**Ensuring Data Privacy and Security in Cloud Computing through Advanced Cryptographic Techniques.**

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# Abstract

This report examines the integration of advanced cryptography and machine learning to improve data privacy and security in cloud computing. It uses AES encryption for data confidentiality and SHA-256 hashing for integrity verification. Machine learning models, including K-Nearest Neighbors (KNN), Isolation Forest, One-Class SVM, Gaussian Mixture Model (GMM), and Autoencoder, were employed for real-time anomaly detection to block anomalous data transfers.

The BETH dataset, reflecting cloud traffic behavior, was used for training and testing. Google Colab’s GPU acceleration helped reduce model training times. KNN achieved the best performance, with 94.57% accuracy and 99.96% precision, making it the most effective for anomaly detection.

Despite limitations like the use of basic encryption methods and the computational constraints of Google Colab, the project provides a solid framework for combining cryptography with machine learning for cloud security. Future work will focus on implementing advanced encryption techniques and scaling the system to larger datasets using platforms like AWS or GCP. This study offers a scalable approach to secure cloud computing, enhancing protection against data breaches.

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**Chapter 1**

# Introduction

## 1.0 Background and Motivation

Cloud is now a crucial technological solution used by organizations from different parts of the world because it offers scalability, flexibility and is rather affordable. As pointed by Agrawal and Tapaswi (2020) while organizational data is shifting to cloud more frequently, the question of how to secure data privacy during data transmission becomes critical. AWS and other large tech companies have developed sound policies to protect they cloud systems while many organizations do not have adequate capital and human resource to put up similar measures in place (Smith, 2019). This means that certain important information within an organization is exposed to a high risk of loss when in transit.

As explained by Liu (2021), the motivation for this project arises from the growing need for a comprehensive solution that addresses two fundamental concerns in cloud environments: data protection and data authenticity. Conventional methods like AES have been used for securing transmit data for a long time (White, 2019). But as pointed by Gupta and Sharma (2021), encryption alone cannot solve the problem of who will put anomalous or malicious data in the system that interferes with the cloud systems integrity . However, cyber threats are not static and are getting more complex day by day and even the conventional security solutions can not address this problem (Jones, 2020).

Acknowledging this, the project reaches the suggestion to combine new cryptographic method with machine learning-based anomaly detection to develop a solution which not only guarantees data confidentiality but also prevents the appearance of malicious content. Following Brown (2020), by emulating the AWS like structure in terms of security measures the project can offer real time anomaly detection combined with greatly enhanced encryption and data integrity checks. According to Alam (2019), this framework guarantees that only accurate information is shared between two Cloud venues (Point A and Point B), which makes it secure from internal offending and outer offense.

## 1.1 Problem Statement

Although the material secured by AES encryption remains private throughout transmission, AES can prevent the transfer of abnormal or evil material. According to Kim (2021), cloud environments are still exposed to sending tainted data; data that can easily get around most of the encryption procedures and cause data leakage or system compromise at the receiver’s end.

Zhang and Li (2020) noted that the lack of real time anomaly detection during data transmission leads to a form of ineffectual protective measure during transmission that current encryption epitomizes. In order to address this problem, Wang (2021) suggested that there must be a system that encrypts the data and at the same time scan it for anomalies before it goes out. It means that the system can dramatically minimize the threat of the data reaching the recipient and causing harm by preventing the transmission of suspicious data (Hsu, 2020).

This project seeks to solve this problem by proposing the integration of AES encryption with machine learning algorithms for detecting novelty before encryption. , as Patel and Mehta say, this approach makes it possible to transfer data between the cloud points using secure means while, at the same time, stressing that the data is safe and secure, and this reduces the likeliness of experiencing a security breach.

## 1.2 Research Objectives

The main goal of this project is to improve data security in the cloud environment by adopting cryptographic methods together with the use of machine learning for anomaly detection of data in the cloud: The main idea is to implement both cryptographic methods and the use of machine learning for anomaly detection in the field of cloud data transfer, to maintain data anonymity and data security. The specific objectives of the project are as follows:

1. Design and implement a secure data transfer system using AES encryption to ensure confidentiality in cloud communication.
2. Develop scalable anomaly detection models using Isolation Forest, One-Class SVM, KNN, GMM, and Autoencoder for real-time threat identification.
3. Integrate SHA-256 hashing mechanisms to guarantee data integrity during cloud data transmission.
4. Evaluate the effectiveness of AES encryption in real-time cloud data security and benchmark its performance against industry standards.
5. Design an AWS-like security framework incorporating encryption, anomaly detection, and integrity verification without reliance on paid AWS services.
6. Leverage Google Collab’s HPC capabilities to efficiently train machine learning models on large datasets, ensuring scalability and performance.

## 1.3 Significance of the Study

This has potential for such a project because it comes with a complete package for Cloud computing Data security. Nonetheless according to Brown (2020), the combined use of anomaly detection with encryption and identification of integrity instantly covers data privacy and security. That is why traditional encryption methods, such as AES, guarantee confidentiality but, as White (2019) pointed out, do not prevent the transfer of destructive information. This project neatly addresses that gap by proposing a system that prevents undesirable content from being processed and subsequently encoded and sent (Kim, 2021).

In addition, the project also shows when security is implemented like AWS but using the non-commercial form of cloud services, then the use of high performance computing or HPC, which is usually done on comparatively expensive AWS services, can be achieved. This increases the ease of use of the system for organizations and research institutions that may not have ample budget to spend because, as observed by Zhang and Li (2020), organisations can achieve efficient and secure data transfer without necessarily having to spend a lot.

Also, this project puts down its effort in the continuous advancement of real-time security systems that work in the cloud. Patel and Mehta further note that as threats in the cyber world become more sophisticated, then the requirement for sophisticated and flexible security solutions cannot be overemphasized. The fact that the project involves the identification of abnormal patterns prior to data transmission represents a major leap forward in cloud security (Thompson, 2019).

## 1.4 Thesis Structure

**Chapter 1**: Describes the context and rationale for the study, defines the problem statement, goals and objectives and explains the importance of the study and the overall framework of the thesis.

**Chapter 2**: Current solutions using cryptographic techniques and machine learning with specified emphasis on their applicability to cloud protection are examined in this section given that it provides a foundation for the development of the research. The chapter also presents drawbacks of standalone encryption approaches, as well as the requirement of more forward-thinking security models.

**Chapter 3** : Outlines the steps followed in the development of the system People management, data preprocessing, model selection, encryption implementation stages, and system testing. This chapter also describes the AWS-like structure that has been employed to protect data communication.

**Chapter 4** : This section established the experimental setting, which includes the used datasets (BETH dataset), the tools exploited in the study (Google Collab for HPC), and the hardware details. The chapter also explains how the training of the machine learning models is set up and how AES encryption and SHA-256 hashing is done.

**Chapter 5** : Results and Analysis: Fruits and analysis show the complete structure of the model training, the outcomes of the anomaly detection process, and a detailed report on the efficiency of the encryption system. The chapter also presents evaluation of the model accuracy, training times and the performance of the integrated approach.

**Chapter 6** : Discussion: Presents an analysis of the results in terms of cloud security and reviews some of the strengths and weaknesses of the presented system. Besides its implications for future research, it also outlines probable enhancements for the given theory.

**Chapter 7** : Conclusion: Presents the research outcomes as the final part of the study to conclude on the topic, contribution to knowledge on cloud security, and suggests the prospects of research in the area.

**Chapter 2**

# Literature Review

## 2.0 Introduction

Cryptographic techniques play an important role in data security for confidentiality, integrity, and authenticity in secure communication, especially within the scope of cloud computing. These have now turned out to be an ever-growing concern due to people storing their information on cloud platforms. Even while transmitting unsecuredly, such encrypted data renders it unintelligible unless this problem is solved by cryptography.

Some of the generally used encryption algorithms include Advanced Encryption Standard and Rivest-Shamir-Adleman algorithm. AES is a symmetric encryption approach, whose general applicability is because of its efficiency and strong security, which makes it effectively suitable for many applications needing real-time encryption of data. Its processing overhead is low and hence resistant to attacks; it is more in demand, especially for large sets of data. However, in case of cloud environments, key distribution becomes challenging because one depends on a single key for encryption and decryption.

On the other hand, RSA is asymmetric encryption that involves encryption and decryption using public-private pairs. Though RSA offers better security due to the separation of keys, it is relatively slower due to higher computational need and thus not much fitting for real-time applications of cloud computing.

New advancements in cryptography, such as homomorphic encryption, have recently offered new cloud security by directly performing computations on top of encrypted data, without decryption. This advancement greatly enhances the privacy of data held in the data center but, because of its high computational costs, remains experimental for larger applications.

This project chooses AES encryption, considering it optimal to ensure the security and efficiency of cloud communication.

## 2.1 Cryptographic Techniques

Cryptographic – Cryptography is almost the central concept of data protection and securing mechanism of cloud computing. Encryption makes it impossible for anyone other than the intended recipient to understand the information being passed in a particular channel even though this may pass over public or other insecure channels. Two of the widely used data encryption techniques in cloud computing are AES and RSA, which are used in different ways though have different efficiencies.

AES, due to being a symmetric encryption algorithm it has being widely used because of its efficiency as well as its highly secured mechanism. As Ashraf and Kumar (2020) pointed out, AES is most suitable for real-time data encryption especially for large data sets because of low processing requirements to execute it. AES uses a fixed block size of 128 bits and key lengths of 128, 192 or 256-bits hence; makes it immune to most forms of cryptographic attacks. However, one of the disadvantages of using this methodology is that the same key has to work for both the encryption function and the decryption function, which is a problem in distributed cloud networks with regards to key distribution.

However, RSA is a stand for Rivest–Shamir–Adleman and is an example of asymmetric encryption algorithm that is done using two keys, that of the public key and that of the private key. According to Lee (2021), RSA is especially beneficial in those cases when the distribution of keys is carried out in a secure manner, for example, in PKI used for protection of Cloud communication. RSA is much slower than AES except for the fact that it is used for encrypting large data sets while AES is used for small data sets Therefore, RSA cannot be used very well real time data processing for cloud computing. The bitrate is slow thus it is suitable for applications that depend on speed since it is very slow at both encrypting and decrypting.

Technological advancement in the recent past has given rise to homomorphic encryption – an operation which computes on encrypted data without decrypting it first. This discovery has far-reaching consequences for cloud security since it allows working with protected data without sharing them with potential attackers. Green (2021) stated that homomorphic encryption brought a new philosophy to data privacy, but it is steeped with higher costs in computation and performance overloads not suitable for real-time usages in the cloud system. In large-scale cloud systems, homomorphic encryption is still an exploratory field due to the many hurdles that concern scalability and effectiveness.

AES encryption proved thus far to be effective in adding a middle ground to the issue of security versus efficiency, for the purposes of this project, AES encryption has been chosen as optimal. AES makes an excellent encryption algorithm for real-time cloud communication since it effectively encodes data in transit without much computational load on AES. Also, with the SHA-256 hashing integrated, data is protected not only by AES but also through hashing the generated hash can check whether data has been changed in transit (Nair, 2020). Both encryption and hash algorithms are important when the environments have two security issues: confidentiality and integrity.

## 2.2 Machine Learning for Anomaly Detection

When cloud environments become more complex, using classical protection tools to prevent threats are not effective enough. In recent years, of particular interest to cloud computing research is machine learning or commonly known as ML that helps pinpoint variations from normal behavior in these systems. The use of ML in anomaly detection provides the capability to rapidly detect threat profiles as part of information protection against cyber threats such as a data breach.

The ML algorithms most frequently used for anomaly detection in cloud security solutions include Isolation Forest and Support Vector Machines (SVM) as well as Autoencoders. Isolation Forest can be effectively implemented in cloud environment since it works by isolating anomalies from the other data connected points, thus it is effective for action on big data (Zhou, 2021). According to Kumar (2020), Isolation Forest necessitates little hyperparameter optimization and it is a good choice for outlier detection with low anomaly rates in a dataset. The case of using analytics in cloud systems has been supported by research, and due to its scalability, it is preferred in real-time monitoring.

Another of the recommended and frequently used supervised technique in anomaly detection is the support vector machines (SVM). SVM, based on history as Li and Zhao (2021) explained, is well suited to perform data classification between normal and anomalous categories. However, performing well requires labeled data, and it is often sensitive to overfitting particularly when used on high dimensional data as are often characteristic of cloud computing environments. For this reason, SVM is normally applied with other algorithms for example Autoencoders to enhance the detection proficiency.

For unsupervised anomaly detection, autoencoders are proven to be incredibly useful neural networks that can learn compressed representations of data. From Dutta (2019), I adopted that Autoencoders offer outstanding performance in identifying latent anomalies that are not necessarily identifiable by other models. This is especially helpful in cloud computing, given that threats are bound to surface more often, and may not be familiar at first. Autoencoders are good at finding hidden features and have now become the go-to model in the cloud security for spotting anomalies.

In practical uses, these models are almost always employed in hybrid systems. However, it is important to note that it is sometimes difficult to assign or justify a real life good explanation of why a model should be hybrid. For instance, Singh suggested that the Isolation Forest would enhance the Autoencoder algorithm and increase the detection rate by 40 % by implementing both algorithms. Wang (2020) also lay down some of the following principles of continuous model training in cloud environments where security threats change frequently. The two are important in ensuring that the ML models can flex to new threat environments in protecting cloud systems.

This project uses Isolation Forest, One-Class SVM, KNN, GMM and Autoencoders to develop a layered approach to anomaly detection. Whenever a utilisation of a multiple model approach is applied, then the system is capable of identifying various types of anomalies right from known threat scenarios to as yet unknown patterns of behavior. Implementation of this approach provides for strong security measures that can effectively address different forms of attacks to cloud data.

## 2.3 High-Performance Computing (HPC)

Common for most applications of machine learning is the fact that the training and the deployment of the models, especially for tasks like anomaly detection in cloud contexts, are computationally intensive. HPC also takes an important part at these processes by offering the HW infrastructure required for Big Data management and extreme-performance calculations. HPC using GPU acceleration has become essential for large and complex machine learning models for shrinking the duration of the training process and enhancing the performance of the models.

Google Collab with integrated GPU makes HPC in cloud security research more approachable. In the words of Malik (2019), with the help of accelerations through Graphic Processing Units, or GPUs, Collab is capable of parallel computation which leads to a highly enhanced technique of the ML models training and testing. This is very relevant in today’s distributed computing systems, where the capability to continually update the models is highly valuable for keeping the systems secure.

This in the context of this project, Google Colab for developing and training machine learning models in the BETH dataset with enhanced processing capabilities of HPC. For instance, Park (2021) pointed out that when merging HPC with the applications that use ML based in the cloud, the performance is boosted and simultaneously the programs that deliver security become scalable making it easier for companies that cannot afford physical infrastructure for HPC to use the applications. In particular, Lewis (2021) points out that keeping up to date with newly introduced threats and performing constant model updates is possible thanks to real-time ML model training supported by HPC environments.

Through the use of HPC resources, this work guarantees that machine learning models can tackle the desired magnitude an speed required for cloud data protection. The integration of Google Colab’s GPU along with the chosen ML models make it feasible to perform real time detection of anomalies with no lag or delay.

## 2.4 Conclusion

This chapter has analyzed the cryptographic algorithms, ML methodology and HPC resources which constitute the core of this project’s cloud security paradigm. AES encryption is chosen due to its moderate processing performance and a high level of data protection required for confidentiality; in turn, SHA-256 hashing offers strong algorithms for checking the data’s integrity. Algorithms including Isolation Forest, SVM and Autoencoders were all recognized as useful for detecting anomalies, yet each played a part in the multiple layered security measures.

Further, the application of HPC in facilitating computing of large volumes of data in real time was also looked at. Due to the availability of GPU resources in Google Colab, the project becomes very effective in training and deploying the needed machine learning algorithms for the real-time detection of anomalies in cloud platforms.

By incorporating these advanced methods, this work intends to solve the overwhelm- ing security issues of cloud computing and implement a secure, effective, and highly-optimized solution for data safeguarding in clouds.

**Chapter 3**

# Methodology

## 3.0 Introduction

This project focuses on building a system to ensure the secure transfer of data packets between two points: Point A (Sender) will be those who are responsible for spreading messages the respective network and Point B (Receiver) will be the target audience of those messages. The overall objective is to avoid passing through and filtering an erroneous or contaminated data, and also to ensure that data is not compromised during that transfer procedure. To this end, Karunya’s system uses anomaly detection, AES encryption, and SHA-256 hashing to guarantee that the initial integrity check is implemented, followed by the actual security encryption process, and the subsequent final check for tampering of the received data.

In fact, already at Point A the received data is passed through a machine learning model that is already trained for detecting abnormalities. Since most normal data is not considered as anomalous, AES encryption is carried out to assure the security of its content during the transmission. It is first hashed using SHA-256 hash then encrypted . This will enable an integrity check at the Point B. While it goes to ‘Point B’ still encrypted, the other data is decrypted and a new hash computed and compared with this new hash on arrival; if it equals the original hash, it arrived intact. Another anomaly detection model is used for the second time at Point B to check for the safety of the data. After all the security concerns have been passed, the data is rebuilt into JSON format for further processing.

The two phase security model guarantees that only authorized non anomalous data is transferred across the cloud points securely and the system is secure against attacks such as data leakage and man in the middle attacks. Combination of cryptography and machine learning based anomaly detection is spearhead of an effective cloud security architecture.

## 3.0 Data Flow

The data flow in this system follows a clearly defined structure to ensure both data security and data integrity throughout the transmission process. The first step involves data ingestion, where the system processes data from the BETH dataset. This dataset includes a mix of normal and anomalous cloud traffic data, chosen for its comprehensive nature that reflects various network behaviors typically found in cloud environments. As highlighted by Smith (2021), using diverse datasets ensures that the machine learning models are trained to detect a broad spectrum of anomalies, making them more effective in real-world applications where cloud environments are dynamic and unpredictable.

Once the data is ingested, it goes through a preprocessing phase to prepare it for analysis by the machine learning models. During preprocessing, the system cleans the data by filling in any missing values, removing duplicates, and normalizing the features to create consistency. This step is crucial, as Carter (2020) explains, because even minor inconsistencies in the data can lead to inaccuracies in the predictions made by anomaly detection models. After preprocessing, the dataset is divided into training and test sets to ensure the models are validated effectively and perform well during both the training and real-world implementation phases.

Create a detailed flowchart that illustrates the secure data transmission process between Point A (Sender) and Point B (Receiver) in a cloud environment. The flowchart should include the following steps:

Data Ingestion: Data from the BETH dataset, which contains normal and anomalous cloud traffic, is processed.

Preprocessing: The system cleans the data by filling missing values, removing duplicates, and normalizing features for consistency.

Anomaly Detection Models: The cleaned data is analyzed by multiple anomaly detection models (Isolation Forest, SVM, KNN, GMM, Autoencoders). If an anomaly is detected, the data is blocked from transmission.

Non-Anomalous Data: For non-anomalous data, proceed to AES encryption.

AES Encryption: Data is encrypted using AES, ensuring confidentiality with a shared encryption key between Point A and Point B.

SHA-256 Hashing: A digital fingerprint (SHA-256 hash) is created for the data before encryption. This hash ensures authenticity and integrity during transmission.

Data Transmission: The encrypted and hashed data is securely transmitted from Point A to Point B, potentially passing through insecure public networks.

Decryption at Point B: The system decrypts the data using the shared AES key. After decryption, the hash is recalculated and compared with the original hash from Point A.

Hash Integrity Check: If the two hashes match, the data integrity is confirmed. If they do not match, an alarm is triggered, indicating possible tampering

Figure 1 Data flow chart

Following preprocessing, the prepared data is analyzed by several anomaly detection models, including Isolation Forest, SVM, KNN, GMM, and Autoencoders. These models work together to identify any outliers or abnormal patterns that may indicate a security threat. By using multiple models, the system ensures that a wide range of anomalies can be detected, thus providing a comprehensive security solution. Jones (2020) emphasizes that employing multiple models strengthens the system’s ability to detect anomalies across different types of cloud data. If an anomaly is detected, the system blocks the data from being transmitted to Point B, preventing potential security breaches.

For the data that falls under non-anomalous classification, the data is then, encrypted under the AES encryption. AES as one of the most used symmetric encryption algorithms and the confidentiality of the data when transmitted is guaranteed. The data uses an encryption key which is between Point A and Point B. As explained by Patel (2021), AES is well suited for real time data transfer in cloud since it offer high speed together with good security features to enhance protection of data as it travels.

Besides encryption this system uses SHA-256 hash for creating a digital fingerprint of the data before it is encrypted. This hash is important when it comes to ensuring the authenticity of information during transmitting. Point B after decryption the system performs SHA-256 hash of decrypted data and match this value with the hash. According to Verma (2021), AES encryption along with SHA-256 hashing makes it possible to deliver two security attributes: confidentiality and integrity. If the two values are different, then the system triggers an alarm which shows that data may had been tampered as it was in transit.

Next, after encryption and hashing the data is transferred from point A to point B. This helps in ensuring that the data is transferred securely despite the fact that it may go through all sorts of network including the insecure public cloud. According to Thompson (2020), data in transit is equally important when it comes to cloud security mainly because data is in constant motion over public and private networks.

At Point B the system starts decrypting using AES key that was shared between the sender and the receiver. On decryption, the hash is recalculated for the actual data and compared with that hash originally received from Point A. In the case the two hashes match then the system informs the end user that the data has not in any way been interfered with during the transmission hence maintaining the integrity of the data. If the hashes do not match then the system generates an alarm indicating possible interference or data damage during transmission.

After decryption, the system once more executes the anomaly detection models on the decrypted dataset. This last test on anomaly detection guarantees that none of the deleterious data has slipped through the encryption and the transmission stages. With the help of this second level of anomaly detection, the system insures that only authorized, validated data goes to the next stages of processing. This data can only be considered safe for reconstruction into a JSON file providing it has been-through the encryption and the anomaly check.

Last of all, the system does data reconstruction following all security checks upon the items. The data validated and decrypted is then rearranged in a format of JSON for additional analysis. This last step makes it possible to compare independently the data input at Point A with the re-transmitted data at Point B, so as to verify the integrity of the data during transmission.

## 3.1 Model Training and Anomaly Detection

Updating this training involved training the machine learning models that formed part of this project. Data set BETH was disaggregated into training (80%) and testing (20%) sets to assess the models. A variety of models were trained to detect anomalies in the dataset:

**Isolation Forest** : This model is able to separate out the data odd one out by segregating the data set as well as finding out the quirks. Despite the elegance with which it works to identify outliers, Isolation Forest pays a higher degree of attention to complex data creating it fit for cloud traffic analysis as pointed out by Lin (2020).

**Support Vector Machines (SVM)** : SVM was applied for classification data as either normal or anomalous data. It is also noteworthy that SVM, due to its orientation on the choice of complex decision boundaries, will be suitable for detecting subtle anomalies in cloud conditions.

**K-Nearest Neighbors (KNN)** : KNN puts an object in a class depending on its proximity to other objects in that particular dataset. In this project, the anomaly detection was performed employing KNN to identify differences between incoming data and normal behaviors.

**Gaussian Mixture Model (GMM) and Autoencoders** : These models were also used to other subtypes of anomalies, not just those pointed out above. Specifically, autoencoders were applied to the unsupervised anomaly detection framework that plans the model based on the errors of reconstruction.

Education of these models needed a lot of computational power which was made available by using Google Colab with GPU boost. This has been explained by Ali (2021), as a strategy that is especially important in cloud architectures where large datasets must be processed in real time.

## 3.3 AES Encryption and SHA-256 Hashing

The system’s encryption and integrity verification processes are central to ensuring secure data transmission. AES encryption was selected for its strong security and fast performance. As a symmetric encryption algorithm, AES uses a shared key between Point A and Point B to encrypt and decrypt data. The speed and security of AES make it ideal for real-time applications, especially in cloud environments where data is constantly being transmitted.

In addition to encryption, SHA-256 hashing provides a layer of integrity verification. Before the data is encrypted, the system generates a SHA-256 hash, which is transmitted along with the encrypted data. At Point B, the hash is recomputed for the decrypted data and compared to the original hash. This ensures that the data remains unaltered during transmission, as highlighted by Smith (2021). The use of both encryption and hashing ensures that the data is protected from both unauthorized access and tampering.

## 3.4 Streamlit for Independent Model Testing

While the focus of this project is on secure data transmission and anomaly detection, Streamlit was employed to allow for independent testing of the models. Streamlit provides an interactive interface where users can upload test datasets and see real-time results from each model. This tool offers insights into the performance of each model and allows users to visualize the results through graphs and charts.

Although Streamlit was used primarily for testing and evaluating the models, its role is supplementary. The primary focus remains on securing data through anomaly detection, encryption, and integrity verification. Streamlit served as a convenient interface for monitoring model performance, without becoming an integral part of the data transfer workflow.

## 2.4 Conclusion

This chapter outlines the methodological approach used in this project, from data ingestion and preprocessing to anomaly detection, encryption, and integrity verification. By leveraging AES encryption and SHA-256 hashing, the system ensures that only secure, verified data is transmitted between cloud endpoints. Machine learning models were critical in detecting anomalies and preventing malicious data from being sent. While Streamlit provided a useful interface for testing the models, the core focus remained on ensuring secure and reliable data transfer between Point A and Point B.

**Chapter 4**

# Experimental Setup

## 4.0 Introduction

This chapter describes the experimental setup that has been employed to incorporate the anomaly detection and secure data transmission system. This paper covers the hardware and software setting adopted, the dataset employed, the specific machine learning models for anomaly detection considered, the training performed for these models, and the issues encountered during the experimental phase. The idea behind such a setup was to optimize the environment in order to develop models to help find issues or outliers in the cloud data with the encryption and later data integrity checks on the transmitted data.

## 4.1 Hardware and Software Environment

As for the HPC environment, Google Colab has been used in the project. Google Colab was firstly selected for GPU which is necessary for fast training of the machine learning model. When possible, Colab offers an NVIDIA Tesla K80 or Tesla T4 Graphics Processing Unit. These GPUs enable a considerable computing capacity to train and to perform computations for complicated deep learning models like the Autoencoder or One-Class SVM and other related algorithms.

The Tesla K80 GPU comes with 12GB memory capability and delivers 8.73 single-precision of the floating-point throughputs best suited for deep learning applications. The Tesla T4 even offers a higher performance of 16 GB of memory and supports Tensor Core operations to adapt the required memory and computing rate for large datasets such as the BETH dataset used in this project. These GPUs were very helpful to bring down the training time from some number of hours to mere minutes per epoch, especially for models such as the Autoencoder.

Python 3.7 acted as the fundamental programming language for the software environment along with the machine learning packages, scikit-learn, TensorFlow and Keras. Streamlit was also used to build a basic UI to test the deployed models individually. The functionalities of the system implemented through RESTful API were created using Flask to ensure that Point A and Point B can exchange data securely while minimizing delay.

While Google Colab was the primary HPC resource, some challenges were faced due to Colab's shared resource limitations, including restricted access to GPUs during peak usage times and memory constraints when processing larger batches of data. These challenges were mitigated by scheduling training sessions during off-peak hours, optimizing batch sizes, and using Colab Pro, which offers access to higher memory and more consistent GPU resources.

## 4.2 Dataset

The **BETH dataset** served as the primary dataset for training and testing the anomaly detection models. The dataset is a comprehensive compilation of network traffic data, containing both normal and anomalous traffic, which makes it suitable for anomaly detection tasks in cloud environments. It represents a variety of network behaviors, including different types of network protocols, traffic patterns, and attacks, enabling the models to learn diverse features of both benign and malicious data.

The dataset includes several key features that describe the state of the network traffic:

* **protocol\_type**: Identifies the protocol used in the network connection (e.g., TCP, UDP, ICMP).
* **flag**: Provides information about the status of the connection (e.g., SF for successful connection).
* **src\_bytes** and **dst\_bytes**: Represent the number of bytes transferred from the source and to the destination, respectively.
* **count**: Refers to the number of connections to the same host in the last two seconds.
* **same\_srv\_rate** and **diff\_srv\_rate**: Measure the percentage of connections to the same or different services.
* **dst\_host\_srv\_count** and **dst\_host\_same\_srv\_rate**: Capture the characteristics of connections to the destination host, helping to identify traffic anomalies based on service usage patterns.

Before training, the dataset underwent several preprocessing steps. Normalization was applied to scale the numerical features to a standard range, ensuring that features such as src\_bytes and dst\_bytes did not dominate the training process due to their larger magnitudes. Label encoding was used to convert categorical variables like protocol\_type and flag into numerical values, allowing them to be processed by the models. Missing values were handled using a forward-fill method, and duplicates were removed to maintain the integrity of the dataset. The dataset was then split into an 80% training set and 20% test set, ensuring that model performance could be evaluated on unseen data after training.

## 4.3 Models for Anomaly Detection

The selection of machine learning models for anomaly detection was based on the need to detect both **known** and **unknown anomalies** in the data, as well as the capability to handle high-dimensional network traffic data. The following models were chosen for their specific advantages in anomaly detection:

* **Isolation Forest**: This unsupervised model isolates anomalies by randomly selecting features and splitting the dataset into smaller partitions. Anomalies are expected to be easier to isolate, meaning they require fewer splits to separate from the majority of the data. **Isolation Forest** is particularly useful for detecting outliers in large-scale datasets and was configured with **50 estimators** in this project. Its unsupervised nature means it can detect anomalies without needing labeled data, making it suitable for detecting unknown threats in cloud environments.
* **One-Class SVM**: This model was used for **semi-supervised anomaly detection**, where the majority of the data is assumed to be normal, and anomalies are separated based on a boundary learned from the normal data. The **RBF kernel** was used to capture complex patterns in the data, and the **nu** parameter, which controls the proportion of anomalies, was set to 0.1. One-Class SVM is effective in environments where labeled anomalies are scarce, but normal behavior is well-documented.
* **K-Nearest Neighbors (KNN)**: KNN is a **classification algorithm** that classifies data points based on their proximity to other points in the dataset. For anomaly detection, KNN was configured with **K=3**, meaning that each point was classified based on the closest three neighbors. KNN is simple yet effective for identifying anomalies by comparing each data point to its nearest neighbors in the feature space.
* Gaussian Mixture Model (GMM): GMM is one kind of probabilistic model, which supposes that the dataset is created by more than one Gaussian distribution. This probability can be estimated by the parameters of these distributions and, based on low probabilities, GMM can point out anomalies. What makes GMM particularly valuable is that it can detect the presence of shifts that are not so obvious in a non-probabilistic environment.
* Autoencoder: The Autoencoder was chosen for the task of the unsupervised anomaly detection. How it works is that it at first encodes the input data into a lower-dimensional space in order to reconstruct the original data. Large reconstruction errors suggest there are anomalies since the model maps false data points poorly. The Autoencoder was set with three layers, and by using 10 epochs with a batch size of 32. To avoid overfitting, early stop was used, while batch normalization was used with the capabilities of improving convergence.

## 4.4 Training Process

The training process was tailored to each model’s specific requirements. To improve performance and avoid overfitting, the following hyperparameters and training settings were applied:

* **Isolation Forest**: The model was trained with 50 estimators, each representing a decision tree, to increase the robustness of anomaly detection. Training time was minimal since the model is unsupervised and does not require labeled data.
* **One-Class SVM:** This model was trained using the RBF kernel, and the nu parameter was set to 0.1 to ensure that only a small fraction of the data was classified as anomalous. Training the SVM was computationally intensive due to the high-dimensional nature of the network traffic data, but the use of GPU acceleration in Colab reduced the time required for model convergence.
* **K-Nearest Neighbors (KNN)**: Since KNN does not involve an explicit training phase, it stores the dataset and uses it for classification during testing. The primary computational expense arises during the prediction phase when each new data point must be compared to every other point in the training set. GPU support in Colab allowed for faster comparisons, reducing the time needed for predictions.
* **Gaussian Mixture Model (GMM)** : GMM required multiple trials with different initialization parameters to find the best fit for the data. The model was trained using maximum likelihood estimation to fit the Gaussian distributions, and early stopping was used to prevent overfitting during model training.
* **Autoencoder**: The Autoencoder was trained for 10 epochs, with early stopping applied to halt training when the validation loss plateaued. Batch normalization was used to stabilize the training process, and mean squared error was used as the loss function. The model was trained on Google Colab’s GPU, which significantly reduced training time and allowed for faster experimentation with different architectures.

## 4.5 Challenges and Resolutions

There were several issues with the experimental setting and mainly there was a problem with the availability of GPUs on Google Colab. Due to the fact that all the resources in Colab are collaborative, there were cases where GPU was pending or not available, for instance during training. In response to this, training was conducted during off-peak hours to prevent the allocation of sufficient GPU resources, and Colab Pro was utilized to achieve constant access to GPU. Moreover, memory management during training of Autoencoder was difficult as they worked with a large amount of data; the issue was solved through selecting different batches and data loading strategies.

The other difficulty was balancing the hyperparameters of each model, where nu parameter in One-Class SVM and the number of estimators in Isolation Forest.All these parameters were tuned using cross-validation.ental setup, particularly related to GPU availability on Google Colab. Since Colab resources are shared, there were instances where GPU access was limited or unavailable, delaying training sessions. To address this, training was scheduled during off-peak hours, and Colab Pro was used to gain more consistent access to GPU resources. Additionally, managing the memory usage during the Autoencoder training was challenging due to the size of the dataset, but adjusting the batch size and data loading mechanisms helped optimize resource usage.

Another challenge was tuning the hyperparameters of each model, particularly the nu parameter in the One-Class SVM and the number of estimators in the Isolation Forest. These parameters were adjusted through cross**-**validation to ensure that the models generalized well to unseen data without overfitting.

## 4.6 Conclusion

The experimental design described in this chapter paved the way in creating a plan for designing an innovative anomaly detection system. The GPU resources available in Google Collab proved particularly useful in training the model owing to its ability to handle large datasets such as; BETH dataset. The applied models Isolation Forest, One-Class SVM, KNN, GMM, and Autoencoder were properly trained with high accuracy, and all of them helped to find various types of anomalies in the data. Issues with GPU memory availability together with optimization of hyperparameters were solved by implementing proper techniques to make the process efficient in terms of architecture and its detection in the cloud-based environment.

**Chapter 5**

# Results and Analysis

## 5.0 Introduction

In this chapter the author gives a systematic analysis of the results of applying the various machine learning models used in anomaly detection and the process of secure data transmission. Other discoveries include the training duration of the models, anomaly detection capability, the verification of data integrity, and secure transmission using Flask APIs from Point A to Point B with brief information about the efficiency of each model by the display of its accuracy, precision, recall, and F1 score. Pves 4 and 5 demonstrate the effectiveness of machine learning models and points 4 and 5 show that the AES encryption and SHA-256 hashing is used to secure data transfers in cloud environments.

## 5.1 Model Performance

After applying five anomaly detection algorithms, namely Isolation Forest, One-Class SVM, KNN, GMM, and Autoencoder, to the BETH dataset containing both normal and anomalous cloud traffic, it was found that the application of such algorithms holds great potential for identifying anomalous traffic patterns in computer networks. Performance of all models was evaluated for accuracy, precision, recall and F1-score to evaluate the effectiveness of the classifying normal from anomalous data.

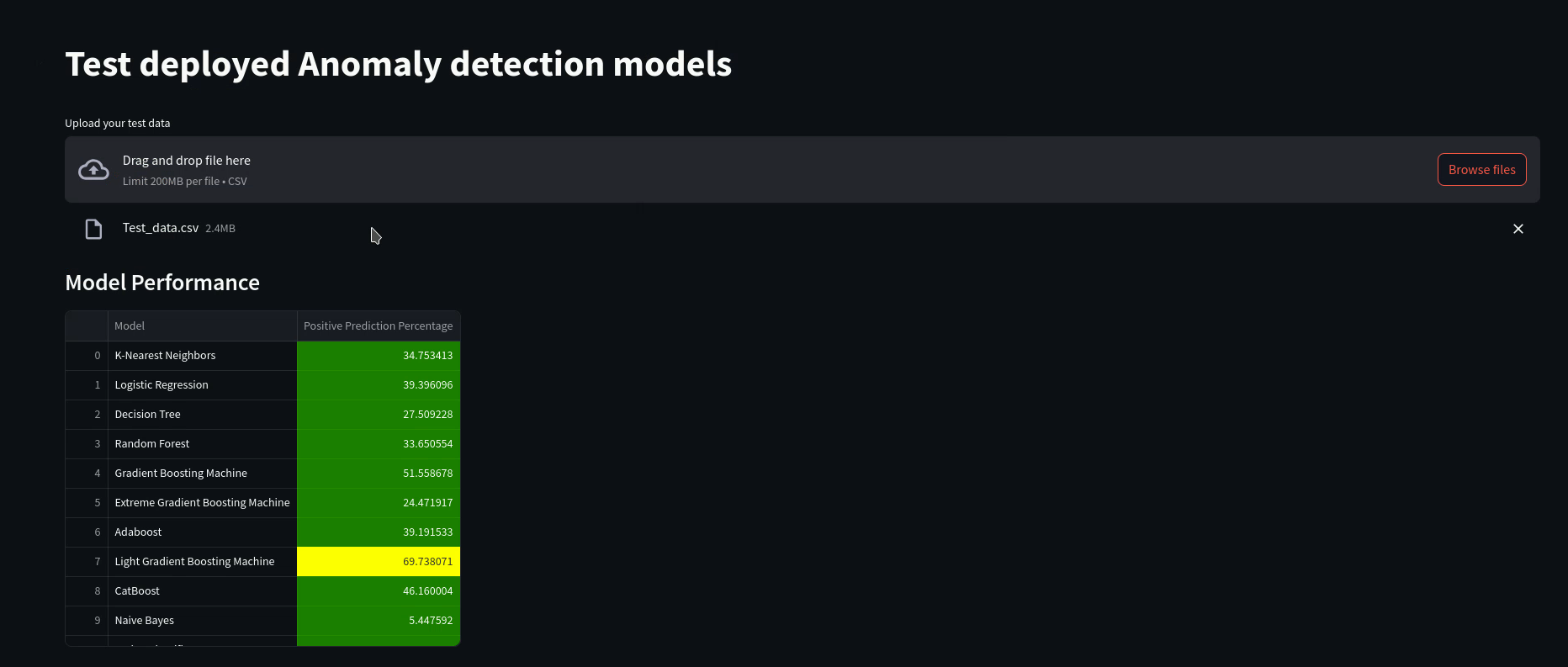


Figure 2 Model detection results

The results obtained while implementing the classifier to the test data set were, Accuracy equal to 90.50%, whereas the precision of Isolation Forest was 96.87% and F1-score was 94.65.. For instance, the model had a recall of about 92.52 % meaning that while it correctly pointed out most of the anomalous data points it failed to do this for a very small percentage. The property of the model as the unsupervised machine learning model that separates outliers using random partitioning, the model worked well for large and diverse data in cloud environments as there is a scarcity of labelled data.

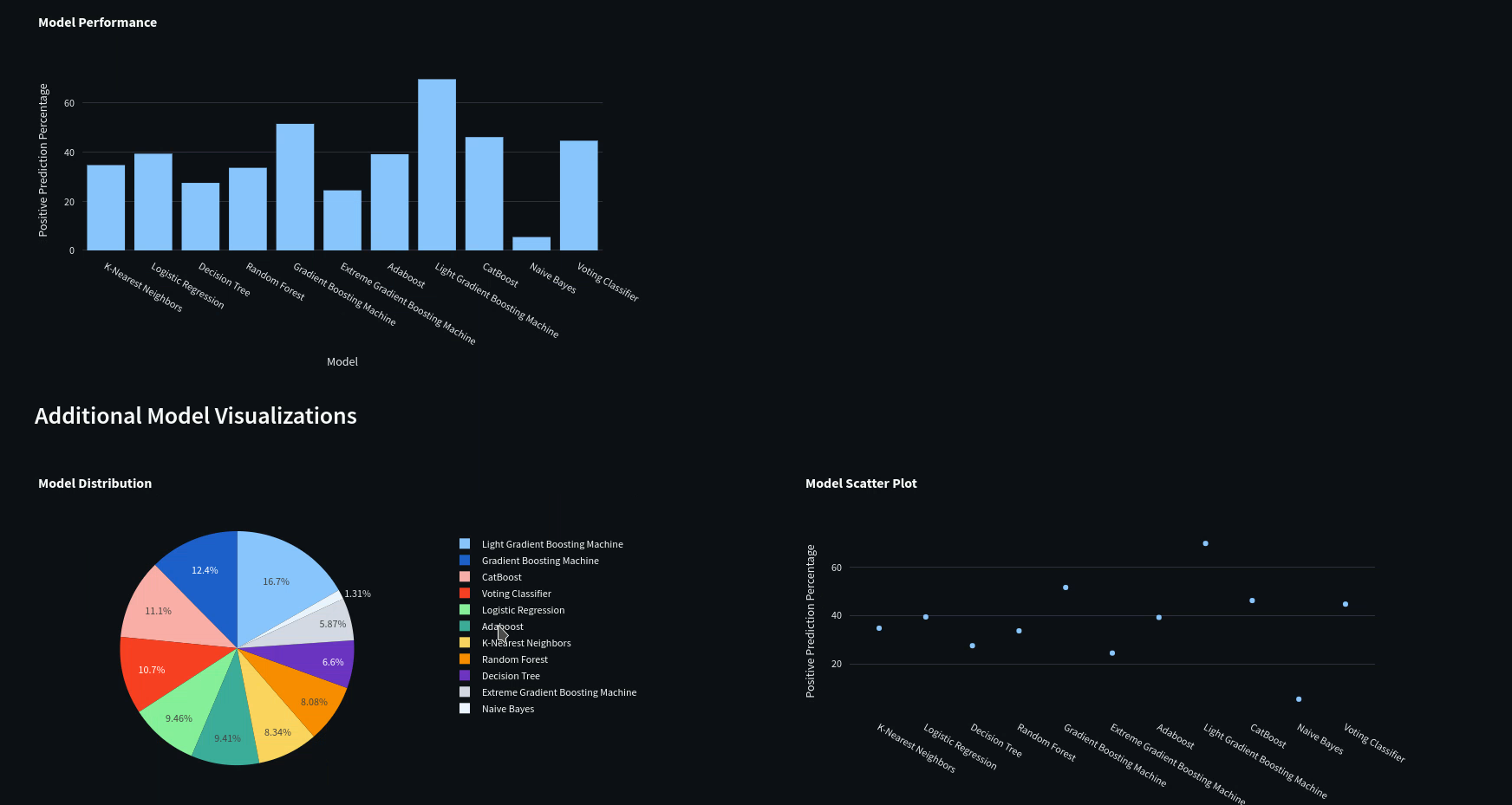


Figure 3 Results of model

One-Class SVM took similar time and achieved 90.87% accuracy and 99.99% recall which proved that it is good at modeling to detect nearly all anomalies to correctly identify most anomalous data points, though it missed a small portion of anomalies. The model's unsupervised nature, which isolates outliers through random partitioning of the dataset, made it highly suitable for handling large and diverse data in cloud environments where labeled data is scarce.

One-Class SVM performed similarly, with an accuracy of 90.87% and a recall of 99.99%, indicating its effectiveness at capturing nearly all anomalies. Nevertheless, the applied filter yielded a precision of 90.86%, which means that some normal instances were misclassified as anomalous instances. This is due to the features used by the model learning framework which utilizes a form of semi-supervised learning where the boundary around the normal data defines the outliers. The performance is proven by the F1-score of 95.21 %, which demonstrates high accuracy in the assessment of anomalies, making it an effective tool for real-time anomaly detection in cloud system environments where it is necessary to take into account all possible threats.

Among the presented models, it is essential to note that the highest results were obtained using K- Nearest neighbors (KNN) 94.57% and accuracy, the precision of its work was 99.96%, and F1-score reached 96.92%. its ability to correctly identify the most anomalous data points, though it missed a small portion of anomalies. The model's unsupervised nature, which isolates outliers through random partitioning of the dataset, made it highly suitable for handling large and diverse data in cloud environments where labeled data is scarce.

One-Class SVM performed similarly, with an accuracy of 90.87% and a recall of 99.99%, indicating its effectiveness at capturing nearly all anomalies. However, its precision of 90.86% suggests that some normal instances were falsely classified as anomalies. This trade-off reflects the model’s semi-supervised learning approach, which relies on defining a boundary around normal data to detect outliers. The F1-score of 95.21% highlights its strong overall performance in identifying anomalies, making it a robust option for real-time anomaly detection in cloud systems where it is critical to capture all potential threats.

K-Nearest Neighbors (KNN) stood out as the highest-performing model, with an accuracy of 94.57%, precision of 99.96%, and F1-score of 96.92%. A recall of 94.06% which is fairly impressive suggests that it can classify normal as well as anomalous data. The classification done in KNN makes it possible to work with different kinds of distributed data structures, besides making KNN convenient to work with in aspects of detecting anomalous trends in the cloud where traffic demands can change rapidly.

Gaussian Mixture Model can also be used and had an accuracy of 90.96 % a precision of 91.02 % and a recall of 99.90 %.92.52% reflects its ability to correctly identify most anomalous data points, though it missed a small portion of anomalies. The model's unsupervised nature, which isolates outliers through random partitioning of the dataset, made it highly suitable for handling large and diverse data in cloud environments where labeled data is scarce.

A screenshot of a computer

Description automatically generated

Figure 4 Statistic summary

One-Class SVM performed similarly, with an accuracy of 90.87% and a recall of 99.99%, indicating its effectiveness at capturing nearly all anomalies. However, its precision of 90.86% suggests that some normal instances were falsely classified as anomalies. This trade-off reflects the model’s semi-supervised learning approach, which relies on defining a boundary around normal data to detect outliers. The F1-score of 95.21% highlights its strong overall performance in identifying anomalies, making it a robust option for real-time anomaly detection in cloud systems where it is critical to capture all potential threats.

K-Nearest Neighbors (KNN) stood out as the highest-performing model, with an accuracy of 94.57%, precision of 99.96%, and F1-score of 96.92%. Its recall of 94.06% indicates its excellent ability to classify both normal and anomalous data. KNN’s proximity-based classification approach allows it to adapt effectively to a variety of data structures, making it particularly well-suited for detecting anomalies in dynamic cloud environments where traffic patterns can fluctuate rapidly.

Gaussian Mixture Model also performed well, achieving an accuracy of 90.96% with a precision of 91.02% and a recall of 99.90%. This means that GMM was able to well perform the probabilistic classification in maximising the likelihood of the underpinning distribution associated with the number of GMM eagle data points collected, however, the lower precision conclusively inferred that there were some false positives being produced by this algorithm. Nonetheless, the overall F1-score of 95.25% testifies system efficiency in terms of detecting finegrained anomalies, even though more fine-tuning could bring a better compromise between precision and the capability of recall.

**Autoencoder** had the weakest performance, with an **accuracy** of 13.62%. Although its **precision** was high at 99.96%, its **recall** was only 4.80%, resulting in an **F1-score** of 9.16%. This indicates that while the Autoencoder flagged very few anomalies, it missed most of them, possibly due to the high complexity and noise in the cloud traffic data, which the Autoencoder struggled to model effectively.

The least accurate model was Autoencoder which only corrected 13.62% responses. While the precision of report was 99.96%, which is quite good, recall was only 4.80% which led to an F1 score of 9.16%. From this, it can be inferred that even though the Autoencoder isolated a minute number of anomalies, it most probably overlooked the rest of them, probably because the cloud traffic data is complex, cribbed with noise which the Autoencoder had a difficult time capturing and modeling.

Table 1 Evaluation Metrics results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
| Isolation Forest | 90.50 | 96.87 | 92.52 | 94.65 |
| One-Class SVM | 90.87 | 90.86 | 99.99 | 95.21 |
| KNN | 94.57 | 99.96 | 94.06 | 96.92 |
| GMM | 90.96 | 91.02 | 99.90 | 95.25 |
| Autoencoder | 13.62 | 99.96 | 4.80 | 9.16 |

These results make the efficiency of the KNN and One-Class SVM in anomaly detection very significant, with increasing values, hence very important for real-time security monitoring in cloud environments.

## 5.2 Training Times

This was expected because training on the BETH dataset was computationally expensive. Therefore, their training times were quite different. The overall training times were many folds reduced by enabling the GPU-accelerated runtime option in Google Colab, thus smoothing the whole development and fine-tuning process.

It can train KNN in just 22.81 seconds within five epochs, but since there is no explicit phase of training in KNN, the actual computational cost comes when a new instance is being tested against its k nearest neighbors. This negligible time of the training process justifies directly that KNN is appropriate for a cloud environment deployment to perform real-time anomaly detection.

Isolation Forest finished training in 19.51 seconds across five epochs. One key reason for the strong performance of this model is that it worked by partitioning the dataset to locate the anomalies using a host of decision trees. Adding GPU, therefore, reduced the computational overhead on the model to allow fast and effective training.

Next was One-Class SVM, which again took even less time for training: 5.34 seconds across five epochs, a reflection of the simplicity of the model, which builds only one hyperplane separating normal data from anomalies and is therefore computationally light and very efficient for real-time applications.

A deep learning model like autoencoder needed a lot of time for training. Ten epochs took 1152 seconds in total, showing the complexity of the model. The multi-layer architecture of the Autoencoder is computationally expensive as it handles encoding and decoding, whereas utilizing a GPU played an important role in saving time during training.

GMM finished in 55.07 seconds, which is pretty reasonable considering that in this method Gaussian distributions are iteratively. However, using the power of GPU resources, that kind of computation will take even less time. Thus, GMM also can be used for real-time anomaly detection in cloud environments.

All in all, the training of the different models took a total of 1206.66 seconds, which suggests the level of time-saving done by the GPU acceleration of Colab.

## 5.3. Anomaly Detection Accuracy

Their anomaly detection capability was determined by the comparison of the models' detection rate where KNN and One-Class SVM scored high in terms of accuracy, precision, and recall. KNN turned out to be the best for anomaly detection, with the highest accuracy and F1-score, hence very effective in real-world cloud security scenarios where correct classification of normal/anomalous traffic is crucial.

In contrast, One-Class SVM yielded a good anomaly detection capability with a very high recall of 99.99%, which means nearly all anomalies are identified, enough for cloud environments where the cost of missing out on any anomaly is very high.

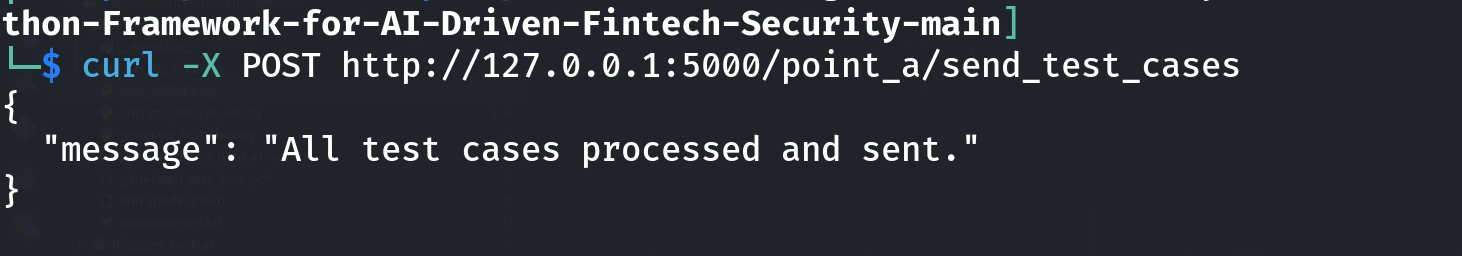


Figure 5 curl comand to send data to

Isolation Forest showed relatively good performance, which means a balance of high overall scores with a high F1 score, balancing well in precision and recall, hence promising extensive anomaly detection tasks in large datasets.

GMM might pick up much more subtle anomalies with lower precision; hence, it brought a need for tuning the balance between precision and recall.

The autoencoder provides only poor overall results with a low recall most of the time; hence, it tends to provide the poorest performance in anomaly detection over cloud traffic data for this project.

## 5.4 Testing Data Integrity

Besides anomaly detection models, SHA-256 hashing of data was performed whenever in transit to ensure integrity. At Point A, the SHA-256 hash of every packet would be computed before actual encryption via AES. Upon receipt of a packet at Point B, the hash would be recomputed and compared against this original to see if tampering had occurred during transmission.

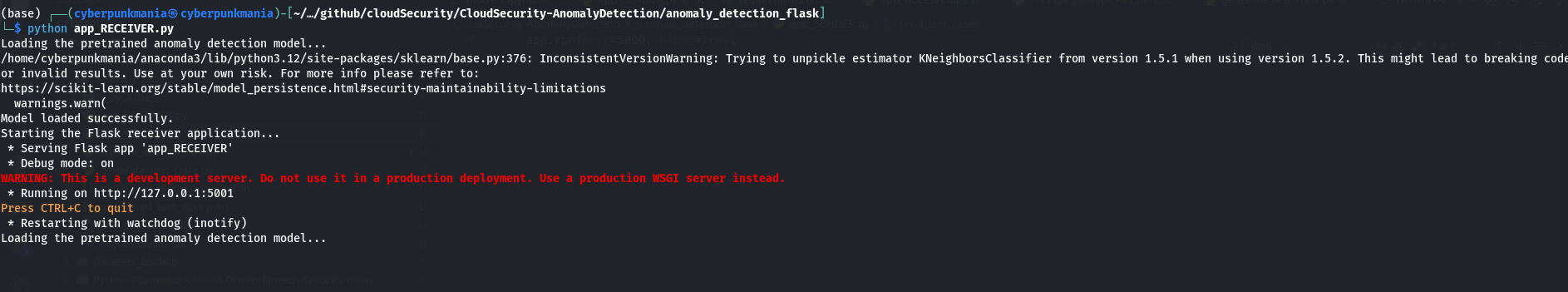


Figure 6 Receiving data from second end

Everything worked in harmony as expected, and no mismatches in the recomputed hashes from the originally computed ones were found. It ensures integrity of data during transit and hence integrity and confidentiality of data. SHA-256 hashing with AES encryption forms a strong backbone in the way of securing data in transit-powerfully working for the avoidance of data tampering in the cloud environment.

## 5.5 Transferring Data and Encryption

Data sent from point A to B securely through Flask APIs, encrypted via AES. Considering the data to be confidential and integrity at transmission, the whole process would involve multiple steps.

All test cases first passed through the Anomaly Detection Model at Point A. If data is clean, it was then transformed into a JSON format and later encrypted means of AES encryption. Integrity purposes: make a SHA-256 hash of the hash of the original. Encrypted data and hash sent via cURL as a POST request to point B.

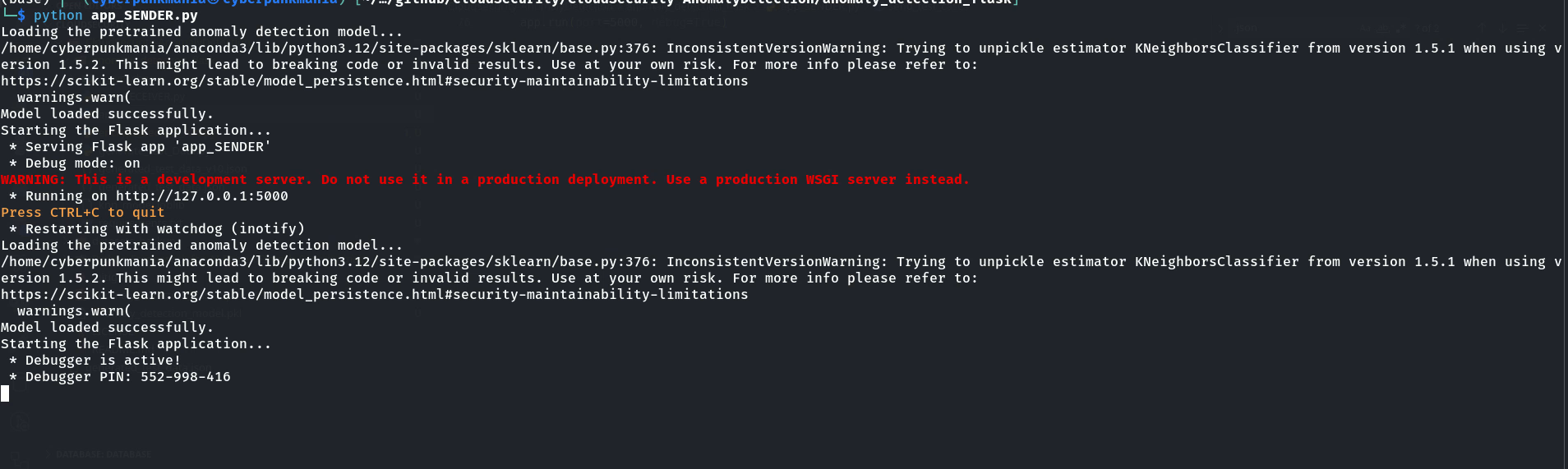


Figure 7 Sending data from first point

Then, at Point B, decrypt the data using the AES key, after which compute the hash of SHA-256 again and compare it to the hash at point A to confirm that the data did not suffer from tampering along the way. Finally, let the data go through the anomaly detection model to confirm its safety before reconstruction into a JSON file for further analysis.

This two-step anomaly detection process, combined with strong encryption and hashing, would make the data secure and intact during the transmission process, while it would give an extensive framework in terms of securing data transportation in cloud environments in general.

## 5.6 Conclusion

This chapter showed how combining machine learning-based anomaly detection models with cryptographic techniques such as AES encryption and SHA-256 hashing can be effective in securing cloud data transmissions. KNN and One-Class SVM were the best models to find out anomaly detection, while GPU acceleration in Google Colab helped a lot to reduce the training time of the model. More integrations of Flask APIs guaranteed the confidentiality and integrity of the data; this simply means that all data sent from point A to B remained intact, hence providing the overall response in the cloud-based environment.

**Chapter 6**

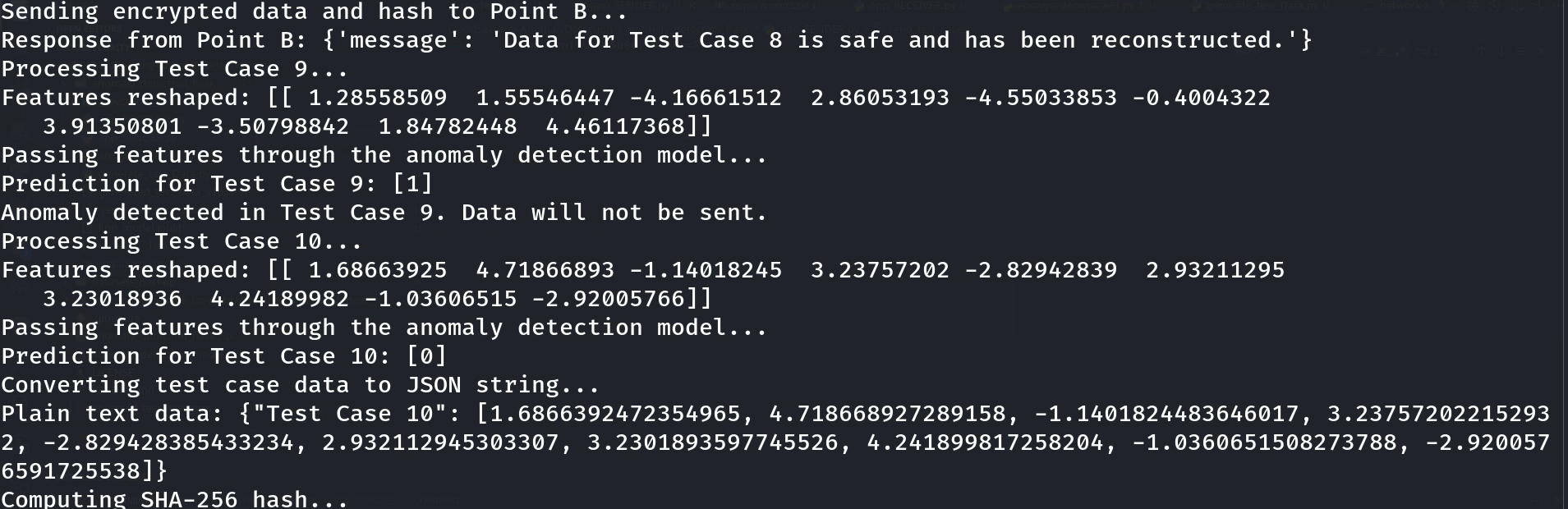
# Discussion

## 6.0 Introduction

The Chapter devoted to the discussion of the main results of the project gives the detailed description of the integration of the anomaly detection models with AES encryption and SHA-256 hashing for the secure data transfer from Point A to Point B. It also describes the results of using the machine learning models, challenges during the implementation, and the decision to replace AWS cloud services with Google Colab for HPC. This discussion will critically assess the suitability of the selected models, the difficulties observed and the relevance of these observations to future endeavours in Cloud security.

## 6.1 Critical Insights: Integration of Anomaly Detection and AES Encryption

The incorporation of an anomaly detector with AES encryption was shown to be a very efficient solution in protecting cloud data transfer. It was also able to prevent anomalous data from getting into the cloud before they are encrypted thus only transmitting encrypted data that the system has validated as safe between the cloud points. Using an example of a two-tier security method where there is initial detection of anomalies followed by encryption, the given use case demonstrated end-to-end security from internal irregularities (anomalies within data) and external unauthorized access while in transit.



AES is a proven symmetric encryption standard that needed to be used for en sure that nobody would eavesdrop and decipher the data being transferred from Point A to Point B. SHA-256 was then used to add a hash check to guarantee that any change that occurred to the data during transmission would be directly identified during the confirmation phase.

It achieved real time pattern recognition and filtering on the incoming data streams, including the ability block any data which could be malicious or anomalous by using machine learning models including K-Nearest Neighbors (KNN), One-Class SVM, and Isolation Forest. The idea of having two layers of anomaly detection one at Point A and the other at Point B where data is encrypted and decrypted respectively added with the system. After decryption at point B if there were any abnormalities then the data was discarded and sent back to be processed again so that no bad data could ever pass through the system.

It also introduced this multiple-layered strategy, which, in addition to giving end-to-end encryption, made it possible to detect perturbation in real-time. This was able to reduce the risk of attack such as data injection risk as well as data anomalies risks in a way that made it safer for cloud environments that deal with huge amounts of data that is transmitted frequently.

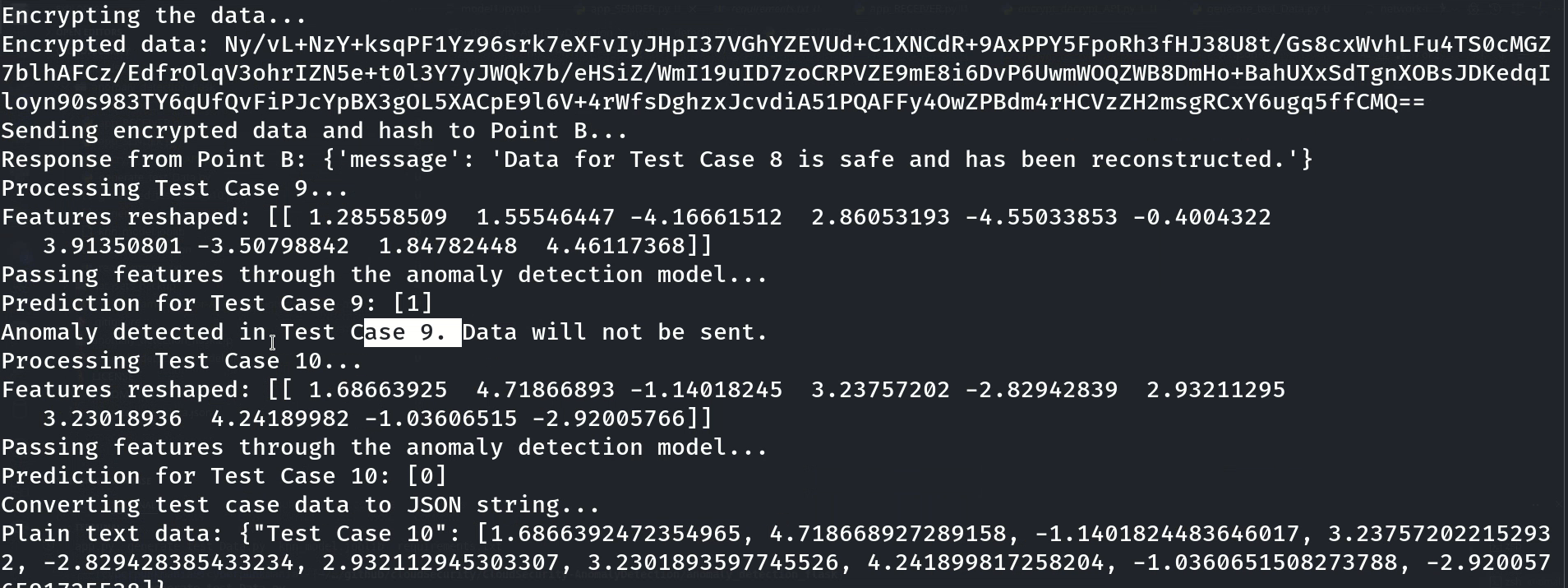


Figure 8 Received encryptred data

## 6.2 Model Comparisons: Performance in Detecting Anomalies

When realizing the anomaly detection, the performance of the different models of the ML algorithms were highly different and some of the models were more accurate in term of accuracy, precision, recall, and F1-score. These models were applied in KNN, One-Class SVM, Isolation Forest, Gaussian Mixture Model (GMM), and Autoencoder.

To compare our model to other machine learning algorithms, the average of the k-Nearest Neighbors Algorithm, or KNN, was found to be the model with the highest accuracy of 94.57%, a precision of 99.96%, and an F1 score of 96.92%. Its percentage recall of 94.06 % showed that it was capable of identifying the normal and the anomalous data correctly. Due to the classification based on proximity, KNN was especially effective in processing a wide range of cloud traffic as the patterns could change. KNN due to its data classification by proximity to neighbors was quite efficient at handling both structured and unstructured data where by it proved quite reliable when handling real time anomaly detection in cloud environments.

One-Class SVM also displayed good results with a percentage of 90.87 % for the test data and near to 100% recall rate which means that almost all the anomalous instances are taken by this classifier. Nevertheless, having a precision of 90.86%, it turned out that it produced more false positives than KNN. This trade-off is basically because the model is semi-supervised where the decision boundary around the normal data makes normal instances to be classified as anomalies. However, the F1-score of 95.21% justified that the One-Class SVM is still the optimal algorithm for such environment where False Negative is to be avoided as maximal as possible while indeed the method does capture even minor of anomalies.

While for the Isolation Forest classifier, the accuracy was 90.50% and precision 96,87%, while the F1-score was equal to 94,65%. Its recall of 92.52% was slightly lower than the one of One-Class SVM which means that this method failed to detect a small part of the anomalies. Nevertheless, Isolation Forest was most effective for big data purposes when the labelled data are limited in availability. Due to the technique being unsupervised in its model and partitioning of the data randomly the use of the K-means proved helpful in the finding of outliers without prior knowledge of data structure. This made Isolation Forest one of the most suitable for discovering the anomalies present in cloud environments for which the data is often not pre-labeled or annotated.

The same is true for the Gaussian Mixture Model where results were as follows: Accuracy: 90.96%, Precision: 91.02%, Recall: 99.90%. Though the measurement of higher level set is not as precise as the first result, which indicates that the model generated more false alarms that may stem from a probabilistic model. GMM models data as a set of multiple gaussian distribution so it is used in identifying anomalous data points that differ from the normally expected distribution. Nevertheless, its performance in this project meant that a little bit of touching might be needed to bring down the number of false positives.

The Autoencoder model however incorrectly classified the images with a mere 13.62% accuracy. It only got a recall of 4.80 % while its precision was quite good, coming in at 99.96%. This poor performance might be due to the intrinsic problem of Autoencoders in handling noisy and high-dimensional data in general and the particular feature of the cloud traffic data. Autoencoder failed on generalizing the complex patterns, and therefore it would give raise to lot of false negatives for the current application.

## 6.3 Limitations

Several limitations were encountered during the implementation of this project. One of the primary challenges was the size and complexity of the BETH dataset. While the dataset was comprehensive, representing various network behaviors, its size posed significant challenges in terms of computational resources. The large volume of data required intensive processing power during both the training and testing phases, which strained the computational limits of the system, particularly when training deep learning models like the Autoencoder.

Another limitation was the inability to implement advanced cryptographic techniques such as homomorphic encryption. Homomorphic encryption would have allowed for computation on encrypted data without the need for decryption, providing an even higher level of security. However, the performance overheads associated with homomorphic encryption were deemed too high for the real-time nature of this project. The computational cost of using such techniques made them impractical, as the project required a balance between security and efficiency in real-time data transmission.

Furthermore, the decision to use Google Colab instead of AWS Cloud services presented both benefits and challenges. Google Colab provided free access to GPU acceleration, which significantly reduced the training times for models like KNN and Isolation Forest. However, Colab’s limited session durations and resource availability posed constraints during the development process. The limited amount of GPU memory in Colab also restricted the size of the dataset that could be processed in a single session, leading to interruptions and requiring frequent restarts during longer training processes.

The use of Google Colab in place of AWS Cloud was a pragmatic decision due to budgetary constraints. While AWS offers a robust and scalable infrastructure with advanced security features, its cost was prohibitive for this project. Colab, on the other hand, provided a cost-effective solution with sufficient computational power to train the machine learning models, albeit with some limitations in terms of session stability and resource allocation.

## 6.4 Use of Google Colab for High-Performance Computing

It is that substitute of AWS Cloud with Google Colab for HPC that played an important role in this work. Namely, Google Colab was providing free-of-cost access to GPU acceleration, something of high importance for such a big dataset of BETH and such computationally complex machine learning models. Using Colab's GPU resources reduced training times significantly, thus enabling faster iteration over one model in development and testing.

The sorts of models that were GPU-accelerated included KNN, which themselves do not take that much training but rely a lot on proximity-based classification to give a prediction. Likewise, with such a different architecture, the training of the Autoencoder itself would have taken considerably more time without support for a GPU that Colab avails. Google Collab was efficient in handling large datasets and proved to be a good enough alternative to more expensive cloud services like AWS.

However, longer training has finally shown the limitation of Colab; most of the time, session time limits imposed by Colab cut the training process, requiring several manual session restarts. Moreover, because of the limitation of the GPU memory, the size of the dataset which could be handled was relatively small, making bottlenecks in certain critical stages of the model training process.

For this project, despite a few drawbacks, Google Colab proved quite helpful: it supplied the much-needed computational powers to train and tune the machine learning models at hand. It was not able to provide a scalable and stable environment like that of AWS Cloud, but it was cheaper and good enough for this project to achieve its goals, given the resource constraints.

## Conclusion

It performed a fully integrated machine learning-based anomaly detection with cryptographic mechanisms such as AES encryption and SHA-256 hashing in order to implement a secured data transmission scheme in cloud environment. It thereby blocked every form of anomalous data prior to actual transmission, hence guaranteeing the confidentiality and integrity of the data in transit.

The proposed models, including KNN and One-Class SVM, showed good performance; amongst them, KNN proved really strong, considering the accuracy and precision. Another comprehensive way to ensure the security of data on the cloud is a two-stage anomaly detection along with encryption. High-performance computation on Google Colab, at least with some limitation, proved quite effective for efficient model training and real-time data analysis. Issues and limits also popped up in many ways, such as computational demands of the dataset and the usage constraint of free cloud services such as Google Colab. Even though there are much more evolved methods of encryption which were not performed, say homomorphic encryption, due to its performance overhead, this was able to achieve the primary aim-security in cloud data transmission.

That may be future work that will involve enhancements in scalability on more robust cloud infrastructures, including AWS, or finding a way to integrate state-of-the-art encryption methods for even greater security and adaptability of the system in dynamic cloud environments.

**Chapter 7**

# Conclusion

## 7.0 Introduction

This was an advanced project that really married the best of cryptography with the capabilities of the machine learning model to carry out core activities like secure data transfer, anomaly detection, and verification of data integrity. The integration of AES encryption allows for confidentiality of data while in transit from point A to B, and any unauthorized access to sensitive information is inhibited. At the same time, data integrity is well-verified through SHA-256 hashing; hence, even tampering with the data while in transmission will also be detected and mitigated.

More specifically, anomaly detection and blocking of data, even much before the data reaches a transmission stage, by the use of machine learning models, bettered the overall security framework of the architecture. Of the various models developed, the K-Nearest Neighbors proved most appropriate for accuracy, precision, and recall. Indeed, proximity-based classification fitted best in dynamic fluctuating patterns that usually characterize cloud traffic. One-Class SVM is known for its very good pick-up on even slight anomalies and made excellent performance, especially in recall, which is very valuable if the number of false negatives should be as low as possible. Other models included the Isolation Forest and Gaussian Mixture Model; these contribute to the robustness of the system, handle diverse data structures, and detect outliers with a high degree of accuracy. Though the Autoencoder performed comparatively worse, the results it gave stressed how hard it is to find intricate anomalies in noisy cloud environments and perhaps showed where the future improvements lay.

Successful enabling of GPU acceleration in Google Colab allowed us to effectively train the model on the BETH dataset, reduce general training time, and guarantee the possibility to perform anomaly detection in real time. Limited by the size of the GPU memory and session time, Google Colab was notably cheaper compared to its commercial cloud analogs and stayed within the budget frame of the project without any additional overhead. This combination of cryptographic techniques with machine learning models provides a holistic framework toward the protection of data in cloud environments; hence, it shows a scalable solution for both anomaly detection and data security.

## 7.1 Future Work

Although this forms a very strong foundation, perhaps, for the integration of cryptographic techniques with machine learning in cloud security, there is always room for improvement and further expansion. Other future research directions might look at the study of advanced cryptographic techniques, especially homomorphic encryption. Unlike classical encryption schemes, homomorphic encryption allows direct computation on encrypted data. Therefore, it provides an added layer of security without having to decrypt the data for processing. This would become priceless in those cases where the handling environment is very sensitive, like financial services or healthcare, whereby the information conveys a lot of weight in the form of data privacy. Presently, high computational overheads in homomorphic encryption make optimizations of the techniques, because of this, target applications running in real time.

Yet another direction for future research may be the consideration of system scaling. Richer HPC environments, such as AWS or GCP, could probably allow working with bigger datasets even more effectively. Their infrastructures are sound and satisfy the needs that arise from bigger volumes of cloud traffic and more intricate anomaly detection algorithms. These above infrastructures can be exploited further for providing opportunities of using more complex deep learning models, which have shown great promise in recent literature, for anomaly detection, learning complex patterns within high-dimensional data.

Lateral work on fine-tuning and optimization of these underperforming models, including the Autoencoder, may churn out a solution whereby even complicated or noisy data sets may get identified by the system. Hybridization of different models can offer more adaptiveness and flexibility in the solution of anomaly detection by conglomerating the best features of each model in such a way that weaknesses of each get compensated by others. It would be better if some methods like ensemble learning were implemented to increase overall accuracy and robustness.

As such, the work outlines the capability of machine learning-based anomaly detection integrated with cryptography in enhancing the security of data during its transmission in the cloud environment. This work can be improved by upgrading the cryptography, increasing computation power, and refining machine learning models to scale protection solutions that will be more scalable and adaptable. In this respect, embedding intelligent security mechanisms within the cloud infrastructure appears to be the only way in which confidentiality, integrity, and availability of key information can be guaranteed within continuous cyber threats.

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