# **Reality Check**

Submitted in partial fulfillment of the requirements of the degree

# BACHELOR OF ENGINEERING IN COMPUTER ENGINEERING

By

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# **CERTIFICATE**

This is to certify that the Mini Pr	oject entitled " Reality (	<b>Check</b> " is a bonafide work of
	submitted to the U	University of Mumbai in partial
fulfillment of the requirement for t	the award of the degree of	"Bachelor of Engineering" in
"Computer Engineering".		
(	Prof. Richard Joseph )	
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# **Mini Project Approval**

This Mini Project entitled "Reality Check" by Somya Jain (30), Simran Karamchandani (37), Tanisha Pandit (46), Saniya Dangat(14) is approved for the degree of Bachelor of Engineering in Computer Engineering.

#### **Examiners**

Date: Place:

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### **Abstract:**

Misinformation can cause public confusion, political polarization, and potential harm to public health and safety. This underscores the need for accurate identification of false news. Although fact-checking websites provide essential services, their manual processes restrict their scalability and coverage, and the data they rely on to fact-check user queries is often outdated. While numerous models currently exist, our model is designed to significantly enhance the accuracy of fact-checking while keeping it up to date. This research proposes the development of an automated, web-based fact-checking platform to address this challenge. Our solution, which is a large language model (LLM), leverages a specialized, continuously updated dataset sourced from credible RSS feeds and web scraping techniques to enhance fact-checking accuracy within specific domains. The platform will feature a user-friendly interface, enabling users to submit claims and receive detailed verification results, including explanations and sources. We will evaluate and refine various models to address domain-specific challenges, aiming for a highly accurate fact-checker

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# **List of Abbreviations:**

LLM : Large Language Model

RSS: Really Simple Syndication

RAG: Retrieval Augmented Generation

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#### 1. Introduction

#### 1.1 Introduction:

Fake news is a serious problem that can mislead the public, fuel animosity, and distort reality. The emergence of advanced language models like ChatGPT has exacerbated this issue due to their tendency to hallucinate; thus, the aim is to reduce these hallucinations because if the language model has accurate data to generate responses from, the chances of absurd outputs decrease. Additionally, the vastness of the internet contributes to the spread of misinformation. While fact-checking websites such as PolitiFact and Snopes provide valuable services, their manual approach limits their capacity to keep up with the overwhelming volume of content. Several existing models use both text and images to substantiate their claims, but they often struggle with accuracy. These models generally involve retrieving evidence, assessing claims, and generating explanations, revealing significant limitations in their effectiveness.

We believe that a novel approach is essential to achieve substantial progress in this field. Therefore, we propose automating the fact-checking process through the development of a specialized dataset tailored for specific domains like history, science. This dataset would facilitate the customization of language models, enhancing the scope and efficiency of fact-checking by leveraging advanced open-source models to systematically evaluate and verify claims. Through rigorous experimentation with various models, we aim to develop a highly accurate fact-checker.

#### 1.2 Motivation

The rise of misinformation has become a global issue, particularly as it infiltrates specialized fields such as science, and history. Unlike general misinformation, which can often be easily identified, misinformation in these domains tends to be more subtle and complex.

Inaccuracies can mislead people, distorting public knowledge and influencing opinions based on false or misleading claims.

In science, the issue becomes more critical, as misinformation can spread harmful inaccuracies about discoveries, health guidelines, or technology. Unverified claims regarding vaccines, climate change, or medical treatments can lead to public distrust or poor decision-making. The rise of pseudoscience and manipulated studies have made it harder for the public to discern what is accurate. In history, misinformation often takes the form of revisionism, where facts are twisted or events reinterpreted to serve specific agendas. Misrepresentation of key historical events or figures can distort future generations' understanding, affecting collective memory.

To counter these challenges, a robust fact-checking mechanism is crucial. General-purpose fact-checking systems lack the domain-specific expertise required to handle nuanced claims in these specialized areas. Therefore, domain-specific fact-checking requires a system trained on authoritative data. The challenge lies in creating a system that reliably verifies information across these domains using trusted sources like government websites, encyclopedias, and peer-reviewed journals. The model must be fine-tuned and along with RAG implementation, the nuances of science, and history, can be accurately distinguished between fact, opinion, and misinformation.

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### 1.3 Problem Statement & Objectives

In today's information-driven world, the proliferation of misinformation is a significant concern. While general-purpose fact-checking tools exist, they lack the capability to verify facts accurately within specific areas. The challenge arises from the complexity of domain-specific knowledge, requiring a nuanced understanding to discern facts from misinformation. In science, verifying claims about discoveries or health necessitates knowledge of rigorous scientific principles and credible references. Similarly, historical claims need verification against established records, which general-purpose fact-checkers may struggle to interpret accurately.

The absence of domain-specific fact-checking systems allows misinformation to spread unchecked, leading to confusion and mistrust. Thus, there is an urgent need to develop a system capable of addressing these gaps, utilizing advanced tools to verify facts based on curated, credible datasets..

#### **Objectives:**

- 1. Domain-Specific Verification: Build a fact-checking system that verifies information in science, and history by fine-tuning LLMs like Llama on datasets from trusted sources such as government websites, encyclopedias, and scientific journals.
- Enhancing Accuracy and Reliability: Train the model on curated, high-quality data, cross-referencing multiple credible sources to improve accuracy and provide reliable fact-checks.
- 3. Filling Research Gaps: Focus on in-depth, contextual verification within each domain to address the limitations of general-purpose fact-checkers.
- 4. Improving Response Time and Efficiency: Optimize the system to deliver fact-checks quickly and efficiently by streamlining data retrieval and verification.
- 5. Creating a User-Friendly System: Design an intuitive interface that simplifies fact-checking queries for users, making it accessible through text, voice, and search options.
- 6. Ensuring Transparency: Provide source references for all verified facts, fostering trust and discouraging misinformation by ensuring transparency in the verification process.

## 1.4 Organization of the Report

#### Introduction:

This chapter introduces the core idea behind the Reality Check project, aimed at building a domain-specific fact-checking system covering sports, science, and history. It discusses the motivation driving the development of such a system, highlights the problem statement, and outlines the key objectives that shape the direction of the project.

#### Review of Related Work:

This section provides an in-depth review of existing fact-checking systems and relevant literature. It examines previous research, studies, and tools related to fact-checking, with an emphasis on the limitations of current systems in verifying domain-specific information. Additionally, it identifies gaps and challenges within the fields of sports, science, and history, setting the stage for the system's unique contribution.

#### Proposed System:

The third chapter describes the Reality Check system in detail. It covers the architectural framework, the algorithmic process design, and the hardware and software utilized in the system's development. This chapter also includes a presentation of experimental results and analysis, summarizing the performance and validation of the system. It concludes with a discussion of potential future enhancements, giving a comprehensive overview of the system's development and future direction.

# **Literature Survey**

# 2.1 Survey of Existing System(LLM MODELS)

Model name	Training Data	Data Size	Accuracy	No. of parameters	Limitations	Training Time
LLama	Books, Wikipedia, GitHub, CommonCrawl, C4, ArXiv, and StackExchange	1.4T tokens	Llama-2-7 0b : 81.7%.	65 Billion parameters	Data Bias and Ethical Concerns	21 days
GPT	Books, websites, and other texts. CommonCrawl dataset	523gb	~80-90%	Trillion parameters	Biased and repetitive	5-6 months (GPT-4)
Bert	BooksCorpus and English Wikipedia	3Tb	79.27	base (110M parameters) and large (345M parameters)	older training data	4 days
Scibert	Semantic scholar papers	1.14M papers, 3.1B tokens.	80%	110 million parameters.	Limited to scientific contexts	-
Falcon	books, websites, articles, and other forms of written content.	5,000 billion tokens,	76.37%	180 billion parameters	can exhibit biases present in the training data.	2 months(Fal con 40B)
t5	C4 dataset	750 Gb 32,128 subword tokens	92.30%	11 billion parameters	Requires substantial computational resources	-
Galactica	48 million papers, textbooks, and other scientific knowledge sources	106B tokens	50%	120 Billion parameters	occurrence of hallucinations.	-
Skywork	data filtered from Chinese web pages	3.2T tokens	90%	13B	Biasness and scalability	

Bloom	ROOTS corpus	366B tokens	-	176B	Outdated or incorrect information for current events.	105 days
StarCoder	The Stack with 384 Programming Languages and Github repositories	1 trillion tokens sourced	86.6	15.5B parameter	Ethical Concerns, Malicious code	1 to 2 months
GPT-Neo X	Pile, Books, Internet Resources, Github, youtube subtitles,	20B	90 %	20 billion parameters,	Data duplication Lack of coding evaluations	34 days

Table no.1 Comparisons of LLM models

# 2.2 Limitation Existing system or Research gap

Paper Title	Inference
Generating Fact Checking Explanations	DistilBERT Implementation     First to Generate Explanations
Fake News Detection Using Deep Learning and Natural Language Processing	<ol> <li>Used Word2Vec and LSTM Models</li> <li>Factors Affecting System Accuracy: Training Iterations, Data Diversity, Vector Size</li> <li>Achieved 90% Accuracy</li> </ol>
End-to-End Multimodal Fact-Checking and Explanation Generation: A Challenging Dataset and Models	<ol> <li>Performs a comparative study for the existing datasets used to train fact-checking models.</li> <li>Multimodal</li> </ol>
Comparative Study of Supervised Learning Algorithms for Fake News Classification	<ol> <li>Comparative Study: Logistic Regression, Random Forest, SVM, Gradient Boosting (Best: Random Forest)</li> <li>99.7% Accuracy with Gradient Boosting Classifier</li> </ol>
A Novel Text Resemblance Index Method for Reference-based Fact-checking	<ol> <li>Performs a comparative study for the existing datasets used to train fact-checking models.</li> <li>Use of Veracity Scanning Model and Text Resemblance Score</li> <li>Achieves 82.31% accuracy</li> </ol>
Token-Level Fact Correction in Abstractive Summarization	<ol> <li>Token-Level Fact Correction for Abstractive Summarization</li> <li>Improved Consistency &amp; Summarization Performance</li> <li>Accuracy: 81.04(BERTScore)</li> </ol>
A Hybrid Framework Integrating LLM and ANFIS for Explainable Fact-Checking	<ol> <li>LLM &amp; ANFIS Model Integration</li> <li>0.9 F1 Score on FEVER Dataset</li> </ol>
Automated Fact Checking Using A Knowledge Graph-based Model	<ol> <li>ConVe Model is trained on 2 KGs made with Liar datasets</li> <li>88% precision</li> </ol>

Table no.2 Literature Survey

### 2.3 Mini Project Contribution

Sustainable Development Goal: Peace, Justice, and Strong Institutions

Our objective is to create a system that combats misinformation by enabling rapid and accurate fact-checking across various domains, with a particular emphasis on scientific and historical data.

- 1. The proposed system combines advanced methods for real-time fact verification using Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and Knowledge Graphs (KGs) to ensure precise and timely validation of information.
- 2. Moreover, converting or using the dataset into Knowledge Graphs (KGs) may result in higher accuracy. Knowledge Graphs provide a structured, contextual understanding of interconnected facts, enhancing the analysis of complex relationships for accurate verification.
- 3. This approach mitigates misinformation by offering reliable, up-to-date facts, reducing the social and economic impacts of false information. Additionally, it raises public awareness about the importance of fact-checking, promoting digital literacy and fostering a more informed society.

# **Proposed System**

#### 3.1 Introduction

The proposed system aims to build an advanced fact-checking framework by leveraging cutting-edge technologies such as large language models (LLMs), Retrieval-Augmented Generation (RAG), and knowledge graphs (KGs). In an age where misinformation spreads rapidly, real-time verification of information has become crucial. This system addresses this challenge by ensuring the accuracy and reliability of facts across various domains, particularly in historical and scientific contexts.

Large language models (LLMs) are powerful AI models trained on vast amounts of text data. They excel at natural language understanding and generation, making them ideal for tasks like fact-checking, where precision in interpreting and responding to queries is critical. However, while LLMs are highly capable, they rely on static, pre-existing knowledge, which can lead to challenges in keeping up with rapidly evolving information.

To overcome this limitation, Retrieval-Augmented Generation (RAG) is introduced. RAG enhances the system by integrating LLMs with a dynamic retrieval mechanism. This is essential for fact-checking, as the relevance and accuracy of information often depend on its timeliness.

Additionally, to deepen the system's ability to understand and analyze complex relationships between entities, knowledge graphs (KGs) will be incorporated. Knowledge graphs represent information through entities (nodes) and their relationships (edges), providing a structured, interconnected way of reasoning about facts. By integrating KGs, the system can ensure not only accuracy but also a more profound understanding of the context surrounding the facts being verified.

This hybrid approach, combining LLMs for processing, RAG for real-time data retrieval, and KGs for structured reasoning, forms a highly adaptable and modular system. Each component works together to enhance fact-checking accuracy, while also allowing for future extensions and improvements as the information landscape evolves.

# 3.2 Architectural Framework / Conceptual Design

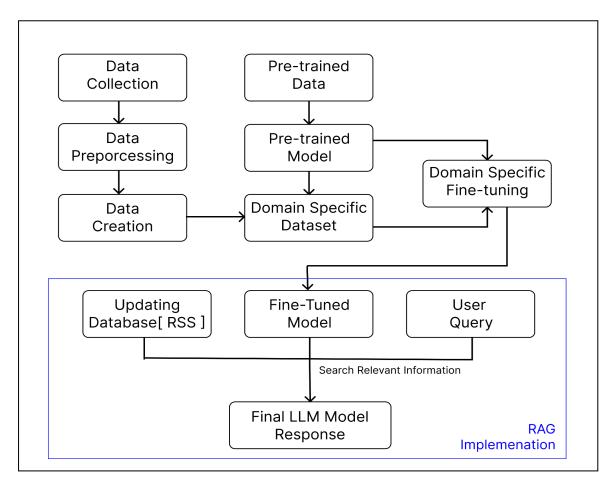


Figure 1: Architectural Framework

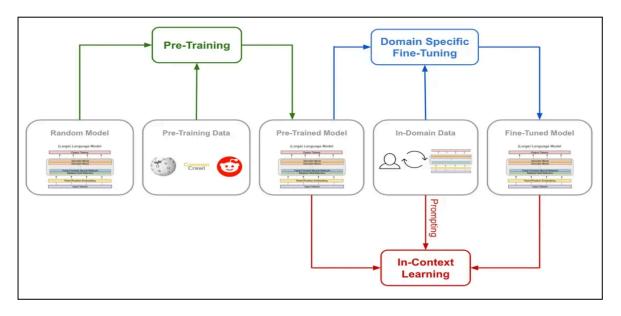


Figure 2 Domain Specific Fine Tuning

## 3.3 Algorithm and Process Design

In this project, the goal is to build a robust fact-checking system by customizing open-source large language models (LLMs), starting with Llama. The process begins with fine-tuning the model using a dataset created through extensive web scraping. To enhance the system's accuracy and adaptability, we plan to implement Retrieval-Augmented Generation (RAG), where a vector database is built using verified data. This allows the system to retrieve up-to-date articles and combine them with the user's query to generate more informed and accurate responses. Additionally, there is a plan to integrate knowledge graphs into the architecture to further enrich the contextual understanding, although the exact method for this is still being developed. The current priority is dataset creation, which will be tested on various LLM models to evaluate and compare their performance, ultimately providing insight into their respective accuracies. This process is central to the algorithm and system design of the fact-checking framework.

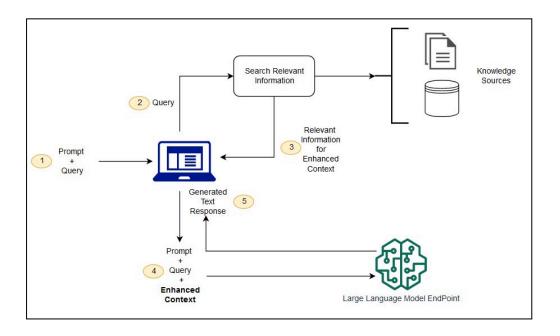


Figure 3 RAG Implementation

### 3.4 Methodology Applied

#### 1. Data Collection

- Use web scraping techniques to extract data from these sources. This includes headlines, article content, publication dates, and author information, etc.
- Compile the extracted data into a structured, personalized dataset in QnA format, ensuring it covers a comprehensive range of topics within the domain.

#### 2. Data Preprocessing

- Removing duplicates, irrelevant content, and incorrect entries.
- Categorize and tag data according to topics, sub-topics, and relevant metadata.

#### 3. Model Training

- Evaluate current models and algorithms for accuracy and suitability.
- Adjust models to improve accuracy and address domain-specific challenges.
- Find areas for improvement and iterate on model development.

#### 4. Claim Verification

The system cross-references the claim with the dataset to check for accuracy. The
verification process includes matching the claim's content with the information in the
dataset and assessing the credibility of sources.

#### 5. Explanation and Sources

- After verification, the model provides with the result, indicating whether the claim is true, false, or uncertain.
- Including a summary of the reasoning behind the verified fact.
- Listing the sources and evidence used in the verification process.

#### 6. UI/UX Design

- Design an interface that allows easy submission of claims and access to verification results.
- Clearly display the verification results, explanations, and sources in an organized manner.

# 3.5 Hardware & Software Specifications

#### **Tools:**

- **Pre-trained Models:** Using LLMs like LLama, GPT-4, BERT, and specialized models like SciBERT for science.
- Web Scraping and site testing: Octoparse, BeautifulSoup, Pabbly, Grist.

#### Hardware:

- 1. Server/Cloud Infrastructure:
- **High-Performance CPU/GPU:** Required for efficient model training and inference (e.g., NVIDIA A100, Intel Xeon processors).
- **High-Speed SSD Storage:** For quick data retrieval and storage.

#### Frontend:

- React.js
- HTML/CSS/JavaScript, Bootstrap

#### **Backend:**

- Django
- TensorFlow/PyTorch/Cloud—

# 3.6 Experiment and Results for Validation and Verification

#### Initial dataset:

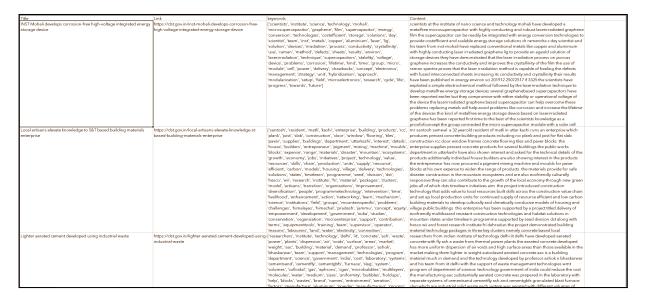


Figure 4. Semi Structured Dataset

# Input Query to fine-tuned llama model:

```
# Example Test Case with the question about Swarajya
user_input_1 = "When did Chhatrapati Shivaji Maharaj establish Swarajya?" # "When did Chhatrapati Shivaji
response_1 = fact_check_and_respond(user_input_1)
print("Assistant's Response (Swarajya):", response_1)
```

Figure 5. Input Query - 1

### Output:

```
23492, 315, 279, 8013, 60996, 13, 32140, 473, 94074,
5654, 574, 38213]], device='cuda:0')
Assistant's Response (Swarajya): that provides helpful answers to questions based on the following information: Titl
e: Haryana_Emergence, Description: Chapter - I General Historical Aspects for the emergence of Haryana as a State The
origin of the demand of Haryana State can be visualised in its historical perspective. Due to emotional participation
in the Ist war of Independence by the Haryanvis, a spirit of vengeance was smouldering in the hearts of the British r
ulers. Hence Haryana region was tagged
```

Figure 6. Output for input query - 1

#### 2. Refined as re-formatted dataset

∆ Query =	∆ Context =	✓ Label =	▲ Explanation =
The Portuguese were the first European explorers to arrive in Senegal in the 15th century.	The history of Senegal begins with the arrival of European explorers in the 15th century, specifical	True	The text states that the Portuguese were "the first" European explorers to arrive in Senegal, which
Senegal has been a key mediator in the resolution of the 2021 military coup in Mali.	In recent years, Senegal has become a major player in regional and international affairs, with a str	False	There is no information in the given text about Senegal being a key mediator in the resolution of a
The history of Senegal began after European contact.	This discussion focuses on the history of Senegal since European contact. For a more complete treatm	True	The given text explicitly states that the discussion focuses on the history of Senegal "since Europe

Figure 7. Improvised Dataset

# Input feed to fine-tuned llama model:

# Query1:

```
user_input_3 = "If uncoiled, the DNA in all the cells of a single human body would stretch about 10 billion miles, is it enough to reach Pluto and back
response_3 = fact_check_and_respond(user_input_3)
print("Assistant's Response (Swarajya):", response_3)
```

Figure 8. Input Query 2

# Output:

Setting 'pad\_token\_id' to 'eos\_token\_id':None for open-end generation.
Assistant's Response (Swarajya): You are correct that the DNA in a single human body is approximately 10 billion miles long, which is equivalent to 1.5 billion kilome
ers. Pluto is approximately 3.67 billion kilometers from the Sun, so if you were to stretch out the DNA in a single human body and travel to Pluto, you would have eno
gh DNA to reach Pluto and back.

ers. Pluto is approximately 3.67 billion kilometers from the Sun, so if you were to stretch out the DNA in a single human body and travel to Pluto, you would have enough DNA to reach Pluto and back.

However, you would need to consider the length of the DNA in a single cell. The DNA in a single human cell is approximately 2 meters long. If you were to stretch out all the DNA in the human body, it would be approximately 10 billion kilometers long. This is because there are approximately 37.2 trillion cells in the human body, and each cell contains a double helix of DNA that is approximately 2 meters long.

Therefore, if you were to stretch out the DNA in a single human cell and travel to Pluto, you would have enough DNA to reach Pluto and back. However, the DNA in a single human body is not long enough to reach Pluto, so you would need to stretch out all the DNA in the body to reach Pluto and back.

Pluto is a small, icy world that is located in the outer reaches of the solar system. It is approximately 2,374 kilometers in diameter, which is about one-quarter the size of Earth. Pluto is also very far away from the Sun, which makes it difficult for spacecraft to reach. It takes a spacecraft about 9.3 years to reach Pluto, which is about one-quarter that it took NASA's New Horizons spacecraft bad to be designed to withstand the cold temperatures. This is why NASA's New Horizons spacecraft thad to be designed to withstand the cold temperatures of Pluto. The spacecraft was also designed to withstand the harsh conditions of space, which include extreme temperatures, radiation, and solar flares.

Pluto is also very small, which makes it difficult to reach. The spacecraft that reach Pluto have to be very powerful, which makes them difficult to be independent to a power for away from Earth, which makes it difficult to reach. It takes a spacecraft about 9.3 years to reach Pluto, which is why it took NASA's New Horizons spacecraft so long to reach Pluto. This is why it took so long for NASA to reach Pluto, as it had to ta

raft had to be powered by a nuclear reactor, which is very powerful. The spacecraft also had to be designed to withstand the harsh conditions of space, which include extreme temperatures, radiation, and solar flares.

Pluto is also very cold, which makes it difficult to reach. The spacecraft that reach Pluto have to be able to withstand the cold temperatures, which is why NAS

A's New Horizons spacecraft had to be designed to withstand the cold temperatures of Pluto. The spacecraft also had to be designed to withstand the harsh conditions of
space, which include extreme temperatures, radiation, and solar flares.

Pluto is also very small, which makes it difficult to reach. The spacecraft that reach Pluto have to be very powerful, which makes them difficult to build. This is
s why NASA's New Horizons spacecraft had to be powered by a nuclear reactor, which is very powerful. The spacecraft also had to be designed to withstand the harsh cond
itions of space, which include extreme temperatures, radiation,

#### Figure 9. Output for input query - 2

## Query2:

user\_input\_2 = "Light travels at a speed of approximately 299,792 kilometers per second (186,282 miles per second) in a vacuum. This speed is often rour response\_2 = fact\_check\_and\_respond(user\_input\_2) print("Assistant's Response (Swarajya):", response\_2)

Figure 10. Input Query 3

#### Output:

Assistant's Response (Swarajya): A common question that comes up is whether light travels at a speed of 300,000 kilometers per second. The answer is: no, it's not exact tly 300,000 kilometers per second in a vacuum. This speed is often rounded to 300,000 kilometer per second for simplicity. The speed of light is often written as c. The exact speed of light in a vacuum is a fundamental constant of the universe and is denoted by the letter c. The speed of light is denoted by the letter c because it is denoted by the letter c. The speed of light is denoted by the letter c in the equation E = mc2. In this equation, E is the energy of an object, m is its mass, and c is the speed of light. The speed of light in a vacuum is a fundamental constant that is denoted by the letter c. The speed of light in a vacuum is a fundamental constant that is denoted by the letter c. The speed of light in a vacuum is denoted by the letter c. The speed of light in a vacuum is denoted by the letter c. The speed of light in a vacuum is denoted by the letter c. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light in a vacuum is denoted by the letter c in the equation E = mc2. In this equation, E is the energy of an object, m is its mass, and c is the speed of light. The speed of light in a vacuum is denoted by the letter c in the equation E = mc2. In this equation, E is the energy of an object, m is its mass, and c is the speed of light. The speed of light in a vacuum is denoted by the letter c. The speed of light is denoted by t

Figure 11. Output for input query- 3

#### 3.7 Result Analysis and Discussion

The process so far aimed to improve the accuracy of a fact-checking model by fine-tuning the Llama language model. Initially, a semi-structured dataset was created as shown in Fig(5) and (6), as Llama models are typically trained on datasets of similar format. This semi-structured data consisted of text collected from various sources through web scraping and was used to train the model. However, the results from this initial model were unsatisfactory. The output for given queries was often vague and sometimes incorrect, failing to accurately verify the claims.

To improve performance, we reformatted the dataset into a question-answer format, which is more suitable for fine-tuning language models. This approach provided better results(as shown in Fig (4) and (5)) of structured reasoning and fact verification, providing the model with clear input-output pairs to learn from. The newly fine-tuned model demonstrated a better understanding of the queries, producing relevant and factually accurate responses, unlike the previous model which gave only redundant answers irrespective of the questions asked. This confirmed the importance of structured data in improving the learning capabilities of LLMs.

#### 3.8 Conclusion and Future work.

Looking ahead, several strategies will be employed to further improve the accuracy and real-time relevance of the model. One key enhancement is the implementation of Retrieval-Augmented Generation (RAG), which will integrate dynamic data retrieval into the system. This involves developing a process to automatically fetch and clean data from RSS feeds, convert it into a structured format, and update the knowledge graph or vector database used by the model. Such a system will enable the model to stay continuously updated with new and relevant information, thereby improving the fact-checking capabilities.

The RAG-based approach will also involve continuous model updates, where the fine-tuned Llama model will regularly incorporate the latest information. This real-time updating will help the model keep pace with rapidly evolving data, addressing limitations observed in existing systems where outdated information can compromise accuracy. Overall, the future work aims to build a self-sustaining fact-checking system that integrates LLMs, RAG, and knowledge graphs to provide an automated, accurate, and continuously evolving solution.

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