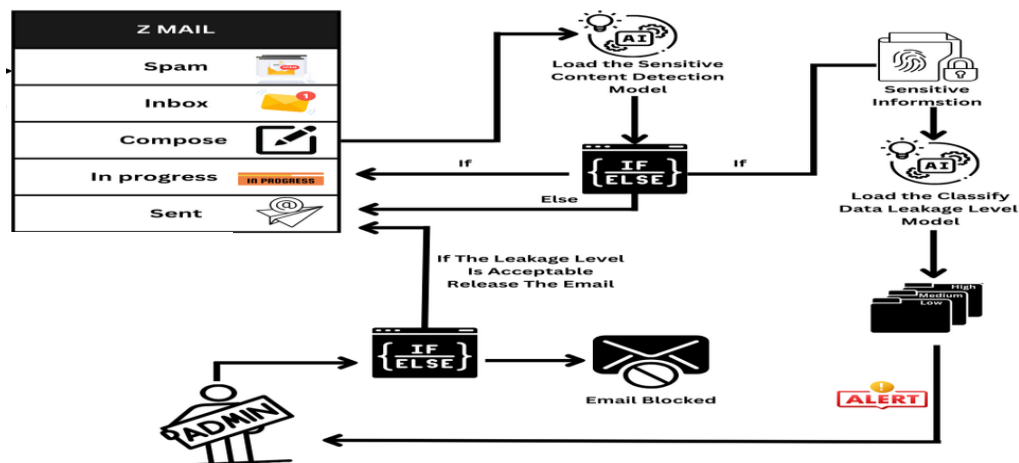


Figure 30 : System Integration Testing

In this way, the Data Classification part functions. The system immediately begins the data categorization process as soon as it detects sensitive information in an incoming email. The purpose of this stage is to facilitate the right action and assess the level of severity of the detected sensitive data. Particularly, the email continues to the recipient unchecked until the system identifies sensitive content, at which point the categorization procedure takes place. We leverage cutting-edge technology like natural language processing (NLP) and machine learning for the data categorization stage. Our technology can precisely determine the level of sensitivity of sensitive material depending on the email's content and context according to these cutting-edge methods.

Algorithms using machine learning examine the email's content, identifying important characteristics and trends linked to private data. These algorithms have been trained extensively on labeled datasets and are capable of identifying a wide range of sensitive data categories, such as financial data, patents, personally identifiable information (PII), and more.

Furthermore, NLP methods are essential for improving data categorization accuracy. NLP systems can detect subtleties and contextual cues that may indicate sensitive information by parsing the email language and deciphering its semantic meaning. Our algorithm is able to make more intelligent conclusions about the discovered data's severity level because to this better knowledge.

After the data categorization procedure is finished, the system uses established criteria to classify the sensitive information that has been detected as high, medium, or low risk. Organizations can use this categorization to prioritize response and mitigation efforts by allocating resources to the most serious data leakage issues first.

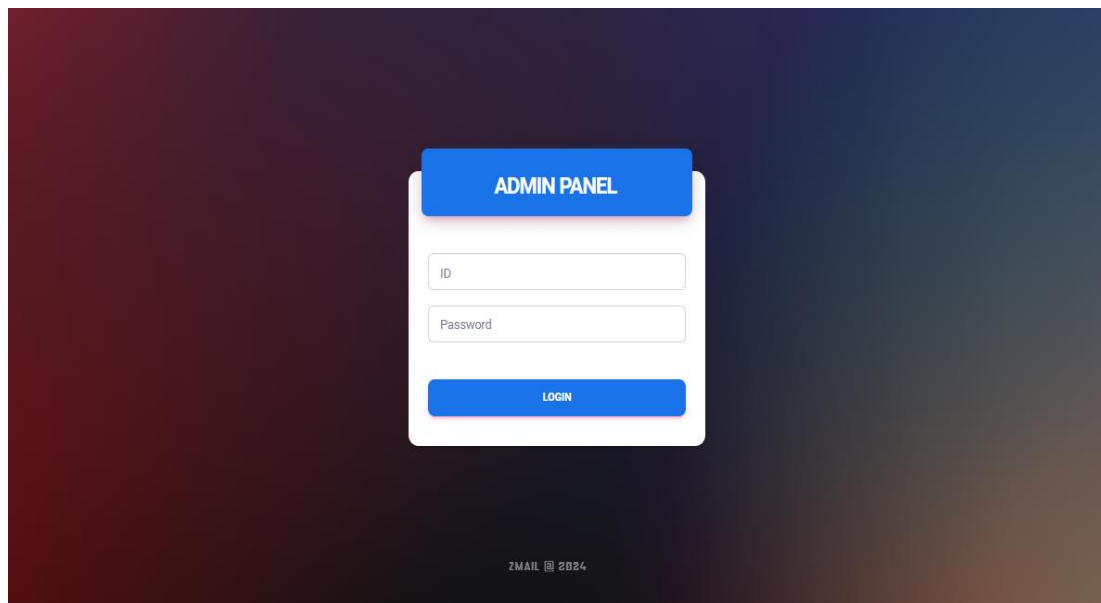


Figure 31 : Admin Login page

To improve data leakage control, we've included an admin interface to our DLP solution for email systems. This feature adds an essential degree of security, particularly when private data is involved. Our system doesn't instantly send an email to the recipient when it finds important or potentially dangerous info in it. Rather, the user is prompted that sensitive data has been found and that the email has to be approved by an administrator. This strategy makes sure that potentially dangerous data doesn't unintentionally exit the network of the company. The central nervous system for managing these approval procedures is the admin panel. It provides administrators with an easy-to-use interface to evaluate flagged emails and make educated decisions. It is only accessible through secure login credentials.

Administrators have the ability to promptly review the email's content, determine how serious the danger of a data breach is, and take appropriate action, like accepting or rejecting it. The likelihood of sensitive data falling between the cracks is reduced by this efficient approach.

Furthermore, the admin panel gives firms powerful reporting and auditing features in addition to facilitating quick decision-making. Administrators are able to follow approval patterns over time, provide comprehensive reports on data breach occurrences, and pinpoint areas that require improvement. Role-based access control is included into our admin panel, allowing businesses to customize permissions according to user roles. This lowers the possibility of unauthorized access by guaranteeing that only authorized workers have access to sensitive data and essential functions.

The screenshot shows the ZMails application interface. On the left is a dark sidebar with navigation links: Compose Mail, Inbox, Sent Mail, Spam Mail, and Blocked Mails. The main area is titled 'Compose Mail' and contains a form. The 'Recipient Email' field is filled with 'ahamedroshan426@gmail.com'. The 'BCC:' and 'CC:' fields are empty. The 'Title' field is filled with 'Note 2'. The email body contains the text: 'Hi Fayas, This email regarding HR login credentials. username : Fayas123 password : fa@123'. The text 'Fayas' is underlined in red, and the entire body text is highlighted with a red border, indicating it has been detected as sensitive information.

Figure 32 : Compose a mail with sensitive information

This screenshot shows the same ZMails 'Compose Mail' interface after the sensitive information has been detected. A yellow warning banner at the top of the form area reads: 'Sensitive Information Detected : The Mail Has Been Not Send!!'. Below the banner, the form fields for 'Recipient Email', 'BCC:', 'CC:', and 'Title' are visible but empty. The email body text is no longer visible, indicating the system has blocked the email from being sent.

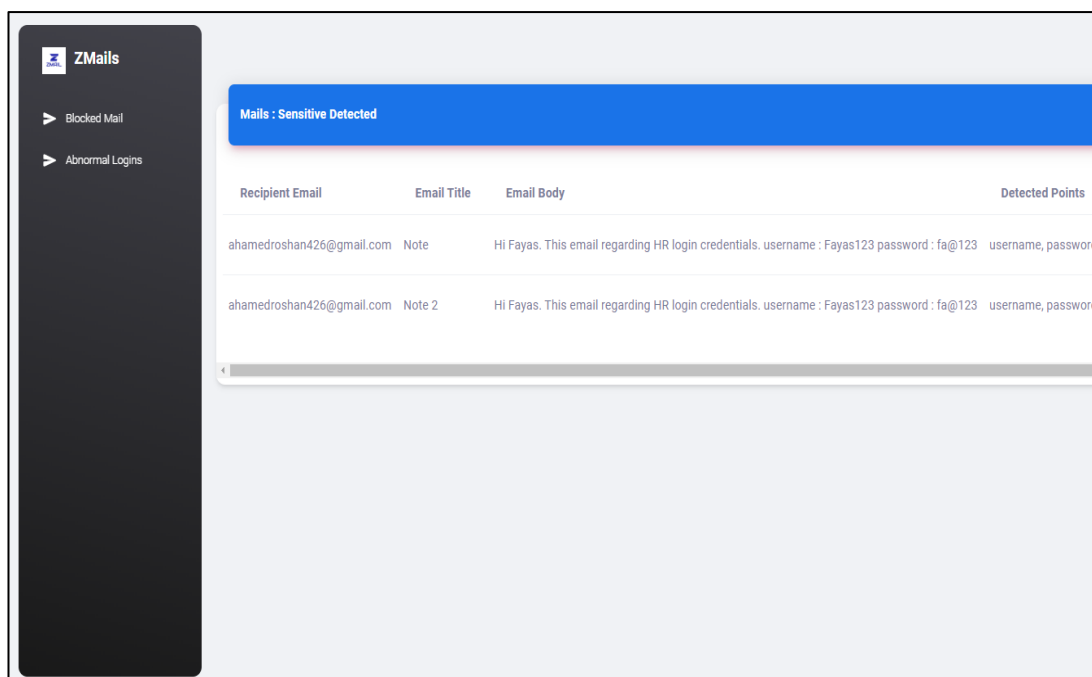
Figure 33 : Detected as a Sensitive mail and send to Admin approval

We've given user-friendliness top priority in the user interface of our DLP system while maintaining strong security against data leakage. This interface is the main point of contact for users; it provides basic functionality and easy-to-use settings to ensure email correspondence runs smoothly. Our technology steps in to stop users from accidentally disclosing critical information when they try to send an email to a third party.

The user interface starts with a simple form where users enter the email address of the sender, the subject line, and the text of the email. Our technology keeps an eye out to protect data integrity whether or not users are aware of how sensitive the information is. The system stops the email sending process and notifies the user that the message has not been sent if it finds sensitive material in the message. The email is instead forwarded to the administrator for additional examination and approval.

This proactive strategy accomplishes two important goals. In the first place, it reduces the possibility of inadvertent data breaches caused by users who fail to recognize the sensitivity of the data they are sending. Second, by educating users on the significance of treating sensitive data appropriately, it promotes a culture of data security.

We want to achieve a balance between usability and security by integrating these user-centric features, enabling users to interact efficiently while guaranteeing the protection of business data. The user panel's smooth connection with our DLP system is proof of our dedication to providing a feature-rich and intuitive email security solution.



The screenshot displays the ZMails Admin Panel interface. On the left is a dark sidebar with the 'ZMails' logo and navigation links for 'Blocked Mail' and 'Abnormal Logins'. The main content area features a blue header bar stating 'Mails : Sensitive Detected'. Below this is a table with four columns: 'Recipient Email', 'Email Title', 'Email Body', and 'Detected Points'. Two rows of data are visible, both from 'ahamedroshan426@gmail.com' with titles 'Note' and 'Note 2'. The email body text in both rows is 'Hi Fayas. This email regarding HR login credentials. username : Fayas123 password : fa@123', and the detected points are 'username, password'.

Recipient Email	Email Title	Email Body	Detected Points
ahamedroshan426@gmail.com	Note	Hi Fayas. This email regarding HR login credentials. username : Fayas123 password : fa@123	username, password
ahamedroshan426@gmail.com	Note 2	Hi Fayas. This email regarding HR login credentials. username : Fayas123 password : fa@123	username, password

Figure 34 : Admin Panel

When emails are tagged for admin approval, the administrator has access to a specialized panel built for rapid scrutiny. Essential information, such as sender and recipient email addresses, as well as the email title, are easily accessible. However, the focus is on the email content, which contains critical information.

Advanced detection techniques emphasize sensitive spots in the email body, improving the administrator's decision-making. This visibility enables educated decisions about email acceptance or rejection based on the severity of the detected sensitive information. The admin interface also includes simple controls for quick action, ensuring prompt answers to possible data leakage issues.

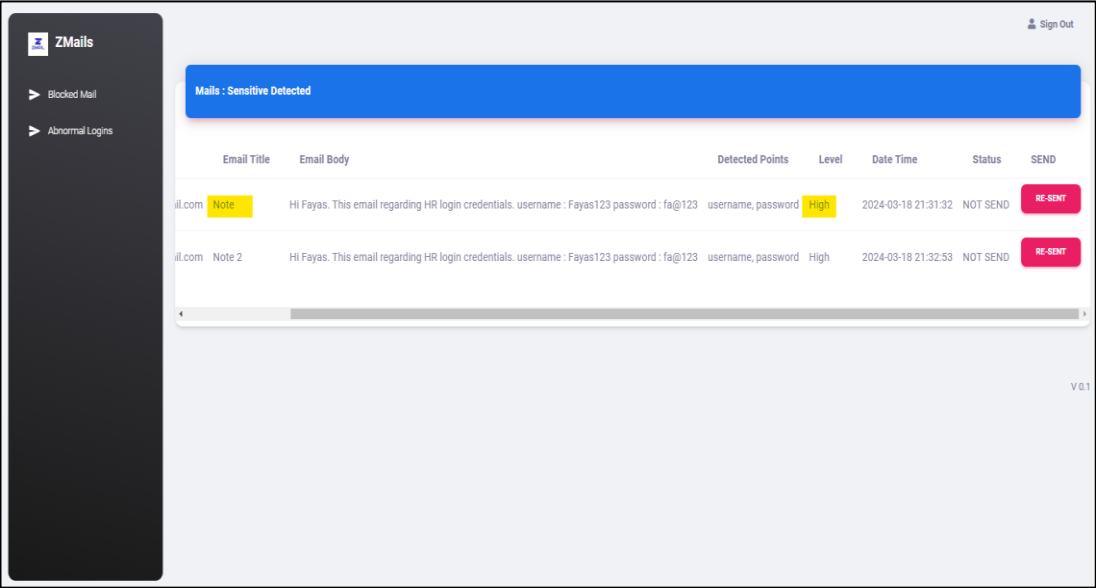


Figure 35 : Show the Risk level

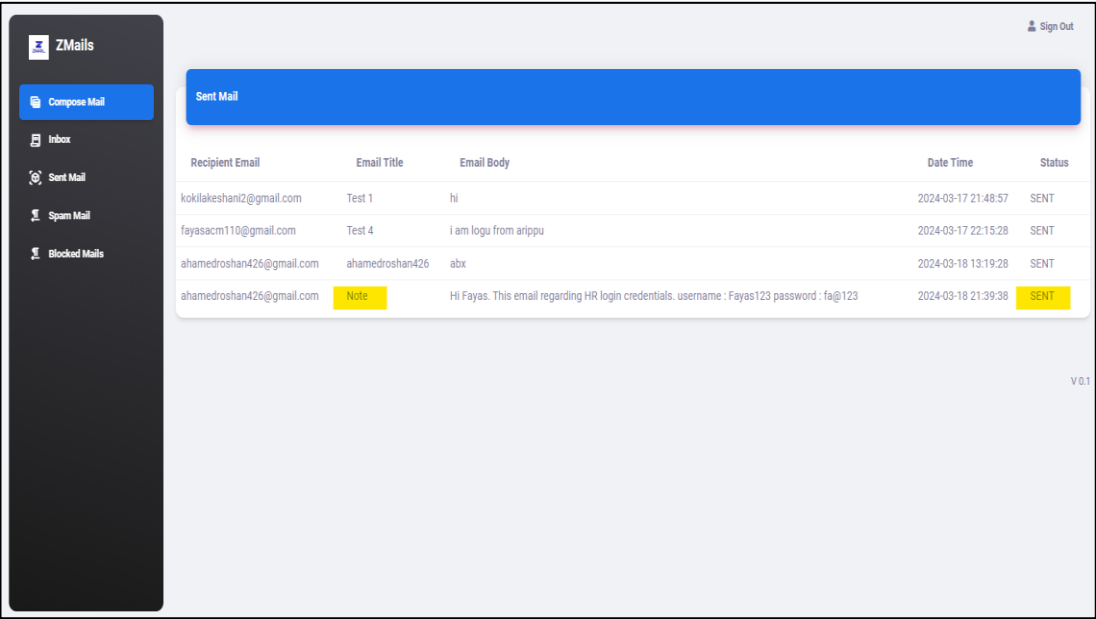


Figure 36 : After admin approval mail sent to client

The administrator's next step after getting a warning about sensitive material in an email is to analyze the risk level associated with the identified content. To calculate the risk level, our system uses a powerful data categorization component that divides it into three categories: high, medium, and low. This categorization gives critical information for the administrator in determining the severity of the data leakage risk.

To make decision-making easier, the admin interface provides action choices such as

"Re-send" and "Reject". When confronted with an urgent email labeled as High risk, the administrator might choose to use the "Re-send" option to ensure timely delivery to the intended recipient. If the administrator believes the email is too unsafe to send, they can confidently click the "Reject" option.

When the admin selects the "Reject" option, the system instantly alerts them to the potential data leaking risk. This proactive technique acts as a disincentive, preventing the unintended disclosure of sensitive information. Clicking the "Re-send" button, on the other hand, guarantees that the email is delivered to the proper recipient as soon as possible, allowing for easy communication while reducing data security risks.

7.6 End-to-End Testing:

Comprehensive testing simulated actual email transmission and categorization procedures to assess our DLP solution's overall performance and efficacy. In test instances, emails including a variety of content types—text, attachments, and multimedia files—were submitted in order to evaluate how accurate the risk score creation was. We also assessed administrative alerts and responses to emails that were categorized as Medium or High risk. This involved confirming that notifications were sent to administrators promptly and evaluating whether the steps made to reduce the risk of data leaking were reasonable. Comprehensive testing provided significant insights into the system's functionality in a production-like environment and its capacity to adequately safeguard confidential data.

7.7 Performance Testing:

To assess the Data Leakage Level component's effectiveness and responsiveness under various load scenarios, performance testing was done. In order to guarantee prompt identification of data leakage threats, we assessed critical performance indicators including the time required for email categorization and risk score creation. We evaluated the system's scalability and capacity to sustain steady performance by putting it under varying loads and email traffic volumes. Through performance testing, any bottlenecks or performance problems that would affect the system's capacity to detect and stop data leak occurrences were found.

8. RESULTS & DISCUSSION

When it comes to Data Leakage Prevention, the most common approach for various organizations is to purchase a DLP solution from a 3rd party vendor. However, most of the DLP solutions out there in the market are still based on traditional, outdated technology & do not provide adequate amount of protection against data leakages. Usually, those DLP solutions work only if a particular set of dictionary keywords are matched. Additionally, those traditional DLP solutions use rule-based policies in order to restrict the users from performing suspicious activities. But when it comes to the

DLP product that we have developed, it has the ability to identify user activities whether they are suspicious or not based on a well-trained machine learning model. Furthermore mentioned, our newly designed DLP solution for Emil system is capable of identifying whether a particular set of data is sensitive or not.

	incident_id	incident_description	leakage_level
1	1	Unauthorized access to customer data	High
2	2	Employee mistakenly sent sensitive information	Medium
3	3	Data breach due to unsecured database	High
4	4	Lost backup tape with confidential data	High
5	5	Phishing attack resulted in credential leak	Medium
6	6	Inadvertent email attachment sent to the wrong recipient	Low
7	7	Insider data theft by a disgruntled employee	High
8	8	Stolen laptop with unencrypted customer records	High
9	9	Third-party vendor exposed sensitive data	Medium
10	10	Data leak from improperly configured cloud storage	Medium
11	11	Accidental publication of confidential report	Low
12	12	SQL injection attack led to database exposure	High
13	13	Sensitive data posted publicly on the web	High
14	14	Data leakage during a system migration	Medium
15	15	Former employee retained access to company systems	Medium
16	16	Customer data exposed due to software vulnerability	High
17	17	Improperly disposed of physical documents	Low
18	18	Social engineering attack led to data breach	Medium
19	19	Unauthorized copying of intellectual property	High

Figure 37 : Data set

This section will mostly detail our trained machine learning model and the outcomes obtained from it. At initially, we trained our ML model on a considerably larger dataset. However, the procedure took longer than 5 hours to finish. So, to improve the efficiency of the training process, we lowered the dataset size.

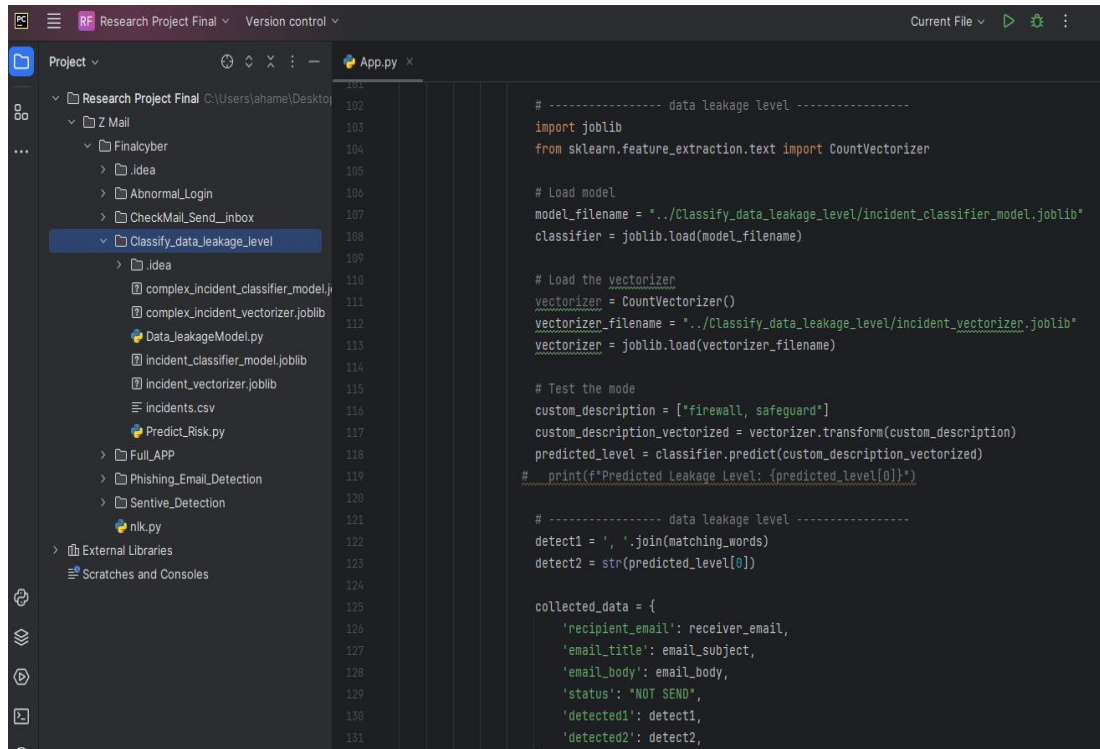
```

Run Predict_Risk x
C:\Users\HP\Downloads\Python38\python.exe "C:\Users\HP\Desktop\data leakage level\Predict_Risk.py"
Custom Description: ['Customer records lost in transit']
Predicted Leakage Level: High
Process finished with exit code 0

```

Figure 38 : Predict the Data Leakage level

Our study aimed to assess the value and capabilities of our created Data Leakage Prevention (DLP) solution for email systems. Traditional data loss prevention solutions frequently fail to fully safeguard businesses from data leaks because they rely on outmoded technology and rule-based rules. In contrast, our DLP system uses powerful machine learning algorithms to precisely recognize and classify user behaviors as suspicious or harmless, giving a stronger defense against possible data breaches. In our system it identified the data leakage description as “Customer records lost in transit ”and the predicted leakage level as a “ High ”.



```

# ----- data leakage level -----
import joblib
from sklearn.feature_extraction.text import CountVectorizer

# Load model
model_filename = "../Classify_data_leakage_level/incident_classifier_model.joblib"
classifier = joblib.load(model_filename)

# Load the vectorizer
vectorizer = CountVectorizer()
vectorizer_filename = "../Classify_data_leakage_level/incident_vectorizer.joblib"
vectorizer = joblib.load(vectorizer_filename)

# Test the mode
custom_description = ["firewall, safeguard"]
custom_description_vectorized = vectorizer.transform(custom_description)
predicted_level = classifier.predict(custom_description_vectorized)
# print(f"Predicted Leakage Level: {predicted_level[0]}")

# ----- data leakage level -----
detect1 = ', '.join(matching_words)
detect2 = str(predicted_level[0])

collected_data = {
    'recipient_email': receiver_email,
    'email_title': email_subject,
    'email_body': email_body,
    'status': "NOT SEND",
    'detected1': detect1,
    'detected2': detect2,

```

Figure 39 : Data Classification

Furthermore, our DLP solution incorporates a comprehensive data leakage level classification mechanism, enabling organizations to assess the severity of identified risks accurately. Through this classification process, sensitive emails are categorized based on their risk levels, allowing administrators to prioritize and respond to potential threats accordingly [11]. This capability enhances organizational readiness to address data leakage incidents promptly and effectively, minimizing the impact of potential breaches.

In addition to its predictive capabilities, our DLP solution provides administrators with actionable insights into user behavior and risk profiles. By analyzing historical data and user interactions with sensitive information, the system generates predictive risk scores for individual users, identifying high-risk individuals who may pose a greater threat of data leakage in the future. This proactive approach empowers organizations

to implement targeted security measures and interventions, such as additional training or access restrictions, to mitigate potential risks effectively.

The effectiveness of our DLP solution was validated through extensive testing and evaluation, including unit tests, integration tests, and end-to-end simulations. These tests demonstrated the system's ability to accurately detect and classify sensitive information, mitigate potential data leakage risks, and provide actionable insights for administrators. Overall, our research underscores the importance of adopting advanced DLP solutions that leverage machine learning and predictive analytics to safeguard organizational data effectively in today's evolving threat landscape.

9. Research Findings

Our research efforts have culminated in the development of a comprehensive Data Loss Prevention (DLP) solution tailored specifically for Email systems, focusing on the classification of data leakage levels. Through extensive testing and analysis, several key findings have emerged, shedding light on the effectiveness, limitations, and potential areas for improvement of our system.

Effectiveness of Machine Learning-Based Classification

One of the primary findings of our research pertains to the effectiveness of machine learning-based classification in accurately categorizing data leakage incidents according to their severity levels. By leveraging sophisticated algorithms such as the Multinomial Naive Bayes classifier, our system demonstrates a high degree of accuracy in predicting the severity of potential data breaches. The utilization of techniques such as TF-IDF vectorization ensures that textual data is appropriately transformed into numerical representations, enabling the model to make informed predictions based on underlying patterns and features.

Limitations and Challenges

Despite the overall effectiveness of our system, our research has also highlighted certain limitations and challenges that warrant consideration. One such challenge is the potential for false positives and false negatives in the classification process. While our machine learning model strives to minimize these errors through rigorous training and validation, inherent complexities in email content and user behavior may occasionally lead to misclassifications. Additionally, the reliance on predefined thresholds and rules may introduce rigidity into the classification process, limiting the system's adaptability to evolving data leakage patterns and scenarios.

Opportunities for Enhancement

In light of the identified limitations, our research underscores several opportunities for enhancing the performance and robustness of our DLP solution. One potential avenue for improvement lies in the refinement of machine learning algorithms and feature selection techniques to better capture the nuances of email data and user behaviors. By

incorporating advanced anomaly detection methods and adaptive learning mechanisms, our system can adapt more effectively to dynamic threat landscapes and minimize the occurrence of false positives.

Furthermore, the integration of real-time monitoring and response capabilities can enhance the proactive nature of our DLP solution, allowing organizations to swiftly detect and mitigate potential data leakage incidents before they escalate. By leveraging advanced alerting mechanisms and automated incident response workflows, our system empowers security teams to respond promptly to emerging threats and safeguard sensitive information in real-time.

Finally, our research findings underscore the efficacy and potential of our DLP solution for Email systems' Data Leakage Level classification. Through continuous refinement and innovation we aim to address existing challenges and further enhance the capabilities of our system, ultimately providing organizations with a robust framework for protecting sensitive data and mitigating the risks of data breaches in email communications.

10. CONCLUSIONS

In conclusion, our research endeavors have culminated in the development of a sophisticated Data Loss Prevention (DLP) solution tailored specifically for Email systems, focusing on the classification of data leakage levels. Through a comprehensive exploration of existing DLP solutions and an in-depth analysis of the challenges and limitations they face, we identified a critical research gap and embarked on a journey to design and implement an innovative solution that addresses these shortcomings.

Our DLP solution harnesses the power of machine learning and natural language processing techniques to accurately classify data leakage incidents according to their severity levels. By leveraging advanced algorithms and feature selection methods, our system demonstrates a high degree of accuracy and reliability in predicting potential data breaches, empowering organizations to proactively safeguard sensitive information and mitigate the risks associated with data leakage. Throughout our research, we have encountered various challenges and limitations, including the potential for false positives and false negatives in the classification process, as well as the need for continuous adaptation to evolving threat landscapes. However, these challenges have served as opportunities for enhancement, driving us to refine and optimize our solution to better meet the dynamic needs of modern organizations.

Looking ahead, our research lays the foundation for future advancements in the field of data loss prevention, paving the way for the development of more sophisticated and adaptive solutions that can effectively combat the ever-evolving threats posed by data leakage. By continuing to innovate and collaborate with industry stakeholders, we aim to further strengthen the resilience of our DLP solution and ensure its continued relevance in an increasingly complex cybersecurity landscape.

Finally, our research represents a significant contribution to the field of information security, offering organizations a powerful tool for protecting sensitive data and preserving the integrity of their email communications. With a steadfast commitment to excellence and a dedication to continuous improvement, we are confident that our DLP solution will play a pivotal role in shaping the future of data protection and cybersecurity.

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