DATA PROCESSING AND ARTIFICIAL INTELLIGENCE FOR ENHANCED INCIDENT MANAGEMENT

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ABSTRACT

At Singapore's various Land Checkpoints, with the large volume of vehicles and commuters passing through, this may inevitably cause incidents which disrupt operations at the Checkpoints. The emergence of Artificial Intelligence, especially Generative AI solutions, provides an opportunity to address some of the gaps in incident management, and reduce disruptions in day-to-day operations. Thus, this project aims to evaluate the effect of the type of prompt engineering technique as well as the size of Large Language Models (LLMs) on information retrieval. The information retrieval process was executed by a simple Retrieval Augmented Generation (RAG) system, which is the process of retrieving information from an external source that was provided to the LLM. The dataset consisted of mock data of past ICA incidents, generated by ChatGPT.

Using 4 Large Language Models, 2 of small size (Llama3-8b-8192, Gemma2-9b-it) and 2 of large size (Llama3-70b-8192, Mixtral-8x7b-32786) as well as Zero-shot prompting and In-context learning, the accuracy of information retrieval from the mock dataset was tested across different LLM sizes and different prompt engineering techniques. The results show that LLMs perform significantly better with zero-shot prompts, with accuracy scores of 90% and 85%, compared to 70% and 75% for small and large LLMs respectively.

1. INTRODUCTION

1.1. Background

The Land Checkpoints in Singapore play a pivotal role in national border security by protecting against the entry of undesirable personnel and cargo [1]. Given the high volume of daily travellers and the complexity of operations at these checkpoints, it is essential to adopt advanced solutions that support the Immigration and Checkpoint Authority (ICA) in their operations. While significant progress has been made in enhancing border clearance process [2] and onsite incident management [3], post-incident management remains a critical area for enhancement. At Land Checkpoints, ICA officers serve as the first responders to security incidents [3], leaving them with limited time to review and extract information from incident reports. This could lead to inaccuracies caused by human fatigue and cognitive limitations. However, the rapid advancement in technology, particularly in Artificial Intelligence (AI), presents new opportunities to enhance operational efficiency and address these challenges.

1.2. Large Language Models (LLMs)

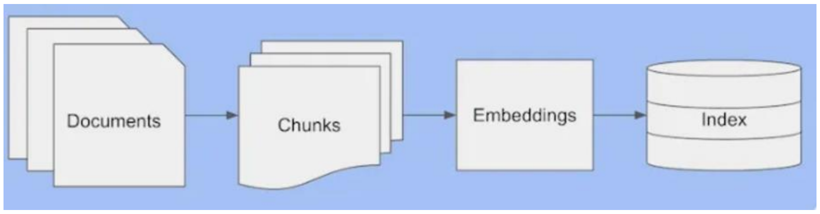
With the rapid growth in the adoption of generative AI solutions such as Large Language Models (LLMs), they have become increasingly vital in many areas. LLMs leverage Natural Language Processing (NLP) to generate text-based responses to human input. They are constructed using multiple layers of neural networks and deep learning techniques, meaning they are trained on extensive datasets to achieve high levels of language understanding and generation. Notably, chatbots powered by LLMs hold significant potential to complement or even replace traditional search engines [4].

1.3. Retrieval Augmented Generation (RAG)

Retrieval Augmented Generation is a technique which combines the strengths of traditional information retrieval systems, such as databases, with the capabilities of LLMs [7]. This approach enables more accurate and specific information retrieval by addressing some of the limitations of LLMs, such as their knowledge cutoff dates. With limited access to real-time and up-to-date information, LLMs may confidently generate a response that is false. Additionally, RAG can provide LLMs access to knowledge in private or specialized domains not readily available in mainstream media. This is particularly useful in this project, where information of past ICA Land Checkpoint incidents is private and not accessible online.

There are 3 stages of RAG - Data Indexing as shown in Figure 1, and Retrieval and Generation as shown in Figure 2.

Figure 1: Data Indexing (Ingestion) process



The Data Indexing process involves taking documents, such as (PDF, CSV) files, and splitting them into manageable chunks. These chunks usually represent 1 idea, in the form of characters, sentences or even paragraphs, and have a predefined size. After which, these chunks will be encoded into embeddings by an embedding model. Embeddings, simply put, represent chunks in continuous vectors high-dimensional space. The embeddings with similar meaning (semantic meaning) will have similar vector representations. These vectors are then stored in a vector database, for easy retrieval and understanding by the RAG.

Figure 2: Retrieval and Generation process

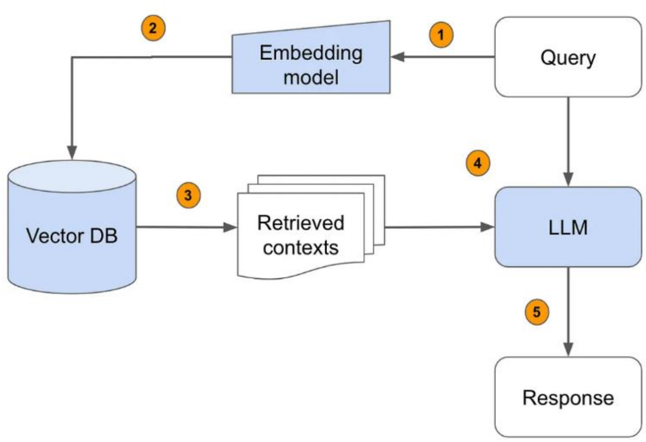


Figure 2 illustrates the Retrieval (steps 1 to 3) and Generation (steps 4 to 5) process. The process steps are as follows:

1. When a user sends a query, it is passed to the same embedding model.
2. The query is converted into a vector representation, which can be understood and processed by the system
3. The query vector is then used to search throughout a vector database. The vector database consists of vector representations of contexts that the model can use to generate a response. Similarity search is being used to find the context that has the greatest semantic similarity to the query. The similarity search uses the Euclidean distance for the purpose above, and its formula, is formally defined below:

$$d(\mathrm{p}, \mathrm{q}) = \sqrt{\textstyle\sum^{n}}_{i=1}(p_i - q_i)^2$$

   Where:
   - p and q are two vectors, p_i and q_i are the individual elements of the vectors.
   - n is the dimensionality of the vectors.
   - d(p, q) represents the Euclidean distance between vectors p and q.

4. The retrieved contexts are then passed to the LLM for the LLM to generate an accurate and coherent response.
5. The LLM considers the retrieved contexts, and the query passed by the user to formulate a complete and relevant response, which contains specific details of the retrieved contexts outside of its previous fixed knowledge base.

1.4. Prompt Engineering

To maximise the effectiveness of LLMs, it is essential to engineer effective prompts. Prompt engineering techniques, such as in-context learning, can help improve the capacity of LLMs on a wide range of common and complex tasks such as question answering and arithmetic reasoning. [5] In-context learning is a technique where demonstrations of the task are provided as part of the prompt. It is important to note that the effect of prompt engineering methods can vary a lot among models [6], thus requiring heavy experimentation to find the optimal combination.

1.5. Objectives

This project aims to evaluate the functionality of various existing LLMs, with a focus on their ability to retrieve information from structured and unstructured data. In the context of our project, structured data refers to dates, time, numbers and texts, while unstructured data in this project refers to the incident details. The goal is to enhance incident management effectiveness at Land Checkpoints. Potential operational scenarios include using LLMs to retrieve information from past incidents, which can aid in trend identification and decision making.

Additionally, the project aims to explore the effectiveness of in-context learning in improving the accuracy of ICA incident information retrieval using LLMs. Identifying the optimal prompt engineering technique is crucial for ensuring that ICA officers can retrieve relevant information efficiently, eliminating the need for additional prompting or manual searches through past reports.

2. METHODOLOGY

2.1. Dataset

Using ChatGPT, 100 sets of mock incident data were generated based on the ICA Incident Report framework, in a csv file format. (Refer to Appendix 1 for sample of generated mock incident data).

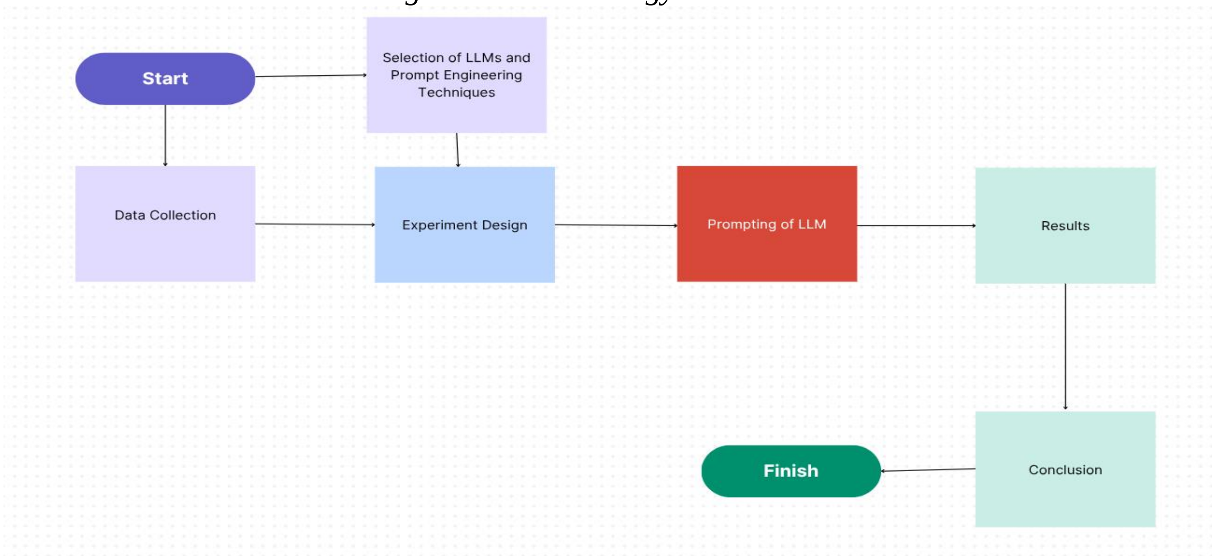
Explanation of Dataset Categories:

Column Name	Column Explanation	Categories or Examples
Date	Date of the incident. Date in DD/MM/YY (2021 – 2024)	2024-03-27
Time	Time of the incident in hour (24-hour) : minute: second	16:45:31
Incident Type	The type of incident that occurred at the checkpoints.	Unauthorised Movement, Chemical Attack, Bomb threats through phone, Handling of Suspicious parcels/letters, Armed Attack, Evasion of Clearance from Singapore
Mode of Conveyance	The vehicle or the transport that the suspect used.	Car, Lorry, Motorcycle, Bus, Bus Hall, Train Hall
Sources of Information	How the ICA officers manage to get their information.	Insider Information, Calls, Voice Comms
Reported by	The rank and name of ICA officer who reported the suspicious incident.	Inspector John Doe
Reported Location	Where the reported incident took place	Possible Locations (Tuas Checkpoint, Woodlands Checkpoint, Woodlands Train Checkpoint)
Incident severity	The severity of the incident	Severity types: (High, Medium, Low)
Incident Details	A Concise 50–200-word summary of the incident type, location, incident severity and action taken	Refer to Appendix 1

2.2. Experimental Setup

Figure 3 below provides an illustration and explanation of the project methodology.

Figure 3: Methodology Flow Chart



- **Data Collection**: ChatGPT Plus was used to generate 100 mock ICA incidents
- **Selection of LLMs and Prompt Engineering Techniques**: 4 LLMs and 2 prompting engineering techniques, zero-shot and few-shot were selected
- **Experiment Design**: A RAG system was developed, using tools such as Python and Langchain, for us to send prompts to LLMs
- **Prompting of LLMs**: A total of 10 prompts for each prompt engineering technique was passed to 4 different LLMs (refer to Appendix 2)
- **Results**: The responses generated by the LLMs were analysed for their accuracy and relevance
- **Conclusion**: The best LLM and prompt engineering for more accurate and relevant information retrieval to enhance land checkpoint operations.

2.3. Selection of Large Language Models

In this project, the LLMs were used to formulate comprehensive and accurate responses retrieved from the data. There are 4 LLMs used, 2 of which had small parameter sizes while 2 had large parameter sizes. The rationale behind having 2 small and 2 large LLMs was to investigate if the parameter size affects quality of output, while this arrangement also helped to find the optimal LLM. The parameter size of an LLM refers to the number of numerical values that an LLM learns during training, allowing it to adjust and understand language. With a greater number of parameters, the LLM can capture more complex language relationships and handle nuanced prompts.

Smaller-sized LLMs	Larger-sized LLMs
Llama3-8b-8192 (8B parameters) Llama3-8b-8192 was built by Meta. It has approximately 8 billion parameters.	**Llama3-70b-8192 (70B parameters)** Llama3-70b-8192 was built by Meta. It has approximately 70 billion parameters.
Gemma2-9b-it (9B parameters) Gemma2-9b-it was built by Google. It has approximately 9 billion parameters.	**Mixtral-8x7b-32876 (46B parameters)** Mixtral-8x7b-32876 was built by Mistral AI. It has approximately 46 billion parameters.

2.4. Selection of Prompt Engineering Techniques

The functionality and relevance to the daily work of ICA officers of various prompt engineering techniques was assessed, and we selected two prompt engineering techniques to be tested in this project, zero-shot prompting and few-shot prompting. Both prompt engineering techniques make use of in-context learning, which is when additional examples or data is included to help the model to understand the prompt better. This allows it to retrieve data that is only relevant to the user's prompt, and structure its response in a desirable manner, like the examples given. In the context of ICA Land Operations, efficiency and accuracy are highly important, hence in-context learning can be able to optimise the LLM's response and retrieval process

2.4.1. Zero-Shot Prompting

Zero-shot prompting, which directly asks the model to perform a task without providing examples, is one of the most popular prompt engineering techniques due to its ease and simplicity. In the day-to-day operations of ICA officers, it is essential to receive immediate and accurate answers, which can be obtained from zero-shot prompting. Additionally, the use of zero-shot prompting does not involve a learning curve as it mimics human dialogue.

Example Prompt using Zero-Shot Prompting:

Who was the suspect involved in an Armed Attack incident on 18 September 2022, at Tuas Checkpoint?

2.4.2. Few-Shot Prompting

Few-shot prompting, which provides a few examples in the prompt to guide the model to perform a task, was chosen due to its ability to improve specificity. Due to the use of examples of desired outputs, the model can understand nuanced expectations. Few-shot prompting is also very adaptable, which is useful when the query requires a specific format or tone that might not be obvious. However, this prompt engineering technique may involve a learning curve as the user needs to learn how to create relevant and useful examples.

Example Prompt using Few-Shot Prompting:

Who was the suspect involved in an Armed Attack incident on 18 September 2022, at Tuas Checkpoint?

Example Question 1: Who was the suspect involved in a chemical attack incident on 1 February

2024, at Woodlands Train Checkpoint? *Example Answer 1*: Johnathan Ang was the suspect in a chemical attack incident on 1 February 2024, at Woodlands Train Checkpoint.

Example Question 2: Who was the suspect involved in a Bomb threat through phone incident on 30 November 2021? *Example Answer 2*: Ng Yi Yuan was the suspect in a Bomb threats through phone incident on 1 February 2024, at Woodlands Train Checkpoint.

2.5. Evaluation Methods

2.5.1. Quantitative Evaluation (Accuracy of Generated Response)

With each prompt created, there was a corresponding answer which was expected to be returned by the LLMs. Each LLM was subjected to 10 rounds of testing (refer to Appendix 2) with each prompt engineering technique (i.e. 20 rounds of testing per LLM, 40 rounds of testing per prompt engineering technique), from which accuracy of the outputs were assessed based on the previously determined expected answer. Each LLM and prompt engineering technique was assigned an accuracy score in percentage based on the number of questions where the output has concepts which matches the expected answer. For example, an LLM tested using zero-shot prompting that produces 5 correct outputs out of 10 prompting tests will be assigned an accuracy score of 50%.

2.5.2. Qualitative Evaluation

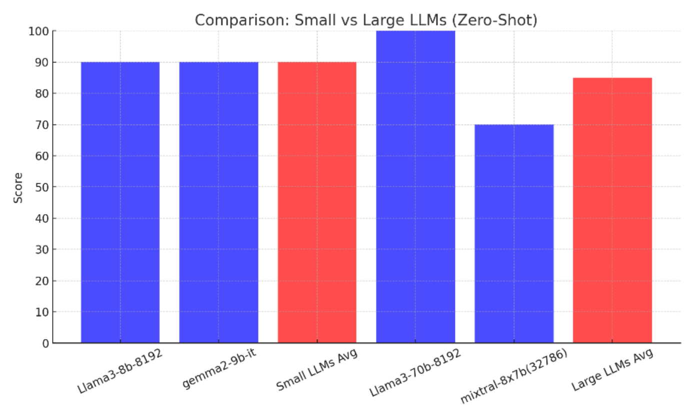
Qualitative evaluation was conducted on each of the LLMs and prompt engineering techniques to assess their functionality and the feasibility of their implementation into the daily functions at Land Checkpoints. The areas assessed include the format of the output of the LLM, the presence or absence of reasoning in the LLM output, and the ease of understanding of LLM output.

3. RESULTS AND DISCUSSION

3.1 Results from Quantitative Evaluation

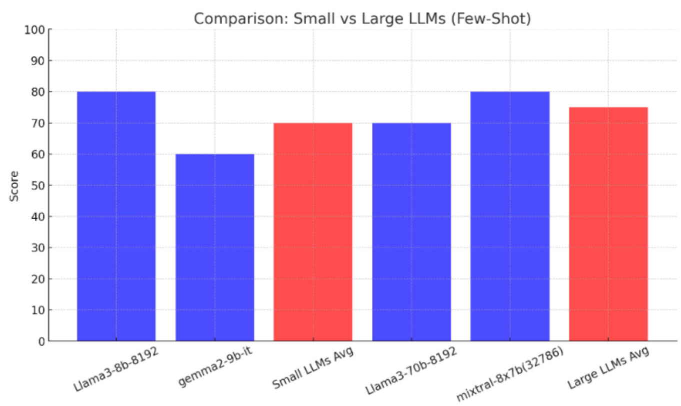
3.1.1. Comparison of Model Sizes for Zero-shot and Few-shot Prompt Engineering Techniques

Figure 4: Overall accuracy score of small vs large LLMs using Zero-shot prompt engineering technique



As illustrated by Figure 4, for Zero-shot prompt engineering techniques, the average accuracy score of small LLMs of 90% is slightly higher than the accuracy score of large LLMs of 85%. Taking into consideration that these LLMs were used for Retrieval Augmented Generation, there are some reasons the smaller LLMs may perform better compared to larger LLMs. For the smaller LLMs, they lack extensive parametric memory, due to the smaller amount of data it is being trained on, hence they are more reliant on retrieved context from external knowledge sources. This allows them to perform well even without in-context learning, as they are able to retrieve context accurately. For larger LLMs, while they may have significantly greater knowledge base from pre-trained data, this may cause them to blend retrieved knowledge with their pre-trained knowledge, rather than just retrieving the contexts as it is. This may cause the larger LLMs to ignore the facts, leading to hallucinations. Additionally, smaller models may be more optimised for retrieval while larger models may be trained for more general purposes due to its larger pre-trained data to answer questions. However, one thing to be note is that these results can also be due to the individual quality of the LLM, as shown by Llama3-70b-8192, having a perfect accuracy score.

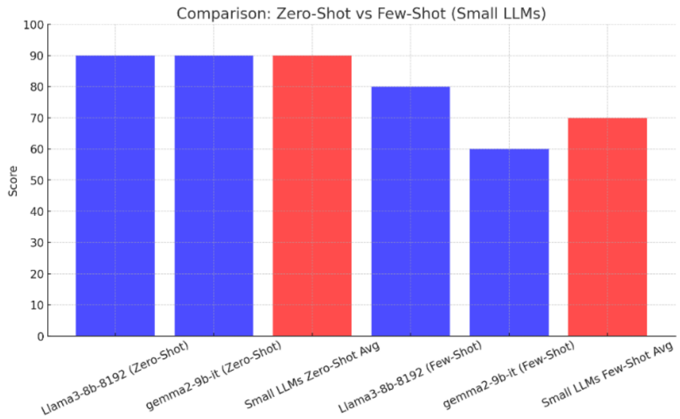
Figure 5: Overall accuracy score of small vs large LLMs using Few-shot prompt engineering technique



As illustrated by Figure 5, for Few-shot prompt engineering techniques, the average accuracy score of small LLMs of 70% is slightly lower than the accuracy score of large LLMs of 75%. Considering that these LLMs were used for RAG purposes, there are a few reasons for the slightly better for larger-sized LLMs in few-shot compared to smaller models. Larger models may have greater in-context learning ability, hence the additional examples provided by the few-shot prompt can allow the larger models to adjust their reasoning based on patterns in examples. Larger models, also trained on a significantly larger amount of data, will be able to filter and decide what context to retrieve from the external knowledge base, compared to smaller models, where if the examples are not very clear, they may struggle to retrieve anything.

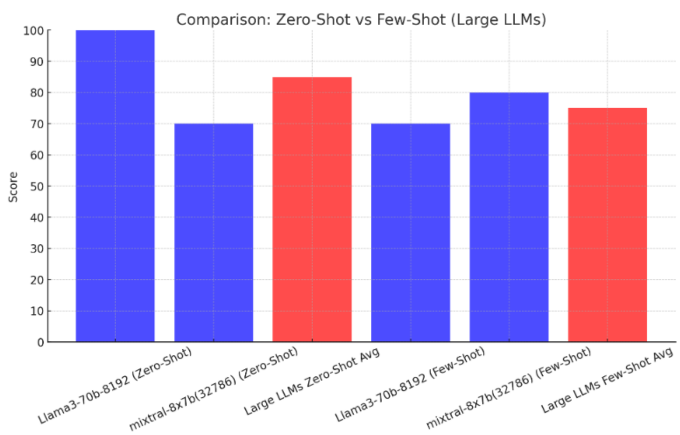
3.1.2. Comparison of Prompt Engineering Techniques for Small and Large LLMs

Figure 6: Overall accuracy score for Zero-shot vs Few-shot prompt engineering techniques for small LLMs



As illustrated by Figure 6, the small LLMs perform significantly better for zero-shot prompt engineering techniques compared to few-shot prompt engineering techniques. The accuracy score when using zero-shot prompt engineering techniques is 90%, higher compared to when using few-shot prompt engineering technique at 70%. This can be attributed to the fact that small-sized LLMs have a small context window, hence with few-shot prompts, they take up valuable context space, so the amount of retrieved context can be limited, hence the answers may miss out certain important details, if the prompt is too long. The examples may also cause the small LLMs to overfit the pattern and ignore the real contexts from the external knowledge base.

Figure 7: Overall accuracy score for Zero-shot vs Few-shot prompt engineering techniques for large LLMs



As illustrated by Figure 7, the large LLMs also perform significantly better, with higher accuracy score when zero-shot prompt engineering technique is used (85%), compared to when few-shot prompt engineering technique is used (75%). The anomaly would be the Mixtral-8x7b-32786, which had a better accuracy score when few-shot prompting was used. The overall trend as well as the anomaly can be explained for a variety of reasons. For the overall trend, the few-shot prompts increase its complexity, compared to zero-shot prompts which are simpler to understand. The increased complexity as well as the examples present in the prompt can lead the large LLMs to hallucinate, compared to zero-shot prompt which priorities retrieval of information from external knowledge base. As for why there was an improvement in the performance of the mixtral-8x7b-32786, the LLM is a Mixture of Experts (MoE) model, thus the number of parameters active at each time per token is reduced. Therefore, with the few-shot prompt, it acts as a guiding framework for the LLM, helping the model to route right retrieved information to the most relevant parameters.

3.2. Qualitative Analysis of Responses by LLMs using Different Prompt Engineering Techniques

Looking at the responses of the small and large LLMs for both zero-shot and few-shot prompt engineering techniques, for zero-shot prompting, the small-sized LLMs, especially the Llama3-8b-8192, had a fixed way of answering, and most of its answers started with the phrase "According to the context...". However, when few-shot prompting was used, the response by the small LLMs structured its response with key words from the prompt present. There was no such problem with larger LLMs. The responses generated by LLMs of both sizes were noticeably shorter when few-shot prompting was used, compared to zero-shot prompting, as the response generated during few-shot prompting was more relevant and left out unnecessary details unlike when zero-shot prompting was used.

4. CONCLUSION

Both small and large LLMs perform similarly for both zero-shot and few-shot prompt engineering techniques. However, using zero-shot prompting with RAG to retrieve information gives the best results, as the accuracy score of small and large LLMs is 90% and 85% compared to when using few-shot prompting with the accuracy score of small and large LLMs at 70% and 75% respectively. While using zero-shot prompting may be the most accurate, few-shot prompting can increase relevancy of response by an LLM.

4.1. Future Work

Future work can explore other types of LLMs, such as OpenAI models (GPT-Turbo4) and HuggingFace models which were unable to be implemented in this project due to cost and limited memory issues. Future work involving predictive analysis can identify trends in certain characteristics of suspicious personnel, allowing for early intervention.

4.2. Limitations of Study

The limited number of LLMs, as well as the number of prompts given to each LLM, could have made the results for the optimal prompt engineering technique less reliable. There was also few number of incidents generated (100), hence the RAG application may not work as well with a significantly increased number of incidents.

5. ACKNOWLEDGEMENTS

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APPENDIX 1 – Sample of Mock Data Generated using ChatGPT

Date	Time	Incident Type	Mode of Conveyance	Sources of Information	Reported by	Reported Location	Severity	Incident Details
19/02/2022	21:57:36	Handling Suspicious letters/parcels	Motorcycle	Calls	ASP Adele Tan	Woodlands Checkpoint	Low	At Woodlands Checkpoint, I noticed a parcel in the motorcycle lane that raised suspicion due to its size and markings. The sender's name was unverified, and upon inspection, a chemical substance was detected inside. The area was secured, and authorities contacted for further investigation. It turned out to be sent by Adam Hisham, who is currently under investigation.
04/03/2021	6:55:23	Evasion of Clearance from Singapore	Motorcycle	Voice Comms	DSP Tan Wei Ming	Woodlands Checkpoint	Low	While at Woodlands Checkpoint, a report via Voice Comms flagged an ongoing evasion of clearance from singapore. Upon inspection, it was clear that the issue required immediate attention. With the cooperation of commuters, the incident was managed swiftly and efficiently.
02/11/2023	3:01:03	Unauthorised Movement	Train Hall	Calls	INSP John Lim	Woodlands Train Checkpoint	Low	At around 12:15, a person was seen attempting to bypass the clearance point in the train hall zone of Woodlands Train Checkpoint. The individual, identified as Chris Tan, was stopped and questioned. It was discovered they were using falsified documents to gain entry. Authorities took over the case.
05/05/2024	13:19:43	Bomb threats through phone	Lorry	Insider Information	SGT Michael Ong	Woodlands Checkpoint	Low	While at Woodlands Checkpoint, a report via Insider Information flagged an ongoing bomb threats through phone. Upon inspection, it was clear that the issue required immediate attention. With the cooperation of commuters, the incident was managed swiftly and efficiently.

Date	Time	Incident Type	Mode of Conveyance	Sources of Information	Reported by	Reported Location	Severity	Incident Details
13/02/2021	18:01:40	Power Failure/System Downtime(Disruption to Operations)	Lorry	Insider Information	INSP Ng Shu Fang	Woodlands Checkpoint	High	During my shift at Woodlands Checkpoint, power was disrupted in the lorry section, halting operations temporarily. Commuters were kept informed, and backup systems were activated within 34 minutes. The issue was due to a short circuit and was resolved promptly by on-site technicians.

APPENDIX 2 – Test Cases for Zero-Shot and Few-Shot Prompts

Zero-Shot Prompts:

- Date and time when ASP Ahmad Faizal reported a medical related incident at Woodlands Train Checkpoint.
  - Correct Answer: 4 October 2024, 5:34pm / 04/10/2024, 17:34:34

- Name of the officer who reported an evasion of clearance from singapore incident on 5 November 2021, around 1am at Tuas Checkpoint.
  - Correct Answer: SGT Michael Ong

- What was the mode of conveyance in an armed attack incident at Woodlands Checkpoint on 16/02/2023.
  - Correct Answer: Bus

- What was the source of information in a bomb threats through phone incident that occurred on 22/10/2024.
  - Correct Answer: Calls

- Where did an unauthorised movement incident happen on 27 January 2023, reported in the wee hours of the morning.
  - Correct Answer: Woodlands Checkpoint

- [Fake Question, test for hallucination]: Incident details of incident DSP Lim Wei Ming reported on 29 March 2022.

- Time difference between when smoke was seen coming from a blue car in Woodlands Checkpoint on 9 March 2023 and when the report is made by the ICA Officer.
  - Correct Answer: 14 hour and 34 minutes

- Who collapsed near the bus hall area at Woodlands Checkpoint on 3 January 2024 and what did he/she suffer from.
  - Correct Answer: Kumar Rajan, Dehydration

- What was the response to a fire-related incident on 24/1/2023, and what was the likely cause of the incident.
  - Correct Answer: ICA Officers used fire extinguishers to douse the flames before firefighters arrived. The fire was traced to an electrical fault

- Give me a description of the vehicle and weapon used by the suspect in an armed attack incident on 12 March 2024.

  - Correct Answer: Red Motorcycle of vehicle plate number SG5157X. Concealed weapon

Few-Shot Prompts:

- Date and time when ASP Ahmad Faizal reported a medical related incident at Woodlands Train Checkpoint. Example(Question): Date and time when ASP Adele Tan reported a handling suspicious letters/parcels incident at Woodlands Checkpoint. Example(Answer): The date and time when ASP Adele Tan reported a Handling Suspicious letters/parcels incident was 19 February 2022, 21:57:36.
  - Correct Answer: 4 October 2024, 5:34pm / 04/10/2024, 17:34:34

- Name of the officer who reported an evasion of clearance from singapore incident on 5 November 2021, around 1am at Tuas Checkpoint. Example(Question): Who was the officer who reported an armed attack incident on 21 August 2022, around 12:45am. Example(Answer): The officer who reported an armed attack incident on 21 August 2022 at 12:45am at Tuas Checkpoint is INSP Ng Shu Fang.
  - Correct Answer: SGT Michael Ong

- What was the mode of conveyance in an armed attack incident at Woodlands Checkpoint on 16/02/2023. Example(Question): What was the mode of conveyance in a fire-related incident at Woodlands Checkpoint on 21/04/2021. Example(Answer): The mode of conveyance at Woodlands Checkpoint on 21/04/2021 is Bus Hall.
  - Correct Answer: Bus

- What was the source of information in a bomb threats through phone incident that occurred on 22/10/2024. Example(Question): What was the source of information in a chemical attack incident that occurred on 20/07/2023. Example(Answer): The source of information of a chemical attack incident on 20/07/2023 was insider information.
  - Correct Answer: Calls

- Where did an unauthorised movement incident happen on 27 January 2023, reported in the wee hours of the morning. Example(Question): Where did a bomb threats through phone incident happen on 16 Novemebr 2021, reported in the evening. Example(Answer): The bomb threats through phone incident happened at Tuas Checkpoint in the evening.
  - Correct Answer: Woodlands Checkpoint

- [Fake Question, test for hallucination]: Incident details of incident DSP Lim Wei Ming reported on 29 March 2022. Example(Question): Incident details of incident INSP John Lim reported on 11 March 2024. Example (Answer): While at Tuas Checkpoint, a report via Insider Information flagged an ongoing evasion of clearance from singapore. Upon inspection, it was clear that the issue required immediate attention. With the cooperation of commuters, the incident was managed swiftly and efficiently.

- Time difference between when smoke was seen coming from a blue car in Woodlands Checkpoint on 9 March 2023 and when the report is made by the ICA Officer. Example(Question): Time difference between when smoke was seen coming from a yellow bus in Tuas Checkpoint on 9 March 2023 and when the report is made by the ICA Officer. Example(Answer): The time difference between when smoke was seen coming from a yellow bus and when the report was made by the ICA Officer is 3 hours and 37 minutes.
    - Correct Answer: 14 hour and 34 minutes

- Who collapsed near the bus hall area at Woodlands Checkpoint on 3 January 2024 and what did he/she suffer from. Example(Question): Who collapsed near the train hall area at Woodlands Train Checkpoint on 17 April 2023 and what did he/she suffer from. Example(Answer): On 17 March 2023, Ryan Lee collapsed near the train hall area. He suffered from a heart attack.
    - Correct Answer: Kumar Rajan, Dehydration

- What was the response to a fire-related incident on 24/1/2023, and what was the likely cause of the incident. Example(Question): What was the response to a fire-related incident on 29/92021, and what was the likely cause of the incident. Example(Answer): On 29/9/2021, Firefighters came promptly to put out the flames, and rescued those in danger. The likely cause of the incident was a short circuit, which led to a fire in the motorcycle area.
    - Correct Answer: ICA Officers used fire extinguishers to douse the flames before firefighters arrived. The fire was traced to an electrical fault
- Give me a description of the vehicle and weapon used by the suspect in an armed attack incident on 12 March 2024. Example(Question): Give me a description of the vehicle and weapon used by the suspect in an armed attack incident on 19 December 2021. Example(Answer): A white car of car plate number SDT5438Z. The suspect used a shiny knife of large size.
    - Correct Answer: Red Motorcycle of vehicle plate number SG5157X. Concealed weapon